Ville Tikka

ON LOAD MODELING OF ELECTRIC VEHICLES—ENERGY SYSTEM VIEWPOINTS

ACTA UNIVERSITATIS LAPPEENRANTAENSIS 1124

Ville Tikka

ON LOAD MODELING OF ELECTRIC VEHICLES—ENERGY SYSTEM VIEWPOINTS

Dissertation for the degree of Doctor of Science (Technology) to be presented with due permission for public examination and criticism in the Auditorium 1318 at Lappeenranta–Lahti University of Technology LUT, Lappeenranta, Finland on the 12th of January, 2024, at noon.

Acta Universitatis
Lappeenrantaensis 1124

Supervisor Professor Samuli Honkapuro
LUT School of Energy Systems
Lappeenranta–Lahti University of Technology LUT
Finland

Reviewers Professor Hannu Laaksonen
School of Technology and Innovations
University of Vaasa
Finland

Dr. Juha Karppinen
Virta Ltd
Helsinki
Finland

Opponent Professor Heikki Liimatainen
Faculty of Built Environment
Tampere University
Finland

ISBN 978-952-412-046-3
ISBN 978-952-412-047-0 (PDF)
ISSN 1456-4491 (Print)
ISSN 2814-5518 (Online)

Lappeenranta–Lahti University of Technology LUT
LUT University Press 2024

Abstract

Ville Tikka
On Load Modeling of Electric Vehicles—Energy System Viewpoints
Lappeenranta 2024
90 pages
Acta Universitatis Lappeenrantaensis 1124
Diss. Lappeenranta–Lahti University of Technology LUT
ISBN 978-952-412-046-3, ISBN 978-952-412-047-0 (PDF), ISSN 1456-4491 (Print), ISSN 2814-5518 (Online)

Customer load modeling is a fundamental component of many business practices in the energy industry, particularly in the electricity distribution and retail sectors. The increasing numbers of electric vehicles (EVs) and thereby the increase in EV charging loads connected to the grids have significant implications for distribution system operators (DSOs) as they may result in increased peak loads, major changes in load profiles, and a need to invest in the infrastructure. It is also worth considering the potential opportunities that dynamic EV charging loads can bring, for instance, for the demand-side management.

The main focus of this doctoral dissertation is to investigate and provide a broad but also detailed overview of the load modeling of EV charging (spatial and temporal) mainly from the distribution system operator's (DSO's) business perspective, but also to cover the perspectives of the other players, such as the electricity retailer and the aggregator.

The main objective of the doctoral dissertation is to offer tools to support and improve the DSO's long-term strategic planning process in order to identify challenges or opportunities of the large-scale EV smart charging. Modeling tools and analysis of EV charging loads also provide important information for other players in the field of energy systems and energy markets. The main focus is on determining the stochastic nature of the charging loads to facilitate load formation and forecasting activities. Spatiotemporal modeling techniques are also applicable for analyzing and managing electricity retailers' or flexibility aggregators' customer portfolios and (load) profile risk.

As the main outcome, the doctoral dissertation shows the variety of EV charging applications and modeling practices. The novelty of the dissertation is in summarizing a wide range of EV charging applications and laboratory experiments to quantify the impacts of EVs on the power system and its various parties. A particular novelty lies in adding the features of the cold environment to the load modeling of EVs, but also in showing that spatial modeling benefits from using convolutional neural network (CNN) models. As the main conclusion, it can be stated that EV charging will have a significant impact on the power system, but the impact will depend on the development of smart charging applications.

Keywords: electric vehicle (EV) charging, distribution system operator (DSO), retail, ag-

gregator, controlled charging, asset management, load modeling

Acknowledgments

This study was carried out in the LUT School of Energy Systems at Lappeenranta–Lahti University of Technology LUT, Finland, between 2010 and 2023.

First of all, I would like to express my deepest gratitude to my supervisor, Professor Samuli Honkapuro for his valuable guidance and patience to wait for the results of the present doctoral dissertation. In addition, I owe my deepest gratitude to my retired supervisor, Professor Jarmo Partanen who offered me the opportunity to work in the Laboratory of Energy Markets and Power Systems, but also guided me in my studies for several years.

I thank the preliminary examiners of the dissertation, Professor Hannu Laaksonen with the University of Vaasa and Dr. Juha Karppinen with Virta Ltd for examining and commenting the manuscript. The comments of the preliminary examiners played a significant role in enhancing the doctoral dissertation.

I would like to extend my sincere thanks to Associate Professor (Tenure Track) Jukka Lassila for unparalleled support in my pursuit of a doctoral degree.

I would express my deepest gratitude to Dr. Hanna Niemelä for helping me to polish the language in several publications, especially in the present dissertation. All remaining errors are my own.

I would like to express my deepest appreciation to my colleagues Dr. Juha Haakana, Dr. Janne Karppanen, Dr. Aleksi Mattsson, Dr. Jouni Haapaniemi, Dr. Gonçalo Pinto Mendes, Dr. Otto Räisänen, Dr. Salla Annala, Dr. Aleksei Romanenko, and Mr. Ville Sihvonen. I also wish to thank all the current and former co-workers in the Laboratory of Energy Markets and Power Systems.

In addition, I wish to thank Mr. Joni Markkula for inspiring discussions and support.

The financial support of Jenny and Antti Wihuri Foundation, Walter Ahlström Foundation, KAUTE Foundation, and Fortum Foundation is gratefully acknowledged.

Thanks to my family and especially to my mother, father, and brother.

Last but not least, I express my gratitude to my loved Anni and Emilia for bearing with me.

Ville Tikka
December 2023
Lappeenranta, Finland

Contents

List of publications

Publication I
Tikka, V., Lassila, J., Haakana, J., and Partanen, J. (2011). "Case study of the effects of electric vehicle charging on grid loads in an urban area." In: *2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies.* Manchester, UK.

The author of this dissertation was responsible for the conceptualization, data gathering, data processing, simulation, and writing of the publication.

Publication II
Tikka, V., Lassila, J., Makkonen, H., and Partanen, J. (2012). "Case study of the load demand of electric vehicle charging and optimal charging schemes in an urban area." In: *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe).* Berlin, Germany.

The author of this dissertation was responsible for the conceptualization, data gathering, data processing, simulation, and writing of the publication.

Publication III
Lassila, J., Haakana, J., Tikka, V., and Partanen, J. (2012). "Methodology to Analyze the Economic Effects of Electric Cars as Energy Storages." *IEEE Transactions on Smart Grid* 3.1, pp. 506–516.

The author of this dissertation was responsible for the data processing, simulation, and co-writing of the publication.

Publication IV
Lassila, J., Tikka, V., Haakana, J., and Partanen, J. (2012). "Electric cars as part of electricity distribution—who pays, who benefits?" *IET Electrical Systems in Transportation* 2.4, pp. 186–194.

The author of this dissertation was responsible for the data processing, simulation, and co-writing of the publication.

Publication V
Tikka, V., Makkonen H., Lassila, J., and Partanen, J. (2014). "Case Study: Smart Charging Plug-In Hybrid Vehicle Test Environment with Vehicle-To-Grid Ability." In: *2014 16th European Conference on Power Electronics and Applications* Lappeenranta, Finland.

The author of this dissertation was responsible for the data processing, measurement setup design and implementation, and co-writing of the publication.

Publication VI
Markkula, J., Tikka, V., and Järventausta, P. (2021). "Local versus centralized control of flexible loads in power grid." In: *CIRED 2021—The 26th International Conference and Exhibition on Electricity Distribution.* Vol. 2021. IET. Institution of Engineering and

Technology, Online conference.

The author of this dissertation was responsible for the data processing, simulation, and co-writing of the publication.

Publication VII
Tikka, V., Haapaniemi, J., Räisänen, O., and Honkapuro, S. (2022). "Convolutional neural networks in estimating the spatial distribution of electric vehicles to support electricity grid planning." *Applied Energy* 328, pp. 120–124.

The author of this dissertation was responsible for the implementation of the concept and model used in the publication, and is the primary author of the paper.

Publication VIII
Tikka, V., Haapaniemi, J., Räisänen, O., Mendes, G., Lassila, J., and Honkapuro, S. (2023). "Electric vehicle charging measurements in the Nordic environment—Charging profile dependence on ambient temperature." In: *CIRED 2023—The 27th International Conference and Exhibition on Electricity Distribution.* Vol. 2023. IET. Institution of Engineering and Technology, Rome, Italy.

The author of this dissertation was responsible for defining the measurement setups, data processing, modeling, simulation, and writing of the publication.

Publication IX
Mendes, G., Tikka, V., Vahidinasab, V., and Aghaei, J. (2023). "Review of Emerging Advanced Smart Charging Flexibility Business Models." In: *CIRED 2023—The 27th International Conference and Exhibition on Electricity Distribution.* Vol. 2023. IET. Institution of Engineering and Technology, Rome, Italy.

The main contributions of the author of this dissertation were joint conceptualization and editing of the contents mainly in the introduction and the section on advanced smart charging business models, as well as presenting the manuscript in the conference.

The publications are in a chronological order. In this doctoral dissertation, the publications are referred to as Publications I–IX. The author's contribution to the publications is described in detail in the Introduction.

Declaration of AI use
During the preparation of this doctoral dissertation, Ville Tikka, the author of the dissertation, used WriteFull in order to develop the presentation of textual information in the summary of the dissertation. After using Writefull, the author reviewed and edited the content and takes full responsibility for the content of the doctoral dissertation.

Nomenclature

Acronyms

AC	Alternating current
aFRR	Automatic Frequency Restoration Reserve
AMR	Automatic meter reading
ANN	Artificial neural network
BEV	Battery electric vehicle
CCS	Combined charging system
CHP	Combined heat and power
CNN	Convolutional neural network
Co2	Carbon dioxide
Co2eq	Carbon dioxide equivalent
CPO	Charging point operator
DC	Direct current
DER	Distributed energy resource
DSO	Distribution system operator
EC	European Commission
EMSP	Electric mobility service provider
EU	European Union
EV	Electric vehicle
EVSE	Electric vehicle supply equipment
FCEV	Fuel cell electric vehicle
FCR	Frequency Containment Reserve
FCR-D	Frequency Containment Reserve for Disturbance Operation
FCR-N	Frequency Containment Reserve for Normal Operation
FFR	Fast Frequency Reserve
HEV	Hybrid electric vehicle
ICE	Internal combustion engine
LV	Low-voltage
mFRR	Manual Frequency Restoration Reserve
MV	Medium-voltage
NTS	National travel survey
OCPP	Open charging point protocol
OEM	Original equipment manufacturer
OSCP	Open smart charging protocol
PHEV	Plug-in hybrid electric vehicle
PV	Photovoltaic
SoC	State of charge
TOU	Time-of-use

TSO	Transmission system operator
V2G	Vehicle-to-grid

Greek alphabet

Φ	Cumulative normal distribution
α	Confidence level
μ_{P}	Customer mean power
σ_{P}	Customer power standard deviation

Latin alphabet

C_{int}	Interruption cost
C_{inv}	Investment cost
C_{loss}	Cost of network losses
C_{opex}	Operational cost
C_{total}	Total investment cost
$P_{\max}$	Peak power
T	Time interval end value
W	Annual energy
$i_{\mathrm{2w},\mu}$	Normalized two-week index (mean value)
$i_{\mathrm{2w},\sigma}$	Normalized two-week index (standard deviation)
$i_{\mathrm{h},\mu}$	Normalized hour index (mean value)
$i_{\mathrm{h},\sigma}$	Normalized hour index (standard deviation)
n_{c}	Number of customers in the group
t	Time index
z	Confidence number

1 Introduction

Customer load modeling is a fundamental component of many business practices in the energy industry, particularly in the electricity distribution and retail sectors. The Finnish distribution system operators (DSOs) manage an asset of €12 billion, which is under constant development, while the electricity retailers are managing a customer portfolio of 3.5 million customers (Energiavirasto, 2023). Major changes in the load have an impact on the whole energy system and especially on the DSO's asset management, but also on the retailers' portfolio risk.

Over the past few decades, the development of electricity distribution has remained relatively stable since the rapid electrification of rural areas in Finland, which began in the 1950s and was mostly completed a decade later. However, recent advances, such as the emergence of centralized and distributed renewable production types, heat pumps, and other smart appliances, have influenced the distribution system. In addition to other novel loads and resources, the increasing adoption of electric vehicles (EVs) has brought new challenges and opportunities to the DSOs. In particular, the charging loads of EVs have unique characteristics that make them among the most dynamic load types that the distribution grids have ever encountered. There are other industrial appliances and some household devices, such as sauna stoves, that are capable of rapid power transitions in a short period of time, but EVs introduce more controllable dynamics, and more importantly, also dynamics in terms of location. EVs can be connected to the grid at various locations, making load forecasting or the availability of demand response resources a more challenging task. Therefore, it is crucial for the DSOs to investigate and understand the load modeling of EV charging from a business perspective to effectively plan and develop the grid infrastructure for the future. The same challenges of changing customer loads are also present for other players in the energy market, such as energy retailers, aggregators, and energy managers.

Historically, household electricity consumption profiles have been well-predictable and, in addition, they have been taken into account in the DSOs' strategic planning processes and development of the grid infrastructure. However, over the past decade, the situation has started to change rapidly as more and more EVs are connecting to the grid behind the customer connection points in private and public locations. EVs have emerged as one of the largest new loads that the distribution grids are facing. The nature of EV charging loads, with their dynamic and variable characteristics, presents challenges, but also opportunities for the DSOs. EV charging loads depend on various factors, such as charging station types, constraints of the charging power level, EV properties, duration of charging, the charging behavior of EV users, and use cases. Therefore, it is critical for DSOs to accurately model and track these factors as EV charging loads become more common. The latest novelty in EV charging is bidirectional power transfer, which enables a wider range of applications and makes the modeling task even more challenging.

To effectively model and analyze EV charging loads, large datasets are often required.

Data-driven analysis can provide valuable information on the behavior of EV users, the demand for the charging infrastructure, and the impact of EV charging on the distribution grid. Models based on wide and reliable datasets offer valuable insights into charging patterns, energy consumption, and other relevant factors, from which DSOs can gain a comprehensive and detailed understanding of the EV charging load characteristics. This understanding can guide strategic planning decisions, development of the grid infrastructure, and resource allocation, among other more technical key aspects of DSO operations, such as daily operating activities. Similarly, modeling results can be utilized to support electricity retailers' portfolio management or to improve aggregators' estimation of the flexibility resource availability.

The increasing numbers of EVs and thereby the increase in EV charging loads connected to the grids have significant implications for DSOs as they may result in increased peak loads, major changes in load profiles, and a need to invest in the infrastructure. It is worth considering also the potential opportunities that dynamic EV charging loads can bring, such as demand-side management. DSOs must strike a balance between addressing the challenges posed by EV charging loads and leveraging the opportunities they present to ensure reliable and efficient operation of the distribution grid.

The main focus of this doctoral dissertation is to investigate and provide a broad but also detailed overview of the load modeling of EV charging (spatial and temporal) mainly from the DSO's business perspective, but also to cover the perspectives of the other players, such as the electricity retailer and the aggregator. The dissertation identifies the main factors to be tracked as EV charging loads are becoming more common. The analysis relies on large datasets and a variety of different types of charging applications.

1.1 Main drivers of the change

The key driver is the increasing awareness of environmental values and the global climate. The emerging concern for the environment and climate change has led to global environmental policies that drive toward carbon dioxide (CO_2) emissions-free societies. For example, the European Union (EU) has set a long-term strategic goal to achieve a climate-neutral economy by 2050 (European Commission, 2019). Similar targets are also set globally, and commitments such as the Paris Agreement (*Paris Agreement* 2015) have been signed. There are several studies indicating that the human-caused climate change is causing serious changes in living environments worldwide (Intergovernmental Panel on Climate Change (IPCC), 2023), and therefore, action must be taken as soon as possible.

1.1.1 Energy sector

As a result of the energy policy drivers, the proportion of renewable energy production is expected to increase globally by 2 400 GW between 2022 and 2027 (International Energy Agency, 2022). Figure 1.1 shows the rapid increase in the renewable electricity production types.

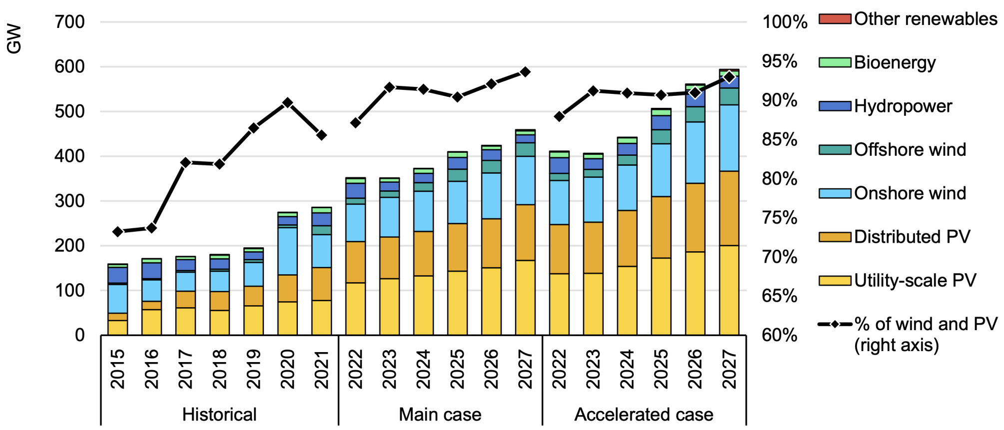


Figure 1.1: Proportion of renewable electricity production globally in 2015–2027 (history and forecast) (International Energy Agency, 2022).

The forecasts and targets are even higher, as stated, for instance, by the report of the Intergovernmental Panel on Climate Change (IPCC) (2023). Major changes in production structures pose challenges not only in the transmission grids but also in the electricity distribution, as the main proportion of the increasing renewable electricity production is small-scale distributed production. A large amount of solar photovoltaic (PV) production introduced to the distribution grid is something that was not fully incorporated in grid planning when the grids were deployed several decades ago. The traditional DSO task has been to manage voltage drops, but recently there have been problems with increasing voltage levels on the customer side, mainly caused by surplus distributed solar power production. As distribution grids were never prepared for such a transformation of the production structure, issues are emerging with increasing voltage levels, which are already visible in continental European grids (Zakeri et al., 2021).

Unique mainly to the Nordic environment, DSOs are also facing a loss of customers in sparsely populated areas (Haakana et al., 2022). The decreasing number of customers combined with the long distances and tight requirements for the security of supply make a unique challenge to tackle. While some areas are losing customers, there are other areas that are gaining in popularity especially during summer and winter vacation periods. Modern vacation homes are well equipped and often connected to electricity grids.

As private transportation is changing, new challenges are arising in areas that are losing customers but also in areas gaining in popularity as vacation destinations.

The set of challenges is substantial for the whole power system and will have an impact on the system in terms of production, transmission, distribution, and consumption. Residential customers are facing major changes related to the changing primary energy of transportation, as EVs are likely to be charged mainly at home(Ward et al., 2023; Autoalan Tiedotuskeskus, 2020). Residential customers will experience the integration of solar PV in their close proximity, as a large proportion of the production capacity is installed in private residences. Many residences are renovated to enhance the efficiency of the energy usage, the most typical example being installation of a heat pump to replace a direct electric space heater or an oil burner.

DSOs are at the core of the system that provides electricity to more demanding customers. Grid development and investment planning are urgent topics in many companies. The Nordic environment can be seen to provide a head start for many companies, as the grids are already dimensioned to withstand rather high heating loads in winter while also delivering electricity to long distances in sparsely populated rural areas. But even more importantly, it is crucial to make wise investment plans as the existing grid infrastructure is already very expensive in comparison with countries where the average loads are lower and the distances are shorter because of the more densely populated areas.

1.1.2 Transportation sector

Decarbonizing transportation is one of the main goals on the way to carbon-neutral society and also to meet the European Union's emissions reduction targets for 2050. The transportation sector produces 28% of the total CO_2 equivalent emissions of the energy sector in Finland, even though the energy usage of the transportation sector is only 16% of the total.

Fossil fuel sources that are today widely used in the transportation sector in developed countries are about to disappear in the coming decades, while the demand for fossil fuels in developing countries is still increasing. The political pressure to reduce CO_2 emissions puts more pressure on fuel taxation. The question often raised is: When does the fuel cost too much? Traditional combustion engines have strong rivaling technologies, such as electric motors and combustion engines capable of using biofuels or hydrogen cells. The electric motors have major advantages over other technologies. First, the electric motor is simple to manufacture, making it often durable and reliable. Second, an electric motor has a superior efficiency compared with internal combustion engines (Ehsani et al., 2010). As a result of the superior efficiency, the energy consumption is noticeably lower than with the rivaling technologies. These competitive advantages make electric cars an attractive option. The electrification of transportation started globally more than a decade ago and is today reaching more than 2.3 million cars a year (International Energy Agency, 2023). In

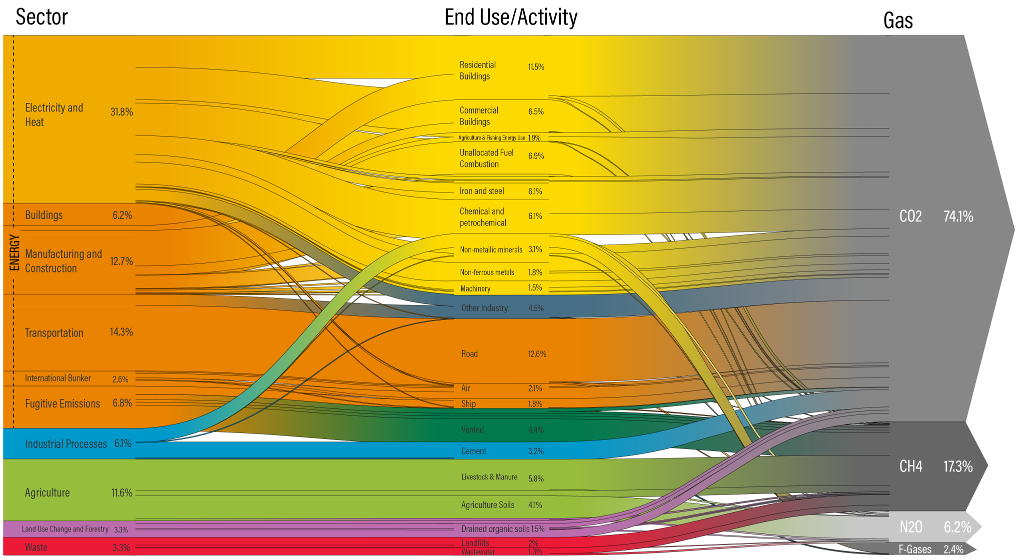


Figure 1.2: World greenhouse gas emissions in 2019 by sector, end use, and gases. Adopted from the Climate Watch platform (Climate Watch Platform, 2022).

Finland, the transition to electric mobility is still modest, but the number of EVs doubles each year. According to current forecasts, the national EV fleet will reach 740 000 cars by 2030 (Vasara et al., 2022). The size of the fleet was 150 000 cars at the end of May 2023. Furthermore, it should be noted that the EV sales have outnumbered the sales of petrol and diesel cars in several months (Traficom, 2023).

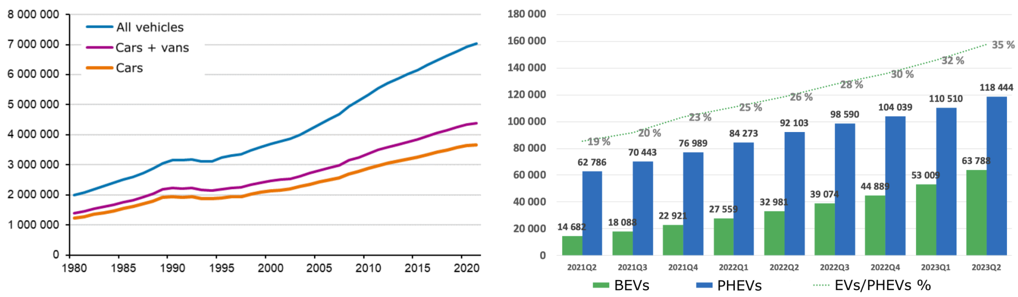


Figure 1.3: Registered vehicles in Finland and the proportion of EVs and PHEVs (Teknologiateollisuus, 2023; Statistics Finland, 2023a; Traficom, 2023).

Pure EVs have rival technologies such as renewable liquid fuels that can be used in conventional vehicles; biogas that can also be used in conversion vehicles; and technologies such as electrolysis-based hydrogen production. The efficiency of the electric vehicle is in a league of its own compared with other technologies, but EVs have a major drawback in terms of driving range. The present technology can provide vehicles with a driving range from a hundred to several hundreds of kilometers, which may seem quite modest in comparison with petrol cars, which have a typical range of up to a thousand kilometers. Plug-in hybrid electric vehicles (PHEVs) play a key role in solving problems related to the driving range, because they can operate short distances in the EV mode and then switch to using an internal combustion engine when the battery is drained. Even though the typical driving distance per person in Finland is only 45 km/d (Lehto, 2018), people still seem to experience range anxiety (Guo et al., 2018). The typical trip lengths are also often relatively short, as shown by an example of the Finnish driving statistics in Figure 1.4.

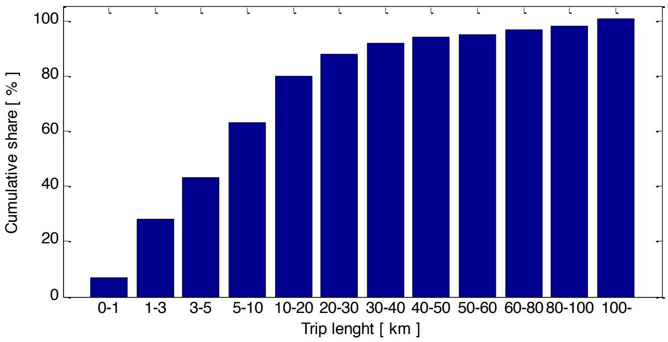


Figure 1.4: Cumulative proportion of trip lengths driven by car in Finland (aggregated data of the national travel survey) (Pastinen et al., 2006; Tikka et al., 2012).

In theory, if all cars could be replaced with electric cars, the yearly electricity usage would increase by 10 TWh in Finland. According to the current production structure in Finland, the production of the required 10 TWh of electricity would increase the CO2-eq emissions by 0.55 Mt carbon dioxide equivalent (CO_2-eq) assuming that the average emissions of the production would be 55 g/CO_2-eq per produced MW (Fingrid, 2022), but replacing 3 million cars with electric ones would reduce the total emissions by approximately 5 Mt CO_2-eq (Traficom, 2022a). If EVs were charged only with renewable energy, the reduction in emissions would be even greater.

Although the distribution networks are facing also many other challenges, the EV charging is one of the major factors that influence the development of loads in the distribution networks. Uncontrolled EV charging has a temporal nature aligned with the other household appliance loads. Often, the EV charging loads occur on the grid at the same time when, for example, lights are on and other household appliances are used. The pattern may break if charging is controlled to gain benefits in the form of cheaper charging or to receive remuneration for acting on someone else's behalf, for example, by joining in a virtual power plant or other demand response activities. The charging applications may have a variety of different targets and beneficiaries. The most typical target could be a smart charging application that aims to provide the cheapest charging event for the homeowner based on a time-of-use (TOU) electricity tariff. In cases where uncontrolled EV charging can be modeled mostly based on statistics (Rautiainen et al., 2012; Z. Liu et al., 2014; LIU et al., 2015; Pareschi et al., 2020) that describe how people travel by car, smart charging applications need more knowledge of the characteristics of the charging application. Similarly, traditional heating loads or other household appliance loads have been modeled primarily based on historical load data (Mutanen et al., 2011). Smart load control changes the nature of load behavior, and the modeling must adapt to the new characteristics (Tuunanen, 2015). The loads can be controlled to gain benefits locally, but control signals can be produced regionally, nationally, or even globally. The frequency of the transmission network or the prices of the electricity market are signals that are temporally synchronous over large geographical areas. If such signals are used to control large volumes of resources in a single low-voltage (LV) network or a medium-voltage (MV) feeder, the impacts on the peak load can be dramatic. EV charging poses a major risk to distribution grids as the charging load is very dynamic, it can reach relatively high powers, and it can be controlled relatively fast.

1.2 The main objectives of the work

The main objective of the doctoral dissertation is to offer tools to support and improve the DSO's long-term strategic planning process in order to identify challenges or opportunities of the large-scale EV smart charging. Modeling tools and analysis of EV charging loads also provide important information for other players in the field of energy systems and energy markets. The main focus is on determining the stochastic nature of the charging loads to facilitate load formation and forecasting activities. Spatiotemporal modeling techniques are also applicable for analyzing and managing electricity retailers' or flexibility aggregators' customer portfolios and (load) profile risk.

In this doctoral dissertation, smart charging may refer to charging with functions such as peak shifting, valley filling, cost minimization, ancillary services, or functions related to vehicle-to-grid applications. The EV charging load differs from traditional static loads by its more uncertain dynamic nature if not actively controlled, and it can occur in different parts of the grid and have different power demand depending on the charging spot. At the same time, the load can have a dynamic behavior due to battery constraints (temperature dependence, charging dynamics due to current rating). The active control changes the load behavior in some applications like in the case of active energy resources, but in many applications the behavior of the load is limited by many boundary conditions that are present only for EV charging. The dissertation focuses on the following objectives to provide in-depth understanding of the impact of EV charging on the businesses of DSOs and other stakeholders in the energy sector in general:

- Identification of the key factors of EV charging that are relevant for the DSO's long-term planning and

- Identification of the key parameters required for efficient modeling of the EV charging profile to support operation and planning activities of other energy system stakeholders.

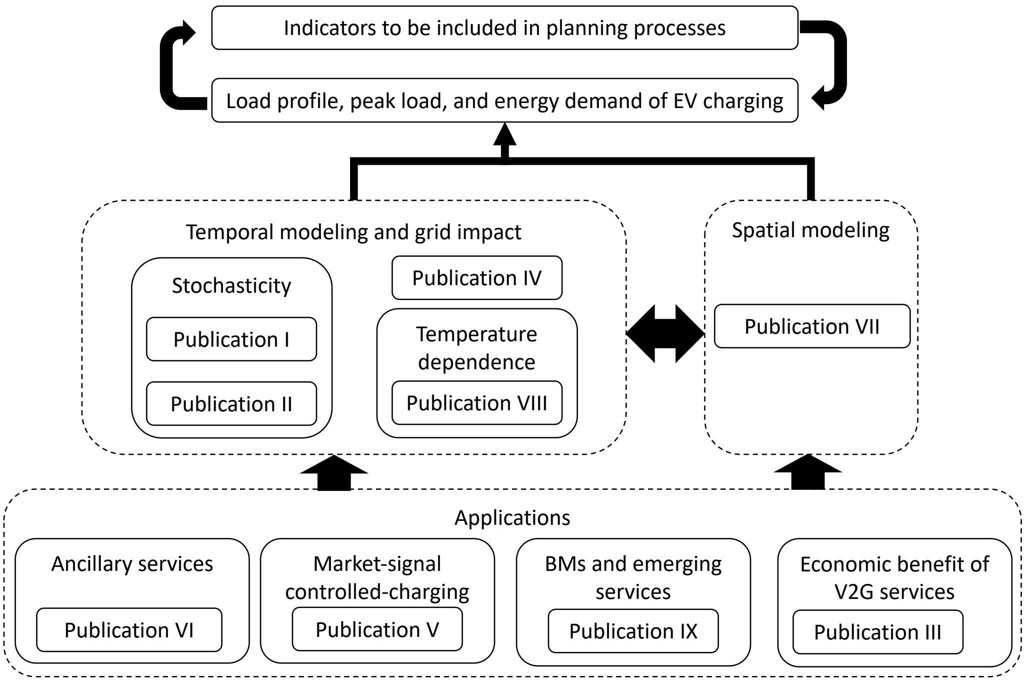


Figure 1.5: Outline of the doctoral dissertation.

The primary outcome of the dissertation is broad understanding and a methodology to assess EV charging loads and the load development. The results are applicable to DSO companies, electricity retailers, aggregators, and also other stakeholders in the energy market that evaluate customer loads. The practical use cases can be related to grid dimensioning, from the customer end to upstream distribution networks. The in-depth understanding of the characteristics of the load profile can be employed in portfolio management, as well as in managing the profile risk of the customers. For aggregators, the load modeling methodology provides a good starting point to estimate the temporal and spatial availability of the flexibility. The dissertation describes the main factors and indicators that are critical to the DSO business and the strategic planning process. The dissertation does not aim to provide one solution for the planning, but rather a methodology or a path to follow in the planning process. The modeling cases and examples focus solely on private customers and households, but the methodology is also applicable to load modeling of other types of customers, such as housing cooperatives, workplace charging, and fleet charging. The modeling relies on publicly available data sources for the sake of transparency and ease of applying the methodology in practice.

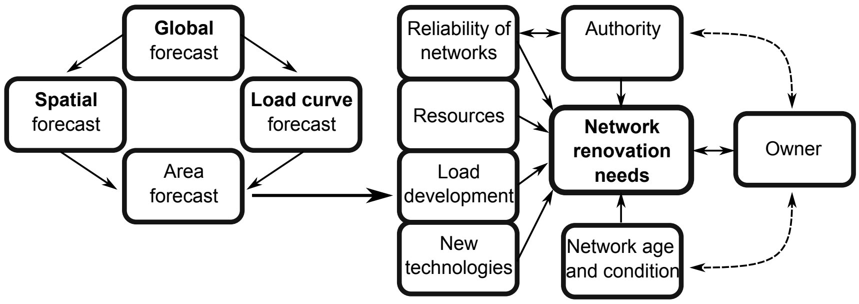


Figure 1.6: Planning process simplified (Willis, 2004; Lassila, 2009)

The main research questions of the dissertation focus on EV charging and the aspects that impact the DSO business. The key objective is to show how various charging applications impact the load profiles. Some of the applications can be seen as assets to manage the load development, but others may have an opposite impact. In other words, other applications contribute to the temporal peak shaving as others cause a dramatic increase in the peak load. The main research questions that the dissertation seeks to answer can be summarized as follows:

- What are the methods applicable to estimate and forecast EV charging loads?
- How can EV charging flexibility be added to load modeling?
- What are the key input variables for the load modeling of EV charging?
- What are the key indicators that DSOs should follow to efficiently prepare for the massive transformation of private traffic?
- How does ambient temperature impact the load profiles?
- What are the value propositions of the vehicle-to-grid (V2G) business models?

1.3 Methods and research data

The doctoral dissertation shows various aspects of the load modeling of EV charging. The research presented in the dissertation mainly applies quantitative methods to emphasize the variety of objective measurements and statistics. The main statistics and measurements are related to passenger traffic as well as the utilization rate and usage patterns of cars, but also to mathematical or numerical analysis of data collected through polls, questionnaires, and surveys. The data are often further developed into a format that better suits the purposes of mathematical analysis.

The modeling presented in the dissertation is mainly carried out as stochastic time series simulation or modeling. The principal stochastic time series modeling technique is Monte Carlo simulation. The models representing individual events or samples are built applying different sampling methods based on statistics and measured data.

The spatial analysis and modeling uses a machine learning technique, more specifically, a convolutional neural network (CNN). The input data of the spatial analysis are Finnish socioeconomic and vehicular data represented in a raster format.

The modeling and scenarios also benefit from the use case and business case definitions and reviews. The definitions provided for the use cases are essential to understand which stakeholders are involved and what their interactions are.

In addition, the analysis uses hourly resolution electricity consumption data, i.e., automatic meter reading (AMR) data gathered from several DSOs in the course of the research. The simulation results are often assessed against actual customer AMR data to gain a more accurate real-world perspective to the matter.

The results are presented as time series, lookup tables, and lists of variables. The author's long history in the EV charging research has shown that the results are highly dependent on the input data, which are constantly changing and evolving as the electric mobility is gaining in popularity. Therefore, when interpreting the results, the main focus should be on identifying the critical inputs that will affect the end results, such as the absolute peak power or temporal features of the peak power in certain areas of interest. The numerical results presented in this dissertation are valuable, but should be applied to further analysis with caution, bearing in mind the current phase of the electrification of the traffic.

1.4 Scientific contribution

The main contribution of the present doctoral dissertation is the description of how EV charging loads can be efficiently modeled for the long-term planning of the distribution grid. The modeling methodology consists of modeling tools for assessing the temporal stochastic properties of the EV charging loads but also estimation of the spatial distribution of the charging loads. The scientific contributions of the dissertation are summarized as follows:

- The dissertation provides broad understanding of the complex modeling problems related to the load modeling of EV charging.

- The dissertation describes a continuous process of how EV charging loads can be included in the strategic planning processes of DSOs, and what the key factors impacting the shape of the load curve are.

- The dissertation shows how real-world characteristics, such as the dependence on ambient temperature, are included in the modeling process.

1.5 Outline of the dissertation

The structure of the doctoral dissertation is the following. After the introduction, the second chapter focuses on the modeling of EV charging. First, the current status of research on EV charging is presented by a review of the extensive literature on the topic. The literature gives the reader a good background of the load modeling of EV charging and of the stochastic properties of the load type under investigation. It also covers the broad background data that are incorporated in the load modeling. The chapter also gives examples of use case definitions.

The third chapter outlines the operating environment to place the studies presented in the dissertation in context. The chapter discusses the planning of distribution grids in brief.

The fourth chapter shows the nature of the impact of EV charging loads on the different stakeholders in the energy system and summarizes the impact of the different use cases on energy systems.

The fifth chapter summarizes the results, discusses the scientific contributions of the work, and concludes the dissertation.

1.6 Summary of the publications

This dissertation consists of nine publications, three of which are peer-reviewed articles in high-level journals, and six of which are peer-reviewed conference papers published in conference proceedings. The publications have been published between 2011 and 2023; the author of this dissertation is the primary author in one journal article and in four conference papers. A summary of each publication is given below:

Publication I demonstrates how the effects of the large-scale electrification of transportation on the distribution grid can be assessed and how the necessary reinforcements can be defined. The publication evaluates the impact of electric vehicle charging on the distribution fees paid by the end customers. The publication demonstrates a stochastic modeling approach to model the impact of electric vehicle charging.

Publication II shows how the effects of the large-scale electrification of transportation on the distribution grid can be evaluated in the case of local peak shaving applications. The publication assesses the potential savings gained by locally controlling the charging of electric vehicles. The publication demonstrates a stochastic modeling approach to model the impact of electric vehicle charging.

Publication III describes a methodology to analyze the economic effects of electric cars as an energy storage on the distribution system. The publication shows how electric vehicles can be used as an energy storage and describes the methodology to estimate the monetary value of such an application.

Publication IV proposes an approach and a methodology to estimate and analyze the impact of electric vehicles on the electricity grid.

Publication V describes a plug-in hybrid vehicle test environment with intelligent charging with a vehicle-to-grid ability. In addition to describing the test bed functionalities, the paper provides examples of real-life smart application testing with a test bed. The paper discusses the TOU tariff-based charging strategy and summarizes the benefits and concerns related to such a charging strategy.

Publication VI compares EV charging control architectures in the case of ancillary services by using real-world measurements from pilot installations. As the main contribution, the existing infrastructure is shown to not support the ancillary service type of applications.

Publication VII investigates the feasibility of the convolutional neural network in the spatial modeling of EV charging. A CNN-based model is proposed to estimate the spatial distribution of the EVs. The main contribution of the publication is to show that convolutional neural networks have advantages over more traditional spatial modeling approaches.

Publication VIII demonstrates that the EV charging load curve is dependent on ambient temperature. The publication uses laboratory measurements to illustrate that charging of EVs at cold ambient temperatures dramatically increases grid loads.

Publication IX focuses on the study of potential V2G business cases. The main aim of the publication is to provide an overview of EV charging applications and especially bidirectional charging applications.

In addition, the author of this doctoral dissertation has published several peer-reviewed publications that support the research on the topic of the dissertation, but are not included in the work. In these publications, the author has modeled and written the majority of the content in the articles. The most relevant publications are listed below.

Tikka, V., Romanenko, A., Alamäki, J., Mashlakov, A., Luoranen, M., Honkapuro, S., and Partanen, J. (2020). Energy flexibility harvesting from data analytics—integration of building energy resources into energy markets. In: *CIRED - Open Access Proceedings Journal*. Vol. 2020. 1. Berlin, Germany: IET, pp. 746–749. DOI: 10.1049/oap-cired.2021.0215

Tikka, V., Romanenko, A., Mashlakov, A., Annala, S., Honkapuro, S., and Parta-

nen, J. (2019b). Novel Technical Solutions as an Enabler of the Small-Scale Demand Response Resources. In: *CIRED 2019 Conference*. Madrid, Spain: AIM. DOI: 10.34890/943

Tikka, V., Mashlakov, A., Kulmala, A., Repo, S., Aro, M., Keski-Koukkari, A., Honkapuro, S., Järventausta, P., and Partanen, J. (2019a). Integrated business platform of distributed energy resources – Case Finland. *Energy Procedia* 158, pp. 6637–6644. ISSN: 18766102. DOI: 10.1016/j.egypro.2019.01.041

Tikka, V., Belonogova, N., Lana, A., Honkapuro, S., Lassila, J., and Partanen, J. (2018b). Control Architecture Requirements of Multitasking Battery Resource Operation. In: *2018 15th International Conference on the European Energy Market (EEM)*. vol. 2018. Ljubljana, Slovakia: IEEE, pp. 1–5. ISBN: 978-1-5386-1488-4. DOI: 10.1109/EEM.2018.8469855

Tikka, V., Makkonen, H., Lassila, J., and Partanen, J. (2014). Case study: Smart charging plug-in hybrid vehicle test environment with vehicle-to-grid ability. In: *2014 16th European Conference on Power Electronics and Applications*. Lappeenranta, Finland: IEEE, pp. 1–10. ISBN: 978-1-4799-3015-9. DOI: 10.1109/EPE.2014.6910765

Tikka, V., Lassila, J., Haakana, J., and Partanen, J. (2016). Electric vehicle smart charging aims for CO2 emission reduction? In: *2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. Ljubljana, Slovakia: IEEE, pp. 1–6. ISBN: 978-1-5090-3358-4. DOI: 10.1109/ISGTEurope.2016.7856250

Furthermore, the author has been actively co-authoring in the following peer-reviewed publications. As a co-author, he participated in writing and content production and provided comments on the manuscripts. The most relevant ones are listed below.

Haakana, J., Tikka, V., Tuunanen, J., Lassila, J., Belonogova, N., Partanen, J., Repo, S., and Pylvänäinen, J. (2016). Analyzing the effects of the customer-side BESS from the perspective of electricity distribution networks. In: *2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. Ljubljana, Slovakia: IEEE, pp. 1–6. ISBN: 978-1-5090-3358-4. DOI: 10.1109/ISGTEurope.2016.7856338

Haapaniemi, J., Tikka, V., Haakana, J., Lassila, J., and Partanen, J. (2016). Aurinkosähkön mahdollisuudet maaseudulla. *Maaseudun uusi aika* (24), pp. 5–19

Lassila, J., Tikka, V., Haapaniemi, J., Child, M., Breyer, C., and Partanen, J. (2016). Nationwide photovoltaic hosting capacity in the Finnish electricity distribution system. In: *European Photovoltaic Solar Energy Conference*. Munich, Germany. DOI: 10.4229/EUPVSEC20162016-6AV.4.11

Breyer, C., Tsupari, E., Tikka, V., and Vainikka, P. (2015). Power-to-Gas as an Emerging Profitable Business Through Creating an Integrated Value Chain. *Energy Procedia* 73, pp. 182–189. ISSN: 18766102. DOI: 10.1016/j.egypro.2015.07.668

Miettinen, J., Tikka, V., Lassila, J., Partanen, J., and Hodge, B. M. (2014). Minimizing wind power producer's balancing costs using electrochemical energy storage. In: *The Nordic Conference on Electricity Distribution Management and Development*. Stockholm, Sweden, pp. 8–9

Makkonen, H., Tikka, V., Lassila, J., Partanen, J., and Silventoinen, P. (2014). Demonstration of smart charging interface in Green Campus. In: *2014 16th European Conference on Power Electronics and Applications*. Lappeenranta, Finland: IEEE, pp. 1–10. ISBN: 978-1-4799-3015-9. DOI: 10.1109/EPE.2014.6910776

Makkonen, H., Tikka, V., Lassila, J., Partanen, J., and Silventoinen, P. (2013). Green campus - energy management system. In: *22nd International Conference and Exhibition on Electricity Distribution (CIRED 2013)*. Vol. 2013. 615 CP. Institution of Engineering and Technology, pp. 1137–1137. ISBN: 978-1-84919-732-8. DOI: 10.1049/cp.2013.1088

Makkonen, H., Tikka, V., Kaipia, T., Lassila, J., Partanen, J., and Silventoinen, P. (2012). Implementation of smart grid environment in Green Campus project. In: *CIRED 2012 Workshop: Integration of Renewables into the Distribution Grid*. Lisbon, Portugal: IET, pp. 240–240. ISBN: 978-1-84919-628-4. DOI: 10.1049/cp.2012.0825

Moreover, the author has published and authored several research reports. The most relevant ones are listed below.

Tikka, V., Lassila, J., and Laine, T. (2021b). *Technical report: Measurements of cold climate EV charging*. LUT Scientific and Expertise Publications, Tutkimusraportit - Research Reports 130. Lappeenranta, Finland: LUT University

Tikka, V., Kalenius, J., Räisänen, O., and Lassila, J. (2021a). *Loppuraportti: Sähköautojen latauksen muodostama kuormitus- ja mitoitusteho erilaisissa toimintaympäristöissä [In Finnish]*. LUT Scientific and Expertise Publications, Tutkimusraportit - Research Reports 131. Lappeenranta, Finland: LUT University

Tikka, V., Belonogova, N., Honkapuro, S., Lassila, J., Haakana, J., Lana, A., Romanenko, A., Haapaniemi, J., Narayanan, A., Kaipia, T., et al. (2018a). *Multi-objective role of battery energy storages in an energy system*. LUT Scientific and Expertise Publications, Tutkimusraportit - Research Reports 75. Lappeenranta, Finland: LUT University

2 Electric vehicle charging

The Only Constant in Life Is Change. – Heraclitus

This chapter focuses on EVs and EV charging. It is often overlooked that electric mobility has a long-standing history going far beyond the mobility that is nowadays mostly based on liquid fuels. The history of electric mobility begins approximately in the early 19th century, with the conception and development of various prototypes and concepts that laid the foundation for the modern electric cars that we see today (Wakefield, 1998).

In addition to a history overview, the chapter focuses on the modeling of EV charging and gives insights into how load modeling has been applied in the grid load analysis and the distribution grid development. Furthermore, the chapter presents methods that are available to address modeling issues. A further focus of the chapter is on the presentation of background data, as they play a key role in the load modeling of EV charging. Referring to the famous citation “The only constant in life is change” by the Creek philosopher Heraclitus, also the EV charging is undergoing a never-ending change. The modeling input variables keep changing and evolving as the number of cars increases and the technology evolves. Thus, rather than locking the view or focusing on a single analysis, a case study, or a set of results, it is much more important to understand the “mechanics” of the peak load and load profile formation.

First, the chapter gives an idea of the history and current technology of EVs and standards related to EV charging. Second, the modeling of EV charging is investigated and the relevant literature is reviewed. Third, an insight into modeling data is given to provide a good understanding of relevant data sources. Finally, the impact of the use case in modeling is discussed.

2.1 History and technology overview

The first steps in electric transportation were made in the 19th century. In the 1820s and 1830s, mainly the inventors and academics Ányos Jedlik, Sibrandus Stratingh, Robert Anderson, and Thomas Davenport created the first very robust electric vehicles (Guarnieri, 2012), powered by nonrechargeable or disposable batteries. These early attempts were primarily aimed at proving the concept rather than introducing practical transportation solutions. The development was continued by Robert Davidson, who developed the first real-size electric locomotive dubbed “Galvani” in 1842 (Post, 1974) (Guarnieri, 2012).

In the mid-19th century, there were major advancements that sped up the development of electric locomotives and cars. The most crucial development to facilitate the storage of electrical energy was a feasible dynamo that would enable the generation of electricity. The first generator that could be coupled with a steam engine was developed by

Zénobe Gramme in 1869. Gramme merged many ground-breaking developments discovered by the Danish engineer Sören Hjorth, the German entrepreneur and inventor Werner Siemens, the Italian scientist Antonio Pacinotti, and the Slovak-Hungarian priest Ányos Jedlik (Guarnieri, 2012). In 1859, the French physicist Gaston Planté released the first lead-acid accumulator that could be charged (Guarnieri, 2012). The first accumulator was developed further by the French chemist Camille Alphonse Faure in 1881 (Guarnieri, 2012).

The rechargeable battery enabled the faster development of EVs in the late 19th and early 20th centuries. In each continent during this time, electric cars gained in popularity for urban transportation because of their quiet operation, ease of use, and lack of emissions compared with internal combustion engine (ICE) vehicles. Companies like Detroit Electric and Baker Electric became well-known manufacturers of EVs, catering primarily to wealthy individuals and women drivers who valued the convenience of electric cars. The development continued and led to technological advancements that enabled longer ranges and higher top speeds. In 1899, Belgian Camille Jenatzy drove the top speed record with his car *Jamais Contente* (Never Satisfied) of 105.88 km/h. This was the first time a land vehicle broke the speed of 100 km/h (Guarnieri, 2012), (Wakefield, 1998).

Despite their advantages, electric vehicles faced challenges from the growing popularity of gasoline-powered cars, which benefited from the expanding road infrastructure and the ability to cover longer distances. In the 1920s, EVs started to gradually disappear (Guarnieri, 2012). Some use cases like golf carts and milk delivery vans in the UK remained (Guarnieri, 2012). The discovery of vast oil reserves and improvements in gasoline engine technology led to the dominance of internal combustion engine vehicles.

The late twentieth century saw a renewed interest in electric vehicles owing to concerns about air pollution and dependence on fossil fuels (Høyer, 2008). Carmakers experimented with hybrid vehicles that combined internal combustion engines with electric propulsion systems. The Toyota Prius, introduced in 1997, became a symbol of this hybrid movement (Høyer, 2008). Meanwhile, advances in battery technology began to pave the way for practical all-electric vehicles.

The 21st century marked a significant turning point for electric vehicles. Technological breakthroughs in battery chemistry and energy storage led to the development of electric cars with longer ranges and more affordable prices. The launch of vehicles like the Tesla Model S and Nissan Leaf brought EVs into the mainstream, showcasing their performance, sustainability, and widespread appeal (Dijk et al., 2013).

In the 2010s, electric mobility underwent significant development and transformation, driven by advancements in technology, growing environmental concerns, and shifting consumer preferences. Along came a significant increase in the variety of EV models available on the market. Traditional automakers and newcomers alike began offering a broader range of EV options, including battery electric vehicles (BEVs) or all-electric vehicles, PHEVs, and other hybrid models. This expansion provided consumers with more choices, catering to different preferences and needs (Dijk et al., 2013).

One of the most crucial developments was the advancement in battery technology. Lithium-ion batteries, which power many modern EVs, became more efficient, offering an increased energy density and longer driving ranges (Dijk et al., 2013). These improvements addressed one of the key concerns of potential EV buyers: range anxiety (Guo et al., 2018). As a result, EVs became more practical for daily use and longer trips.

In the 2010s, Tesla played a significant role in driving the popularity of electric vehicles. After the launch of the Tesla model S, electric cars started to gain traction in sales. Tesla's approach in design and technological decisions disrupted the traditional automotive industry. Electric mobility became associated with a high performance due to the instant torque delivery of electric motors. This led to the emergence of electric sports cars and supercars that rivaled their internal combustion engine counterparts in terms of acceleration and top speed (Thomas et al., 2019). Other automakers soon started to announce plans to electrify their offerings.

In addition, in the 2010s, many governments worldwide introduced incentives to promote electric mobility. These incentives included tax credits, rebates, reduced registration fees, and access to bus lanes with EVs. Additionally, stricter emissions regulations and fuel efficiency standards set by many governments encouraged automakers to invest in electric vehicle technology to meet environmental targets (Asgarian et al., 2023). The major automakers announced their commitment to electrify their fleets. Some companies pledged to produce a certain percentage of electric vehicles within a specific time frame (Motavalli, 2021). These commitments signaled a long-term shift toward electric mobility within the automotive industry.

The growth of electric vehicle adoption in the 2010s led to a greater focus on the charging infrastructure. Governments, businesses, and utilities began to consider investing in the construction of public charging networks to address the concerns of potential electric vehicle buyers about access to convenient and reliable charging options (Kumar et al., 2021). The increasing concerns about climate change and environmental sustainability motivated consumers to consider cleaner transportation alternatives including electric vehicles, which have zero tailpipe emissions and which are becoming popular as a way to reduce individual carbon footprints. Additionally, the decade saw the electrification of public transport systems, with electric buses gaining traction in urban areas as cities sought cleaner and quieter alternatives to traditional diesel buses (Flaris et al., 2023), thus contributing to reducing air pollution and improving the quality of urban life.

In general, the 2010s were a major disruption for traditional mobility and a decade of transformation for electric mobility (Dijk et al., 2013), marked by advances in technology, changes in consumer perceptions, and increased support from governments and industry stakeholders (Asgarian et al., 2023). The groundwork laid during this period set the stage for an even more substantial growth and innovation in the electric vehicle sector in the years to come.

2.1.1 Modern electric vehicles and charging infrastructure

In recent decades, the automotive landscape has undergone a remarkable transformation, spearheaded by the emergence of EVs. These vehicles, driven by the dynamic synergy of technological innovation, environmental consciousness, and evolving consumer preferences, have redefined the concept of personal mobility. Modern EVs can be categorized by the type of their power train:

- Battery Electric Vehicles (BEVs): Exclusively powered by electricity, BEVs emit zero tailpipe emissions. Prominent examples include, for example, Tesla cars or Nissan Leaf. Nowadays, nearly all automobile manufacturers offer a BEV alternative.
- Plug-in Hybrid Electric Vehicles (PHEVs): Combining electricity and ICE, PHEVs offer flexibility for short-range electric operation and extended gasoline-powered trips (also diesel, ethanol, bio-petrol, bio-diesel, or synthetic liquid fuels).
- Hybrid Electric Vehicles (HEVs): Featuring a mixture of electric and internal combustion propulsion, hybrid electric vehicles (HEVs) optimize fuel efficiency while employing regenerative braking to recharge their modest batteries.
- Hydrogen Fuel Cell Electric Vehicles (FCEVs): Fueled by hydrogen gas, fuel cell electric vehicles (FCEVs) employ fuel cells to produce electricity, emitting only water vapor.

This doctoral dissertation focuses on cars that can be charged from the grid, as they are the most relevant ones when considering the impact on the electricity infrastructure and energy markets. FCEVs are also contributing greatly to the demand of electric energy, but the energy is transferred to the vehicle as hydrogen, which is produced from renewable energy sources. Electric cars have evolved significantly in the past decade, even if only observed through registration statistics. The average battery capacity has increased considerably in recent years. Early model EVs had battery capacities of 20 to 30 kWh, which was mainly enough to provide a driving range for traffic in the city. Today, typical battery sizes are notably larger, up to 100 kWh and above. Figure 2.1 shows the average battery size of the cars requested in Finland over the past ten years.

The total battery storage capacity has risen considerably, but also individual cars have double that capacity compared with the early stage EVs. The increased battery capacity also means that high-power charging is now able to increase the charging power even further without significantly changing the battery chemistry toward power-oriented battery types.

Modern electric vehicles support standard charging interfaces (IEC, 2017), allowing inoperable charging sessions to take place at almost any location, whether it is home charging

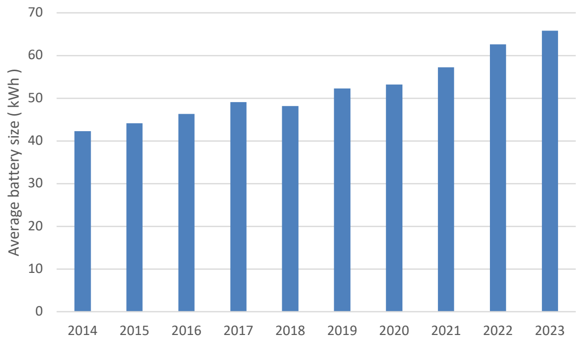


Figure 2.1: Average battery size of the BEVs registered in Finland in 2014–2023.

or a public charging place. The charging infrastructure has developed considerably over the years, as shown in Figure 2.2. Public chargers are also rather well distributed across the whole country; even the sparsely populated northern regions of the country have a good coverage of chargers.

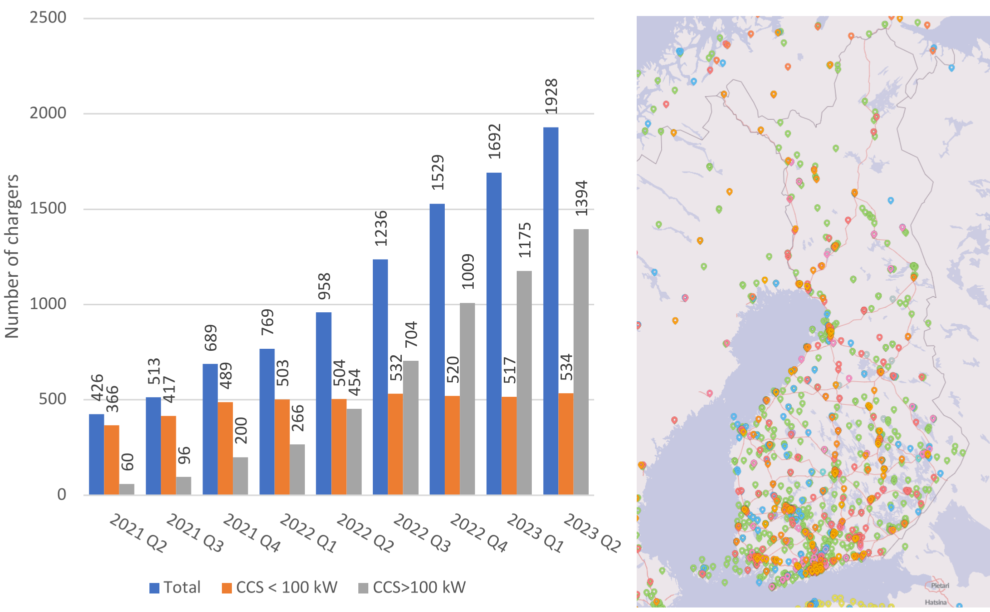


Figure 2.2: Number of public fast chargers (only CCS) in Finland in 2021–2023. The statistics (Teknologiateollisuus, 2023) and spatial distribution of chargers (all public charging points), (note that the map does not list all chargers in Sweden and Norway (Latauskartta, 2023).

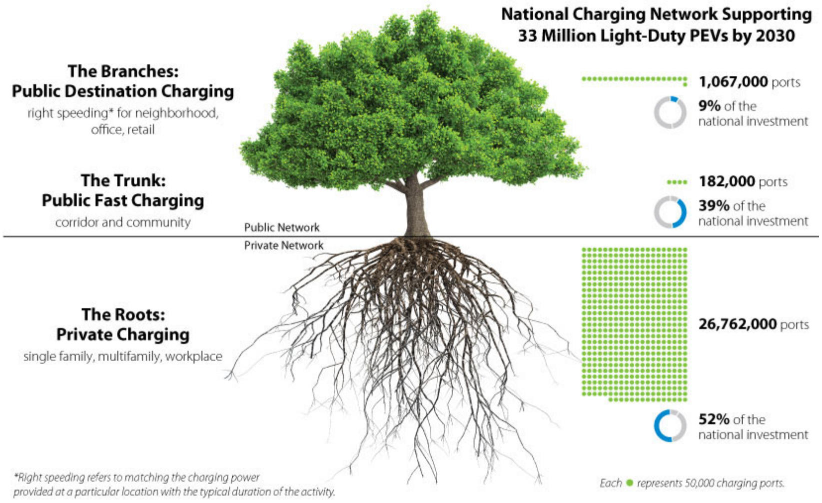


Figure 2.3: New conceptual model to direct the planning of a national electric vehicle charging network, proposed in the 2030 National Charging Network report (Ward et al., 2023)

.

Public chargers are an essential part of the charging infrastructure, but home charging is the fundamental root of the system. The National Renewable Energy Laboratory (Ward et al., 2023) has used the tree analogy to illustrate the charging infrastructure, describing the fundamental division between private and public charging (Figure 2.3). The number of charging points for private charging is estimated to be 20 times compared with the public charging infrastructure. This also leads to the conclusion that private charging taking place in homes and businesses will be the core of the charging infrastructure.

2.1.2 Charging standards

Standard: "something established by authority, custom, or general consent as a model or example; something set up and established by authority as a rule for the measure of quantity, weight, extent, value, or quality" [1]

To standardize: "to bring into conformity with a standard especially in order to assure consistency and regularity" [2]

In the United States, many EVs released in the late 1990s and early 2000s, such as the GM EV1, Ford Ranger EV, and Chevrolet S-10 EV, preferred the use of (single-phase AC)

[1] *Merriam-Webster*, s.v. "standard," https://www.merriam-webster.com, accessed December 13, 2023.

[2] *Merriam-Webster*, s.v. "standardize," https://www.merriam-webster.com, accessed December 13, 2023.

electric vehicle supply equipment (EVSE). These devices were equipped with an inductive connector (Magne Charge) (Woody et al., 1997) or a conductive connector (usually AVCON) (Avcon, 2000). GM, Nissan, and Toyota were in favor of the inductive system, while DaimlerChrysler, Ford, and Honda supported the conductive system.

The number of cars started to increase in the 2010s, which quickly led to the development of charging connectors for EV charging. The Society of Automotive Engineers (SAE) and the European Automobile Manufacturers' Association (ACEA) devised a plan to incorporate common DC wires into existing AC connector types, creating a single "global envelope" that would be compatible with all DC charging stations (ACEA, 2011). The proposal started the adoption of a combined charging system (CCS) (combo 1 in the United States and combo 2 Europe), which is the standard today in most countries around the world along with the Type 2 alternating current (AC) plug (Type 1 in the United States) and CHAdeMO. The current key standards in EV charging that define the physical interface but also the communication interfaces are the following:

- ISO/IEC 15118: The standard facilitates communication between EVs and EVSE. Charging parameters are sent based on user needs and charging profiles from the charging point operator (CPO). The latest update includes protocols for bidirectional charging. The standard consists of seven separate documents: ISO 15118-1: General information and use-case definition; ISO 15118-2: Network and application protocol requirements; ISO 15118-3: Physical and data link layer requirements; ISO 15118-4: Network and application protocol conformance test; ISO 15118-5: Physical and data link layer conformance test; ISO 15118-8: Physical layer and data link layer requirements for wireless communication; and ISO 15118-20: 2nd generation network and application protocol requirements.

- IEC 62196: The standard defines the basic requirements for the conductive crackling of EVs. This set of standards sets out the requirements and tests for plugs, sockets, vehicle connectors, and vehicle inlets used for the conductive charging of electric vehicles. The plugs, socket-outlets, vehicle connectors, and vehicle inlets specified in this series of standards are used in the EV supply equipment according to the IEC 61851 series or IEC 62752 and in electric vehicles according to ISO 17409 or ISO 18246. Furthermore, these plugs, socket-outlets, vehicle connectors, and vehicle inlets provide additional contacts that support specific functions related to the charging of electric vehicles, such as ensuring that power is not supplied unless a vehicle is connected and that the vehicle is immobilized while still connected. Similar requirements are contained in SAE J1772, which is widely applied in the US.

- IEC 61850: A group of standards defining communication protocols for intelligent electronic devices at substations, and a foundational standard for smart grids.

- IEEE 2030.5: The standard enables utility management of distributed energy resources, such as electric vehicles, through demand response, load control, and time-of-day pricing.

- Chinese GB/T: The competing GB/T charging standard is a set of GB/T standards, primarily in the GB/T 20234 family, for AC and DC fast charging of electric vehicles used in China. The standards were revised and updated most recently in 2015 by the Standardization Administration of China. GB/T 18487 provides general requirements for conductive charging systems, having similar definitions to IEC 61851. GB/T 20234 provides physical requirements for connectors and interfaces, corresponding to IEC 62196 and SAE J1772. GB/T 27930 specifies communication requirements, corresponding to ISO 15118 and SAE J1772 (State Grid Corporation of China, 2013).

In addition to the official standards, several systems and initiatives are maintained by various associations and are widely adopted and partially included in the ISO, IEC, and IEEE standards:

- CHAdeMO: A protocol developed in Japan by the CHAdeMO Association that accompanies its specific CHAdeMO plug, allowing physical bidirectional DC charging. The name is an abbreviation of "CHArge de MOve" (which the organization translates as “charge for moving”) (CHAdeMO, 2010). CHAdeMO defines the physical plug and communication requirements of fast direct current (DC) charging up to 500 kW. It is adopted in major part by the IEC and the EN (61851-23, 61851-24, 62196-3), and the IEEE (2030.1.1) (CHAdeMO, 2023).

- Open Charge Point Interface (OCPI): The protocol supports connections between electric mobility service providers and CPOs, allowing EV users to access different charging points and streamline payments across jurisdictional borders, thus helping to support EV uptake through roaming. OCPI supports the most functionalities, including smart charging, among different roaming protocols, and is commonly used in the European Union. The EV Roaming Foundation states that the main aim is: “To allow any EV driver to charge at any charging station in the EU: simplify, standardize, and harmonize” (EV Roaming Foundation, 2023).

- OpenADR: The architecture is maintained by the OpneADR alliance. The main aim of the OpenADR is to: “standardize, automate, and simplify Demand Response (DR) and Distributed Energy Resources (DER) to enable utilities and aggregators to cost-effectively manage growing energy demand & decentralized energy production, and customers to control their energy future.” OpenADR has a wide adoption across the globe (OpenADR, 2023).

- Open Charging Point Protocol (OCPP) and Open Smart Charging Protocol (OSCP): The protocols are maintained by the Open Charge Alliance. Open Charging Point Protocol (OCPP) is an application protocol that enables communication between EV charging stations and a central management system, similar to how cell phones

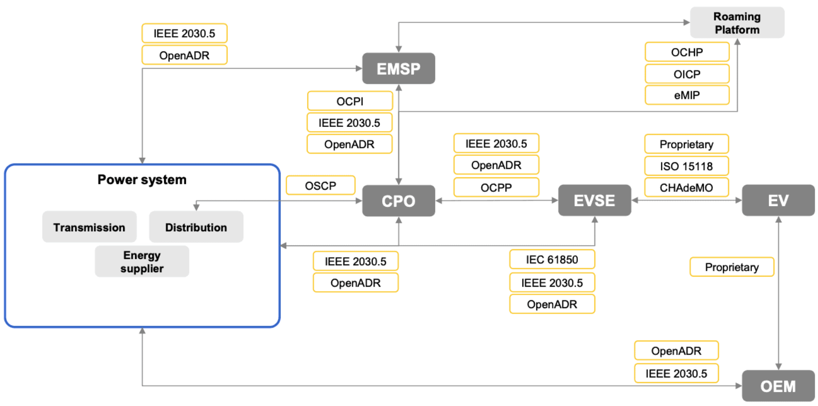


Figure 2.4: EV charging standards in simplified EV charging communication protocols and architecture (Lopes et al., 2022).

communicate with cell phone networks. It is used to manage the charging of EVs. Open Smart Charging Protocol (OSCP) communicates predictions of locally available capacity to the charging station operators. The current version contains use cases with more generic terms to allow integration of solar photovoltaics (PVs), batteries, and other devices, although the use of OSCP is still limited (Open Charge Alliance—About Us, 2023).

Figure 2.4 shows the most relevant standard in a simplified EV charging architecture. The interactions between the CPO, the EVSE, and the EV enable the basic charging functionality but also provide a basis for further smart applications. The CPO interacts with power system parties and the electric mobility service provider (EMSP) to enable services like roaming.

The standards provide a basis for the EV charging business that nowadays uses plugs defined by IEC 62196-1. IEC 61851-1 extends the definition to the basic physical interface between the car and the charger. The different charging modes define the capabilities and features of each charging model:

- Mode 1: It is an AC charging method that is mainly used to charge light vehicles, such as mopeds, with a low current. This mode is not applicable to EVs that are mainly used for passenger cars. For safety reasons, the use of Mode 1 is not allowed in certain countries, including the United States.

- Mode 2: An AC approach can be employed as a short-term or interim solution before more advanced techniques become more widespread. In Mode 2, the charging “apparatus” is located in a charging cord. The charging apparatus provides basic safety features, such as earthing continuity monitoring.

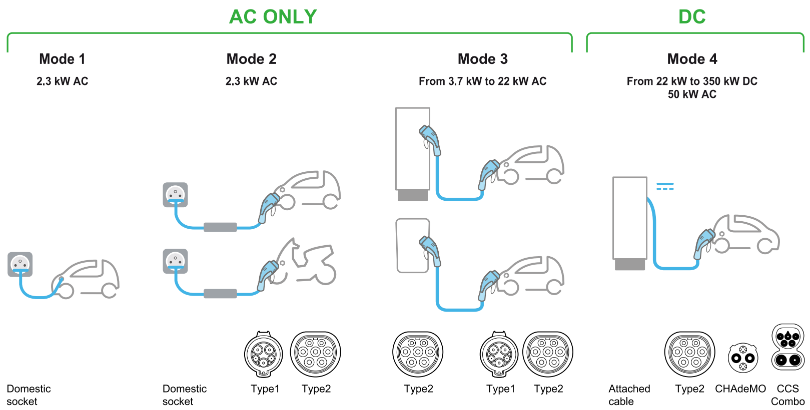


Figure 2.5: Charging plug and charging modes (Schneider Electric, 2023).

- Mode 3: It is the recommended AC method for day-to-day charging and includes important smart features, such as a communication connection between the EV and the charging equipment, so that the charging power can be controlled during a charging event. A Mode 3 plug called Type 2 is the *de facto* connector in Europe, suggested to be used as the minimum required connector by the EU directive (*EUR-Lex - 32014L0094 - EN - EUR-Lex* 2023).
- Mode 4: It is the only charging mode that uses an external charger with a DC output. This mode can provide up to 350 kW of power, which is delivered directly to the battery, bypassing the on-board charger. Because of the high power level, this mode requires a higher level of communication and more stringent safety measures.

Figure 2.5 shows a summary of the charging plugs and charging modes. This dissertation focuses mainly on applications that can be enabled by mode 3 chargers. The most unidirectional charging applications can be implemented by controlling the onboard chargers through the communication link defined in mode 3 charging. The applicable cases are described in Publication I, Publication II, and Publication VI. The bidirectional cases are based on the ISO 15118-20 extension that defines the bidirectional charging communication for AC or DC charging. Bidirectional use cases are considered in the pilot case demonstration, which is described in Publication V. Publication IX investigates bidirectional charging business cases in the distribution network flexibility services.

2.2 EV charging modeling

EV load modeling is used to predict the energy and temporal conditions of the charging event when charging EVs at any given time. It is essential to model EV charging from the viewpoint of the distribution grid to ensure reliable and effective integration of EVs into the existing electrical grid. Two main elements must be taken into account in this modeling process: load profile modeling and peak load modeling. The modeling of the load profile involves forecasting the electricity consumption patterns of EVs connected to the distribution network over time. This not only helps utilities and grid operators understand when and how much energy will be required for charging, but also provides important information to other key players, such as the electricity retailer or engineering agencies performing a planning task involving EV charging. Peak load modeling, on the other hand, is used to anticipate the maximum amount of electricity that will be required to charge EVs at any given moment.

This dissertation presents EV charging models that mainly use event-based simulation to sample random charging events combined with Monte Carlo simulation to replicate the driving patterns of passenger cars. Monte Carlo simulation is a method of using random sampling and statistical analysis to model and analyze complex systems or processes. It is similar to playing games of chance and is used in a variety of fields, such as finance, engineering, physics, and operations research, to make predictions, assess risks, and solve problems that cannot be solved analytically. The main steps of the modeling can be summarized as follows:

- Simulation begins by describing a complex problem or system that is challenging to analyze mathematically or through deterministic approaches. This could include elements of uncertainty, variability, or a multitude of interconnected components. This stage is often presented as a flowchart.
- Random sampling: Establishing the parameters and variables that have an effect on the problem. Introducing randomness by generating random samples (frequently following known probability distributions) for these parameters.
- Simulation: Execution of a large number of trials or iterations, each with different sets of random values for the parameters. This produces a range of potential scenarios or outcomes for the problem.
- Aggregation and Analysis: Gathering the results of all iterations to statistically analyze the data to draw conclusions about the behavior of the system. This may involve calculating averages, standard deviations, probabilities, or other pertinent statistics.
- Results: Monte Carlo simulation provides a distribution of possible outcomes or a range of values for the problem being studied. It allows one to estimate probabilities, make predictions, assess risks, and gain insight into the behavior of the system under different conditions.

There are successful examples of Monte Carlo models in EV load modeling (Ni et al., 2020a) or (Ni et al., 2020b), but also in other fields of distribution system modeling,

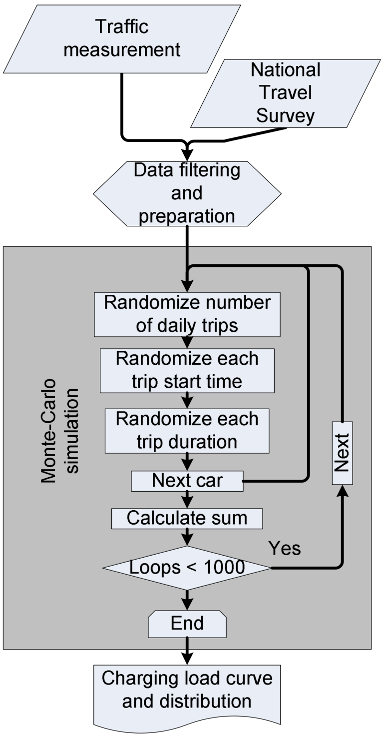


Figure 2.6: Example of the Monte Carlo method applied to EV load modeling (Tikka et al., 2011) © 2011 IEEE.

such as analysis of distribution transformer aging (Affonso et al., 2018). This dissertation also benefits from Monte Carlo simulations in Publication I, Publication II, and Publication VIII. Figure 2.6 shows an example of a Monte Carlo simulation applied in Publication I. The model is highly flexible and can easily be extended with features, such as smart charging control from different perspectives. Publication II shows an example of how a similar model can be used to model smart charging that obeys a simple power limit set by the grid interconnection point.

Stochastic models, such as Monte-Carlo-based simulation models, are based on estimations of transition probabilities for the states of vehicles, which are then used to simulate how EVs may be used randomly by individuals but still based on real-life statistics. The EV charging load is dynamic by nature as it can have a variety of different power levels and can appear in different locations on the grid. The temporal characteristics of the EV charging load are often defined by behavioral factors, such as daily driving routines and habits related to the charging event. Several studies show that there are close relationships between the EV driver behavior and the charging event. For example, the modeling study (Pagani et al., 2019) states that by building an agent-based model, the characteristics of each individual event can be captured and spatially allocated. Many studies show broader modeling approaches where spatial features do not play a central role. The stochastic modeling approach has been applied in a wide variety of studies (Hilshey et al., 2013; Ashtari et al., 2012; Lojowska et al., 2012; Iversen et al., 2017; Moreira et al., 2011; Wang et al., 2018; Ni et al., 2020b); also the author of this dissertation visited stochastic EV charging modeling in case studies of Publication I and Publication II. Many studies provide a good perspective on local grid impacts caused by uncontrolled and uncoordinated charging of the EVs. Studies mainly agree that uncontrolled charging is going to be a major burden for distribution grids (Ray et al., 2023; Gönül et al., 2021; Al-Hanahi et al., 2021). Wider national studies applied to distribution grids also indicated a significant increase in peak loads on the grid (Moreira et al., 2011). Even though the impact on the grid might seem major, one must bear in mind that the prevailing guidance and methodology on grid dimensioning play a key role in defining what kind of additional load the grid can handle. For example, studies conducted in Nordic countries show that the impact of the EV charging flow on the grid remains modest, and (Z. Liu et al., 2014) states that the average energy consumption of electric vehicles (EVs) while charging is not particularly high. However, if the penetration level of EVs is high, the maximum load of the charging process can be considerable, which is consistent with other studies. In the case of dumb charging, the peak load of the charging coincides with the peak hours of the original electric load, which can put an additional strain on the grid. Therefore, it is important to recognize that the capacity of the grid to accept additional load is highly dependent on the base load structure, the temporal features of the load, and the dimensioning factors of the grid (planning guidance and safety margins). In the Nordic environment, grid planning mainly follows the techno-economic principle (Lakervi et al., 1995). In principle, all decisions made in planning aim at an optimal cost investment C_{total}, which can be expressed as:

$$\min C_{\text{total}} = \min \int_0^T C_{\text{inv}}(t) + C_{\text{opex}}(t) + C_{\text{loss}}(t) + C_{\text{int}}(t)dt \tag{2.1}$$

$$\approx \min \sum_0^T C_{\text{inv}} + C_{\text{opex}} + C_{\text{loss}} + C_{\text{int}}, \tag{2.2}$$

where C_{inv} is the investment cost, C_{opex} is the operational cost, C_{loss} is the cost of network losses, C_{int} is the interruption cost, and the interval $[0,T]$ is the observed investment period. The above-mentioned equation is often expressed in an approximated format as most of the cost components are valued and calculated as present values. Publication III investigates and describes further the methodology of how EVs can be shown as a significant benefit for the distribution grids. When EV charging is modeled and the impacts on the grid are analyzed, a broader look should always be taken at the matter instead of just assuming that EV charging will be fully uncontrolled and uncoordinated.

Although the impact of uncontrolled charging on the grid is well known, there is still a major knowledge gap related to cases where most of the EV charging is to be controlled smartly. The development of EV charging technology has been rapid over the past decade. At the beginning of the EV revolution in 2010, there were no complete standards for the European market to define how EVs should be charged. Moreover, estimations and assumptions of the modeling parameters were on the naive side, for example, many studies assumed that the EV battery sizes are only 20–30 kWh, whereas at present we commonly have batteries that are in the range of 40–100 kWh (according to the registration statistics in Finland) (Traficom, 2023). Furthermore, it is also worth considering the charging power and how the power ranges were defined in the early days of the EV revolution. Many studies stated that fast charging was assumed in the modeling, translating into a power range of some tens of kilowatts (Masoum et al., 2010; Alaoui et al., 2003). Modern EVs and EV chargers are capable of handling powers up to 350 kW (IEC, 2017).

2.2.1 Deterministic model

The modeling can be performed by various methods, some of which are more suitable for the task than others. The simplest method is deterministic load modeling. In the deterministic load modeling of EVs, it is assumed that the parameters of EVs are already known. This means that EVs are treated as stationary energy storages with predetermined available periods. For example, the arrival and departure times of vehicles are already known by the power grid operator, allowing them to schedule the EVs in a similar way to energy storage systems. Additionally, the daily travel distance is another simplification parameter, so it is assumed that the travel distance of the EVs is fixed. This makes it easy to calculate the required energy for charging the EV. Other simplification assumptions include starting charging at a fixed time, a fixed energy requirement for all EVs, a known departure time, and the same battery capacity for all vehicles. Publication IV presents the usage of deterministic load modeling while also providing valuable information on the input parameters that can be used in the EV load modeling. The deterministic model is not the most sophisticated approach for load modeling, but if there are no input data available for more detailed models, it is the only feasible solution. At present, the input data for the load modeling of EV charging are mostly freely and openly available (Räisänen et al., 2020).

2.2.2 Markov chain

The mobility characteristics and available charging facilities of an EV largely determine its charging behavior. However, it is challenging to forecast this behavior, but it can be facilitated by using random techniques, such as state, stay time, and state transition probability, to illustrate the anticipated behavior. The Markov process can be used to illustrate the connection between the starting point, the destination, and the duration of each EV charging event.

The Markov chain can be used to model the temporal features of the EV charging, as shown in (H. Liu et al., 2023), but also to the spatial allocation of the EV charging load (Shepero et al., 2018). There are also studies that combine Monte Carlo simulation and Markov chain (Iwafune et al., 2020).

2.2.3 Other modeling methods

There are many other methods to model the EV charging load, such as fuzzy logic modeling, artificial neural networks, probabilistic fitting, robust optimization, information gap decision theory, or methods of recurrent time series analysis.

Fuzzy logic modeling is a mathematical method that is used to manage uncertainty and inexactness in problem-solving and decision-making. Unlike the traditional binary logic, which is based on definite true or false values (0 or 1), fuzzy logic allows levels of truth or inclusion in a set. It is especially useful in cases where the data are unclear, obscure, or subjective, making it a beneficial tool in various areas, such as control systems, artificial intelligence, and decision support systems. Fuzzy logic could be applicable, for instance, in an EV charging control system in simulation (Faddel et al., 2017).

An artificial neural network (ANN) (often also referred to as neural network) is a type of computational model based on the structure and functioning of biological neural networks, such as the human brain. It is a fundamental element of machine learning and artificial intelligence. ANNs are composed of interconnected nodes, known as artificial neurons or perceptrons, which are arranged in layers. Generally, these layers include an input layer, one or more hidden layers, and an output layer. Each connection between neurons has a weight, and neurons use an activation function to process their weighted inputs and generate an output. ANN-based models are very common nowadays in all fields of modeling. In the context of EV load modeling there are a large number of studies that employ ANN models; for example, Zeynali et al. (2020) use an ANN to generate household scenarios for a stochastic model. Again, Zhu et al. (2019) compare the ANN with other more advanced machine learning models in the domain of load modeling of EV charging. This dissertation shows an example of using a CNN in the spatial modeling of EV charging in Publication VII. The CNN is a subgategory or specific type of ANN typically used to detect a pattern from pictures or other picture-like content. The CNN has been also used to classify geospatial datasets. The common reason for all types of ANNs is that they require rather large amounts of training data in order to achieve any model accuracy.

To further categorize EV load modeling, the models can be divided into two main classes. First, we have temporal modeling-oriented models and second, spatial models. The temporal models aim to model temporal features, such as timing and magnitude of the peak load, often in contrast to other loads in the case area or facility. The models benefit from having as much historical statistics and time series data as possible describing the behavior of the vehicle user. Spatial models, on the other hand, benefit from spatially distributed data and statistics. If the spatial model aims to model or forecast also temporal features, spatially determined time series data are required. The models can also be combined to analyze the impact of the charging load on the georeferenced outputs. This is highly beneficial for the distribution grid planning process.

2.3 Background data of EV charging modeling

It is clear that a variety of factors have to be taken into account int the evaluation of electric vehicle charging. Electric cars are distinct from traditional loads, because their energy consumption does not take place at the same location where the battery is charged or connected to the grid. Additionally, the vehicle can be recharged at multiple locations in the distribution network. The charging power of the vehicle is not always determined by the charger of the vehicle; it can be restricted, for instance, by the power limit of the charging device. Moreover, high-power direct current charging points can also be used for vehicle charging.

It is essential to take into account potential factors that could impact the results of the modeling in the short or long term when modeling these phenomena. Much research has been conducted on the modeling of electric vehicle charging, providing useful information on the effect of electric vehicles and a valuable background for identifying the relevant input data sources. For example, (Rautiainen et al., 2016a; Sausen et al., 2019; LIU et al., 2015) propose methods for modeling electric vehicle charging based on passenger transportation surveys. Some studies also consider measured driving cycles of EVs (Yang et al., 2017), but often this type of data gathering may raise privacy concerns and can also be challenging to implement in practice. Thus, travel surveys have been identified as the most prominent input data for the EV load modeling. Pareschi et al. (2020) evaluate the accuracy of the EV load modeling, showing that travel surveys, if used as the basis for modeling, are a very suitable input for the modeling of EV loads, and the forecasting modeling can reach a high accuracy. The author of this dissertation has also presented multiple examples where national travel survey data have been used as the main model input. Publication I, Publication II, and Publication VIII are mainly based on interpreting travel survey data. The data are also refined and validated with case area traffic measurements. The main source of data for these modeling examples was mainly travel surveys, but many other sources also contribute to accurate modeling. Nevertheless, it is reasonable to include input data also from other sources in the modeling. In terms of essential background information for the analysis, the following can be considered:

- Driving statistics:
  - Distribution of trip lengths
  - Distribution of arrival and departure times

  - Socioeconomic characteristics
- Technical constraints on vehicle charging:
  - Rated power and other limitations of vehicle chargers
  - Technical constraints of charging points and charging areas
  - Charging efficiency and power losses
  - Statistical data on the temperature-dependent energy content of charging events
- Vehicle energy usage:
  - Statistics on vehicle energy usage
  - Statistics on the temperature-dependent energy usage of vehicles
- Statistics on charging behavior:
  - Timing of charging on residential properties
  - Proportion of charging at other locations
- Environmental conditions:
  - Purpose of the building or area
  - Background load of the location (especially in the context of intelligent control)
  - Charging use case (home charging, office charging, noncontrolled, controlled, purpose of the controlling)

2.3.1 National travel surveys

A national travel survey (NTS) is a monitoring study that describes the travel habits of the residents of Finland. Finnish NTSs aim to provide an overview of the Finnish mobility and the factors influencing it, as well as to examine the demographic, regional, and temporal variations in personal travel between population groups. The surveys have been conducted approximately every six years in 1980, 1986, 1992, 1998–1999, 2004–2005, 2010–2011, 2016, and 2021 (Kallio et al., 2023; Liikennevirasto, 2018).

2.3.2 Other surveys and questionnaires

The supporting data can also be acquired by various surveys and questionnaires. The most prominent survey types that can be used to model the charging loads of EVs are the previously introduced NTSs and the surveys on the charging behavior of EV users. The

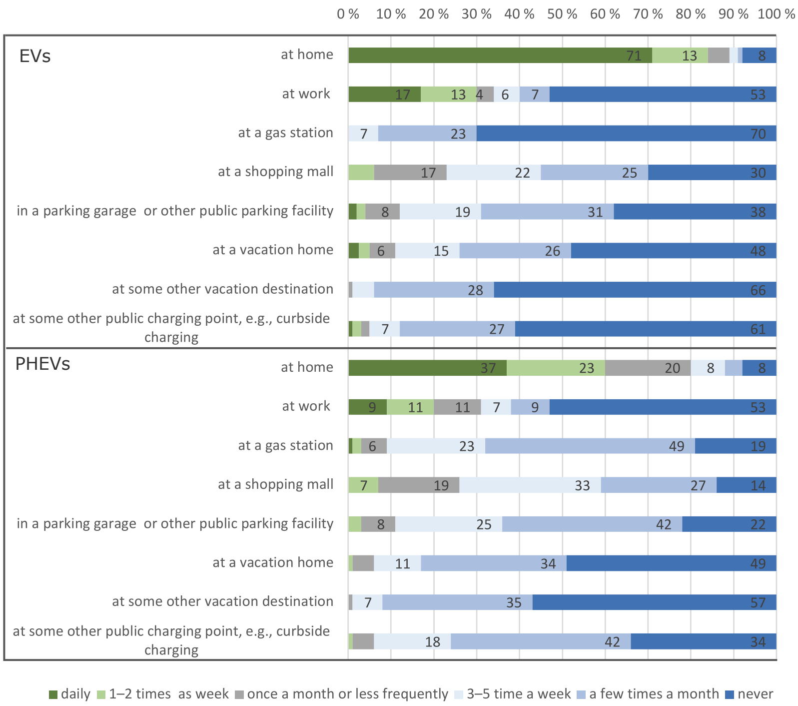


Figure 2.7: EV charging proportions by location (translated from Finnish and redrawn) (Autoalan Tiedotuskeskus, 2020).

charging survey by Autoalan Tiedotuskeskus (2020) examined charging at home, at work, and at various public charging points. In addition to the frequency of charging, it was also examined whether the vehicle was powered from a dedicated charging station specifically designed for the car or from a regular household outlet. Figure 2.7 shows the proportions of locations where the EVs are charged. From the modeling perspective, surveys like this are essential when modeling has to take into account not only the total energy but also the peak power. If cars are often charged at other locations than those focused on in the study, then the analysis ends up overestimating the charging demand. Modeling in Publication VIII incorporates proportions of charging in the load profile, peak load, and total energy estimations.

2.3.3 Spatial statistics

The spatial distribution of EV charging loads can be modeled to provide a basis for more advanced load modeling and asset management of distribution grids, but also for retailers to manage spatial load formation. This process involves understanding of the load formation and load development. Spatial modeling is used to estimate the distribution of loads connected to the grid in a given area, based on data like changes in socioeconomic factors, area development plans, and surveys of the geographical target area. This information can then be used to create area-specific load profiles or to estimate changes in existing load curves. These load curves are then used for the load flow analysis of the grid in its current state and to predict its future development, which can be used in grid development plans. EV charging loads have unique characteristics, as they can be connected to the grid at various locations. Publication VII investigates spatial modeling and how it can support the design and operation of distribution networks. The proposed model provides a tool to estimate the initial locations or home locations of EVs. If the home locations of loads are known, they can be modeled based on the distributions of arrival and departure times and trip lengths of the EVs, and the technical boundaries of the connection point and the vehicle. Load profile modeling can be based on stochastic models, neural network models, agent-based models, or real measurement data from EV charging stations or the AMR infrastructure. The input data for such a model can be nearly from any data source that has been georeferenced to a known coordinate system. Figure 2.8 illustrates an example of spatially distributed data that were used in the spatial modeling in Publication VII.

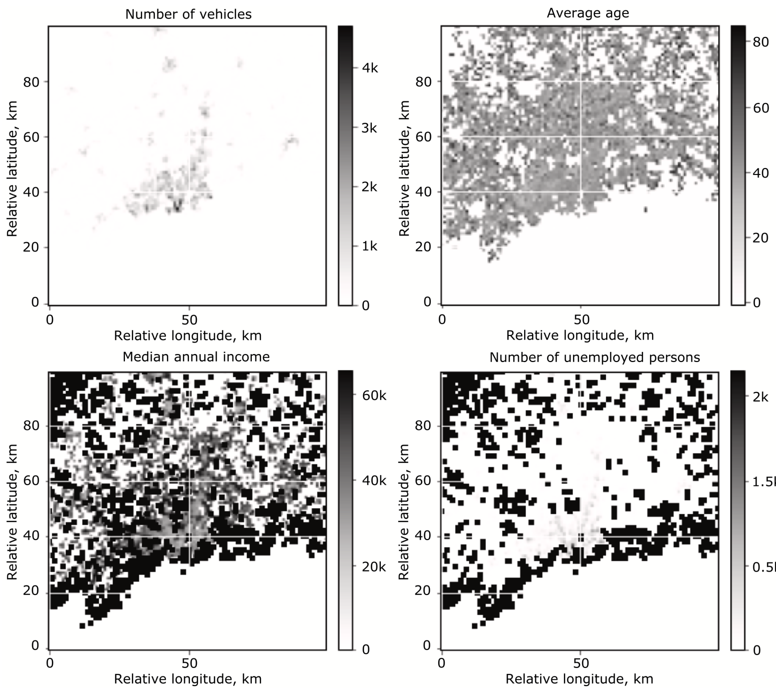


Figure 2.8: Example of spatially distributed data: Spatially distributed socioeconomic data in Finland. The top-left subfigure shows the total number of cars registered per node, the top-right subfigure the average age of the persons per node, the bottom-left subfigure the annual median income of the households, and the bottom-right subfigure the number of unemployed persons per raster node (Tikka et al., 2022) © 2022 Elsevier.

2.3.4 National registers

A variety of registers that are administered by governmental agencies of organizations are a valuable resource for modeling tasks in different fields of science. In particular, for the EV load modeling, there are, for example, statistics of vehicle registrations by Traficom (Traficom, 2022b), socioeconomic and, building data by Statistics Finland (Statistics Finland, 2022), and weather statistics by the Finnish Meteorological Institute (Finnish Meteorological Institute, 2023). In addition, building infrastructure statistics and other geospatial data (Maanmittauslaitos, 2023), such as roads and other map features, may improve the spatial modeling results in some cases. Publication VII shows an example of employing temperature statistics to enhance load modeling based on measured temperature-dependent behavior of the EVs. Publication VIII investigates the utilization of geospatial socioeconomic data for spatial modeling of the EV distribution. In addition to previously mentioned data sources, there are many other data sources that could enhance modeling of various smart charging schemes. Fingrid's open data portal (Fingrid, 2023e) provides access to information about ancillary services, but also to data from the energy market. When the modeling focuses on smart applications, such as frequency containment reserves or price-signal-controlled charging, it is very beneficial to have historical statistics of the signals that control smart applications.

2.3.5 Other resources to support modeling

In addition to well-maintained and official data sources, there are many other resources that may benefit EV load modeling. For instance, the increase in the EV energy consumption in cold environments is a well known phenomenon, but actual data or measurements are difficult to find. There are studies that indicate that EVs consume more energy in cold environments. A study implemented in laboratory reports that the energy consumption increases considerably in a cold environment and notes that measurement data or statistics available on the phenomenon are sparse (Zhou et al., 2023). Another study shows actual field measurement data and concludes also that the increase in consumption is well noticeable when the temperature drops below zero (Hao et al., 2020). In addition to scientific research, various data are available from magazines and associations that have conducted field experiments with a variety of cars. When using data that have been acquired through a poorly documented process, one must always bear in mind its possible impacts on the outcomes of the analysis. There are good examples of valuable data sources that could be used to establish the temperature-dependent behavior of the charging model. The TM magazine and the Norwegian Electric Vehicle Association provide a good coverage with a variety of car brands and models tested in different temperatures. Figure 2.9 shows the compilation of the consumption statistics.

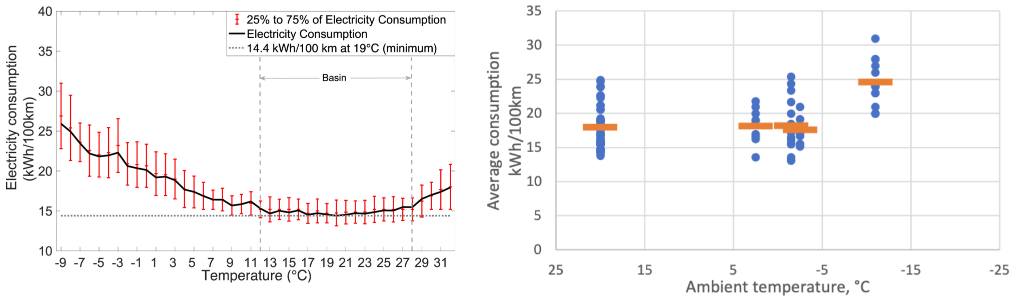


Figure 2.9: Estimates of car power consumption in different temperatures. The left-hand image shows a field test conducted for a large mass of vehicles (Hao et al., 2020). The right-hand figure shows data compiled from various sources (Tikka et al., 2023).

2.4 Use cases

Definition of the use case is among the most important aspects when modeling the EV charging load, and it is even more important when considering smart charging applications. Smart charging applications are often complex and involve participation of multiple parties to gain benefits. To successfully analyze the impacts of smart charging, it is a good practice to start by defining the smart charging use case. Definition of the use case helps in identifying the stakeholders or actors of the use case and clarifies interactions between the actors.

The modeling results are highly dependent on how cars are charged, in other words, what the charging use case is. The present dissertation focuses solely on home charging, but even within the scope of home charging, the variety of use cases may be substantially large. Publication I considered a simple home charging approach where charging is not controlled. On the other hand, Publication II and Publication III addressed smart charging with dynamic load control. The purpose of the study is also to recognize all the stakeholders involved in the charging event. The following section gives an example of simple prototype use case definitions.

2.4.1 Uncontrolled home charging

The most commonly known use case is uncontrolled home charging, which is also often referred to as dumb charging. This was the typical approach as the EVs started to become more common. The approach requires a minimal amount of technology and nearly compares to any other electricity-consuming home appliance usage.

The primary actor of the use case is the EV owner, whose main goal is to drive the EV from point A to point B. To succeed in this goal, the driver aims to keep the state of charge (SoC) of the EV battery as high as possible to enable flexible operation of the car. The car driver mainly charges the car at home, which has an electricity connection point provided by the DSO and an electricity tariff set by the electricity retailer. Thus, the driver may end up paying for varying tariff structures because of the separate billing of the network service fee and the consumed energy.

- Primary actor: the EV owner
- Primary goal: To keep the battery SoC as high as possible to enable flexible car use
- Other actors: the DSO and the electricity retailer
- Preconditions: the EV owner has access to the charging infrastructure

2.4.2 Dynamic load control

In addition to the previous use case, smart applications like dynamic load control require technical abilities and a communication link to operate. The primary goals of the driver remain the same as in the previous use cases, but the charging event is now dependent on the dynamic load limit in the parking area or building. The EV driver aims to have a full battery by the time in the morning when it is time to start the daily routines. The technical capabilities are enabled by the technical aggregator, which can be an application or a technical solution operating locally on the parking site.

- Primary actor: the EV owner
- Primary goal: To keep the battery SoC as high as possible to enable flexible car use
- Other actors: the DSO, the electricity retailer, and the technical aggregator (or service provider)
- Preconditions: the EV owner has access to the charging infrastructure and sufficient hardware and communication abilities in order to enable flexibility

2.4.3 Ancillary service smart charging

This more advanced use case of EV charging has a primary goal similar to the uncontrolled use case, but the objective is extended to gaining economic benefit by participating in ancillary services supporting the electricity grid, such as frequency containment reserve (FCR). Publication VI analyzes a possibility to use the EVs as an FCR. Flexible car usage remains the primary goal, meaning that the car battery SoC has to stay high to maintain flexible car use, but some part of the capacity is reserved for ancillary services. Similar to the first use case, the car connects to the grid through a home connection point, making the DSO one of the use case actors. In this case, the electricity tariff is also provided by the electricity retailer. The fourth actor of the use case is the aggregator that provides the customer contract and the technical ability to produce ancillary services. The fifth actor in the use case is the transmission system operator (TSO), which benefits from the service provided by the car owner and the aggregator. This arrangement also changes the money flow to bidirectional. The aggregator receives ancillary service remuneration from the TSO and forwards it to the resource provider according to the contract.

- Primary actor: the EV owner
- Primary goal: To keep the battery SoC as high as possible to enable flexible car use
- Other actors: the DSO, the electricity retailer, the TSO, and the aggregator
- Preconditions: the EV owner has access to the charging infrastructure and sufficient hardware and communication abilities in order to provide ancillary services

2.4.4 SPOT-price-based cost minimization

Similar to the previous use case, the SPOT tariff use case requires technical abilities and a communication link to operate. The primary goals of the driver remain the same as in the previous use cases, but the charging event now depends on the electricity price. The EV driver aims to have the lowest possible charging cost and eliminate any noticeable impact on the car use. The total cost depends on the electricity and service tariffs. The technical capabilities are enabled by the technical aggregator, which may also be an electricity retailer. The aggregator is often dependent on the electricity marketplace, which is the platform for the formation of the electricity price. Publication V investigates SPOT-tariff-based control schemes in the context of EV charging.

- Primary actor: the EV owner
- Primary goal: To charge the car at a lowest possible cost before morning to enable flexible car use
- Other actors: the DSO, electricity retailer, and the technical aggregator
- Preconditions: the EV owner has access to the charging infrastructure and sufficient hardware and communication abilities in order to enable flexibility

2.4.5 TOU tariff contol

Similar to the previous use case, the TOU tariff use case requires technical abilities, but the technical solution can be as simple as a timer that triggers charging as soon as, for example, the night-time tariff begins. The primary goals of the driver remain the same as in the previous use cases, but the charging event now depends on the tariff price and the TOU schedule. The EV driver aims to have the lowest possible charging cost and remove any noticeable impact on the car use. The technical capabilities could be enabled by the DSO providing a control signal via an AMR meter. Such a control signal has a major impact on the stochasticity of the charging loads.

- Primary actor: the EV owner
- Primary goal: To keep the battery SoC as high as possible to enable flexible car use
- Other actors: the DSO and the electricity retailer
- Preconditions: the EV owner has access to the charging infrastructure

2.4.6 Other bidirectional use cases

Bidirectional charging is part of a larger marketplace concept that allows EV users, prosumers or homeowners, building managers, and distribution network operators, which could be traditional DSOs or other types of operators, such as energy communities, to interact and exchange EV charging flexibility. V2G use cases can have various objectives, and modeling such a behavior requires careful definition of each use case. A broader overview of the opportunities of V2G is given in Publication IX, which focuses on the business models related to local flexibility services provided by EVs. Publication III shows the economic benefits of bidirectional charging for distribution networks and explains the estimation of the economic potential of the V2G services. The study does not consider any particular use case, but rather focuses on identifying how the economic dynamics of the mobile energy storage behaves when considering peak cutting applications. The publication highlights that the implementation of EVs as distributed energy resources (DERs) can help to reduce the additional charging peak loads caused by EV charging. However, this type of arrangement is complex and will require considerable technological advancement in EV control systems and seamless integration with the DSO.

3 Operating environment

The operating environment is one of the largest external factors that affect the load modeling of EVs as it lays the basis and the environment where EVs can be charged. The influence is noticeable especially if anything other than uncontrolled charging is observed. For example, tariff structures, marker access, ancillary services, or data availability are the factors that have a significant impact on the value proposition of different smart charging applications. This chapter describes the Finnish operating environment in brief to provide the context for the smart applications presented in this dissertation.

3.1 Production

Finnish electricity production is a mix of different types of production forms, such as nuclear power, hydro power, combined heat and power (CHP), and wind power. In addition, solar PV is an emerging production type that is gaining traction on the market. The total consumption of electric energy was 81 TWh in 2022, which is noticeably less than in the previous year (Statistics Finland, 2023b). With a longer observation period, the consumption does not show any clear trends on the historical data, as illustrated in Figure 3.1. Furthermore, the increasing proportion of wind power is clearly visible, increasing steadily each year. In comparison with the year 2021, domestic electricity production remained the same while the net electricity imports decreased by 30%. This was due to the termination of Russian electricity and gas imports, as well as the rise in energy prices, which had an effect on the purchase and use of electricity (AST, 2022). The high electricity costs in 2022 also caused a decrease in demand. Fossil-free electricity production was at an all-time high, accounting for 75% of the total electricity production in 2022 (Statistics Finland, 2023b).

The wind power capacity has been on a steady increase for several years, gaining 2000 MW of new installed capacity between 2022 and 2023. A prognosis of the wind power capacity by the Finnish TSO Fingrid shows that the wind power capacity will exceed 10 000 MW by 2026 (Fingrid, 2023c). Compared with the wind power capacity, the average electricity demand in Finland is 9200 MW (Statistics Finland, 2023b). Figure 3.2 shows an estimation of the deployment and spatial distribution of the wind power capacity.

The increase in renewable capacity is not without its downsides, which must be addressed. Solutions are versatile and multifaceted, including applications on the production, transmission, distribution, and demand side. The efficient utilization of renewable production requires seamless integration of the demand side into the infrastructure, so that the demand can respond effectively to the fluctuating production (Järventausta et al., 2015). The hydrogen-based solutions in industry and heavy transportation are also estimated to substantially increase the demand for electricity. It should also be kept in mind that carbon-free electricity is the key enabler for the hydrogen economy, and a large share of

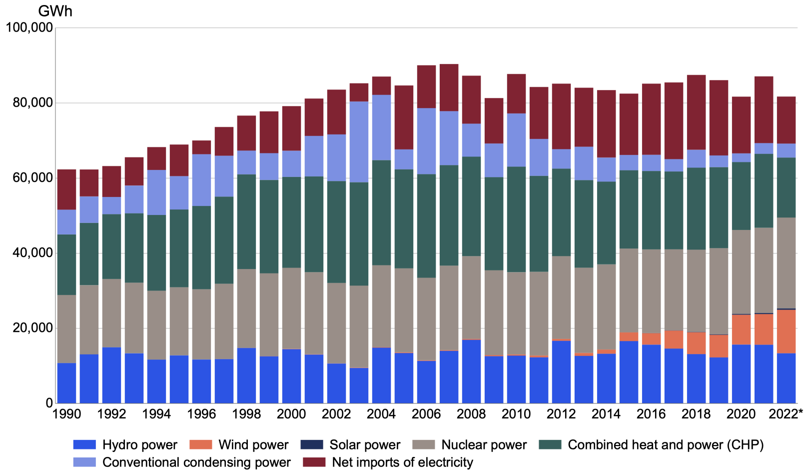


Figure 3.1: Supplies and total consumption of electricity, 1990–2022* (Statistics Finland, 2023b).

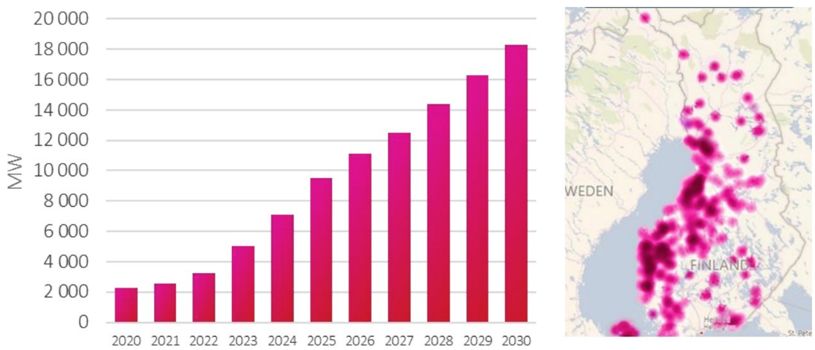


Figure 3.2: Finnish TSO's estimation of the wind power capacity deployment in the coming years (Fingrid, 2023c).

renewable capacity will be consumed in producing hydrogen (Sivill et al., 2022).

Electric mobility is among the key solutions on the demand side that can adopt and absorb a substantial share of the varying renewable production. The justification for this statement is that EVs are typically driven only a few hours a day, which often allows the battery to be harnessed to other tasks, such as peak shaving or other smart charging applications. Bidirectional operation extends the capabilities of the vehicle battery even further. The total storage capacity of the present European Commission (EC) fleet in Finland is 3000 MWh (end of June 2023, includes only BEVs). The estimation is based on aggregated statistics of the vehicle registration statistics (Traficom, 2022b) and brand- and model-specific battery capacities gathered from manufacturers' documentation and advertisements.

3.2 Transmission grid

The Finnish TSO Fingrid operates a transmission grid that is part of the Nordic transmission grid interconnected with Sweden, Norway, and Denmark. The grid is connected to Estonia with a DC link (Fingrid, 2023b). The transmission grid operates at high voltages of 100–400 kV with mostly a meshed network structure. The transmission grid delivers electricity to the distribution grids operated by DSOs.

Fingrid is responsible for the technical performance and security of the Finnish power system, as well as for tasks of national balance responsibility and national imbalance settlement. This is done in a fair and equal manner toward all electricity market participants (system responsibility) (Fingrid, 2023b).

In addition to the operation and development of the transmission grid, Fingrid's responsibility to maintain secure and reliable operation of the power system requires it to maintain and develop marketplaces for the reserve and balancing power. The purpose of both markets is to keep the electricity system in equilibrium. Although they share this target, the two markets are operated in different domains, the balancing power operating in the hourly market domain and the reserves in the more technical domain mostly operated in real time.

The balancing energy market is a market that operates in 15 min time frames. The aim of the market is to keep the system in balance as closely as possible. The balancing energy bids are given 45 min before the operating time window. The bids can be down- or up-regulation bids. In the operating time frame, the bids are used in a cost order, starting from the cheapest. Depending on the state of the power system, the operating time can be down- or up-regulated (Fingrid, 2023d).

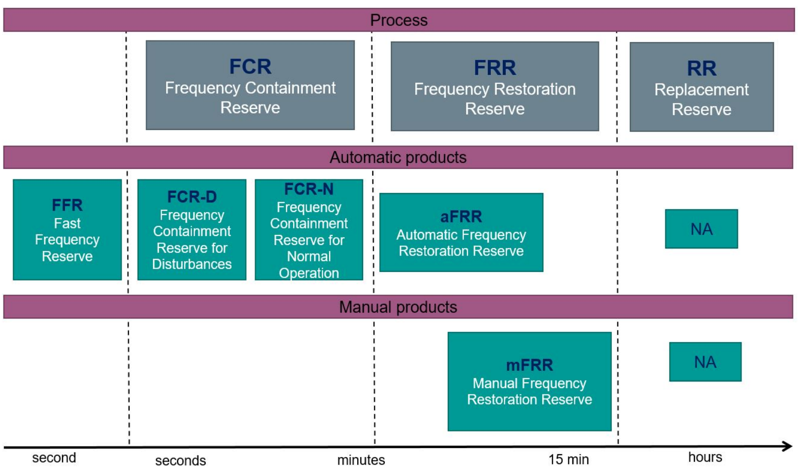


Figure 3.3: Reserve products on different time scales (Fingrid, 2023d).

The reserve market contains several products, each of which makes a valuable contribution to the power system. The products are divided into different time frames, the fastest fast frequency reserve (FRR) operating in almost real time, and supported by products that respond quickly, i.e., the frequency containment reserve for normal operation (FCR-N) and the frequency containment reserve for disturbance operation (FCR-D). The reserve procurement process is divided into two separate markets: first, the annual market, which has annual bids for resources that should participate in the market for the whole year, and second, the hourly market that allows reserve producers to bid for certain hours only (Fingrid, 2023d).

The automatic frequency restoration reserve (aFRR) is mainly reserved for major disturbances and operates within minutes from activation. Reserve capacity is acquired from the annual and hourly markets. The hourly capacity quota is announced by the Fingrid based on the state of the power system and the foretasted demand for the reserve. The automatic frequency restoration reserve (mFRR) is a reserve that implements the balancing energy market. The reserve is activated by the Nordic TSOs based on demand (Fingrid, 2023d).

From the perspective of electric mobility, markets that allow bidding for specific hours are highly interesting. The mobile resource can participate in markets only when it is available. Often, the resources are bid to the market as an aggregated resource. This type of approach creates additional flexibility from the viewpoint of an individual resource.

3.3 Distribution grid

The main function of electricity distribution is to provide electricity from the power distribution network to customers anywhere in the grid area with a good quality of supply. The operating voltage varies between 0.4–100 kV. A typical MV grid is operated approximately at 20 kV, but also other voltage levels exist. The distribution system was built several decades ago, and it is today under constant renovation. The oldest parts of the grid are still up to 50 years old. The distinguishing feature of the distribution grid is that planning periods are typically long, up to 40 years. The distribution business is a highly capital-intensive business. Finland, in most parts, is a sparsely populated country, meaning that long distribution lines are required for a relatively small number of customers. In Finland there are 77 DSOs in operation, and their total network asset is approximately €12 billion (Energiavirasto, 2023).

In general, the distribution business can be divided into two parts: first, the operation that involves mainly operating the grid on a daily basis as efficiently as possible, and second, the planning that involves making long-term decisions under uncertainty. Strategic analysis is the foundation for strategic decisions that support the long-term planning of grids. Strategic analysis requires inputs of available technologies, technology costs, reliability of different technologies, owners' objectives, and economic parameters (Lassila,

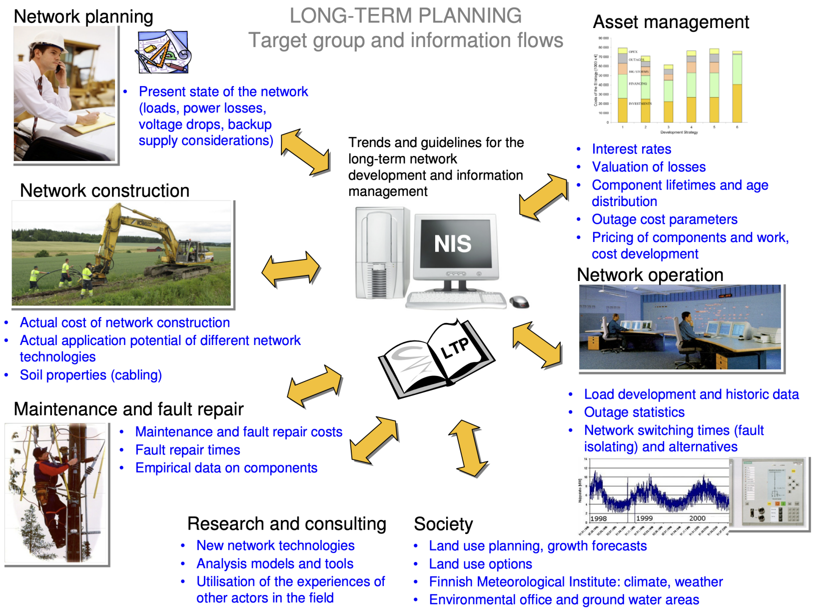


Figure 3.4: Information flows in the DSO's long-term planning process (Lassila, 2009).

2009). The process focuses mainly on grid technology, but can greatly benefit from reliable load forecasts and scenarios that model potential new technologies impacting the load behavior. The transmission capacity of the grid is the main parameter considered in the planning process. In general, all meaningful indicators are relevant inputs to take into account when performing network planning activities. Figure 3.4 identifies the relevant information flows and target groups involved in the long-term planning process.

Grid planning is also driven by the requirements for the security of supply, according to which customers in urban areas should not experience outages longer than 6 h. A similar requirement is established for rural areas, but the recovery time from the outage should be 36 h at the maximum. The law explicitly states that a storm or a severe weather event is not a "force majeure" (*Sähkömarkkinalaki* [Electricity Market Act], in Finnish, 2023).

DSOs' security of supply requirements combined with the sparsely populated country makes the planning tasks very challenging. In addition to the difficult starting point, the load behavior is changing dramatically in rural areas. The network faces changing load profiles and increasing peak loads; as traditional heating systems are changed over to heat pumps, loads are harnessed to demand response (Tuunanen, 2015). Moreover, electric mobility is an additional load that is relatively high in many cases compared with the load accumulated from other household appliances. Although loads change and new loads are introduced, distributed production, especially solar PV, is increasing its popularity in rural areas. High fluctuation in loads and production is likely to cause voltage quality problems (Haapaniemi et al., 2022). When all factors and future scenarios are incorporated into the

DSO's strategic planning, it becomes a highly complex problem to manage.

3.4 Electricity market

The electricity market has been gradually opened to competition in the Nordic countries, starting in Norway and continued by Sweden (in 1996), Finland (in 1998), and Denmark (in 2000) (Lundgren, 2012). In the retail sale of electricity, electricity retailers sell electricity to end users. Finland has approximately 3.5 million electricity consumption points (Energiavirasto, 2023), each with the option of freely choosing the electricity retailer. Electricity production must also be open to free competition.

The competition in the retail business is open, but the physical transmission of electricity takes place through a distribution grid that operates under a regulated monopoly. The setting creates quite a unique operating environment, as the DSOs have very little control over the load that is transmitted through their grids. The only restriction for the power flow should be the customer's main fuse. The DSOs are obligated to ensure that competition between retailers is not restricted and that each customer can freely choose the retailer (*Sähkömarkkinalaki* [Electricity Market Act], in Finnish, 2023).

The retailer purchases electricity from the SPOT market or by using bilateral contracts and directly interacting with the supplier or the producer. The SPOT market is operated by Nord Pool, an operator of the electricity market in Northern Europe that covers 16 countries, providing trading, clearing, settlement, and related services both day-ahead and intraday (Nord Pool, 2023).

The electricity market consists of several integrated markets that are used to match the load and generation in the long and short term. Long-term products are mainly financial derivatives, such as futures, that allow hedging of the portfolio. In long-term market transactions, the time frame is up to several years. The final day profile of the portfolio can be refined as the time frame of the physical trade approaches. The market participant has the opportunity to participate in the day-ahead and intraday markets prior to the physical trade of electricity.

After the delivery, market clearing, where a possible imbalance in supply and consumption is cleared, takes place (the process is called balance settlement). If an imbalance exists, it is charged either an up- or down-regulation price, depending on the case. The electricity market includes imbalance settlement services that confirm the amount of electricity that each market participant has consumed or generated, and who is responsible for paying for each kilowatt-hour. The electricity market requires that electricity production and consumption are kept in equilibrium at all times. Each of the balance responsible party must plan its activities and make every effort to maintain this balance. However, in reality, there will always be deviations from the plans as a result of the forecasting involved. The balance error or deviation from the planned is called imbalance (ESett,

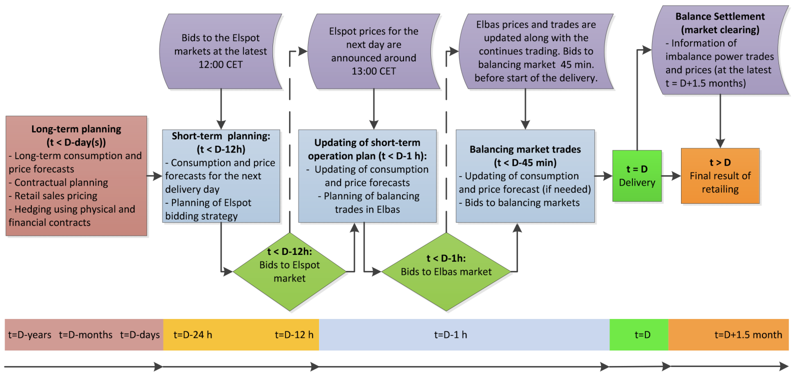


Figure 3.5: Electricity retailer's planning periods and market time frames (Valtonen, 2015).

2023).

In the electricity system, collaboration of all the parties involved is required. Electric energy must travel through multiple grid operators before it reaches the consumer, and there must always be someone to purchase it. Consequently, the electricity sales sector cannot operate without communication with the other parties in the electricity markets or in the power system.

Retailers are required to participate in data exchange, for instance, by providing details about electricity deliveries and by acquiring customer data from a centralized data storage. Primarily, data exchange takes place through Datahub, operated by the Finnish TSO Fingrid (Fingrid, 2023a). Electricity retailers and distribution system operators are legally required to use Datahub services when engaging in the electricity retail market (*Sähkömarkkinalaki* [Electricity Market Act], in Finnish, 2023). Service providers that offer their services to electricity consumers and market participants can also benefit from Datahub.

Figure 3.5 summarizes the retail market and illustrates the retailer's planning periods prior to market time frames.

4 Considerations of EV charging impacts on the power system

The trend toward sustainable transportation is gaining traction, and EVs are becoming more widespread. This chapter focuses on the publications of this doctoral dissertation and highlights their main results and observations. The chapter seeks to provide a comprehensive overview of the various aspects of EV charging and its effects on the power system. These considerations are essential to gain a better understanding of the impacts of EV charging on the power system.

4.1 Electricity distribution system

Typical household loads consist of many rather static loads, such as electric stoves, ovens, toasters, and boilers. In the Nordic countries and especially in Finland, also electric sauna stoves are a substantial load having a power from several kilowatts to more than ten kilowatts. A common factor for most of these electrical appliance loads is that they are highly dependent on the user's personal preferences. In other words, inhabitants' behavioral routines create load patterns produced by electric appliances.

Traditional grid dimensioning is based on type loads for each type of customer group. The recommendation (Sähköenergialiitto ry SENER, 1992) describes the dimensioning practices for the type loads that have been widely used in distribution grid planning, but also by retailers when forecasting the load profile and total demand of the customer portfolio. The load profiles have been updated to meet the present electricity consumption behavior (Mutanen et al., 2019), but the same principles for using the type curves remain.

In the definition of the type curve, customers are divided into groups based on their consumption type, such as a detached house with electric space heating or an apartment house with electric space heating. Formation of the type curve requires a substantial amount of data to provide a good and feasible type curve that could be used for further analysis of the power system. The mean and standard deviation curves can be formed as follows:

$$\mu_{\mathrm{P}}(t) = \frac{W}{8736} i_{2\mathrm{w},\mu}(t) i_{\mathrm{h},\mu}(t), \tag{4.1}$$

$$\sigma_{\mathrm{P}}(t) = \frac{W}{8736} i_{2\mathrm{w},\sigma}(t) i_{\mathrm{h},\sigma}(t), \tag{4.2}$$

where μ_{P} is the mean power of the present type load customer, W is the customer's annual energy, $i_{2\mathrm{w},\mu}$ is the normalized two-week index, and $i_{\mathrm{h},\mu}$ is the normalized hour index.

Similarly, σ_{P} is the standard deviation of the present type load customer, W is the customer's yearly energy, $i_{2\mathrm{w},\sigma}$ is the two-week index, $i_{\mathrm{h},\sigma}$ is the normalized hour index, and t is the time index (hour of year). Thus, the maximum power of the customer can be approximated by the probabilistic method as follows:

$$P_{\max}(t) = n_{\mathrm{c}}\mu_{\mathrm{p}}(t) + z\sqrt{n_{\mathrm{c}}}\sigma_{\mathrm{p}}(t), \tag{4.3}$$

where $P_{\max}$ is the present estimated maximum load of the customer group, n_{c} is the number of customers in the group, and z is the confidence number defined as follows:

$$\Phi(z) = P(Z \leq z) = 1 - \frac{\alpha}{2}, \tag{4.4}$$

$$z = \Phi^{-1}(\Phi(z)), \tag{4.5}$$

where α is the confidence level, and Φ is the cumulative normal distribution. The method is well proven and widely used to describe the mean value of load curves and the probabilistic maximum value at the desired confidence level.

Modern smart appliances that are controlled with various signals create an additional uncertainty element in the dimensioning of the grids. The smart EV charging is an interesting example of this. The EV smart charging can be controlled with different kinds of signals, such as network frequency, SPOT market price, or other market-derived signal. Common for all these signals is that there is no stochasticity in the response to these signals. Rautiainen et al. (2016b) show that SPOT price-controlled charging is likely to accumulate high peak powers on LV transformers and LV grids. This also leads to load accumulation to a higher grid level, if not controlled or constrained in any way. Haapaniemi (2022), Lummi et al. (2016), and Rautiainen et al. (2017) study how this kind of event could be controlled with power-based distribution tariff structures. Distribution tariff structures are a passive approach to cope with the problem. Publication II studies a case where the whole LV distribution network would be actively constrained with a dynamic power limit. The study concludes that even with a 100% EV penetration level, the maximum load of the LV network would not exceed the maximum power of the case without any EVs in the area. Figure 4.1 shows an example graph of the simulations.

In their report, Tikka et al. (2021a) demonstrate a similar simulation model and control strategy that has been applied at the apartment building level. The results clearly indicate that the maximum powers at the apartment building level can be maintained within the main fuse limits by employing dynamic load control. The model shown in the report is based on the model specified in Publication I and Publication II, but the input data have

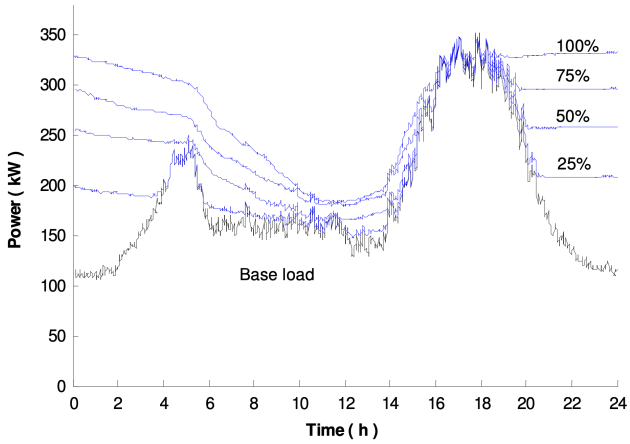


Figure 4.1: Smart charging curves of BEVs with penetration levels of 25%, 50%, 75%, and 100% (412 cars) (Tikka et al., 2012) © 2012 IEEE.

been updated with the latest statistics available. The simulation example shown in Figure 4.2 assumes a 100% EV penetration level, which means that in this particular example there are on average 1.35 cars per apartment and a total of 15 apartments.

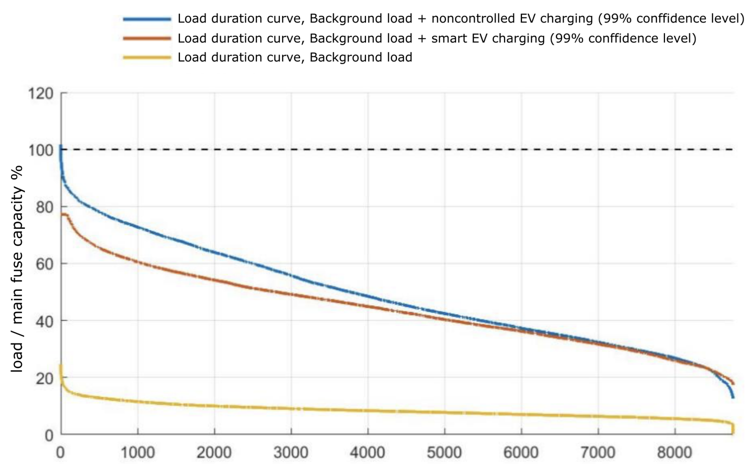


Figure 4.2: Continuity curve of the peak powers in the case of EV charging in parking areas of apartment buildings (Tikka et al., 2021a).

The example shows that the building grid interconnections in the sample case were originally dimensioned to handle almost tenfold loads, and thus, adding EV charging loads to these buildings is hardly a challenge. Dynamic load control cuts down the highest peak hours allowing to maintain the load under the main fuse limit. However, in comparison with the cases shown in Figure 4.1, where there are several hundreds of EVs, the load per unit or the load per EV is much lower than in the case where there are fewer cars. The stochasticity of the EV charging plays a crucial role, even when smart charging applications are introduced. Nevertheless, it is critical to recognize how the charging of EVs is taking place and what kind of smart charging application has been implemented.

A similar example of simulation results is shown in Figure 4.3, where the simulation is performed in 550 individual row houses. The results show that before the introduction of EVs, the maximum loads were below the maximum allowed current limit of the main fuse. The uncontrolled charging causes nearly a half of the cases to exceed the allowed main fuse limit, but the dynamic load control is able to reduce the number of cases exceeding the main fuse limit to 60 cases out of the total of 550.

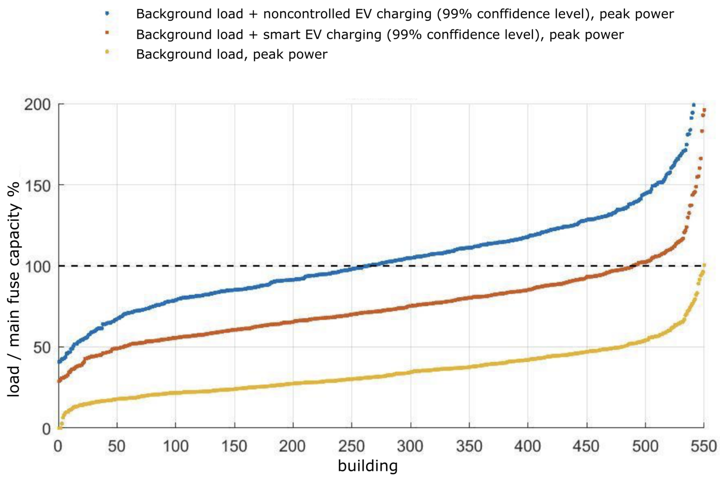


Figure 4.3: Continuity curve of the peak powers in the case of EV charging in parking areas of an apartment buildings (Tikka et al., 2021a).

It is pointed out that the presented examples are estimations of 100% penetration levels, which will not be reality in the near future. However, it is worth considering what the impact on the distribution grid will be. As the future scenario covers a rather long period, it would be useful to study more advanced approaches to manage loads on the distribution grid and possible congestion situations. Publication IV reviews the opportunities for bidirectional charging for local flexibility, in other words, how birectional EV charging could be harnessed to support distribution grids. The potential of V2G to provide technical flexibility is considerable, ranging from participation in electricity markets to provision of balancing and system-level services for transmission and distribution network operators. To ensure the success of V2G business models, it is essential to understand their value proposition. Figure 4.4 illustrates the business models identified in the different domains of the distribution system.

The business models are presented at a rather high level, but can be effectively used to

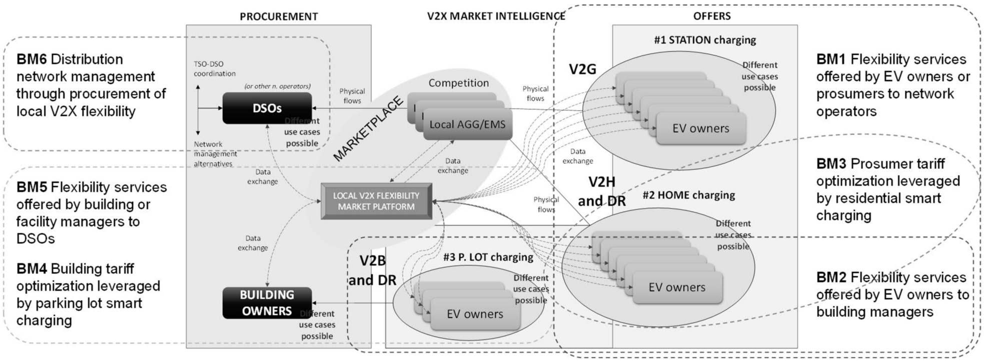


Figure 4.4: Concept of a bidirectional charging marketplace with a wide range of potential business models (Mendes et al., 2023) © 2023 IET.

identify value propositions and value chains. The value of a business model is highly dependent on the current regulatory environment. When the regulatory environment fails to enable the functionality of new business models, it also invalidates the value proposition. The regulatory framework is constantly evolving and updated, and thus, it is important to identify what business models might emerge in the future. The identified business models and meaningful value propositions are also driving the change in the energy system and can influence the regulatory framework.

Publication III reduces the abstraction level and investigates the value of energy storage as an alternative to grid investments. The approach presented in the publication shows that there is an opportunity to create added value with the EV battery when it is not actively used for the primary use case of the car, i.e., driving. The present energy market or the regulatory environment does not provide a great incentive for such an option. At present, a DSO is not allowed to directly control customer loads (*Sähkömarkkinalaki* [Electricity Market Act], in Finnish, 2023). In theory, DSOs could purchase resources from the market, but such a flexibility market does not exist yet. There are EU-level activities in several research projects that either review the potential flexibility markets (Fournely et al., 2022) or provide demonstrations of such a flexibility and market transactions (Khomami et al., 2020). Thus, it is worthwhile to study further how EVs can be harnessed to provide a valuable flexibility resource for the distribution grids.

Publication III discusses the use of EVs as energy storages in distribution grids and describes the methodology to estimate the monetary value of the flexibility resource. The modeling of the bidirectional charging relies on the same principles that apply to unidirectional charging. The main methodology of the study can be summarized as shown in Figure 4.5.

In Publication III, it is assumed that the optimization of network capacity is the primary objective. It is also shown that the advantages of energy storage are heavily dependent on

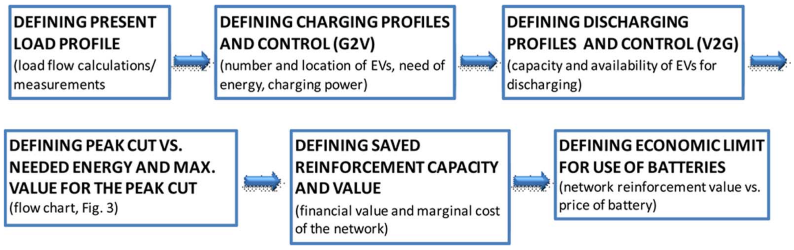


Figure 4.5: Main steps of the modeling of the economic benefits of V2G applications from the DSO's point of view (Lassila et al., 2012) © 2012 IEEE.

the shape of the base load in the network. The maximum operating time and the shape of the load curve are closely related. If the peak of the load curve is sharp, the peak operating time of the battery becomes shorter. If the load profile is more even without a sharp peak, peak cutting applications with a battery energy storage are not feasible. If the peak operating time is short, as is often the case in low-voltage networks, the benefit of the storage can be considerable. From the grid's perspective, the use of the energy storage evens out the load curve, frees up network capacity, and improves the utilization rate of the network capacity. Figure 4.6 illustrates how the required storage develops as the peak cutting level increases. The further the peak load is pushed down, the more storage capacity is required.

Figure 4.7 shows the dynamics of the economic feasibility of an energy storage. The best result can be achieved if the storage is only used to reduce the sharpest peak loads or only the highest peaks. The analogy applies also to bidirectional charging, as only a small fraction of the EVs' battery capacity is available for such activities. It must be taken into account that the primary use of EVs is transportation, and that other applications should not interfere too much with the primary application, i.e., driving the EV.

The temporal modeling can be further extended by adding a spatial dimension to the model. Publication VII investigates the spatial distribution of EVs by processing and analyzing socioecomonic data in the CNN model. The modeling shows promising results of using the CNN model for this task. Similar spatial modeling has been typically carried out using models based on self-organizing maps (Kohonen, 1990). In another study, Chen et al. (2022) investigated a similar problem set by negative binomial regression models, which include a "neighboring effect" similar to CNN models. The neighboring effect refers to a modeling phenomenon where a neighboring spatial area might explain the target variable in the observed spatial location. The CNN model aims to capture the neighboring effect and thus improve the modeling accuracy. The main concern with the CNN model is that it requires a large amount of learning data, like any other ANN model.

Figure 4.8 shows the flowchart of how spatial modeling can be included in the distribution system planning process. The process in question is characterized by the utilization of a

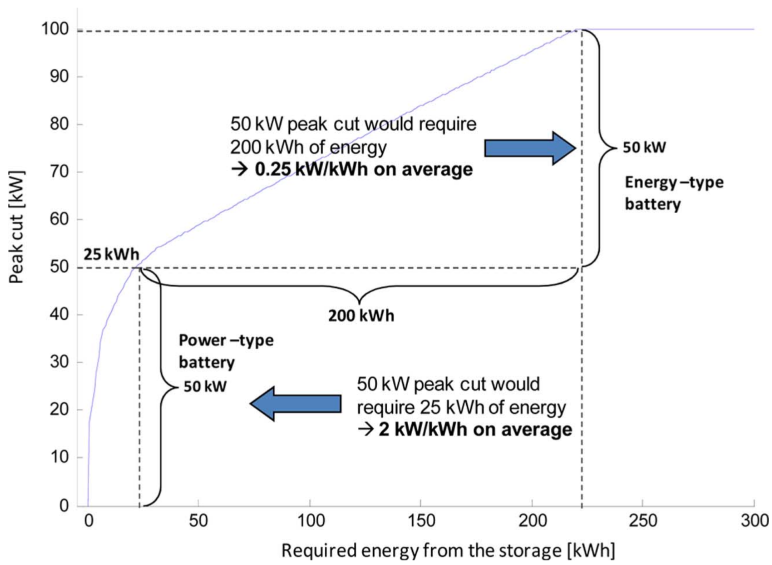


Figure 4.6: Dynamics of the energy storage applications in distribution grids against the storage size (Lassila et al., 2012) © 2012 IEEE.

large amount of data, which is handled through stochastic processing, probabilistic techniques, and time series analysis. With the increasing importance of EV charging loads, it is advisable to explore which tools can be employed to make the network planning process as effective as possible. The new spatial analysis tools are a most welcome addition to the planning process, as they can reduce the uncertainty in spatial dimensions.

4.2 Electricity retailer and aggregators

The electricity retailer is an essential player in the energy system. The aim of the retail business is to maintain the profit gain by selling electricity in a competitive market, which means in practice that the retailer must have tools to maintain sales and purchase portfolios as accurately as possible to make profit. The advancements in the customer's end loads make the task even more challenging. The loads are becoming seemingly unpredictable if they are not analyzed carefully. As mentioned in the previous section, load forecasting has previously been performed with relatively old methods, and the rapid transformation of transportation has created a need to update methods.

Electricity retailers do not have the burden of maintaining the physical grid, but the economic consequences can be still significant if electric mobility is not correctly included in the analysis, and the forecast horizon of the retailer is from hours to years ahead. The rapid change in electric mobility causes an increase in energy demand and significant changes

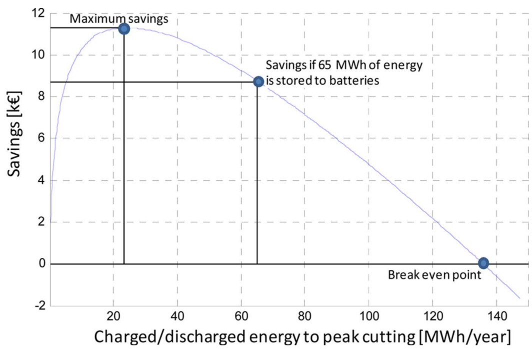


Figure 4.7: Economic dynamics of the energy storage applications in distribution grids in contrast to the storage size (Lassila et al., 2012) © 2012 IEEE.

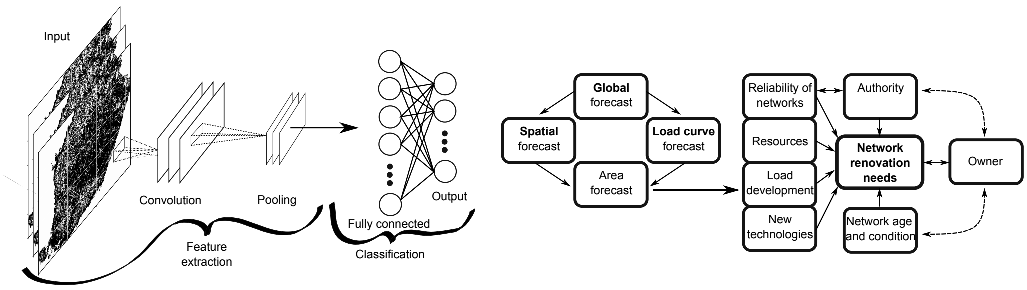


Figure 4.8: Simplified illustration of the drivers of the DSO network renovation and spatial load forecasting (right) and simplified illustration of the CNN model (left) (Tikka et al., 2022) © 2022 Elsevier.

in the load profile, which can be seen to impact the retailer's profile risk. The high profile risk introduces a higher uncertainty and is often likely to increase the retailer's imbalance costs. For instance, if cars are charged in an uncontrolled manner, the main peak is timed to coincide with the typical household loads. An example of such an EV charging load profile is shown in Figure 4.9.

In the example case, the simulated charging load profile closely corresponds to the household load. This supports the fact that if charging is uncontrolled, the charging starts at the same time as other appliances are used. In the example, the charging load is simulated for the area of 11 apartment buildings comprising a total of 412 apartments. The simulation assumes a 25% penetration level, which means that there are 100 EVs worth of charging demand.

The study was carried out in 2010, when the number of EVs was low, but the profile and the energy demand are still valid today in the modeling standards. The author of the dissertation has contributed to the modeling of EV charging for a decade, which has been

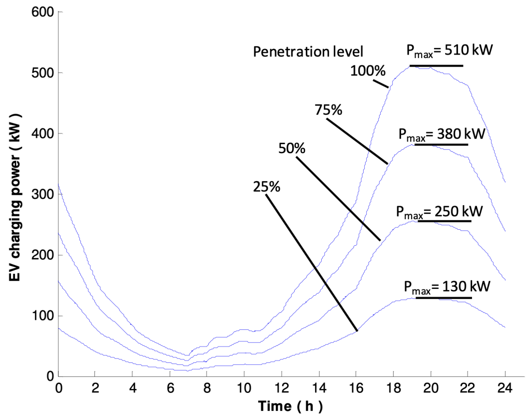


Figure 4.9: Load profile of uncontrolled EV charging (Tikka et al., 2011) © 2011 IEEE.

a period of major transformation from the viewpoint of transportation. In the past ten years, the availability of input data has increased considerably while also the selection of EVs has increased from a few models from a few manufacturers to more than 100 models from tens of manufacturers (Traficom, 2022b). While the number of cars has increased significantly, the car technology has developed and also the knowledge of actual charging curves has increased.

Section 4.3 discusses observations obtained by measuring EVs in a laboratory environment and further, how the observed features can be included in the modeling. These external features, such as ambient temperature, are often neglected, but Simolin (2022) points out that there are "nonidealities" that impact the charging load modeling. The author also mentions that these features impacting the charging curves have not been taken into account in many studies. This doctoral dissertation shows how low ambient temperatures cause substantial changes in the load curve and the peak load. These changes are also of significance from the retailer's perspective and require the models to be updated accordingly.

4.3 Impact of ambient temperature

The profiles are dynamic in nature, as multiple external signals can impact the way load profiles are shaped. The most common external characteristic is ambient temperature, which causes the energy demand of EVs to vary but also introduces major changes to the load profile. Publication VIII studies the impact of ambient temperatures on the energy demand of EV charging events and the shape of the load profile.

When the ambient temperature decreases below zero, EVs consume not only more energy while driving, but also more energy during the charging event. The first and most obvious reason for the change in the load profile is the increased energy demand as a result of the increasing energy demand for driving. This feature changes slightly the stochastic properties of how the peak load of multiple vehicles is formed; a higher energy demand causes the loads to overlap more, and constitutes the basis for a slightly higher peak load. The second reason for the load profile of different shape is the introduction of preheating or defrosting of cars prior to driving. This additional morning peak is not the most relevant one when analyzing the impact of the distribution network, but considering the management of the profile risk of the retailer customer portfolio, this highly temperature-dependent peak becomes extremely important. Third, when the temperature is in the range from -10°C to -20°C or even lower, the EV charging introduces yet another temperature-dependent phenomenon that impacts the load profiles. In extreme subzero temperatures, most cars use additional energy to heat up the battery to a temperature where it can be safely charged; this introduces additional delays in charging events, but also requires considerable amounts of additional energy. Figure 4.10 shows a comparison between the simulated charging curves at ambient temperatures of +20°C and -20°C.

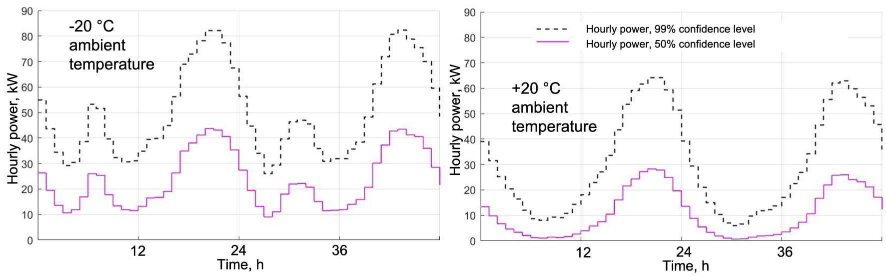


Figure 4.10: Uncontrolled EV charging load profile; a comparison of charging events at +20°C and -20°C ambient temperatures. The right graph shows the charging load profile simulated for the ambient temperature of +20°C, and the left graph when the temperature parameter is changed to -20°C (Tikka et al., 2023) © 2023 IET.

The comparison shows that the probabilistic peak load is substantially larger at low temperatures; this is mainly caused by the increase in energy demand, which increases the charging time. The increased charging time changes the stochastic properties of the accumulated charging event, i.e., more overlapping charging events. The mean value profile can be used to estimate the total energy demand of the simulated group of charging events.

The total energy is also affected by the preheating cycle that takes place before driving. This introduces a substantial power peak for the morning hours. Assuming that a similar model would be modeled for office parking, the preheating cycle would appear right before the end of office hours. This observation emphasizes that when charging is modeled, it is crucial to understand what the charging use case is and what the main objectives of the car user are. For example, in the Nordic countries, preheating or defrosting is a feature that must be included in the modeling.

4.4 Smart charging to minimize the charging cost

In addition to temperature, it is highly likely that charging can be controlled. Different control strategies change the behavior of the load considerably, which can be challenging if not taken into account. Publication V shows a pilot demonstration of SPOT-tariff-controlled charging. The actual smart charging strategy carried out on the test bed is shown in the second graph from the top. In the uncontrolled charging scheme, it is assumed that the car is charged immediately after plugging in with a nominal power of 3 kW. The paper shows that if the uncontrolled charging cost is compared with smart charging that minimizes the charging cost, the total charging cost decreases to 50% of the comparison cost. The absolute savings are not significant, but this creates the consumer an incentive to control charging if the control can be enabled with ease and without a significant additional investment cost. In the smart charging strategy, it is assumed that the charging takes place when the Nord Pool Spot price is at the lowest and the charging window is met. This example study shows energy savings per week, but it must be kept in mind that the electricity SPOT prices are constantly changing, and absolute savings are highly dependent on fluctuating SPOT prices.

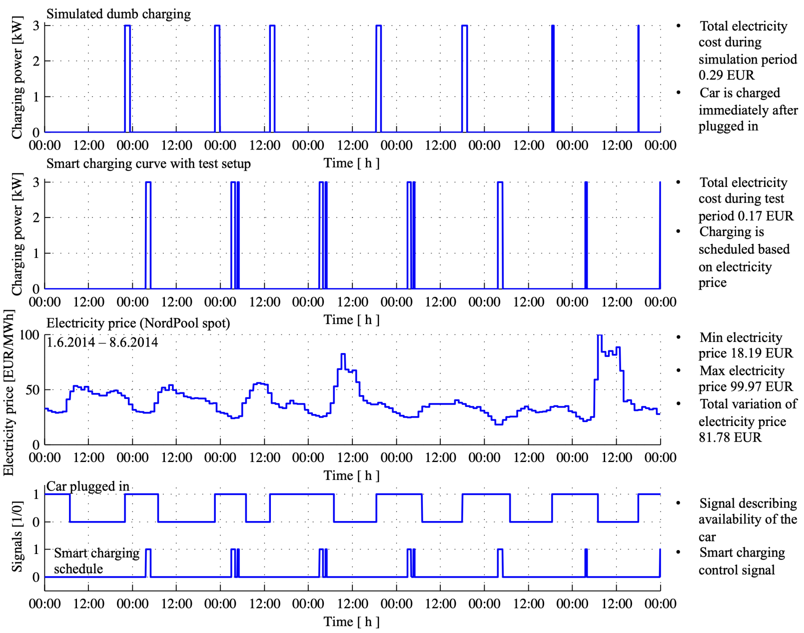


Figure 4.11: Smart charging test executed in the demonstration setup. The charging events in the top graph are simulated to provide a reference point (Tikka et al., 2014) © 2014 IEEE.

Smart charging does not necessarily benefit the grid. Applications that are controlled by synchronized control signals, such as SPOT price or, for instance, grid frequency, introduce a control logic that has no stochasticity besides the availability of the resources.

If all the resources are given the same control signal, each resource available executes the control at the same time. The issues have been recognized in various studies, and there are means to tackle this kind of behavior. Several studies propose novel tariff structures to manage high peak powers (Rautiainen et al., 2017; Lummi et al., 2016; Haapaniemi, 2022).

4.5 Local flexibility

Local flexibility, i.e., DSO congestion management is a highly interesting type of flexibility that can be implemented with unidirectional charging, or it can gain additional benefits if charging is bidirectional. Simple smart charging is often used to manage loads at the building or parking area level. Publication II and Publication VIII consider similar dynamic load management, but the first study addresses the flexibility of a whole LV transformer area. The second example, in turn, studies flexibility at the building level. In both examples, the objective is to keep the power below a certain predefined level.

The main outcome of the studies is that dynamic load control greatly increases the hosting capacity of a building or a parking area. The total energy demand is hardly any challenge for the grids, but the timing of the uncontrolled charging load often is; thus, the dynamic load control is highly beneficial, not only for the grid area where the charging takes place but also for a wider grid area.

4.6 Transmission system

EVs are also a valuable resource for the electricity production and transmission. The fundamental requirement for the electricity grid is that production and demand are always in perfect balance. The frequency of the power system is a direct and real-time indicator of the balance between electricity production and consumption. When there is more consumption than production, the frequency of the grid drops, and when there is more production than consumption, the frequency increases. Basic physics dictates that all generators and loads contribute to the frequency (by producing active power), which is the same in all parts of the grid that are interconnected with AC links. FCR is the resource that maintains and fine-tunes the frequency of the grid. FCRs are special in that they must respond quickly and accurately to changes in frequency in order to prevent further deviation and restore the power balance. The frequency of the grid is constantly changing as production and consumption fluctuate, usually only within a range of +/- 0.05 Hz, and it is kept close to its nominal value of 50 Hz by adjusting the production capacity or managing the loads. The ultimate responsibility for maintaining the frequency of the system lies with the TSO.

Publication VI studies how EVs can contribute to maintaining the frequency of the grid within the nominal range. This research demonstrates that EVs can be used as part of FCR markets when combined with local control and, in certain cases, with a dedicated demand response infrastructure (measuring devices, servers, services, and telecommunications). However, the use of the existing AMR infrastructure of the DSO causes delays that currently prevent EV batteries from being used as a flexibility resource in the primary reserve markets. But if the local control is applied, the tested EVs could qualify in the FCR markets, either in FCR-N or FCR-D.

4.7 Summary and discussion

The variety of opportunities of EV charging and the possible range of applications are extremely wide, and this doctoral dissertation analyzed only a few examples of possible charging scenarios. There is a significant potential in EV charging as EVs are generally untapped resources for most of the time (parked most of the day). The easy-to-access smart charging is already available for EV drivers, and the charging can be optimized to the cheapest hours by using a simple mobile application (Gridio, 2023). Furthermore, there are smart chargers that can enable dynamic load control at the building level to keep the charging load below the allowed current limit of the main fuse. The more advanced applications, such as local flexibility and bidirectional charging applications, are still mostly found in academic studies and pilot experiments, although in some cases, commercial pilots exist.

Applications or control strategies that do not match well together or their impact is not positive for all the parties of the energy system are likely to emerge. The most obvious case would be smart home charging, which benefits the EV user. The load control at the customer end is usually implemented without knowledge of the retailer. Therefore, the control might introduce an additional risk share to the retailer's customer portfolio, but usually, the dynamics of the customer demand response can be learned and modeled. The setting becomes more challenging, if loads are controlled to manage congestion in the distribution grid. From the retailer's perspective, this type of demand response might not seem something that can easily be modeled or included in the forecasting. To avoid conflicts, there should be good and seamless integration between all parties in the power system.

The electrification of mobility is still in an early stage in Finland. There were about 182 000 EVs and PHEVs in Finland at the end of June in 2023 (Traficom, 2023). Most cars are still of the first or second generation EVs and possibly do not support all possible charging applications. The current measures in the planning activities preparing for the increasing numbers of EVs mainly aim to forecast how uncontrolled charging appears in the grids and the retailer portfolio. As the number of EVs increases, the smart application becomes more and more important for several reasons:

- The large number of EVs is likely to cause a need for grid reinforcement if not managed properly. The charging can be managed by implementing dynamic load control already at the building or parking area level, as suggested for instance in (Tikka et al., 2021a). In addition, it is important that the communication between the parties of the energy system is enhanced even further.

- Smart applications, such as FCR applications or local flexibility, can be used to support the grid and the power system. Applications are likely to become more economically feasible as power systems face an increasing amount of fluctuating renewable production while EVs also become more common. There are still regulatory questions to be solved to fully harness the potential.

- Bidirectional charging may stand out as a valuable resource if there are standardization and original equipment manufacturers (OEMs) to support it. Prominent business cases are found in charging places where cars are kept for longer periods of time (e.g., transportation hubs, home charging, airports, hotels). Fast or ultra fast chargers may not benefit from bidirectional charging as the primary target is to spend as short a period of time as possible at the charger.

Table 4.1 summarizes the impact of various applications on the different parties of the power system. Most of the smart applications result in positive impacts on the power system, but some conflicts also exist.

Table 4.1: Impacts of different EV charging application to energy market parties.

	Ancillary services: FCR-N, FCR-D, others	Local flexibility for DSO: congestion management, peak shaving	Local flexibility for prosumer or parking area: peak shaving, dynamic load control	Market signal controlled charging: SPOT-price-based cost minimization	Uncontrolled charging, non-managed
Prosumer	+	+	+++	+++	-
CPO	+	++	++	+	N
Aggregator	+++	+++	++	+	N
Retailer	N	---	+	++	+
DSO	-	+++	+	---	--
TSO	+++	+	+	+	-
Production	-	N	N	-	-

+ positive impact, N neutral impact, - negative impact

The applications have a significant impact on how each party of the energy system perceives the impacts of EV charging. Some applications, such as power-intensive ancillary services, benefit the TSO and the aggregator without interfering with the other participants' business. Other applications that might be more energy-intensive, such as flexibility services for the distribution grid, are likely to have a negative impact on the management of the retailer's portfolio, assuming that there is no good coordination between the retailer, the aggregator, the DSO, and the TSO. Ancillary support services aimed for the TSO are prone to create additional stress to the DSO's grid. If not coordinated, this is likely to create a conflict between the TSO's and the DSO's interests. The coordinated operation has been studied and discussed in research initiatives (Attar et al., 2024; Givisiez et al., 2020), but common practices are yet to be established. A similar conflict emerges if consumers control their loads to minimize the charging cost (SPOT-price based). In this case, the consumer benefits and the DSO faces the downsides of the smart charging as peak loads are likely to increase. To conclude, the benefits are highly dependent on the application and the use case. In addition, to harmonize and manage the impacts, it would be beneficial to ensure smooth coordination between different energy market parties.

5 Conclusion

As the main outcome, the doctoral dissertation shows the variety of EV charging applications and modeling practices. The novelty of the dissertation is in summarizing a wide range of EV charging applications and laboratory experiments to quantify the impacts of EVs on the power system and its various parties. A particular novelty lies in adding the features of the cold environment to the load modeling of EVs, but also in showing that spatial modeling benefits from using CNN models. As the main outcome, it can be stated that EV charging will have a significant impact on the power system, but the impact will depend on the development of smart charging applications. Uncontrolled charging is, in many cases, likely to considerably increase the grid load and also cause specific and highly regional overloading scenarios. In many cases, the load can be managed by implementing a simple dynamic load control that reduces the peak loads. The statement cannot be generalized too far as the grid environment varies case by case.

It is also likely that smart applications will include applications that may not benefit distribution grids and cause more congestion problems. The SPOT-price-based control taking place at the customer end is likely to cause such an issue. However, there are measures that may tackle the issue. Novel tariff structures are one option to control the customer end load development, but also EV charging can be used to provide local flexibility. Nevertheless, the new control strategies still lack many conceptual definitions, architectural refinements, and standardization before they are ready for the market.

Although new applications are not yet reality, the DSOs are recommended to investigate a variety of use cases that smart charging applications might enable. A review of business models is essential to identify the most prominent value propositions in the field. If the value proposition is strong, it is worth studying further and including the approach in future scenarios. The dissertation shows that value can be gained in several stages of the system, making cases that enable value stacking more prominent.

In general, the most relevant factors in EV charging modeling to be monitored are:

- The number of EVs and their spatial distribution, which can be explained and estimated based on the socioeconomic statistics supported by registration statistics.
- Major changes in the driving statistics. Modeling is highly sensitive to the driving statistics and the charging behavior.
- Vehicle technology developments and especially developments in battery technology. The major changes in the battery size can have a significant impact on the charging behavior and thereby also on the properties of the load profile.
- Ambient temperature. Ambient temperature should always be included in the modeling to achieve accurate estimates of the energy demand and the load profile.

- Use cases—How cars are charged. The most prominent impact on the load profile is caused by changes in the customer use case. To make futureproof scenarios, it is essential to analyze novel use cases that might appear feasible in the near future.

Regardless of the stakeholder in question, the same modeling principles apply. The load profile is the same for all the players in the energy system. It is also noteworthy that most charging schemes involve most of the stakeholders of the energy system, and in many cases there is already some data flow present, at least AMR meter hourly series. As the final conclusion, the modeling practices and indicators are the same for all stakeholders in the energy system. If some of the above-mentioned indicators change, the impact is always visible for all the stakeholders involved.

5.1 Scientific contribution

The doctoral dissertation outlines the relevant factors that have the most significant effect in the load modeling of EV charging. Load modeling is at the core of several parties operating in the field of electricity distribution and electricity markets. The models presented in this work can be used in the DSO asset management process, as well as in the operational tasks in the daily operation of the distribution grids. A similar modeling approach provides a valuable tool to analyze the development of loads in the near future in order to maintain the development of the transportation system. The dissertation highlights the most important factors and variables that have to be considered when operating in the energy-system-related business, whether it is infrastructure-related or more market-oriented operation. Identification of the impacting factors also serves as a good starting point for constructing scenarios in business development.

The main contributions of the dissertation are:

- Identification of the most relevant factors of EV charging that impact the accumulation of peak power in the electricity grid, the energy content, and the shape of the load curve.

  The factors vary depending on the output factors that are observed. The energy content is highly dependent on the kilometers driven, but also on the charging preferences, i.e., whether the car is charged daily or less often. The energy content also depends on the ambient temperature, because the cold environment increases the energy consumption when driving but also during charging because of the auxiliary battery heating. Often, the energy content is also bounded by the capacity limits of the battery (technical or defined by the user). The energy content also heavily depends on the charging locations. Peak power is a result of multiple factors. The most significant factor that affects the peak power is the distribution of the arrival time. The shape of the arrival time distribution mainly defines the accumulation of the peak power. Further, the duration of the charging event impacts the peak power as the overlap of the charging events is likely to increase. The charging time is mostly dependent on energy and charging power, but also ambient temperature may have an impact on the charging power and also on the total energy charged to the battery of the EV. The final shape of the load curve is defined by the parameters described earlier. The shape and temporal timing of the EV charging load curve is also dependent on the preheating of the vehicles in the morning or when leaving the workplace. The factors defined previously are all relevant to smart EV charging applications, but the maximum power, energy content, and final shape of the load curve are highly dependent on smart charging applications and use cases.

- Scientifically proven modeling methods to analyze EV smart charging (flexibility), which has an impact on various players in the energy sector.

  As discussed previously, the characteristics of the charging load curve depend on several factors that are highly relevant when analyzing the impact of the charging on the DSO, the retailer, or the aggregator. From the DSO's perspective, the probabilistic features of the load profile are the most critical parameters that should be known well in order to be able to sufficiently prepare for the future electricity demand. The retailer benefits from the same features, but for different reasons. The retailer aims to model the next-day demand as closely as possible to manage the balance of the sales portfolio. The aggregator is often more interested in the flexibility that the EV charging can provide, and thus, the focus lies not only on the demand curve, but also on the availability of resources.

- Showing that the CNN-based spatial modeling can be used to estimate the combination of temporal and spatial features of the EV smart charging.

  The results of the model are adequate to support the network planning of the DSOs, as the model is obviously able to demonstrate an increased likelihood of the occurrence of EVs. However, because of the scarcity of samples from the minority class in the existing datasets, it is uncertain to what extent the model can be of benefit to the network planning with the current dataset. When the model architecture and parameters are refined, it is probable that the model performance can be further enhanced. In conclusion, CNN has great potential for modeling spatial EV distribution.

- Identification of potential business cases of V2X technologies for the power system.

  EVs are becoming increasingly common, and it is essential to better understand bidirectional charging strategies and the support services that they enable. The study reviewed six different business models for bidirectional charging flexibility to gain an insight into where the value proposition lies. The review helps in identifying the most prominent business cases.

5.2 Further research

This doctoral dissertation shows a novelty in smart charging application modeling, but as previously stated, the transition of the transportation system to be based on electricity is extremely rapid. Therefore, the research presented in this dissertation requires constant upgrading to keep up with the change. The particular issue identified during the dissertation process is that many smart applications are not enabled owing to the lack of a proper communication infrastructure. Or, to be more precise, the physical communication link often exists, but the data exchange architecture and definitions do not support the novel applications. The topic calls for more research, activities in standardization, and commercial piloting.

Furthermore, the spatial modeling showed significant indications of its usefulness, but a lot of work remains to be done. It is worth investigating in future studies how the CNN model could be improved and whether additional input data could enhance its performance. The dataset was limited to socioeconomic factors and vehicle registration statistics, and thus, the further development of the model could benefit from information on land use, road network, and other infrastructure. Furthermore, because the model showed potential for use in spatial analysis, it could be employed also in many other cases. For example, the customer loss in rural areas is often attributed to changing socioeconomic factors and infrastructure, making it a suitable use case for the proposed model.

References

ACEA (2011). *ACEA position and recommendations for the standardization of the charging of electrically chargeable vehicles*. Tech. rep. Brussels, p. 5.

Affonso, C. M. and Kezunovic, M. (2018). Probabilistic Assessment of Electric Vehicle Charging Demand Impact on Residential Distribution Transformer Aging. In: *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*. IEEE, pp. 1–6. ISBN: 978-1-5386-3596-4. DOI: 10.1109/PMAPS.2018.8440211.

Alaoui, C. and Salameh, Z. M. (2003). Experiments in fast charging lead acid electric vehicle batteries. In: *IEEE Vehicular Technology Conference*. Vol. 58. 5. Institute of Electrical and Electronics Engineers Inc., pp. 3326–3331. DOI: 10.1109/VETECF.2003.1286292.

Asgarian, F., Hejazi, S. R., and Khosroshahi, H. (2023). Investigating the impact of government policies to develop sustainable transportation and promote electric cars, considering fossil fuel subsidies elimination: A case of Norway. *Applied Energy* 347, p. 121434. DOI: 10.1016/J.APENERGY.2023.121434.

Ashtari, A., Bibeau, E., Shahidinejad, S., and Molinski, T. (2012). PEV charging profile prediction and analysis based on vehicle usage data. *IEEE Transactions on Smart Grid* 3(1), pp. 341–350. DOI: 10.1109/TSG.2011.2162009.

AST (2022). *On the suspension of electricity imports from Russia*. URL: https://view.news.eu.nasdaq.com/view?id=b62aadb50d4d3bd34550a8d2b09b7f6df%7B%5C&%7Dlang=en (visited on 09/19/2023).

Attar, M., Repo, S., Mutanen, A., Rinta-Luoma, J., Väre, T., and Kukk, K. (2024). Market integration and TSO-DSO coordination for viable Market-based congestion management in power systems. *Applied Energy* 353, p. 122180. DOI: https://doi.org/10.1016/j.apenergy.2023.122180. URL: https://www.sciencedirect.com/science/article/pii/S0306261923015441.

Autoalan Tiedotuskeskus (2020). *Ladattavien autojen käyttäjätutkimus-selvitys ladattavien hybridien ja täyssähköautojen käyttötavoista*. Tehcnical report, p. 47.

Avcon (2000). *Avcon Products*. URL: https://web.archive.org/web/20100312013907/http://www.avconev.com/.

Breyer, C., Tsupari, E., Tikka, V., and Vainikka, P. (2015). Power-to-Gas as an Emerging Profitable Business Through Creating an Integrated Value Chain. *Energy Procedia* 73, pp. 182–189. DOI: 10.1016/j.egypro.2015.07.668.

CHAdeMO (2010). *General Outline of "CHAdeMO Association"*. Tech. rep.

CHAdeMO (2023). *Fact sheet | CHAdeMO*. URL: https://www.chademo.com/about-us/fact-sheet (visited on 09/18/2023).

Chen, S., Sedghi Gamechi, Z., Dubost, F., Tulder, G. van, and Bruijne, M. de (2022). An end-to-end approach to segmentation in medical images with CNN and posterior-CRF. *Medical Image Analysis* 76, p. 102311. DOI: 10.1016/J.MEDIA.2021.102311.

Climate Watch Platform (2022). *Climate Watch Historical Country Greenhouse Gas Emissions Data*. Technical report. World Resources Institute. URL: https://www.climatewatchdata.org/ghg-emissions.

Dijk, M., Orsato, R. J., and Kemp, R. (2013). The emergence of an electric mobility trajectory. *Energy Policy* 52, pp. 135–145. DOI: 10.1016/j.enpol.2012.04.024.

Ehsani, M., Gao, Y., and Emadi, A. (2010). *Modern electric, hybrid electric, and fuel cell vehicles : fundamentals, theory, and design*. 2nd. CRC Press, p. 534. ISBN: 978-1420053982.

Energiavirasto (2023). *Sähkömarkkinat | Energiavirasto*. URL: https://energiavirasto.fi/sahkomarkkinat (visited on 09/11/2023).

ESett (2023). *eSett in Brief | Nordic Imbalance Settlement | eSett*. URL: https://www.esett.com/about/esett-in-brief/ (visited on 09/11/2023).

EUR-Lex - 32014L0094 - EN - EUR-Lex (2023). URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%7B%5C%%7D3A32014L0094 (visited on 09/05/2023).

European Commission (2019). *Going climate-neutral by 2050—A strategic long-term vision for a prosperous, modern, competitive and climate-neutral EU economy*. Publications Office. DOI: 10.2834/02074.

EV Roaming Foundation (2023). *EV Roaming Foundation*. URL: https://evroaming.org/about-us/ (visited on 09/18/2023).

Faddel, S., Mohamed, A. A., and Mohammed, O. A. (2017). Fuzzy logic-based autonomous controller for electric vehicles charging under different conditions in residential distribution systems. *Electric Power Systems Research* 148, pp. 48–58. DOI: 10.1016/j.epsr.2017.03.009.

Fingrid (2022). *Sähköntuotannon ja -kulutuksen CO2-päästöarviot*. URL: https://www.fingrid.fi/sahkomarkkinainformaatio/co2/ (visited on 09/17/2023).

Fingrid (2023a). *Datahub services - Fingrid*. URL: https://www.fingrid.fi/en/electricity-market/datahub/datahub-services/ (visited on 09/11/2023).

Fingrid (2023b). *Electricity system of Finland - Fingrid*. URL: https://www.fingrid.fi/en/grid/development/electricity-system-of-finland/ (visited on 09/11/2023).

Fingrid (2023c). *Fingrid*. URL: https://www.fingrid.fi/ (visited on 09/18/2023).

Fingrid (2023d). *Reserves and balancing power - Fingrid*. URL: https://www.fingrid.fi/en/electricity-market/reserves%7B%5C_%7Dand%7B%5C_%7Dbalancing/%7B%5C#%7Dreserve-products (visited on 09/13/2023).

Fingrid (2023e). *Welcome - Fingridin avoin data*. URL: https://data.fingrid.fi/en/ (visited on 09/11/2023).

Finnish Meteorological Institute (2023). *About us - Finnish Meteorological Institute*. URL: https://en.ilmatieteenlaitos.fi/about-us (visited on 09/11/2023).

Flaris, K., Gkritza, K., Singleton, P. A., Graul, A. R., and Song, Z. (2023). Riders' perceptions towards transit bus electrification: Evidence from Salt Lake City, Utah. *Transportation Research Part D: Transport and Environment* 117, p. 103642. DOI: 10.1016/J.TRD.2023.103642.

Fournely, C., Pecjak, M., Smolej, T., Turk, A., and Neumann, C. (2022). Flexibility markets in the EU: Emerging approaches and new options for market design. In: *International Conference on the European Energy Market, EEM*. Vol. 2022-Septe. IEEE Computer Society. ISBN: 9781665408967. DOI: 10.1109/EEM54602.2022.9921138.

Givisiez, A. G., Petrou, K., and Ochoa, L. F. (2020). A Review on TSO-DSO Coordination Models and Solution Techniques. *Electric Power Systems Research* 189, p. 106659. DOI: https://doi.org/10.1016/j.epsr.2020.106659. URL: https://www.sciencedirect.com/science/article/pii/S0378779620304624.

Gönül, Ö., Duman, A. C., and Güler, Ö. (2021). Electric vehicles and charging infrastructure in Turkey: An overview. *Renewable and Sustainable Energy Reviews* 143, p. 110913. DOI: 10.1016/J.RSER.2021.110913.

Gridio (2023). *Gridio*. URL: https://www.gridio.io/ (visited on 09/11/2023).

Guarnieri, M. (2012). Looking back to electric cars. In: *2012 Third IEEE HISTory of ELectro-technology CONference (HISTELCON)*. IEEE, pp. 1–6. ISBN: 978-1-4673-3079-4. DOI: 10.1109/HISTELCON.2012.6487583.

Guo, F., Yang, J., and Lu, J. (2018). The battery charging station location problem: Impact of users' range anxiety and distance convenience. *Transportation Research Part E: Logistics and Transportation Review* 114, pp. 1–18.

Haakana, J., Haapaniemi, J., Räisänen, O., Vilppo, J., and Lassila, J. (2022). Joustava ja toimintavarma sähkönjakeluverkko - Liiketoimintamahdollisuudet ja sääntely. URL: https://lutpub.lut.fi/handle/10024/164029.

Haakana, J., Tikka, V., Tuunanen, J., Lassila, J., Belonogova, N., Partanen, J., Repo, S., and Pylvänäinen, J. (2016). Analyzing the effects of the customer-side BESS from the perspective of electricity distribution networks. In: *2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. Ljubljana, Slovakia: IEEE, pp. 1–6. ISBN: 978-1-5090-3358-4. DOI: 10.1109/ISGTEurope.2016.7856338.

Haapaniemi, J. (2022). Power-Based Electricity Distribution Tariffs Providing An Incentive To Enhance The Capacity Effectiveness Of Electricity Distribution Grids. PhD thesis. LUT University. ISBN: 978-952-335-786-0.

Haapaniemi, J., Supponen, A., Räisänen, O., Haakana, J., Vilppo, J., Repo, S., and Lassila, J. (2022). *Laaja-alaisen aurinkosähkö on yleistymisen huomioivat sähköoverkon mitoitusperiaatteet [In Finnish]*. Technical report. Lappeenranta: LUT University.

Haapaniemi, J., Tikka, V., Haakana, J., Lassila, J., and Partanen, J. (2016). Aurinkosähkön mahdollisuudet maaseudulla. *Maaseudun uusi aika* (24), pp. 5–19.

Al-Hanahi, B., Ahmad, I., Habibi, D., and Masoum, M. A. S. (2021). Charging Infrastructure for Commercial Electric Vehicles: Challenges and Future Works. *IEEE Access* 9, pp. 121476–121492. DOI: 10.1109/ACCESS.2021.3108817.

Hao, X., Wang, H., Lin, Z., and Ouyang, M. (2020). Seasonal effects on electric vehicle energy consumption and driving range: A case study on personal, taxi, and ridesharing vehicles. *Journal of Cleaner Production* 249, p. 119403. DOI: 10.1016/J.JCLEPRO.2019.119403.

Hilshey, A. D., Hines, P. D. H., Rezaei, P., and Dowds, J. R. (2013). Estimating the Impact of Electric Vehicle Smart Charging on Distribution Transformer Aging. *IEEE Transactions on Smart Grid* 4(2), pp. 905–913. DOI: 10.1109/TSG.2012.2217385.

Høyer, K. G. (2008). The history of alternative fuels in transportation: The case of electric and hybrid cars. *Utilities Policy* 16(2), pp. 63–71. DOI: 10.1016/j.jup.2007.11.001. URL: https://linkinghub.elsevier.com/retrieve/pii/S0957178707000768.

IEC (2017). *Electric vehicle conductive charging system - Part 1: General requirements*. IEC, p. 287.

Intergovernmental Panel on Climate Change (IPCC) (2023). *Climate Change 2022 – Impacts, Adaptation and Vulnerability*. Cambridge University Press. ISBN: 9781009325844. DOI: 10 . 1017 / 9781009325844. URL: www.environmentalgraphiti.org%20https://www.cambridge.org/core/product/identifier/9781009325844/type/book.

International Energy Agency (2022). *Renewables 2022, Analysis and forecast to 2027*. Technical report. International Energy Agency, p. 158. URL: https://www.iea.org/reports/renewables-2022;%20License:%20CC%20BY%204.0.

International Energy Agency (2023). *Global EV Outlook 2023*. Tech. rep. Geo, p. 140.

Iversen, E. B., Moller, J. K., Morales, J. M., and Madsen, H. (2017). Inhomogeneous Markov Models for Describing Driving Patterns. *IEEE Transactions on Smart Grid* 8(2), pp. 581–588. DOI: 10.1109/TSG.2016.2520661.

Iwafune, Y., Ogimoto, K., Kobayashi, Y., and Murai, K. (2020). Driving Simulator for Electric Vehicles Using the Markov Chain Monte Carlo Method and Evaluation of the Demand Response Effect in Residential Houses. *IEEE Access* 8, pp. 47654–47663. DOI: 10.1109/ACCESS.2020.2978867. URL: https://ieeexplore.ieee.org/document/9026984/.

Järventausta, P., Repo, S., Trygg, P., Rautiainen, A., Mutanen, A., Lummi, K., Supponen, A., Heljo, J., Sorri, J., Harsia, P., Honkiniemi, M., Kallioharju, K., Piikkilä, V., Luoma, J., Partanen, J., Honkapuro, S., Valtonen, P., Tuunanen, J., and Belonogova, N. (2015). *Kysynnän jousto-Suomeen soveltuvat käytännön ratkaisut ja vaikutukset verkkoyhtiöille (DR pooli)—Loppuraportti [In Finnish]*. Technical report. Tampere: Tampereen teknillinen yliopisto.

Kallio, R., Kärkinen, T., Mutikainen, J., and Supponen, A. (2023). *Henkilöliikennetutkimus syksy 2022*. Tech. rep. URL: www.hlt.fi.

Khomami, H. P., Fonteijn, R., and Geelen, D. (2020). Flexibility market design for congestion management in smart distribution grids: The dutch demonstration of the interflex project. In: *IEEE PES Innovative Smart Grid Technologies Conference Europe*. Vol. 2020-Octob. IEEE Computer Society, pp. 1191–1195. ISBN: 9781728171005. DOI: 10.1109/ISGT-EUROPE47291.2020.9248970.

Kohonen, T. (1990). The self-organizing map. In: *Proceedings of the IEEE*. Vol. 78. 9, pp. 1464–1480. DOI: 10.1109/5.58325.

Kumar, R. R., Chakraborty, A., and Mandal, P. (2021). Promoting electric vehicle adoption: Who should invest in charging infrastructure? *Transportation Research Part E: Logistics and Transportation Review* 149, p. 102295. DOI: 10.1016/j.tre.2021.102295.

Lakervi, E. and Holmes, E. J. (1995). *Electricity distribution network design*. 2nd. P. Peregrinus on behalf of the Institution of Electrical Engineers, p. 325. ISBN: 0863413099.

Lassila, J. (2009). Strategic development of electricity distribution networks - Concept and methods. PhD thesis. Lappeenranta University of Technology, p. 156. ISBN: 978-952-214-872-8.

Lassila, J., Haakana, J., Tikka, V., and Partanen, J. (2012). Methodology to Analyze the Economic Effects of Electric Cars as Energy Storages. *IEEE Transactions on Smart Grid* 3(1), pp. 506–516. DOI: 10.1109/TSG.2011.2168548.

Lassila, J., Tikka, V., Haapaniemi, J., Child, M., Breyer, C., and Partanen, J. (2016). Nationwide photovoltaic hosting capacity in the Finnish electricity distribution system. In: *European Photovoltaic Solar Energy Conference*. Munich, Germany. DOI: 10.4229/EUPVSEC20162016-6AV.4.11.

Latauskartta (2023). *Latauskartta*. URL: https://latauskartta.fi.

Lehto, H. (2018). *Finnish National Travel Survey 2016 Harmonised Passenger Mobility Statistics*. URL: https://www.traficom.fi/sites/default/files/media/file/Fact-Sheet-National-Travel-Survey-HLT2016.pdf (visited on 09/17/2023).

Liikennevirasto (2018). *Suomalaisten liikkuminen*. Tech. rep.

Liu, H., Shen, H., Hu, W., Ji, L., Li, J., and Yu, Y. (2023). Electric Vehicle Load Forecast Based on Higher Order Markov Chain. In: *2023 5th Asia Energy and Electrical Engineering Symposium (AEEES)*. IEEE, pp. 1203–1207. ISBN: 978-1-6654-9054-2. DOI: 10.1109/AEEES56888.2023.10114238.

Liu, Z. and Wu, Q. (2014). EV charging analysis based on the National Travel Surveys of the Nordic Area. *IEEE Power and Energy Society General Meeting* 2014-Octob(October). DOI: 10.1109/PESGM.2014.6939315.

LIU, Z., WU, Q., CHRISTENSEN, L., RAUTIAINEN, A., and XUE, Y. (2015). Driving pattern analysis of Nordic region based on National Travel Surveys for electric vehicle integration. *Journal of Modern Power Systems and Clean Energy* 3(2), pp. 180–189. DOI: 10.1007/S40565-015-0127-X.

Lojowska, A., Kurowicka, D., Papaefthymiou, G., and Sluis, L. van der (2012). Stochastic Modeling of Power Demand Due to EVs Using Copula. *IEEE Transactions on Power Systems* 27(4), pp. 1960–1968. DOI: 10.1109/TPWRS.2012.2192139.

Lopes, L., Warichet, J., Alva, C. A. H., Köykkä, J., Guyon, J., Bernal, A., Husar, J., McKimm, R., Yang, Z., Park, W. H., Vergara, D., and Oliveira, L. de (2022). *Grid Integration of Electric Vehicles, A manual for policy makers*. Tech. rep. International Energy Agency. DOI: 10.1787/39f72d07-en.

Lummi, K., Rautiainen, A., Järventausta, P., Heine, P., Lehtinen, J., and Hyvärinen, M. (2016). Cost-causation based approach in forming power-based distribution network tariff for small customers. In: *2016 13th International Conference on the European Energy Market (EEM)*. Vol. 2016. IEEE, pp. 1–5. ISBN: 978-1-5090-1298-5. DOI: 10.1109/EEM.2016.7521251. URL: http://ieeexplore.ieee.org/document/7521251/.

Lundgren, J. (2012). Market Liberalization and Market Integration Essays on the Nordic Electricity Market. PhD thesis. Umeå University. ISBN: 978-91-7459-523-9. URL: https://www.diva-portal.org/smash/get/diva2:570731/FULLTEXT01.pdf.

Maanmittauslaitos (2023). *Download geospatial data - National Land Survey of Finland*. URL: https://asiointi.maanmittauslaitos.fi/karttapaikka/tiedostopalvelu (visited on 09/11/2023).

Makkonen, H., Tikka, V., Lassila, J., Partanen, J., and Silventoinen, P. (2013). Green campus - energy management system. In: *22nd International Conference and Exhibition on Electricity Distribution (CIRED 2013)*. Vol. 2013. 615 CP. Institution of Engineering and Technology, pp. 1137–1137. ISBN: 978-1-84919-732-8. DOI: 10.1049/cp.2013.1088. URL: https://digital-library.theiet.org/content/conferences/10.1049/cp.2013.1088.

Makkonen, H., Tikka, V., Kaipia, T., Lassila, J., Partanen, J., and Silventoinen, P. (2012). Implementation of smart grid environment in Green Campus project. In: *CIRED 2012 Workshop: Integration of Renewables into the Distribution Grid*. Lisbon, Portugal: IET, pp. 240–240. ISBN: 978-1-84919-628-4. DOI: 10.1049/cp.2012.0825.

Makkonen, H., Tikka, V., Lassila, J., Partanen, J., and Silventoinen, P. (2014). Demonstration of smart charging interface in Green Campus. In: *2014 16th European Conference on Power Electronics and Applications*. Lappeenranta, Finland: IEEE, pp. 1–10. ISBN: 978-1-4799-3015-9. DOI: 10.1109/EPE.2014.6910776.

Masoum, A. S., Deilami, S., Moses, P. S., and Abu-Siada, A. (2010). Impacts of battery charging rates of plug-in electric vehicle on smart grid distribution systems. In: *IEEE PES Innovative Smart Grid Technologies Conference Europe, ISGT Europe*. IEEE Computer Society. ISBN: 9781424485109. DOI: 10.1109/ISGTEUROPE.2010.5638981.

Mendes, G., Tikka, V., Vahidinasab, V., and Aghaei, J. (2023). Review of Emerging Advanced Smart Charging Flexibility Business Models. In: *CIRED 2023 - The 27th International Conference and Exhibition on Electricity Distribution*. June. Rome, pp. 12–15.

Miettinen, J., Tikka, V., Lassila, J., Partanen, J., and Hodge, B. M. (2014). Minimizing wind power producer's balancing costs using electrochemical energy storage. In: *The Nordic Conference on Electricity Distribution Management and Development*. Stockholm, Sweden, pp. 8–9.

Moreira, C., Lopes, J. P., Almeida, P. R., Seca, L., and Soares, F. J. (2011). *A Stochastic Model To Simulate Electric Vehicles Motion And Quantify The Energy Required From The Grid*. URL: http://repositorio.inesctec.pt/handle/123456789/2210.

Motavalli, J. (2021). *Every Automaker's EV Plans Through 2035 And Beyond - Forbes Wheels*. URL: https://www.forbes.com/wheels/news/automaker-ev-plans/ (visited on 09/12/2023).

Mutanen, A., Lummi, K., Pertti, J., Sähkötekniikan, J., and Yliopisto Helmikuu, T. (2019). *Valtakunnallisten tyyppikäyttäjämäärittelyiden päivittäminen ja hyödyntämisen periaatteet verkkopalvelumaksuihin liittyvissä tarkasteluissa [In Finnish]*. Technical report. Tampere: Tampere University.

Mutanen, A., Ruska, M., Repo, S., and Järventausta, P. (2011). Customer classification and load profiling method for distribution systems. *IEEE Transactions on Power Delivery* 26(3), pp. 1755–1763. DOI: 10.1109/TPWRD.2011.2142198.

Ni, X. and Lo, K. L. (2020a). A Methodology to Model Daily Charging Load in the EV Charging Stations Based on Monte Carlo Simulation. In: *2020 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*. IEEE, pp. 125–130. ISBN: 978-1-7281-5736-8. DOI: 10.1109/ICSGCE49177.2020.9275644. URL: https://ieeexplore.ieee.org/document/9275644/.

Ni, X. and Lo, K. L. (2020b). A Methodology to Model Daily Charging Load in the EV Charging Stations Based on Monte Carlo Simulation. In: *2020 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*. IEEE, pp. 125–130. ISBN: 978-1-7281-5736-8. DOI: 10.1109/ICSGCE49177.2020.9275644. URL: https://ieeexplore.ieee.org/document/9275644/.

Nord Pool (2023). *About us | Nord Pool*. URL: https://www.nordpoolgroup.com/en/About-us/ (visited on 09/11/2023).

Open Charge Alliance—About Us (2023). *Open Charge Alliance*. URL: https://www.openchargealliance.org/about-us/about/ (visited on 09/18/2023).

OpenADR (2023). *OpenADR*. URL: https://www.openadr.org.

Pagani, M., Korosec, W., Chokani, N., and Abhari, R. (2019). User behaviour and electric vehicle charging infrastructure: An agent-based model assessment. *Applied Energy* 254, p. 113680. DOI: 10.1016/j.apenergy.2019.113680.

Pareschi, G., Küng, L., Georges, G., and Boulouchos, K. (2020). Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data. *Applied Energy* 275, p. 115318. DOI: 10.1016/J.APENERGY.2020.115318.

Paris Agreement (2015). online. URL: https://treaties.un.org/pages/AdvanceSearch.aspx?tab=UNTS%7B%5C&%7Dclang=%7B%5C_%7Den.

Pastinen, V., Lehto, H., Valkonen, M., Kärkinen, T., and Pitkänen, L. (2006). *Henkilöliikennetutkimus 2004–2005*. Tech. rep. WSP LT-Konsultit.

Post, R. C. (1974). ELECTRO-MAGNETISM AS A MOTIVE POWER: Robert Davidson's "Galvani" of 1842 on JSTOR. *Railway & Locomotive Historical Society (R&LHS)* 130, pp. 5–22. URL: https://www.jstor.org/stable/43520448.

Räisänen, O., Haapaniemi, J., Tikka, V., Haakana, J., Lassila, J., and Partanen, J. (2020). Open Data in the Development of Future Electricity Distribution Systems. In: *2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*. IEEE, pp. 655–659. ISBN: 978-1-7281-7100-5. DOI: 10.1109/ISGT-Europe47291.2020.9248979.

Rautiainen, A., Lummi, K., Järventausta, P., Tikka, V., and Lana, A. (2016a). Control of electric vehicle charging in domestic real estates as part of demand response functionality. In: *IET Conference Publications*. Vol. 2016. CP686.

Rautiainen, A., Repo, S., Järventausta, P., Mutanen, A., Vuorilehto, K., and Jalkanen, K. (2012). Statistical charging load modeling of PHEVs in electricity distribution networks using National Travel Survey data. *IEEE Transactions on Smart Grid* 3(4), pp. 1650–1659. DOI: 10.1109/TSG.2012.2206411.

Rautiainen, A., Lummi, K., Järventausta, P., Tikka, V., and Lana, A. (2016b). Control of electric vehicle charging in domestic real estates as part of demand response functionality. In: *IET Conference Publications*. Vol. 2016. CP686. Institution of Engineering and Technology. ISBN: 9781785611384. DOI: 10.1049/CP.2016.0614.

Rautiainen, A., Lummi, K., Supponen, A., Koskela, J., Repo, S., Järventausta, P., Honkapuro, S., Partanen, J., Haapaniemi, J., Lassila, J., Haakana, J., and Belonogova, N. (2017). Reforming Distribution Tariffs of Small Customers: Targets, Challenges and Impacts of Implementing Novel Tariff Structures. *researchportal.tuni.fiA Rautiainen, K Lummi, A Supponen, J Koskela, S Repo, P Järventausta, S HonkapuroInternational Conference and Exhibition on Electricity Distribution, 2017•researchportal.tuni.fi* 2017(1), pp. 2857–2860. DOI: 10 . 1049 / oap - cired . 2017 . 0887. URL: https://researchportal.tuni.fi/en/publications/reforming-distribution-tariffs-of-small-customers-targets-challen.

Ray, S., Kasturi, K., Patnaik, S., and Nayak, M. R. (2023). Review of electric vehicles integration impacts in distribution networks: Placement, charging/discharging strategies, objectives and optimisation models. *Journal of Energy Storage* 72, p. 108672. DOI: 10.1016/j.est.2023.108672.

Sähköenergialiitto ry SENER (1992). *Verkostosuositus SA 10:92. Verkon mitoitusenergiat [In Finnish]*. printed.

Sähkömarkkinalaki [Electricity Market Act], in Finnish (2023). 9.8.2013/588. URL: https://www.finlex.fi/fi/laki/ajantasa/2013/20130588.

Sausen, J. P., Abaide, A. R., Adeyanju, O. M., and Paixão, J. L. (2019). EV Demand Forecasting Model Based on Travel Survey: A Brazilian Case Study. *2019 IEEE*

PES Conference on Innovative Smart Grid Technologies, ISGT Latin America 2019. DOI: 10.1109/ISGT-LA.2019.8894955.

Schneider Electric (2023). *Electrical installation wiki*. URL: https://www.electrical-installation.org/enwiki/File:DB431414%7B%5C_%7DEN.svg%7B%5C#%7Dfile.

Shepero, M. and Munkhammar, J. (2018). Spatial Markov chain model for electric vehicle charging in cities using geographical information system (GIS) data. *Applied Energy* 231, pp. 1089–1099. DOI: 10.1016/j.apenergy.2018.09.175. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261918314922.

Simolin, T. (2022). Electric Vehicle Charging Load Management Algorithm and Modelling Perspectives. PhD thesis. Tampere University.

Sivill, L., Bröckl, M., Semkin, N., Ruismäki, A., Pilpola, H., Laukkanen, O., Lehtinen, H., Takamäki, S., Vasara, P., and Patronen, J. (2022). *Selvitys ja tutkimustoiminta Utrednings-och forskningsverksamhet Vetytalous-mahdollisuudet ja rajoitteet*. Tech. rep. Helsinki: Valtioneuvoston kanslia. URL: https://julkaisut.valtioneuvosto.fi/bitstream/handle/10024/163901/VNTEAS%7B%5C_%7D2022%7B%5C_%7D21.pdf?sequence=1%7B%5C&%7DisAllowed=y.

State Grid Corporation of China (2013). *S EV infrastructure and standardization in China!* Tech. rep. URL: https://wiki.unece.org/download/attachments/12058681/EVE-07-14e.pdf?api=v2.

Statistics Finland (2022). *Statistics Finland – About the site*. URL: https://www.stat.fi/org/tietoa%7B%5C_%7Dsivustosta%7B%5C_%7Den.html (visited on 03/25/2022).

Statistics Finland (2023a). *A total of 7,823 new passenger cars were registered in August 2023*. URL: https://www.stat.fi/julkaisu/cl8cr4gq57npj09w2i9r1lrky (visited on 09/12/2023).

Statistics Finland (2023b). *Overall electricity consumption decreased by 6 per cent and wind power production was at a record high in 2022 - Statistics Finland*. URL: https://www.stat.fi/en/publication/cl8lmyfdcqgc70dukvv6dsrdd (visited on 09/11/2023).

Teknologiateollisuus (2023). *Sähköisen liikenteen tilannekatsaus Q2/2023*. URL: https://emobility.teknologiateollisuus.fi/fi/toimiala/tilastot (visited on 09/18/2023).

Thomas, V. J. and Maine, E. (2019). Market entry strategies for electric vehicle start-ups in the automotive industry – Lessons from Tesla Motors. *Journal of Cleaner Production* 235, pp. 653–663. DOI: 10.1016/J.JCLEPRO.2019.06.284.

Tikka, V., Belonogova, N., Honkapuro, S., Lassila, J., Haakana, J., Lana, A., Romanenko, A., Haapaniemi, J., Narayanan, A., Kaipia, T., et al. (2018a). *Multi-objective role of battery energy storages in an energy system*. LUT Scientific and Expertise Publications, Tutkimusraportit - Research Reports 75. Lappeenranta, Finland: LUT University.

Tikka, V., Belonogova, N., Lana, A., Honkapuro, S., Lassila, J., and Partanen, J. (2018b). Control Architecture Requirements of Multitasking Battery Resource Operation. In: *2018 15th International Conference on the European Energy Market (EEM)*.

Vol. 2018. Ljubljana, Slovakia: IEEE, pp. 1–5. ISBN: 978-1-5386-1488-4. DOI: 10.1109/EEM.2018.8469855.

Tikka, V., Haapaniemi, J., Räisänen, O., and Honkapuro, S. (2022). Convolutional neural networks in estimating the spatial distribution of electric vehicles to support electricity grid planning. *Applied Energy* 328, p. 120124. DOI: 10.1016/j.apenergy.2022.120124.

Tikka, V., Kalenius, J., Räisänen, O., and Lassila, J. (2021a). *Loppuraportti: Sähköautojen latauksen muodostama kuormitus- ja mitoitusteho erilaisissa toimintaympäristöissä [In Finnish]*. LUT Scientific and Expertise Publications, Tutkimusraportit - Research Reports 131. Lappeenranta, Finland: LUT University.

Tikka, V., Lassila, J., Haakana, J., and Partanen, J. (2011). Case study of the effects of electric vehicle charging on grid loads in an urban area. In: *2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies*. IEEE, pp. 1–7. ISBN: 978-1-4577-1421-4. DOI: 10.1109/ISGTEurope.2011.6162667.

Tikka, V., Lassila, J., Haakana, J., and Partanen, J. (2016). Electric vehicle smart charging aims for CO2 emission reduction? In: *2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. Ljubljana, Slovakia: IEEE, pp. 1–6. ISBN: 978-1-5090-3358-4. DOI: 10.1109/ISGTEurope.2016.7856250.

Tikka, V., Lassila, J., and Laine, T. (2021b). *Technical report: Measurements of cold climate EV charging*. LUT Scientific and Expertise Publications, Tutkimusraportit - Research Reports 130. Lappeenranta, Finland: LUT University.

Tikka, V., Lassila, J., Makkonen, H., and Partanen, J. (2012). Case study of the load demand of electric vehicle charging and optimal charging schemes in an urban area. In: *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*. IEEE, pp. 1–7. ISBN: 978-1-4673-2597-4. DOI: 10.1109/ISGTEurope.2012.6465687.

Tikka, V., Makkonen, H., Lassila, J., and Partanen, J. (2014). Case study: Smart charging plug-in hybrid vehicle test environment with vehicle-to-grid ability. In: *2014 16th European Conference on Power Electronics and Applications*. Lappeenranta, Finland: IEEE, pp. 1–10. ISBN: 978-1-4799-3015-9. DOI: 10.1109/EPE.2014.6910765.

Tikka, V., Mashlakov, A., Kulmala, A., Repo, S., Aro, M., Keski-Koukkari, A., Honkapuro, S., Järventausta, P., and Partanen, J. (2019a). Integrated business platform of distributed energy resources – Case Finland. *Energy Procedia* 158, pp. 6637–6644. DOI: 10.1016/j.egypro.2019.01.041.

Tikka, V., Räisänen, O., Haapaniemi, J., Mendes, G., Lassila, J., and Honkapuro, S. (2023). Electric Vehicle Charging Measurements In The Nordic Environment—Charging Profile Dependence On Ambient Temperature. In: *27th International Conference on Electricity Distribution*. June, pp. 3240–3244. DOI: 10.1049/icp.2023.0873.

Tikka, V., Romanenko, A., Alamäki, J., Mashlakov, A., Luoranen, M., Honkapuro, S., and Partanen, J. (2020). Energy flexibility harvesting from data analytics—integration of building energy resources into energy markets. In: *CIRED - Open Access Proceedings Journal*. Vol. 2020. 1. Berlin, Germany: IET, pp. 746–749. DOI: 10.1049/oap-cired.2021.0215.

Tikka, V., Romanenko, A., Mashlakov, A., Annala, S., Honkapuro, S., and Partanen, J. (2019b). Novel Technical Solutions as an Enabler of the Small-Scale Demand Response Resources. In: *CIRED 2019 Conference*. Madrid, Spain: AIM. DOI: 10.34890/943.

Traficom (2022a). *Liikenteen kasvihuonekaasupäästöt ja energiankulutus | Tieto Traficom*. URL: https://tieto.traficom.fi/fi/tilastot/liikenteen-kasvihuonekaasupaastot-ja-energiankulutus?toggle=L%7B%5C%22%7Ba%7D%7Dhteet%20ja%20lis%7B%5C%22%7Ba%7D%7Dtiedot (visited on 09/17/2023).

Traficom (2022b). *Traficom – The Finnish Transport and Communications Agency*. URL: https://www.traficom.fi/en/traficom/about-traficom (visited on 03/25/2022).

Traficom (2023). *Ensirekisteröityjen ajoneuvojen käyttövoimatilastot*. URL: https://tieto.traficom.fi/fi/tilastot/ensirekisteroityjen-ajoneuvojen-kayttovoimatilastot?toggle=L%7B%5C%22%7Ba%7D%7Dhteet%20ja%20lis%7B%5C%22%7Ba%7D%7Dtiedot%7B%5C&%7Dtoggle=Tilastokuvaus (visited on 09/12/2023).

Tuunanen, J. (2015). Modelling Of Changes In Electricity End-Use And Their Impacts On Electricity Distribution. PhD thesis. LUT university. ISBN: 9789522658845.

Valtonen, P. (2015). Distributed energy resources in an electricity retailer's short-term profit optimization. PhD thesis. Lappeenranta: Lappeenranta University of Technology. ISBN: 978-952-265-899-9. URL: https://urn.fi/URN:ISBN:978-952-265-899-9.

Vasara, P. and Lehtinen, H. (2022). *Sähköisen liikenteen tiekartta*. Tech. rep. AFRY AB.

Wakefield, E. H. (1998). *History of the Electric Automobile: Hybrid Electric Vehicles*. URL: https://books.google.fi/books?hl=en%7B%5C&%7Dlr=%7B%5C&%7Did=lOObEAAAQBAJ%7B%5C&%7Doi=fnd%7B%5C&%7Dpg=PP2%7B%5C&%7Ddq=history+of+electric+vehicles%7B%5C&%7Dots=-P4L1w2h9J%7B%5C&%7Dsig=ZdeyHNKIGJhJPfSy8I4kDwZt%7B%5C_%7DvQ%7B%5C&%7Dredir%7B%5C_%7Desc=y%7B%5C#%7Dv=onepage%7B%5C&%7Dq=history%20of%20electric%20vehicles%7B%5C&%7Df=false (visited on 08/13/2023).

Wang, Y. and Infield, D. (2018). Markov Chain Monte Carlo simulation of electric vehicle use for network integration studies. *International Journal of Electrical Power & Energy Systems* 99, pp. 85–94. DOI: 10.1016/J.IJEPES.2018.01.008.

Ward, J., Isaac, R., Walsh, P., Killen, W., Myers, L., Motsinger, S., Jenn, A., Crisostomo, N., Podkaminer, K., Klein, G., Rodgers, A., Wishnia, A., Berube, M., Gonder, J., Muratori, M., Meintz, A., Yip, A., Rickard, J., Stone, E., Deneen, M., Farrell, J., and Gearhart, C. (2023). *The 2030 National Charging Network Demand, Estimating US Light-duty*. Technical report. Denver: National Renewable Energy Laboratory, p. 67. URL: https://www.nrel.gov/docs/fy23osti/85654.pdf.

Willis, H. L. (2004). *Spatial Electric Load Forecasting*. 2nd ed. Raleight, North Carolina: CRC Press, p. 1244. ISBN: 978-0824748753. URL: https://www.amazon.com/Spatial-Electric-Forecasting-Engineering-Willis-ebook/dp/B00OD51I7C.

Woody, G. and Downer, S. (1997). *Espacenet—search results*. URL: https://worldwide.espacenet.com/patent/search/family/024727504/publication/US5703462A?q=pn%7B%5C%%7D3DUS5703462.

Yang, T., Xu, X., Guo, Q., Zhang, L., and Sun, H. (2017). EV charging behaviour analysis and modelling based on mobile crowdsensing data. *IET Generation, Transmission & Distribution* 11(7), pp. 1683–1691. DOI: 10.1049/IET-GTD.2016.1200. URL: https://onlinelibrary.wiley.com/doi/full/10.1049/iet-gtd.2016.1200%20https://onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2016.1200%20https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-gtd.2016.1200.

Zakeri, B., Cross, S., Dodds, P. E., and Gissey, G. C. (2021). Policy options for enhancing economic profitability of residential solar photovoltaic with battery energy storage. *Applied Energy* 290(March), p. 116697. DOI: 10.1016/j.apenergy.2021.116697. URL: https://doi.org/10.1016/j.apenergy.2021.116697.

Zeynali, S., Rostami, N., Ahmadian, A., and Elkamel, A. (2020). Two-stage stochastic home energy management strategy considering electric vehicle and battery energy storage system: An ANN-based scenario generation methodology. *Sustainable Energy Technologies and Assessments* 39, p. 100722. DOI: 10.1016/j.seta.2020.100722. URL: https://linkinghub.elsevier.com/retrieve/pii/S2213138820302447.

Zhou, H., Ma, K., Liu, Y., Li, J., Yu, H., An, X., Liang, Y., Xu, H., Hu, X., and Zhang, H. (2023). Research on the influence of soak in the cold environment on the energy consumption of electric vehicles. *Energy Reports* 9, pp. 656–661. DOI: 10.1016/J.EGYR.2023.05.113.

Zhu, J., Yang, Z., Mourshed, M., Guo, Y., Zhou, Y., Chang, Y., Wei, Y., and Feng, S. (2019). Electric Vehicle Charging Load Forecasting: A Comparative Study of Deep Learning Approaches. *Energies* 12(14), p. 2692. DOI: 10.3390/en12142692.

Publication I

Tikka, V., Lassila, J., Haakana, J., and Partanen, J.
Case Study of the Effects of Electric Vehicle Charging on Grid Loads in an Urban Area

Reprinted with permission from
2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies
Manchester, UK, 2011

Case Study of the Effects of Electric Vehicle Charging on Grid Loads in an Urban Area

Ville Tikka, Jukka Lassila, Juha Haakana, Jarmo Partanen, *Member, IEEE*

***Abstract*—The number of electric vehicles (EVs) is rapidly increasing, and the upward trend seems to be continuing also in the future. The increasing number of electric vehicles causes a need to develop the charging infrastructure, and moreover, it is necessary to analyze the network effects of the simultaneous charging of numerous electric vehicles. A further interesting question is how all this affects the distribution fee paid by the electricity end-user. In this paper, the challenge is approached by an actual case example. The data used in the simulation are collected by measuring the traffic flow of the road leading to the case area. The aim of this paper is to demonstrate how the grid effects of large-scale electrification of transportation can be assessed and to define the needed reinforcements and effects on the distribution fee paid by the end customers. The data are processed by applying the Monte-Carlo method. The network effects and the change in the distribution fee are evaluated. The key result is that EV charging causes a substantial amount of additional load to the grid. Hence, the distribution fee may increase if the charging system is not intelligent.**

***Index Terms*-- Load modeling, electric vehicles, power distribution, smart grids**

I. Introduction

THE European Union energy policy has created pressure to increase energy efficiency in all areas of energy consumption. About 20% of greenhouse gases in Europe are produced by transportation because of fossil fuels are widely used in vehicles. Even little improvements towards alternative energy sources would considerably decrease the total level of greenhouse gases produced. Electrification of transportation is one solution among others to improve the energy efficiency and move towards alternative energy sources in transportation. Therefore, it is essential to investigate how the electrification of transportation affects the electric grid, and whether EVs or plug-in hybrid electric vehicles (PHEVs) can support or even improve the grid somehow or whether there are only adverse effects on the horizon as electric vehicles gain popularity.

The worst-case scenario would be that the electrification of transportation increases the power demand during high-power hours (power peaks) and causes a need to increase the grid capacity. On the other hand, the best case would be that a large number of EVs connected to the grid would be acting as a large distributed energy storage, which would even out high power peaks and smooth the load curve of individual feeders. An optimal solution would be a compromise that would serve both the needs of the Distribution System Operator (DSO) and the electricity end-user or the electric vehicle user. However, in this paper, the focus is on the grid-to-vehicle (G2V) perspective.

In order to grasp the effects of large-scale electrification on the distribution grid, it is important to understand how distribution grids have traditionally been dimensioned, and what aspects have to be taken into account. Dimensioning of distribution grids is discussed for instance in [1] and [2], and the network effects of EVs are in [3]–[6]. Load modeling of EV charging is discussed in [7]; yet many questions still remain open. This paper focuses on demonstrating tools to handle the grid load in order to be able to analyze the grid effects more precisely in further studies.

If we add electric vehicles to a traditional distribution grid, the number of aspects affecting the dimensioning of the grid increases considerably. Electric vehicles are significantly different from traditional stationary loads that we have been used to see connected to the grid. A traditional load is typically stationary and fixed to one place, whereas an electric vehicle is almost independent of location and can be connected to the grid in different locations at different times. The power demand of EV charging can also vary depending on the mileage driven.

In the Nordic countries, traditional heating loads have been predicted with reasonably good results by using a temperature forecast and type load curves. Electric vehicles are somewhat independent of the ambient temperature (the use of vehicles is assumed possible in all conditions) and further, load classification may be challenging. Load forecasting has to be made by other methods, such as traffic measurements or travel surveys. The accuracy of the load forecast is strongly dependent on the input data of the forecast model. Thus, it is emphasized that it is highly important to recognize the possible error factors and their effects on the forecast model.

The main target of this paper is to show by a case example how the grid effects of large-scale electrification of transportation can be assessed.

The authors are with the Department of Electrical Engineering, Lappeenranta University of Technology, Lappeenranta, Finland, (e-mail: Ville.Tikka@lut.fi; Jukka.Lassila@lut.fi; Juha.Haakana@lut.fi; Jarmo.Partanen@lut.fi).

The key points of the case study are:

- Grid load effects of EV charging
- Estimating the change in the distribution fee under large-scale electrification of transportation
- Application of traffic flow measurement data to grid planning

In this paper, the vehicle-to-grid (V2G) ability of EVs and charging management are left outside the scope of the study. In the paper, there is only one example of the network effects in a case where the charging load is partly controllable. The control scene used in the analysis of this paper is based on a simulation model and information available on the unused battery capacity of vehicles.

II. Measurement and Background Data

In this chapter, the case area, background data, and traffic measurements are illustrated. Also parameters used in the simulation are explained and introduced in brief.

The case area shown in Fig. 1 is a small urban area in Southern Finland. There are 412 apartments in 11 apartment houses, 700 inhabitants, and 412 parking places (one parking place per apartment) with a wintertime preheating facility. The low-voltage grid in the area consists of two 20/0.4 kV low-voltage substations with an annual peak power of about 200 kW per substation; for both stations approximately 400 kW in total. In the wintertime, all 11 houses are heated by district heating, and thus, changes in the outside temperature have only a slight effect on the electricity consumption. The road to the area is a dead end (no through-traffic), which makes it an ideal target for traffic measurement.

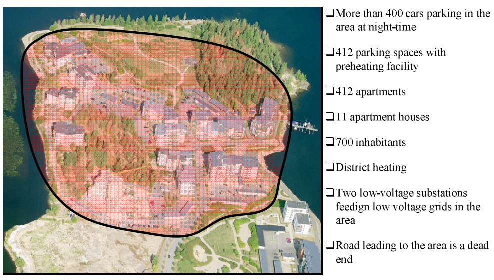


Fig. 1. Case area Pikisaari district of the City of Lappeenranta in Southern Finland.

To demonstrate the application of the forecasting methodology, traffic was measured for a month. Fig. 2 shows the average daily distribution of cars arriving and leaving the area. Working hours can be easily spotted in the figure; there is a significant peak at 8 am when cars are leaving the area and at 17 pm when cars are arriving back in the area.

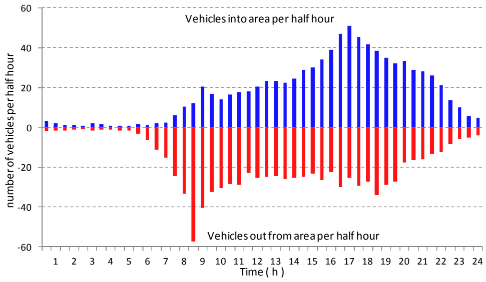


Fig. 2. Average workday traffic flow on the road leading to the case area.

For a more accurate load forecast, the traffic survey period should be longer. In this example, the average is calculated for 20 workdays. In addition, further travel surveys should be carried out to define the exact kilometers driven by cars. Yet another, more expensive option would be to equip cars with GPS trackers. That way, there would be exact data available on the driving lengths or trips, and furthermore, starting and ending times of single trips would be recorded.

In this paper, the vehicle kilometers by car are estimated by using the Finnish National Travel Survey (NTS). The survey includes all transportation (cars, motorcycles, busses, biking, etc). The cars are assumed to be EVs or PHEVs with high-capacity batteries. Charging losses are neglected; however, average consumption can be slightly overestimated in order to compensate charging losses. The average energy consumption of EVs (and PHEVs when driven with electricity) is assumed to be 0.2 kWh/km, which is the commonly used estimate in the Nordic countries. A lower consumption estimate can be used in southern countries, where interior heating is not required in vehicles. The properties of electric and hybrid vehicles are discussed in [8].

The average vehicle kilometers travelled by car in Finland is 52 km/day. The NTS survey made with a similar area profile as the current case area shows that about 30% of all trips (by bus, car, walk, etc.) are made by car. If the traffic measurement results shown in Fig. 3 are compared with the NTS data, it can be seen that with the population of 700 persons, there should be at least 200 persons traveling by car during a day. In Fig. 3, it can be seen that at noon there are at least 200 vehicles outside the case area. However, the measurement has certain deficiencies. For instance, it is not known how many cars there are actually on the move during the day (based on the traffic flow measurement), because cars cannot be identified by the measurement device. Nevertheless, the collected data are sufficient for demonstration purposes, and the total energy and charging overlapping can be estimated. The energy used during the day depends on the total vehicle kilometers travelled during the day. The average vehicle kilometers per day can be estimated by the NTS data. Charging overlapping can also be estimated by the average vehicle kilometers and the distribution of the times of arrival at home.

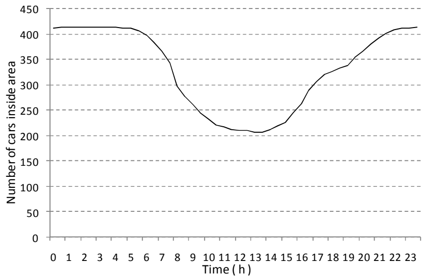


Fig. 3. Number of cars in the case area. The numbers are based on actual traffic flow measurement in the case area.

The total number of trips per day in the case area is about 2000 of which 30% are made by a car, based on an estimation made by using the NTS data. Instead of the NTS, actual measurement data from the case area show that the total number of vehicles in the area is about 900 per day. Of this number, about 100 trips are public transportation and other service traffic. For this reason, the total amount of traffic in the 100% penetration level simulation is assumed to be 800 trips per day. The measurement was calibrated with a few hours of video surveillance. In the calibration, it was noticed that roughly 10% of all the traffic was other (busses, service traffic, taxis, etc.) than trips made by inhabitants of the case area.

In the simulation, the NTS data are also used to define the trip length distributions for each hour. Because the data in the survey are national, they had to be filtered to match the case area (Southern Finland, urban areas, apartment houses). Therefore, the number of data points (trips) are decreased from the total of 11 000 in the NTS to 1 600 trips. The trip lengths are then added together to form a distribution of the total trip lengths for the trips driven through some other stopping point before finally arriving at home. In this operation, the number of data points is decreased to about 600.

Trip lengths are mostly short, but there are also a few longer trips, as can be seen in Fig. 5. Weibull distribution is chosen to be used in the distribution fitting. As can be seen also in Fig. 4, the Weibull density function fits well with the initial data.

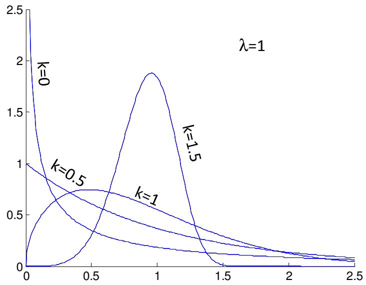


Fig. 4. Weibull probability density function (Scale parameter λ=1 and shape parameter k=0, 0.5, 1, 1.5).

Fig. 5 illustrates the Weibull parameters and a few example histograms of the trip length distribution. The maximum likelihood method is used in the Weibull parameter fitting.

Hour	Scale parameter	Shape parameter
1	20.0	1.0
2	6.0	1.0
3	23.0	1.0
4	0.0	0.0
5	0.0	0.0
6	0.0	0.0
7	0.0	0.0
8	9.3	1.1
9	7.7	1.0
10	11.9	1.6
11	13.9	0.8
12	16.2	0.9
13	21.2	1.1
14	26.3	1.1
15	22.4	1.2
16	28.1	1.1
17	43.5	1.0
18	47.4	1.0
19	34.9	1.0
20	43.6	1.1
21	65.1	1.0
22	63.4	1.1
23	39.8	1.5
24	91.4	1.1

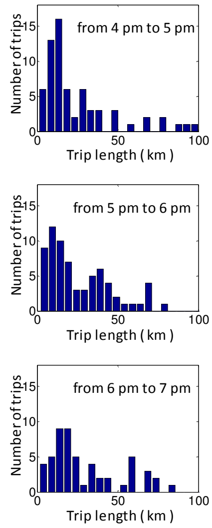


Fig. 5. Weibull parameters for each hour and data sample histograms.

Because of the lack of data points in a few early hours, the parameters are slightly manipulated. Even though the parameters are not all accurate, the simulations results are reasonably reliable because of the low significance of the early hours (from midnight to 6 am) in the simulation model.

A. Power flow

The power flows at the low-voltage substations are also measured to give an insight into the ratio of the EV charging load to the base load in the area. In this case, the highest base load values occur in the afternoon and evening hours, as can be noticed in Fig. 6.

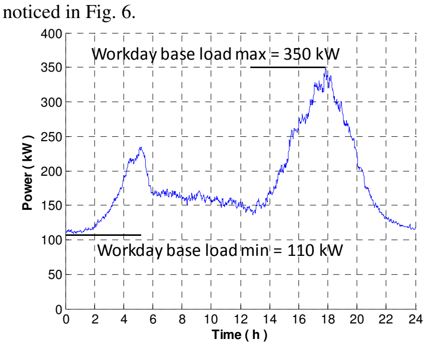


Fig. 6. Measured workday base load in the case area.

Thus, the inaccurate Weibull distribution parameters in the early hours play no critical role in this study. It will be a concern of the further studies how these few night hours can be assessed in a reliable way.

Also the temporal distribution of power peaks is investigated for the base load and the charging load. Intelligent charging is also discussed with an example case.

III. Analysis and Methodology

The methodology is introduced in brief, bearing in mind that the key target of the paper is to illustrate the application of the forecast methodology by a case example. The simulation is based on the Monte-Carlo method. Single vehicles trips are randomly selected based on the input data. The traffic measurement is distributed by normal distribution, and thus, when the departure time of vehicles is selected, the distribution type is taken into account. The selection cycle is repeated multiple times to define the statistical characteristics of the vehicle charging. The simplified methodology is presented in Fig. 7. However, only the key elements of the simulations are presented in this paper, and the error and sensitivity analyses are neglected.

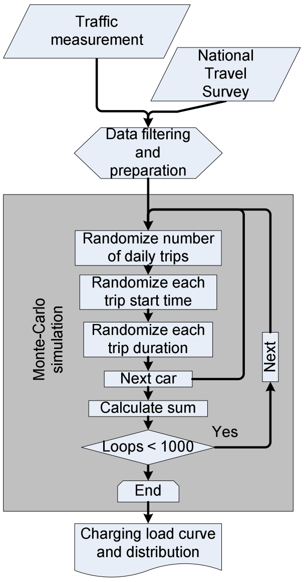


Fig. 7. Flow chart of the simulation process.

We can roughly estimate the grid load by comparing the traffic measurement data with the load curve presented in Fig. 6 and Fig. 8. There is significant similarity in the shapes of the load curve and the traffic flow curve in Fig. 2. First, if a 100% EV penetration level is assumed, in the afternoon there are about 100 vehicles arriving in the area per hour. At the same time, the load curve reaches its highest workday value as can be seen in Fig. 8. Secondly, if it is assumed that loading starts immediately when the vehicles arrive in the area, the charging load will be considerable.

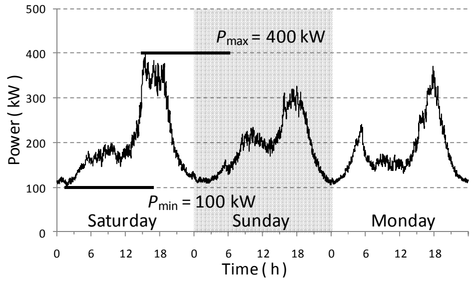


Fig. 8. Power measurement data from the area (without charging load).

The assumption is that the grid load will increase substantially during the base load peak hours. With the additional charging load estimations, the change in the distribution fee could be estimated. Also an estimation of intelligent charging could be provided by using the simulation model and the simulation results.

Simulation assumptions:

- Charging starts immediately when the vehicle arrives home
- Charging power is constant 3.6 kW per car
- The energy consumption of the vehicle is 0.2 kWh/km
- Charging can be done only at home
- The battery capacity of the vehicle is sufficient for most (all) of the daily trips

A. *Charging load simulation (dump charging)*

Simulation is made by applying different penetration levels; 25%, 50% 75%, and 100%. The lowest 25% penetration scenario may be realized in the near future, and therefore, it needs a closer look. With the low penetration level, the highest mean value of the EV charging load is 40 kW in the case of dump charging. In Fig. 9, the charging load curves with different penetration levels are presented.

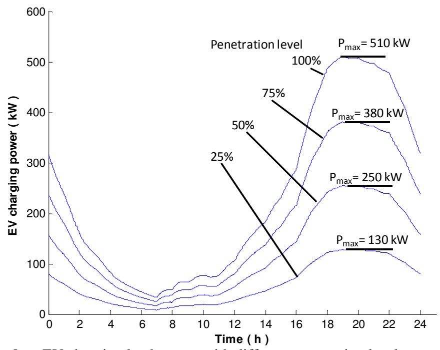


Fig. 9. EV charging load curves with different penetration levels.

The load varies from 0 to 510 kW, and the peak hour is at 19 pm. The total energy charged during a day is 3.3 MWh in the case of the 100% penetration level. Based on the amount of energy, it can be said that with the fleet of 400 vehicles, the average daily kilometers driven are 41 km/day. Compared with the NTS average of 52 km/day/car, the result is reasonable.

The main interest is in the hours from 16 pm to 23 pm, when the case area base load is at the highest level. In Fig. 2 and Fig. 6, we can see that the steepest upward slope starts at 16 pm, right before the base load starts to increase in the area. Based on this, it can be stated that the simulation model is well synchronized with the base load in the case area.

Fig. 10 shows the sum base load and the EV charging load. As can be noticed, the load power peak increases substantially even with the low penetration levels.

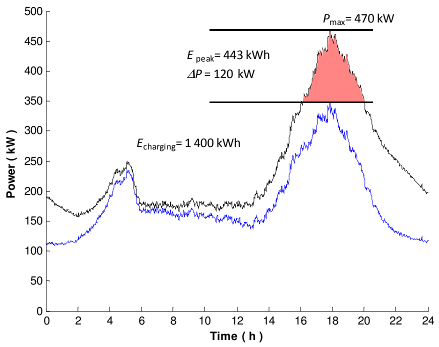


Fig. 10. Workday base load and EV charging load (25% penetration level).

With the 25% penetration level, the total peak load is 470 kW, which is 120 kW (35%) more than the original base load peak in workdays. The base load daily energy is 4.37 MWh/workday and the charging load energy with the 25% penetration level is 1.40 MWh/workday. Thus, the total energy increases by about 30%. Because the electricity consumption in the case area is not very energy intensive, the increase in the energy is also relatively high.

In this paper, the actual (physical) network effects are neglected to keep the focus on the grid loads. It is a question of further studies how the low-voltage grid can handle the charging loads presented in this paper.

With the 100% penetration level, the total load peak is 830 kW, which probably leads to a need to replan the whole low-voltage grid again, unless it is heavily overdimensioned. In practice, also some confidence levels of the base load and the EV charging loads must be considered when planning the reinforcements. The EV charging load confidence levels are discussed later in this paper.

B. *Smart charging*

The major challenge is not to simulate the loads caused by the smart charging of EVs, but to define how much electricity end-users are willing to allow their loads to be controlled. A further question is what kinds of incentives could be used to make the end-users willing to let their loads to be controlled by the DSO or some other aggregator. Smart charging is discussed in more detail for instance in [9]–[12]. In this paper, smart charging refers to a control scheme the goal of which is to improve the overall efficiency of the distribution grid and to decrease power peaks caused by EV charging.

In this particular case example, it is assumed that most of the EV charging loads can be delayed by a few hours in the evening time, without compromising the usability of the vehicles. The assumption is based on the NTS data, because the data show that most of the trips ending at home in the evening time are usually the last trips of the day. After the last trip, the vehicle stays at home all night and can be charged at any time during the night.

Based on the presented assumptions, charging can be optimized to the night hours when the base load of the area is at lowest.

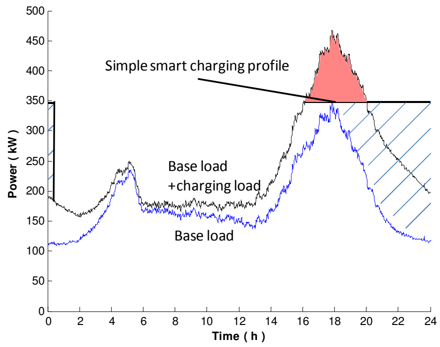


Fig. 11. Simple smart charging profile to be used for peak cutting purposes (25% penetration level).

C. *Cost analysis*

The cost of an additional load can be assessed by marginal cost, as discussed in [3]. The marginal cost represents the cost of the network replacement value and the highest load value of the year. In practice, it describes how much each peak load kilowatt hour costs for the distribution company. In the case grid, the suitable marginal cost is 300 €/kW. In the case of the 25% penetration level, the additional peak load ΔP (mean value of the charging load at the peak hour) of 120 kW corresponds to a 36 k€ grid investment $C_{\text{Reinforcement}}$ in the near future:

$$C_{\text{Reinforcement}} = \text{Average marginal cost} \cdot \Delta P \tag{1}$$

It must be borne in mind that the grid may be overdimensioned, and there is no immediate need for the reinforcement. Thus, every case must be dealt with individually when considering the reinforcements. Moreover, it has to be kept in mind that every additional peak load kilowatt added to the grid always has a price, even when a reinforcement is not needed.

The load curve confidence level must also be examined when considering a grid reinforcement. In Fig. 12, the load value of the peak hour is illustrated with different confidence levels.

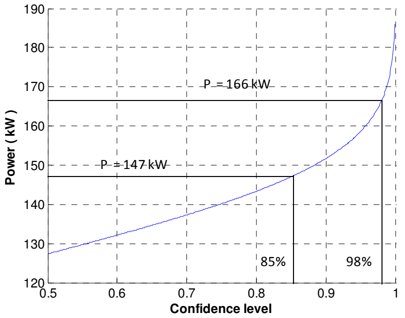


Fig. 12. Charging power at 6 pm with different confidence levels (25% penetration level).

For example, if a 98% confidence level (2% possibility for underestimating the load level) is selected, the additional load would be 166 kW, which corresponds to a 50 k€ reinforcement cost. At the 95% confidence level, the additional load would be 147 kW and the reinforcement cost 44 k€. In the end, it is a question about risk management of the DSO, that is, what kind of a confidence level is used in the load estimations and load flow calculations.

In the case of the controlled EV charging with the 25% penetration level, there is no significant power increase at the peak hours. The grid load curve is more leveled and the peak-operating time is increased, and therefore, the distribution fee paid by the end-user may even be decreased. A rough estimate of the change in the distribution fee paid by the end-customer can be made based on the delivered energy and the peak power.

The increase in the distribution fee can be evaluated by comparing the annual cost of the reinforcement $C_{\text{Annualreinforcement}}$ with the annual energy transferred $E_{\text{Annualtotal}}$:

$$\text{Network value per delivered energy} = \frac{C_{\text{Annual reinforcement}}}{E_{\text{Annual total}}} \qquad (2)$$

The value of the grid in the case area (including the marginal cost of the medium-voltage level 300 €/kW and the primary substation level 100 €/kW) is assumed to be 350 k€ and the annual costs of reinforcements 20.4 k€/a (i = 5%, t = 40 a). By (2), the network value per delivered energy is 1.27 cent/kWh (dimensioned to a 500 kW peak power).

In the case of dump charging with the 25% penetration level, the annual cost of reinforcements is 2.10 k€/a (i = 5%, t = 40 a, total investment 36 k€). Therefore, the annual cost is increased to 22.5 k€/a and the value per delivered energy is increased to 1.42 cent/kWh. Compared with the original value of 1.27 cent/kWh, the increase is 12%. Therefore, the distribution fee paid by the end-customer may need to be raised significantly even with low penetration levels.

In the case of smart charging with the 25% penetration level, the delivered energy increases by 1.4 MWh/day and no reinforcement is needed. Therefore, the value per delivered energy is 0.97 cent/kWh by (2), which is 23% less than the original 1.27 cent/kWh. In this case, the distribution fee may be even lowered. In order to evaluate the distribution fee paid by the end-customers, a more extensive grid load analysis is needed, since the peak operating time is different in different areas.

IV. Conclusion

Electric vehicles and vehicle charging stations will be part of the future grids. Charging of the electric vehicles may cause substantial effects to the grid in some cases if the charging is not controlled. In the case area, the value of the transferred energy is increased up to 12% with the 25% electric vehicle penetration level and even above this with higher penetration levels. The peak power increases by 34% with the 25% penetration level in the case of dump charging. With the 100% penetration level, the grid peak load may even double if the charging is not controlled.

With smart charging, the value of the transferred energy is decreased to 23%; consequently, it may even be possible to avoid an increase in the distribution fee paid by the end-customers or even to decrease the fee with the 25% electric vehicle penetration level.

Although the parameters and the simulations involve many assumptions and uncertainty, the results show that it is important to be able to manage or control electric vehicle charging in some way.

Even though this study was made for a particular case example, the methodology presented in the paper can also be used in other studies.

The main outcomes of this paper are:

- According to the grid load simulations, large-scale electrification of transportation and uncontrolled charging may cause serious reinforcement needs to the distribution grid.
- Load power peaks increase substantially if electric vehicle charging is not controlled, even with low penetration levels.
- The distribution fee paid by the end-customer may need to be increased significantly in the case of uncontrolled charging. In the case of optimized smart charging, there is an opportunity to lower the distribution fees.
- The developed simulation model helps in defining the charging effects of electric vehicles in a residential area. The simulation is based on actual traffic flow in the case area.

V. References

[1] E. Lakervi, E. J. Holmes, *Electricity distribution network design, 2nd ed.,* London: Peter Peregrinus, 1995, p. 325, ISBN 0-86341-309-9

[2] E. Lakervi, J. Partanen, "*Sähkönjakelutekniikka*" (*Electricity distribution Technologies*), Helsinki: Otatieto, 2008, p. 285, (In Finnish)

[3] J. Lassila, T. Kaipia, J. Haakana, J. Partanen, P. Järventausta, A. Rautiainen, M. Marttila, and O. Auvinen, "Electric Cars – Challenge or Opportunity for the Electricity Distribution Infrastructure?" *European Conference on Smart Grids and Mobility,* Würzburg, Germany, 2009.

[4] W. Kempton, and J. Tomic, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *Journal of Power Sources* 144, pp. 268–279, 2005.

[5] W. Kempton, and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources* 144, pp. 280–294, 2005.

[6] S. Rahman, and G.B Shrestha, "An investigation into the impact of electric vehicle load on the electric utility distribution system," *IEEE Trans. Power Delivery,* vol. 8, Issue: 2, pp. 591–597, Apr. 1993.

[7] A, Rautiainen, S. Repo, P. Järventausta, A. Mutanen, Statistical charging load modelling of PHEVs in electricity distribution networks using National Travel Survey data, Rep., 2011, Tampere University of Technology

[8] M. Ehsani, Y. Gao, and A. Emadi, *Modern Electric, Hybrid Electric and Fuel Cell Vehicles*, Second Edition, Taylor and Francis Group, Boca Raton Florida USA, 2010, 534 p.

[9] T. K. Kristoffersen, K. Capion, P. Meibom, "Optimal charging of electric drive vehicles in a market environment," *Applied Energy*, Volume 88, Issue 5, May 2011, Pages 1940-1948

[10] J.A. Pecas Lopes, S.A. Polenz, C.L. Moreira, R. Cherkaoui, "Identification of control and management strategies for LV unbalanced microgrids with plugged-in electric vehicles," *Electric Power Systems Research*, Volume 80, Issue 8, August 2010, Pages 898-906

[11] A. Rautiainen, S. Repo, P. Järventausta, "Intelligent charging of plug-in vehicles," *Nordic Electricity and Asset Management Conference (NORDAC), 2010*

[12] E. Sortomme, M.M. Hindi, S.D.J. MacPherson, S.S. Venkata, "Coordinated Charging of Plug-In Hybrid Electric Vehicles to Minimize Distribution System Losses," *Smart Grid, IEEE Transactions on*, vol.2, no.1, March 2011, pp.198-205'

VI. Biographies

Ville Tikka was born in Savitaipale, Finland, in March 1984. He received his M.Sc degree from Lappeenranta University of Technology (LUT) in 2010.
Since then he has been a Doctoral Student at LUT. His main area of interest is modeling of the grid effects of electric mobility.

Jukka Lassila was born in Ilomantsi, Finland, in February 1975. He received the M.Sc. and D.Sc. (Tech.) degrees in electrical engineering from Lappeenranta University of Technology (LUT), Lappeenranta, Finland, in 2000 and 2009, respectively.
He is a Post Doctoral Researcher at LUT and is also Director of Asset Vision Ltd., a consultant company. His main area of interest is electricity distribution systems, especially strategic planning of medium- and low-voltage networks.

Juha Haakana was born in Ruokolahti, Finland, in December 1984. He received the M.Sc. degree from Lappeenranta University of Technology (LUT), Lappeenranta, Finland, in 2008.
Since then, he has been a Doctoral Student at LUT. His main area of interest is long-term developing of electricity distribution systems.

Jarmo Partanen received the D.Sc. (Tech.) degree in electrical engineering from Tampere University of Technology, Tampere, Finland, in 1991.
He has been a Professor at Lappeenranta University of Technology (LUT), Lappeenranta, Finland, since 1994. He is currently the Head of the Institute of Energy Technology at LUT. His main fields of interest are smart grids, electricity market, RES and regulation of electricity distribution business.

Publication II

Tikka, V., Lassila, J., Makkonen, H., and Partanen, J.
Case study of the load demand of electric vehicle charging and optimal charging schemes in an urban area

Reprinted with permission from
2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)
Berlin, Germany, 2012

2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), Berlin

Case Study of the Load Demand of Electric Vehicle Charging and Optimal Charging Schemes in an Urban Area

Ville Tikka, *Student Member, IEEE*, Jukka Lassila, *Member, IEEE*, Henri Makkonen, Jarmo Partanen, *Member, IEEE*

***Abstract*—The interest in electric vehicles (EVs) is rapidly increasing, and the upward trend seems to continue also in the future. As a result of the increasing energy consumption, the grid infrastructure has to be developed further, and moreover, it is necessary to analyze the network effects of the electric vehicle charging. In this paper, the challenge is approached by an actual case area in Finland and simulated EV traffic. The data used in the simulation are collected by measuring the traffic flow on the road leading to the case area. The objective of the paper is to demonstrate how the grid effects of large-scale electrification of transportation can be addressed, and what data are required to assess the additional charging load in a feasible manner. The data are processed by applying the Monte-Carlo method, and also a sensitivity analysis is performed.**

***Index Terms*-- Load modeling, electric vehicles, power distribution, smart grids, smart charging**

I. Introduction

THE energy policy of the European Union has created a pressure to increase energy efficiency in all sectors of energy consumption. About 20% of greenhouse gas emissions in Europe are produced by transportation, because fossil fuels are still widely used in vehicles. Electric vehicles (EVs) are probably among the most promising alternatives towards CO_2 free transportation. Even a small proportion of EVs in transportation would lead to a substantial decrease in emissions. Therefore, it is essential to investigate how the electrification of transportation affects the electric grid, and whether EVs or plug-in hybrid electric vehicles (PHEVs) can support the grid or whether there are only adverse effects on the horizon as electric vehicles gain in popularity.

While electrical mobility is winning popularity, the electricity grid itself is also under major transformation. EVs will be part of future grids similarly as distributed generation, grid automation, and energy storages. The structure of the electricity retail market may also undergo changes as a result of the new business model is to be launched among EV charging services.

To be able to analyze the grid impact of electric vehicle charging, the issue needs to be addressed from all relevant directions. First of all, it has to be borne in mind that unlike traditional loads, an EV charging load may be positioned in different locations. Secondly, the charging need may also vary in a seemingly random way. Thirdly, the charging time is dependent on the moment at which the vehicle is plugged into the grid. Consequently, the various combinations of these factors may lead to very complex computations. However, a similar approach can be taken to large volumes of EV charging loads as with traditional household loads: a single event may be difficult to predict, but a large number of events seem to follow some kind of a pattern. Grid load estimation for grid development purposes and a confidence level approach are covered in [2]. Dimensioning and maintenance of the distribution grids are discussed in [1] and [2].

It is relatively easy to model an additional load caused by dump charging to the grid by assuming some random penetration levels. Although studies of this kind may provide worst-case scenarios, in practice there is a need for estimates of the actual number of EVs. In particular, if there are problems to be expected with the existing load already, an additional EV charging load will complicate matters even further.

It is difficult to determine which penetration level should be used and for what time period. Moreover, it may be demanding to estimate how charging will or should be arranged. Will there be dumb charging spots only or will there be a combination of different charging methods? The network effects of EVs are discussed in [3]–[5]. Feasibility of the Vehicle to Grid (V2G) technology is analyzed in [6].

If we can show that EVs will not cause any additional peak loads to the grid at high penetration levels, the problems with the future schemes can be solved, at least to a certain extent. Naturally, there are many areas in Finland and the Nordic countries where an increase in the peak load cannot be covered without major investments to grid automation or cables.

This paper provides a case example of how the EV charging demand can be modeled to answer the needs of the smart charging scheme. The EV charging demand will be demonstrated by modeling the use of personal vehicles in an actual urban case area, which was introduced in a previous study [3].

A simple smart charging control algorithm is presented in the study to demonstrate the charging demand results for the

The authors are with the Department of Electrical Engineering, Lappeenranta University of Technology, Lappeenranta, Finland, (e-mail: Ville.Tikka@lut.fi; Jukka.Lassila@lut.fi; Henri.Makkonen@lut.fi; Jarmo.Partanen@lut.fi).

978-1-4673-2597-4/12/$31.00 ©2012 IEEE

case area. The Monte Carlo Method (MCM) is taken as a stochastic approach because of the simplicity of the method. As the system does not involve any time-consuming calculations, a slow method such as MCM provides a feasible approach to the topic.

The key points of the case study are:

- Grid load effects of the EV smart charging
- Data generation, acquisition, filtering and optimization algorithms
- Charging load demand and use of charging spots

II. The Case Area and Background Data

In this chapter, the case area, background data, and traffic measurements are illustrated. In addition, parameters used in the simulation are explained and introduced in brief.

A. *The case area*

The case study in this paper is based on an actual case area in Southern Finland. The case area is illustrated in Fig. 1.

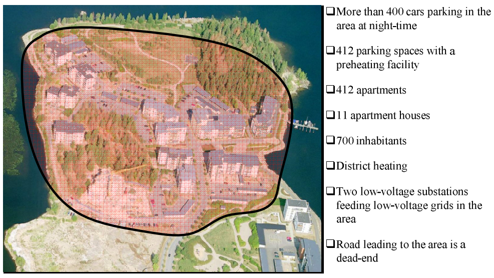


Fig. 1. Case area: Pikisaari district of the city of Lappeenranta in Southern Finland.

The area consists of 11 apartment houses with 412 apartments. In the parking lots of the case area there are 412 parking spaces. The parking spaces are usually occupied during the night hours, while during the daytime most of the parking spaces are empty. Every parking space is equipped with a winter preheating facility (engine block-heater pole), which can be used for slow EV charging in most cases when the EV penetration level in the area is low.

The low-voltage grid in the area consists of two 20/0.4 kV low-voltage substations with an annual peak power of about 200 kW per substation; for both stations approximately 400 kW in total. In the wintertime, all 11 houses are heated by district heating, and thus, changes in the outside temperature have only a slight effect on the electricity consumption. The road to the area is a dead end (no through-traffic), which makes it an ideal target for traffic measurement.

B. *Base load*

The power flows at the low-voltage substations are also measured to give an insight into the ratio of the EV charging load to the base load in the area. In this case, the highest base load values occur in the afternoon and evening hours, as can be seen in Fig. 2.

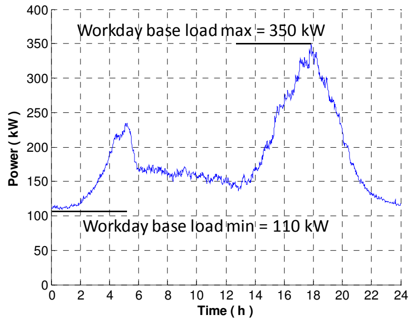


Fig. 2. Measured workday base load in the case area.

In [3] it was noticed that the base load peak and the charging load may overlap substantially during the evening hours causing a notable peak load increase in the case of dump charging. The cost of the delivered energy will also increase if the EV charging is not controlled. It was also shown that an alternative charging scheme may significantly improve the situation.

C. *National Travel Survey*

In this paper, the vehicle kilometers by car are estimated by using the Finnish National Travel Survey (NTS) by the Finnish Transport Agency. The survey includes all transportation (cars, motorcycles, busses, biking, etc). The cars are assumed to be EVs or PHEVs with high-capacity batteries. Charging losses are neglected; however, the average consumption can be slightly overestimated in order to compensate the charging losses. The National Travel Survey is discussed in more detail in [6].

D. *The traffic measurement*

To demonstrate the application of the forecasting methodology and smart EV charging, traffic was measured for a month. Fig. 3 shows the average daily distribution of cars arriving and leaving the area. Working hours can be easily spotted in the figure; there is a significant peak at 8 am when cars are leaving the area and at 17 pm when cars are arriving back in the area.

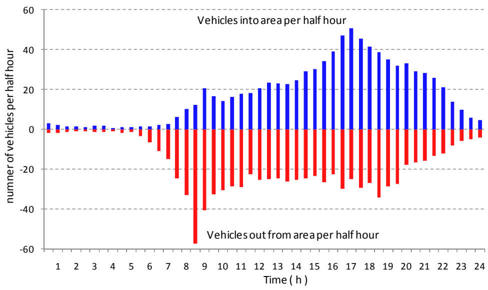


Fig. 3. Average workday traffic flow on the road leading to the case area.

III. Simulation Assumptions

In Finland, the cost of fossil fuels is rapidly increasing, and therefore, driving with internal combustion engine (ICE) vehicles becomes more expensive. Based on the National Travel Survey (NTS) [7], it can be estimated that the average driving distances per person by car are about 52 km/d and 18980 km/a. In most cases, modern electric vehicles are already capable of covering the distances travelled per day. In fact, the typical trip length is less than 100 km for 93% of the car trips, as can be seen in Fig. 4. Many EVs already offer a driving range of well above 100 km; EVs are discussed in more detail for instance in [8].

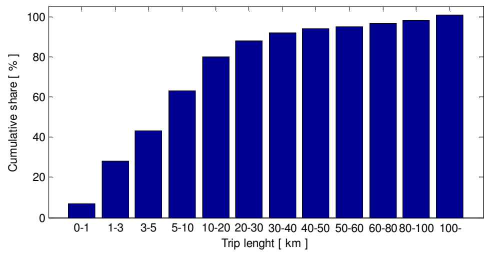


Fig. 4. Distribution of trip lengths driven by car in Finland [6].

Nevertheless, EVs may not yet be a feasible alternative because of their high purchase price compared with similar ICE vehicles, even though the running cost is lower with EVs than with ICEs. In the near future, we also expect to see a reduction in the battery cost, and when the battery cost becomes lower, also the EV prices will probably come down. The sale of hybrid vehicles (HEV) has started well in Finland, and hence, we may also assume an increase in the sale of Plug-in Hybrid Vehicles (PHEV) in the next few years. Table 1 provides an estimate of the PHEV and EV sales in Finland for the near future.

TABLE 1
PHEV AND BEB PENETRATION SCENARIOS BASED ON THE REPORT OF THE MINISTRY OF TRANSPORTATION AND COMMUNICATION IN FINLAND [9]

	Year	Share of new cars		Cumulative sales (number of cars)		Share of the vehicle kilometers by car	
		PHEV	BEV	PHEV	BEV	PHEV	BEV
Slow scenario	2020	5%	2%	38 000	12 000	2%	0.5%
	2030	20%	10%	207 000	92 000	8%	4%
Medium scenario	2020	10%	3%	66 000	13 000	3%	0.6%
	2030	50%	20%	480 000	16 000	19%	7%
Fast scenario	2020	40%	6%	190 000	26 000	8%	1%
	2030	60%	40%	960 000	45 000	38%	19%

As shown in Table 1, the sales of EVs and PHEVs in Finland are not the most optimistic. In this paper, simulations are performed with low penetration levels as Table 1 suggests, but also with a higher penetration level in order to demonstrate the optimization based on the NTS data.

In the simulation, it is assumed that the PHEV has an average battery size of 6 kWh with a standard deviation of 1 kWh. The battery size is randomized for each car based on the normal distribution. In the case of BEVs, the average battery size is assumed to be 25 kWh with a standard deviation of 2 kWh. Also in the case of BEVs, the battery size is randomized based on the normal distribution.

The average energy consumption of EVs (and PHEVs when driven by electricity) is assumed to be 0.175 kWh/km, which is the estimate commonly used in the Nordic countries. The energy consumption of the cars is chosen to be based on the normal distribution with an average of 180 Wh/km and variance of 5 Wh/km. The majority of the randomized consumption values are in the range from 165 kW/km to 195 Wh/km. A lower consumption estimate can be used in southern countries, where interior heating is not required in vehicles. The properties of electric and hybrid vehicles are discussed in [8].

If the driving distance is longer than the battery capacity allows, it is assumed that the car operated in that case is a PHEV. After the vehicle battery has been used up, the vehicle is assumed to be driven with an internal combustion engine (ICE). If there are several trips from and to home during a day, the vehicle is considered to be charged only after the last arrival at home. For instance, if a car arrives at home at 6 pm and leaves at 7 pm to a grocery store, then returns at 8 pm and stays at the home for the rest of the evening, the battery is assumed to be charged after the last home arrival at 8 pm. The trips are added up and the charging need is determined. Driving in the EV mode (driving the PHEV by electricity) is always prioritized. A more detailed description about the data processing can be found in [3].

IV. Smart Charging Scheme

An EV charging load was modeled in [3] and also studied in [10]. The same simulation model as in [3] is used to provide demand curves for EV and PHEV charging (time when charging has to or can be carried out and how much batteries need to be charged).

Fig. 5 presents the number of EVs in the case area during the daytime. Such data can be used as input data for the optimized EV charging simulations. In this particular case, the number of vehicles in the area during the day is quite high, almost half of the parking capacity. The accuracy and deficiencies of the measurement are discussed in [3]. The primary objectives of this paper are to provide a case example, to test the smart charging scheme, and provide a parameter sensitivity analysis, and therefore, the accuracy of the simulation data is considered sufficient for the purpose.

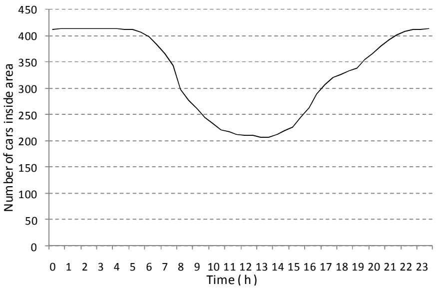


Fig. 5. Number of cars in the case area. The figures are based on an actual traffic flow measurement in the case area.

Another essential input for the simulation is the distances (kilometers) travelled by a car. For the time being, the only feasible way to access such information is to use the data provided by the NTS. The data are described in [7] and used in the EV charging load modeling in [3] and [10].

The optimization target in this case is to charge all vehicles when the grid load is at lowest. Other optimization schemes, such as a price-based approach are studied in [11]–[13]. Smart charging is discussed in [13].

The target of the optimization algorithm in this study is to charge the batteries in the cars as quickly as possible, simultaneously keeping the grid load as low as possible. In this case, the charging would start after the afternoon peak load hours. The number of EV charging would increase as the base grid load decreases. In practice, all of the cars would be charged before morning.

The optimization algorithm requires information on how long the cars are available for charging in order to predefine the charging scheme for each car. Furthermore, the limits of the charging power have to be known, as well as the estimated charging need for each car. Based on this knowledge, the optimization can be carried out. In the following, the optimization algorithm used in the simulation is presented in a pseudo-code format:

1. Estimate the base load curve (empirical data)
2. Estimate the number of cars driving into the area
3. Estimate the number of cars driving out from the area
4. Randomize one parking event and charging need
    a. Arrival time
    b. Departure time
    c. Driven kilometers (charging need)
5. Calculate optimal charging schedule for a car
    a. Find base loads minimum in a charging window
    b. Add charging power to base load curve
6. Repeat lines 4 and 5 until estimated number of parking events is full
7. Repeat lines 4-6 and calculate mean after every loop
    a. Evaluate change of the charging load mean value to break the looping

The optimization algorithm can be also simplified to:

$$\min(P(t)_{\text{charging}} + P(t)_{\text{base load}}) \tag{1}$$

where P_{charging} is the total charging load, $P_{\text{base load}}$ is the base load, and t is the time index. Equation (1) must satisfy the following:

$$E_{\text{charging}} = \int P(t)_{\text{charging}} dt \tag{2}$$

where E_{charging} is the total charging energy in the optimization time window defined by the number of cars in the area and charging need of the cars.

The charging time is dependent on the power and charging need of the car. The higher the charging power is, the shorter the charging time is; or the more drained the battery is, the longer the charging time is. The charging time is limited by the parking time of the car, or actually, the time limit is set by the time at which the car is plugged into the charging socket. In the simulation, it is assumed that the cars are plugged in just after the last arrival at home. Therefore, the parking time equals the time the car is plugged in. Departure time at the morning is randomized based on the traffic measurement data. The charging window is decreased by 8 hours at the morning to ensure flexible use of the cars.

The initial charging power is assumed to be 3.6 kW because of the infrastructure already available in the case area. Each wintertime preheating facility is considered suitable as a charging spot, and in each electricity socket there is a circuit breaker of 16 A. In addition, a simulation with three-phase 3x16 A (11 kW) charging is made for an option of an advanced charging infrastructure.

The charging power is assumed to be constant during charging. In an actual application, the charging power may vary during the charging cycle. With the high-power charging, the charging cycle is also usually ended with a lower power in order to let the battery cells to balance the charge.

V. Sensitivity Analysis

This chapter focuses on the simulation results obtained with different parameters in order to identify the most important factors affecting the charging demand, and eventually, the grid load. Fig. 6 shows how the charging load differs in the case of PHEVs or BEVs only.

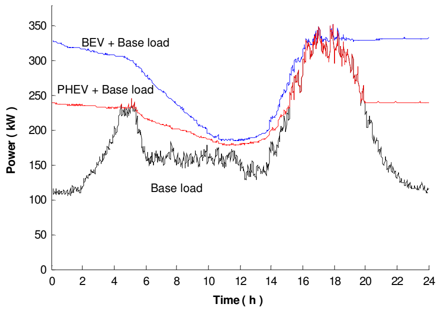


Fig. 6. Sum of the base load and charging curves in the case of smart charging with PHEVs and BEVs.

As can be seen in the figure, the change in the charging curve is substantial; there is a difference of almost 100 kW in the charging power. This can probably be explained by the average kilometers traveled by car in Finland. As stated above, the average kilometers traveled by car are 52 km/d, and if a PHEV consumes 0.180 kWh/km in average, the average total energy is 9.4 kWh, which is above the average battery capacity used in the simulation. The average battery capacity in the BEV is 25 kWh, which covers most of the daily kilometers.

Fig. 7 shows the charging load with different penetration levels in the case of BEVs.

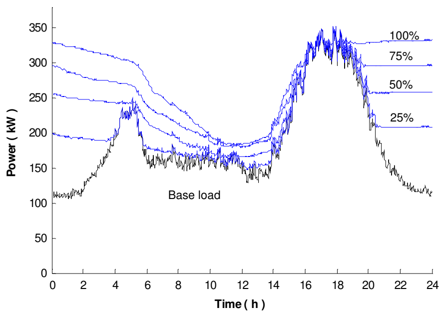


Fig. 7. Smart charging curves of BEVs with penetration levels of 25%, 50%, ,75% and 100% (412 cars).

It can be seen that an increase in the penetration level increases the average load level during the night-time, but does not cause an additional peak load. It seems that the case grid can handle the full penetration level of BEVs in the case of the grid-optimized smart charging. The total energy charged is linearly dependent on the penetration level. In the case, the grid peak load does not depend on the penetration level because of the high base load peak.

Fig. 8 presents a case where 25% of the total charging energy is assumed to be charged in the workplace.

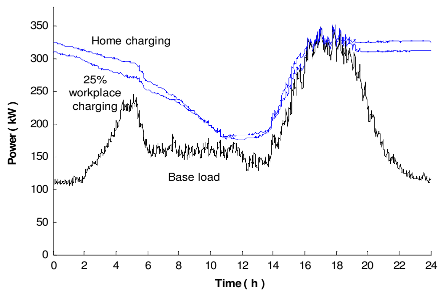


Fig. 8. Smart charging curve of BEVs in the case where 25% of the energy is charged in the workplace (penetration level 100%).

Fig. 8 shows a similar result as in Fig. 7 with a penetration level of 75%. The result seems trivial, because the optimization algorithm faces no restrictions even with the 100% penetration level in a case where all the charging is made at the home charging spot. If 25% of the energy is charged in some other place, the need for charging energy is 75% of the total.

Fig. 9shows the difference in the charging curve with different charging powers.

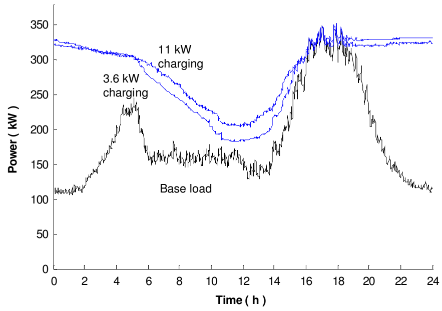


Fig. 9. Smart charging curve of BEVs with single-phase charging and with three-phase charging.

The difference in the charging curve is small only few kilowatts. Fig. 10 Shows the Smart charging curve of PHEVs with single-phase charging and with three-phase charging.

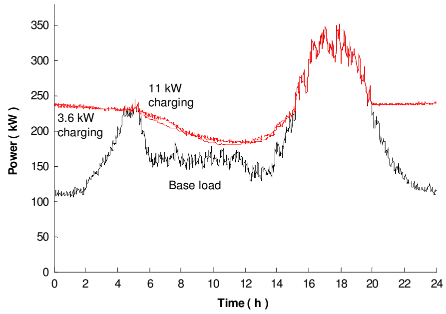


Fig. 10. Smart charging curve of PHEVs with single-phase charging and with three-phase charging.

Also in the case of PHEVs, the optimized charging curve is similar with 3.6 kW and 11 kW. The main reason why total charging power is in the same level both in 3.6 kW and 11 kW charging modes is that charging need is satisfied in the charging window also with lower power of 3.6 kWh.

A. *Energy*

The amount of the total energy in daily charging is at highest in the case of BEV charging with 100% penetration level. The total charging need would be roughly 3.8 MWh/d, but because of the battery capacity and limited charging window total charging energy is 2.3 MWh/d, 60% of total. The accuracy of the initial traffic measurement can be questioned, but in this case the main goal to demonstrate the smart charging scheme, is achieved. Based on the simulation the 40% of the energy limitation was caused by battery size and 60% of the limitation caused by the charging window.

In the case of PHEV smart charging the total charging energy is 1.2 MWh/d, 30% of the total charging need. Most of the charging limitation is caused because of the smaller batteries in the cars.

The accuracy of traffic modeling will be enhanced in further studies in order to provide results that can be used in the strategic grid planning for future.

VI. Analysis and Results

The results of the simulation model can be interpreted in many ways. It was shown in [3] how the grid load can be maintained under the highest peak simply by delaying the start of the charging event. In this simulation, the idea is brought one step further, and the charging load is not just delayed, but it is optimized to determine the moment of the lowest base load.

With this optimization, the grid load can be kept as low as possible, while also the ramping of the load is much lower. Fig. 7 shows the charging load curve with different penetration levels. As also Fig. 9shows, even with the highest penetration levels, the charging load does not increase the base load peak at all. Such a grid load would provide an opportunity to reduce the transmission fee paid by the end-customer, because the cost of the distributed energy is lower. The more energy can be delivered, and the lower the peak power is, the cheaper the energy is to be delivered. In other words, the more invariable the power is, the more inexpensive the energy is to be delivered.

A. *Cost analysis*

The cost of an additional load can be assessed by marginal cost, as discussed in [3]. In this case the value of delivered energy is decreased, because grid does not need reinforcements, but delivered energy is increased. The marginal cost represents the cost of the network replacement value and the highest load value of the year. In practice, it describes how much each peak load kilowatt hour costs for the distribution company. The existing grid has value which can be evaluated by the means of:

$$C_{Value} = \text{Average marginal cost} \cdot P_{Peak} \qquad (3)$$

where $\underline{C}_{\text{Value}}$ is the annual cost of the grid, P_{Peak} is assumed peak power (grid dimensioning power). The value of the grid in the case area (including the marginal cost of the medium-voltage level 300 €/kW and the primary substation level 100 €/kW) is assumed to be 350 k€ and the annual costs of grid 20.4 k€/a (i = 5%, t = 40 a).

In the case of the smart BEV charging with the 100% penetration level, there is no noticeable power increase at the peak hours. The grid load curve is more leveled and the peak-operating time is increased, and therefore, the distribution fee paid by the end-user may even be decreased. A rough estimate of the change in the distribution fee paid by the end-customer can be made based on the delivered energy and the peak power.

The decrease in the distribution fee can be evaluated by comparing the annual cost of the reinforcement C_{Value} with the annual energy transferred $E_{\text{Annualtotal}}$:

$$\text{Network value per delivered energy} = \frac{C_{\text{Annual reinforcement}}}{E_{\text{Annual total}}} \qquad (4)$$

By (4), the network value per delivered energy is 1.27 cent/kWh (dimensioned to a 500 kW peak power).

In the case of smart BEV charging with the 100% penetration level, the delivered energy increases by 2.3 MWh/day and no reinforcement is needed. Therefore, the value per delivered energy is 0.84 cent/kWh by (4), which is 34% less than the original 1.27 cent/kWh. In this case, the distribution fee may be even lowered. In order to evaluate the distribution fee paid by the end-customers, a more extensive grid load analysis is needed, since the peak operating time is different in different areas.

VII. Conclusion

Is seems that electric vehicles and vehicle charging stations will be part of the future grids. In some cases, charging of the electric vehicles may cause substantial effects on the grid if the charging is not controlled. If the charging can be controlled, the grid load impact is minor. In the extreme scenario, the distribution fee may decrease.

In the case area, the value of transferred energy is increased up to 50% with the 100% electric vehicle penetration level, and even above this with higher penetration levels, but the peak power of the grid remains unchanged. In this particular case, the grid-optimized smart charging scheme seems to have proven its usefulness.

The parameter sensitivity analysis did provide much useful information in this particular case. The deeper analysis will be presented in the further studies with a more challenging base load.

With smart charging, the value of transferred energy is decreased to 34%; consequently, it may even be possible to avoid an increase in the distribution fee paid by the end-customers or even to decrease the fee with the 100% electric vehicle penetration level.

Even though this study was made for a particular case example, the methodology presented in the paper can also be used in other studies.

The main outcomes of this paper are:

- According to the grid load simulations, large-scale electrification of transportation with grid-optimized smart charging will not cause pressure to reinforce the grid.

- There is an opportunity to reduce the distribution fees if the grid-optimized smart charging is used.

- The developed simulation model helps in defining the charging effects of electric vehicles in a residential area. The simulation is based on actual traffic flow in the case area.

- The optimization algorithm will be applied also to the further studies.

VIII. References

[1] E. Lakervi, E. J. Holmes, *Electricity distribution network design, 2nd ed.,* London: Peter Peregrinus, 1995, p. 325, ISBN 0-86341-309-9.

[2] E. Lakervi, J. Partanen, "*Sähkönjakelutekniikka*" (*Electricity distribution Technologies*), Helsinki: Otatieto, 2008, p. 285, (In Finnish).

[3] V. Tikka, J. Lassila, J. Haakana, J. Partanen, "Case study of the effects of electric vehicle charging on grid loads in an urban area," *Innovative Smart Grid Technologies (ISGT Europe), 2011 2nd IEEE PES International Conference and Exhibition on* , vol., no., pp.1–7, 5–7 Dec. 2011, doi: 10.1109/ISGTEurope.2011.6162667.

[4] J. Lassila, T. Kaipia, J. Haakana, J. Partanen, P. Järventausta, A. Rautiainen, M. Marttila, and O. Auvinen, "Electric Cars – Challenge or Opportunity for the Electricity Distribution Infrastructure?" *European Conference on Smart Grids and Mobility,* Würzburg, Germany, 2009.

[5] S. Rahman, and G.B Shrestha, "An investigation into the impact of electric vehicle load on the electric utility distribution system," *IEEE Trans. Power Delivery,* vol. 8, Issue: 2, pp. 591–597, Apr. 1993.

[6] J. Lassila, J. Haakana,V. Tikka, and J. Partanen, "Methodology to Analyze the Economic Effects of Electric Cars as Energy Storages," *Smart Grid, IEEE Transactions on* , vol.3, no.1, pp.506–516, March 2012,

[7] National Travel Survey 2004-2005, (Henkilöliikennetutkimus 2004–2005), WSP LT-Konsultit Oy, Ministry of Transport and Communications, ISBN 951-803-682-9, in Finnish.

[8] M. Ehsani, Y. Gao, and A. Emadi, *Modern Electric, Hybrid Electric and Fuel Cell Vehicles*, Second Edition, Taylor and Francis Group, Boca Raton Florida USA, 2010, 534 p.

[9] Electric Vehicles In Finland - Report (Sähköajoneuvot Suomessa – selvitys) 6.8.2009, Biomeri Oy, Ministry of Transport and Communications, [Online]. Available: http://www.tem.fi/files/24099/ Sahkoajoneuvot_ Suomessa-selvitys.pdf, in Finnish.

[10] A, Rautiainen, S. Repo, P. Järventausta, A. Mutanen, Statistical charging load modelling of PHEVs in electricity distribution networks using National Travel Survey data, Rep., 2011, Tampere University of Technology.

[11] T. K. Kristoffersen, K. Capion, P. Meibom, "Optimal charging of electric drive vehicles in a market environment," *Applied Energy*, Volume 88, Issue 5, May 2011, pp. 1940–1948.

[12] C. Yijia, T. Shengwei, L. Canbing, Z. Peng, T. Yi, Z. Zhikun, L. Junxiong, "An Optimized EV Charging Model Considering TOU Price and SOC Curve," *Smart Grid, IEEE Transactions on* , vol.3, no.1, pp.388-393, March 2012, doi: 10.1109/TSG.2011.2159630.

[13] A. Rautiainen, S. Repo, P. Järventausta, "Intelligent charging of plug-in vehicles," *Nordic Electricity and Asset Management Conference (NORDAC), 2010.*

IX. Biographies

Ville Tikka was born in Savitaipale, Finland, in March 1984. He received his M.Sc degree from Lappeenranta University of Technology (LUT) in 2010.
Since then he has been a Doctoral Student at LUT. His main area of interest is modeling of the grid effects of electric mobility.

Jukka Lassila was born in Ilomantsi, Finland, in February 1975. He received the M.Sc. and D.Sc. (Tech.) degrees in electrical engineering from Lappeenranta University of Technology (LUT), Lappeenranta, Finland, in 2000 and 2009, respectively.
He is a Post Doctoral Researcher at LUT and is also Director of Asset Vision Ltd., a consultant company. His main area of interest is electricity distribution systems, especially strategic planning of medium- and low-voltage networks.

Henri Makkonen was born in Helsinki, Finland, in November 1984. He received his M.Sc. degree from Lappeenranta University of Technology (LUT) in 2008.
Since then he has been a Doctoral Student at LUT. His main area of interest is smart grid technology.

Jarmo Partanen received the D.Sc. (Tech.) degree in electrical engineering from Tampere University of Technology, Tampere, Finland, in 1991.
He has been a Professor at Lappeenranta University of Technology (LUT), Lappeenranta, Finland, since 1994. He is currently the Head of the Institute of Energy Technology at LUT. His main fields of interest are smart grids, electricity market, RES and regulation of electricity distribution business.

Publication III

Lassila, J., Haakana, J., Tikka, V., and Partanen, J.
Methodology to Analyze the Economic Effects of Electric Cars as Energy Storages

Reprinted with permission from
IEEE Transactions on Smart Grid
3.1, pp. 506–516, 2012

Methodology to Analyze the Economic Effects of Electric Cars as Energy Storages

Jukka Lassila, Juha Haakana, Ville Tikka, and Jarmo Partanen, *Member, IEEE*

***Abstract*—The nature of transport and energy use is radically changing along with the upward trend of electric vehicles. The rapid technological development of electrical vehicles opens new opportunities from the electricity distribution point of view. Efficiency can be improved by implementing energy storages to the grid and cutting the load peaks by feeding power on peak hours from the energy storages to the grid. Electric vehicles with vehicle-to-grid (V2G) properties provide an opportunity to meet this challenge. In this paper, the challenge is approached from the economic perspective of an electricity distribution company. The key target of the paper is to determine whether there is economic potential for energy storages in networks in general. To this end, a generic model is introduced to analyze the feasibility of electric vehicles as energy storages in distribution networks. The methodological framework presented in the paper provides an opportunity for distribution system planners to estimate the preliminary feasibility of energy storages. The focus is on the discharging (vehicle to grid) perspective. The paper answers, for instance, the question of how to define the feasible level of energy storages (batteries) in the distribution system. In the paper, for background information, an extensive literature review is provided on electric vehicles.**

***Index Terms*—Economic effects, electric vehicles, electricity distribution business, energy storages.**

I. Introduction

THE PRESENT electricity distribution has reached its final milestone. Aging infrastructure, challenges in supply reliability, and the problems to use the network as an open marketplace are realities of today. It is no longer a question about reasonable dimensioning of cables or choosing a feasible renovation technology but it is a question about a revolutionary change in the development and operation of the vital infrastructure; in other words, the development of smart grids. The challenge of the existing power systems has been the large daily variation in the load levels; the power demand in the grid may vary tens or even hundreds of percents during the day. When the network dimensioning is based on the peak power, the overall efficiency can be rather low from the capacity point of view. For instance in the low-voltage networks, peak operating times vary from 1500 to 2500 h per year.

For the operators and owners of electricity distribution utilities (companies), this revolution poses an incredible challenge, but also at the same time, an opportunity to renovate the network asset to the next level. There is a risk for the overlapping of the present peak load and the peak caused by the charging of electric vehicle (EV) batteries. This may lead to a substantial increase in peak loads and thereby to reinforcement needs in the networks. Finally, this may raise the distribution fee paid by the electricity end-users.

This paper aims at developing a methodology by which key issues related to the network economic effects of EVs and energy storages can be addressed. Even though the results are based on information of actual distribution companies, the main focus of the paper is on the methodological development work. The target is to establish a generic model by which the feasibility of EVs as energy storages can be determined. However, the results are interesting and they show that there are economic incentives for bidirectional energy storages, especially as the battery technology is constantly developing. Even though the paper presents some results by a case network, the objective is not to give any exact values for a network analysis, but to present the information and the method required in general. Thus, the paper provides tools for a network analyzer to determine the feasibility of energy storages in different cases. Although there is a lot of uncertainty considering background information and parameters used in the study, preliminary feasibility analyses can be carried out using the best assumptions available. Later on, when the EV penetration level is higher, the input data used previously can be replaced with up-to-date information. Uncertainty is strongly related to the penetration schedules, behavior of EVs, effects of environmental conditions (for instance, cold winters in the Nordic countries), and development of the efficiency of the charging and discharging processes.

Definition of the network effects requires understanding of the wide-scale use of electric vehicles (EVs) and the long-term development of the distribution infrastructure. The theme of EVs has been discussed from various aspects in several publications and forums (e.g., an overview of the EV technology is given in [1]–[4], load leveling is addressed in [5] and [6], batteries are discussed in [7] and [8], and charging interfaces (outlets) are studied in [9] and [10]). Each of these references provides understanding of EVs in a certain specific area. However, the economic network effects of EVs [11]–[13] have mostly been neglected. More typically, the research focuses on the development of the electro-mechanical properties of EVs and determining the technical effects of vehicle charging. For the time being, there is no methodology to define the economic effects of the wide-scale penetration of EVs from the perspective of

Manuscript received March 25, 2011; revised July 05, 2011; accepted August 30, 2011. Date of publication November 14, 2011; date of current version February 23, 2012. Paper no. TSG-00112-2011.

The authors are with the Department of Electrical Engineering, Lappeenranta University of Technology, 53851 Lappeenranta, Finland, (e-mail: Jukka.Lassila@lut.fi; Juha.Haakana@lut.fi; Ville.Tikka@lut.fi; Jarmo.Partanen@lut.fi).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSG.2011.2168548

TABLE I
LITERATURE REVIEW ON EVs AND ELECTRICITY DISTRIBUTION. (+ + + = Main Theme, ++ = In An Important Role, + = Mentioned In the Publication)

Publication	Content			Energy flow		Grid perspective					Charging and control			Business			Other			
	Theoretical	Simulation + case	Case (measurements)	G2V	V2G, V2H	Network effects	EVs as part of **Smart Grids**	Load modeling and forecasting	Load leveling (peak cutting)	Power quality	Ev charging standards	Control of charging	Communication and data interface	Distribution business	Electricity markets	Costs, cost optimization	Penetration perspective	EV and battery technology	Simulations and statistical analysis	Environmental effects
[14] Balcells and Garcia (2010)		o	o	o		++		+		+++	++	+						+	++	
[15] Blumsack et al. (2008)	o			o		++		++	++							+			++	+++
[16] Clement-Nyns et al. (2010)	o			o		+++	+	++	+	++			+	+	+		+		+++	
[17] Cvetkovic et al. (2009)		o	o	o	o	+	++			++		+++	++		+			++	+	
[18] Dyke et al (2010)		o	o	o	o	++	+	+++	+	+		+			+		+	++	++	+
[13] Fernandez et al. (2011)		o		o		+++	+	++	+		++	+		++		++	++	+	++	+
[19] Kempton (2005a)	o				o	++	++	+				+	+		+++	++		++	++	
[12] Kempton (2005b)	o				o	+	++	+	+			+	+	+	++			+		+
[5] Koyanagi (1998)	o	o		o	o	++		++	+++								+		++	
[20] Kristoffersen et al. (2010)	o	o		o	o		+	++				+			+++		+	+	++	+
[21] Mets et al. (2010)	o			o	o	++	+	+++	++	+		++	+						++	
[22] Moses et al. (2010)	o	o		o		++	++	+		+++	++	+					+		++	
[23] Pecas Lopes et al. (2010)	o			o	o	++	++	+	+	++	+	+++	+						++	
[24] Pillai and Bak-Jensen (2010)		o		o		+++	+	++		++	+	+					++		+	+
[25] Qian and Zhou (2011)	o			o		++	+	+++			+	+			+		+	++	++	
[26] Rahman and Shrestha (1993)	o	o		o		+++		+++	++			+					+		++	
[27] Rautiainen (2010)	o			o		+	+++	+		+	+	++	++		++					
[28] Rua et al. (2010)	o			o	o		+++				+++	++	+++		+					
[29] Saber et al. (2011)	o			o	o	+	++	+++	++						+	+++			++	+++
[30] Sekyung et al. (2010)	o				o			++				++	+		++				++	
[31] Sortomme et al. (2010)	o			o		+++		++	++	+	+	+		+			+		++	+

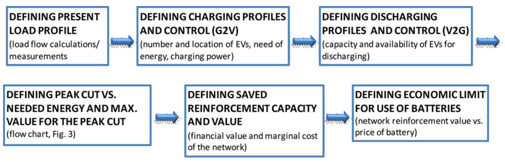


Fig. 1. Main steps in the methodology.

the power distribution system. This is the case especially in the area of vehicle-to-grid operation. From the viewpoint of network asset management, the economic consequences of electrification of transport and the implementation of energy storages remain unclear. In Table I, a literature review considering EVs and distribution networks is presented. It has to be borne in mind that the publications presented in the table do not fully cover the research area of EVs. Nevertheless, the literature samples show that although several scientific papers have been published on EVs over the past few years, the economic effects of EVs (the column *Distribution business*) on the electricity distribution have mostly been neglected.

II. Problem Description

The focus in the paper is on the methodology development for the feasibility studies on the distribution network capacity. The key is to find out whether there is overall economic justification for energy storages in distribution systems. In other words, are the benefits from the released distribution capacity higher than the costs of the use of energy storages (batteries)? The main steps of the developed methodology are presented in Fig. 1.

One important requirement for the usage of energy storages (batteries) owned by customers is that their costs are compensated to the customer. This can be done for instance by a decreased electricity distribution fee or through some service agreement (for instance, direct payments, subsidized leases, a lifetime battery warranty of the vehicle battery pack [32]). In the service agreement, the terms under which the energy storage (EV) is available for the network operator are agreed upon. To this end, this study provides knowledge for the distribution network operators on the requirements that should be taken into account in the service agreement.

Another requirement for the flexible and controllable use of energy storages is a communication connection between the EVs and the network operator. All market actors have an increasing need for timely and accurate metering data, in order to realize the new potentials of innovative energy products [33]. It is highly probable that EVs will be equipped with (real-time) communication to enable intelligent charging and discharging [34], [35].

By intelligent charging and discharging functions, the original load curve can be smoothed. This releases network capacity, and the network efficiency will be higher. Although the released network capacity does not bring any direct financial benefit for the network operator, with intelligent charging functions, the peak increase and overlapping caused by EVs can be avoided. Network reinforcement investments can be postponed, which has a positive impact on the electricity distribution company. Additional possible benefit of energy storages may come from a decrease in network losses. Moreover, challenges related to short interruptions and voltage quality experienced by the customer can be avoided by energy storage systems. However, in this paper, these perspectives are not taken into account.

A. Required Information and Subtasks

Optimized use of distribution capacity can be described by the cost function

$$\min \int_0^t (C_{\text{Inv-Net}}(t) + C_{\text{Opex-Net}}(t) + C_{\text{Inv-Storage}}(t) + C_{\text{Opex-Storage}}(t))\, dt \quad (1)$$

where:

$C_{\text{Inv-Net}}(t)$	investment costs of the network;
$C_{\text{Opex-Net}}(t)$	operational costs of the network;
$C_{\text{Inv-Storage}}(t)$	investment costs of the energy storage;
$C_{\text{Opex-Storage}}(t)$	operational costs of the energy storage.

$C_{\text{Opex-Storage}}$ can be defined as a function of investment costs and capacity (kWh) of the storage and allowed charging cycles in the storage lifetime.

To be able to define the feasibility of EVs as energy storages and the optimized use of distribution capacity, background information is required and several subtasks have to be solved. Load curves play a significant role in the analyses. Together with the battery characteristics, this information can be used to analyze possible peak cuts and the size of the energy storages required. As a result, the type of the batteries to be applied to the V2G process can be defined; that is, whether the battery is of power-optimized or energy-optimized type. For the determination of the EV charging profile, information on the penetration of EVs and estimation of their load curves are needed. A paucity of information required to define reliable charging profiles (load curves) is one of the main challenges. This is due to the relatively small number of EVs presently in use and the charging measurements available. However, from a methodological point of view, the lack of actual EV measurement data does not prevent from developing a generic model by which the grid effects can be analyzed. Later on, when the penetration level is higher and EVs are used as primary cars, the input data used previously can be replaced with actual charging data in the model.

III. Methodology for Analyzing Load Curves for Energy Storages

There are incentives to consider energy storages as a means to shave the peak and to smooth the load curves. The hourly load varies greatly in the networks. This is illustrated in Fig. 2, where the annual load measurement of a medium-voltage feeder is presented. The question is: how much the peak power could be decreased by utilizing a feasible amount of energy storages on the network, and secondly, how would it affect the future reinforcement needs in the network and distribution fee paid by the end-customer?

In order to define the feasibility of energy storages, an analysis model has to be developed. The method to define the effects of energy storages on the distribution networks is based on optimization of the charging and discharging moments, taking into account the physical limits of storages and electricity consumption in the area (the shape of the base load curve). The developed model is demonstrated in Fig. 3, where the simplified flow chart of the process is presented. In this study, MatLab software was used. The process starts with manual filtering of the input data (load measurements). The target of the filtering is to detect possible measurement errors in the data. The algorithm consists of two loops; one inside another to define the optimal usage of the energy storage. In the *inner loop* (indicated by a box in Fig. 3), the load data are stepped through index by index by comparing each load value with the cut level. The cut level defines the level

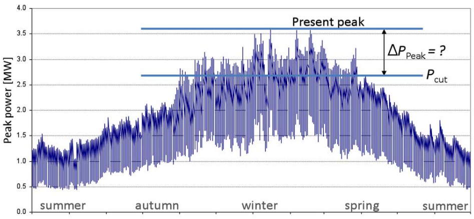


Fig. 2. Annual load curve of the medium-voltage feeder and potential to decrease peak power by energy storages.

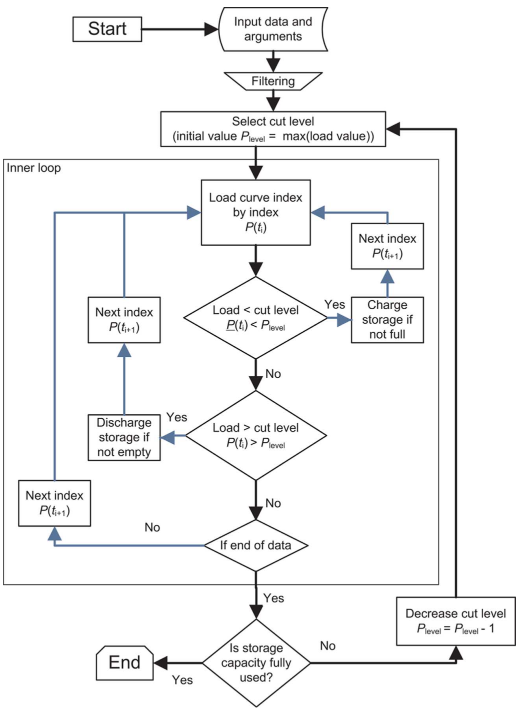


Fig. 3. Flow chart of the peak cutting process.

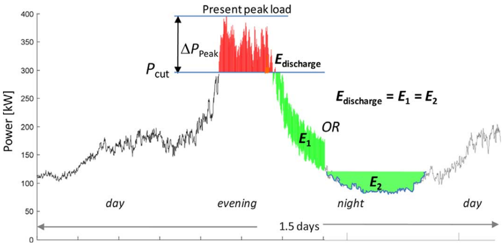


Fig. 4. Load curve with peak cut and energy storing (200 kWh). In the second charging alternative (E_2) charging is delayed to low-load moments.

to which the supply power from the network is adjusted. If the cut level is lower than the base load, the storage is discharged to the grid. The amount of discharged energy depends on the difference of the cut level and the base load and the state of charge in the storage. If the base load is lower than the cut level and the storage is not fully charged, energy is taken from the grid to the storage. If the storage is not fully used, the *outer loop* repeats the inner loop by lowering the cut level until the storage capacity is fully used. The process is similar but reverse to the discharging process. The charging and discharging processes can be limited by setting maximum values for the power. Power limitations come for instance from the distribution or transformer capacity and power electronics arrangements.

The inner loop is repeated until the storage capacity is fully utilized or the utilization is limited by other restrictions such as charging power. The shape of the base load curve has a strong effect on the type of the algorithm ending signal. For instance, if the peak operating time is short (high and short-run peaks), the cut loop can be stopped by the maximum discharge power level of the storage. If the peak is square shaped (high- and long-lasting peaks), the stop signal can be caused by the storage maximum capacity level.

There are several alternatives to adjust charging. One option is to start charging of the storage immediately after the load peak has been cut and the base load is getting lower. In the other option, storage charging is delayed and adjusted to the lowest load periods, for instance to night hours. In the first option, the target is to guarantee that the storage is as full and available as soon as possible when the next need for peak cutting occurs. In the second option, the target is to shorten the times when the demand for power from the grid is relatively high. This way, network losses can be minimized. However, in the second option there is a higher risk because of unpredictable changes in the load levels. For instance, the low-load period can be shorter than estimated, and the storage is not ready when the next load peak occurs. Fig. 4 provides an example of the peak cutting and two main alternatives for charging.

In the optimization process, several technical restrictions or limitations have to be taken into account. For instance, the size of the energy storage (battery) and the maximum allowed charging and discharging powers set limits for the use of the storage. In (2)–(4), conditions for the charging and discharging processes are presented. Equation (3) is based on the assumption that charging is started immediately after peak cutting (E_1 in Fig. 4). Losses are taken into account in the process in (4). The issue is discussed in more detail in Section V.

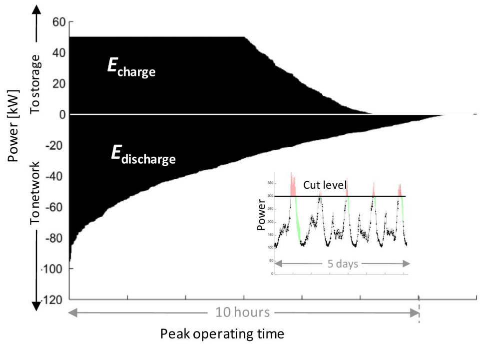


Fig. 5. Example: peak operating time of the storage (charging and discharging). Operating times are gathered from the period of 5 days.

$$E_{\text{discharge}} = \begin{cases} \int_{t1}^{t2} (P(t) - P_{\text{cut}})\, dt, & \text{if } P(t) > P_{\text{cut}} \\ 0, & \text{if } P(t) \leq 0 \end{cases} \tag{2}$$

$$E_{\text{charge}} = \begin{cases} \int_{t1}^{t2} (P_{\text{cut}} - P(t))\, dt, & \text{if } \begin{cases} P(t) < P_{\text{cut}} \\ P_{\text{cut}} - P(t) \leq P_{\text{charge}} \end{cases} \\ \int_{t1}^{t2} P_{\text{charge}}\, dt, & \text{if } P_{\text{cut}} - P(t) \geq P_{\text{charge}} \\ 0, & \text{in all other cases} \end{cases} \tag{3}$$

$$E_{\text{discharge}} = \eta \cdot E_{\text{charge}}. \tag{4}$$

The operation of the storage depends on the targets set for peak cutting and restrictions for the charging hours. In Fig. 5, an example of the peak operating times of an energy storage are presented. The peak operating time depends on the load curve and the technical limitations of the storage system. In the figure, the maximum charging power (to the storage) is limited to 50 kW and discharging power (to the network) to 100 kW. These limitations are only illustrative and they may come from the capacity of the supply in the storage system. Higher peak powers require high capacity and expensive power electronics arrangements.

When the optimization of the network capacity is the main target, the benefit of the energy storages depends strongly on the shape of the base load in the network. If the peak operating time is short, as it is often in the low-voltage networks, the benefit of the storage can be significant. From the grid point of view, the use of energy storages smooths the load curve and releases network capacity.

The size of the storage is a question that has to be solved by analyzing the network effects by varying the storage sizes. In Fig. 6, the energy taken from the storage is varied, and the effect on the peak cut is presented. It can be seen that for instance in the load curve of Fig. 4, the storage with a capacity of 25 kWh would decrease the peak by 50 kW. If the size of the storage is

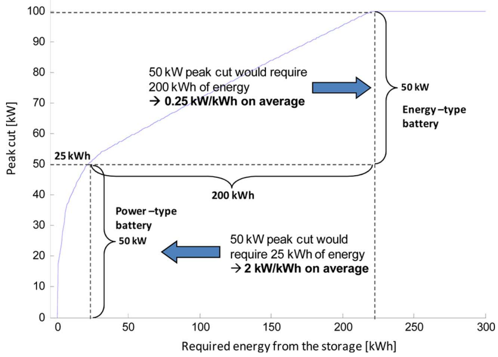


Fig. 6. Example of effect of the energy needed for the peak cut. The example is related to the load curve of Fig. 4.

TABLE II
COMPARISON OF STATIC ENERGY STORAGES AND ELECTRIC VEHICLES

	Local energy storage	Electric vehicle
Type: storage or load	well known, fully controllable	may change, partly controllable
Size of storage available	well known	unknown, depends on the number and use of EVs
Location of storage	stationary in time and in geographical perspective	place and time of the storageunknown

increased, the next 50 kW peak cut will require about 200 kWh of storage.

It can be also seen from the figure that if the case were based on a centralized battery storage, the demand for discharging power would be quite high compared with the size of the storage (50 kW vs. 25 kWh). On the other hand, if it is a question about distributed storages, that is, several EVs with V2G properties, the discharging power per battery unit would be significantly lower.

This shows that in the case environment, the benefit of the storage is high already with a small size of the energy storage. The economic feasibility of the energy storage is studied later in this paper.

IV. Methodology for EVs as Energy Storages

In the previous section, the principles of energy storages and peak cutting were described. In addition to stationary and local energy storages, there are incentives to consider EVs as mobile energy storages to shave the peak and to smooth the load curves. EVs as energy storages (V2G) have been discussed for instance in [19] and [29], [30] and [36]. The most significant differences of EVs compared with stationary energy storages are related to the location, capacity, and discharging and charging powers of the energy storage (Table II). An EV is a mobile load, and the energy source and location of the EV may change in an unpredictable way. EVs are dynamic loads and dynamic storages at the same time; the type of connection (G2V or V2G), timing, and geographical location are variable, unknown factors. This is a challenge for the network analyzers.

Despite the present promising and upward trend of EVs, the schedule of their penetration is still unknown. This has an effect on the scheduling of the network renovation projects. The electrotechnical properties of vehicles are developing at a rapid pace, even though EVs are not yet widely adopted in practice. This makes it more difficult to estimate the feasible driving distances, charging rates, and charging speeds. Also the present distribution infrastructure sets limitations on large-scale adoption of EVs.

In order to be able to define the network effects, information has to be gathered from numerous sources. The overall situation of transportation can be found for instance from nationwide passenger transport statistics. They show how, when, and how often traditional cars are used nowadays, what are the travel distances driven, and in which way the environmental factors such as house and workplace locations influence the car use. Although the statistics describe the use of existing non-electric transportation, the information can be used to some degree in EV studies also. The accuracy of the analyses can be improved by gathering street- or block-specific information on the number of registered cars. This kind of information is usually provided by local authorities.

Besides the driving habits and energy consumption of EVs, charging opportunities in different locations (including slow charging, fast charging, and battery replacement services) also have an effect on the amount of power taken from the electric grid (with respect to time) by a fleet of EVs. However, fast charging and battery replacement are not considered in this work.

The energy consumption (kWh/km) of an individual EV depends on many factors. These include the efficiency of the charging-discharging cycle (including the efficiencies of the charger and the battery), the efficiency of the regenerative braking system, the energy needed for heating and air-conditioning, the drag coefficient, the rolling resistance, the mass of the vehicle, and the driving cycle.

In our studies, the total load curves (the base load added with the charging load) are generated by applying the analysis tool developed by the research group. In the tool, the analyzer can adjust the charging curves by weighting the number of EVs for certain hours so that they reflect the situation in the case area. The charging curves are obtained based on the feeder-specific base load as presented in

$$P(t) = P_{\mathrm{base}}(t) + n_{\mathrm{EV}}(t) \cdot P_{\mathrm{supply}}. \qquad (5)$$

P_{base} is the base load of the feeder without EVs, P_{supply} is the maximum charging power of the EVs, and n_{EV} is the number of EVs. The base load is defined by traditional power calculations, which are specified by actual power flow measurements. In this case, the base load is from winter season, when the consumption is at highest (electric heating of houses, saunas, etc.) in the case network.

The methodology developed for the charging and discharging processes is presented next. In Fig. 7, a charging curve for EVs on an example day is presented. The figure shows a case where charging is adjusted to low-load moments on the feeder. It is a more or less theoretical perspective, but it provides an estimate of the possible distribution of cars (between hours). The need for energy for driving is E_{cars} and the increase in the load level is ΔP_{cars}, which depends on the base load as illustrated in the

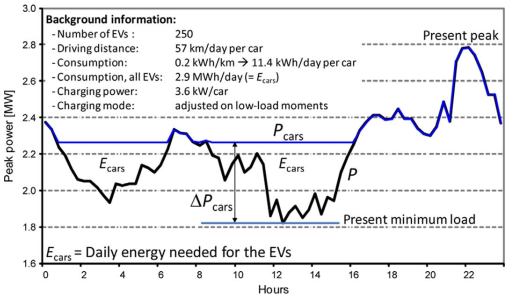


Fig. 7. Optimized charging on a feeder for a day. The lower curve represents the existing peak load of the day, while the upper curve represents the load when the charging power is taken into account.

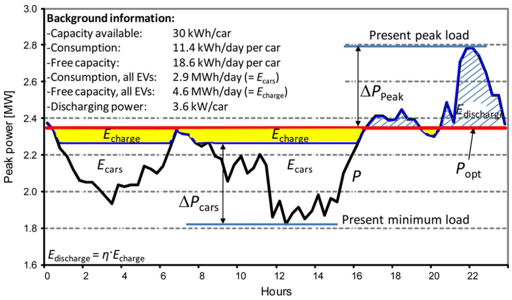


Fig. 8. Additional energy (E_{charge}) needed to decrease the peak load.

figure. The case is calculated for a medium-voltage feeder with 250 EVs.

From the distribution company's point of view, an interesting question is whether it is possible to decrease the present peak load of the network by using EVs as energy storages on the network. This could be done by utilizing the free capacity available in the EV batteries and the discharging energy that is not needed for driving to be supplied to the network on peak hours.

The balance can be found by taking into account the base load curve of the feeder, the energy needed for driving, and the capacity of batteries to store and discharge the additional energy. A theoretical example is presented in Fig. 8.

The following definitions are included in the analysis:

$E = \int P(t)dt$	Energy distributed in a medium-voltage network, EVs not included	(6)
$E_{cars} = \int \Delta P_{cars} dt$	Energy required by EVs	(7)
$E_{discharge} = \int \Delta P_{Peak} dt$	Energy needed for a peak decrease	(8)
$E_{charge} = \dfrac{E_{discharge}}{\eta}$	Additional energy charged to batteries	(9)
$E_{cap} = \sum (E_{battery})$	Total capacity of batteries in EVs	(10)
P_{opt}	Load curve (load level) when charging of EVs and the peak decrease have been taken into account	
ΔP_{cars}	Charging power, time dependent, optimized to base load	

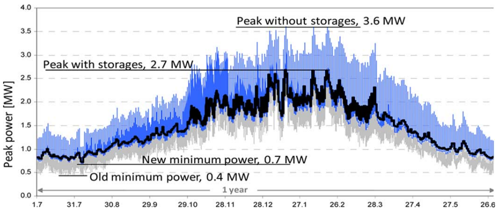


Fig. 9. One-year load curve with EVs but without energy storages (the topmost curve) and in the situation where EVs and energy storages are included (in the middle). The bottom curve combined with the topmost curve illustrates the powers without EVs and storages.

In Fig. 8, a theoretical case of charging and discharging for a day was presented. To get a wider perspective of the benefits of the energy storages, a longer period of base load data has to be analyzed. From the viewpoint of the network capacity, the focus is on peak load periods. In the Nordic countries, the peak loads of the feeders occur in the winter period. The question is now: are there such continuous peak hours and days in which the energy available from EVs will not be enough to cut the peak to the desired level? In Fig. 9, the results of energy storage analyses for the whole year on the case feeder are presented. The highest curve represents the situation with EVs but without energy storages. In this case, charging of EVs is adjusted to low-load moments by which a peak increase can be avoided. Thus, the maximum peak remains the same as without EVs. The curve in the middle depicts the load curve of the feeder when EVs and energy storages have been taken into account. The limit for the maximum theoretical cut in the peak power for the case feeder comes from the available amount of supply power of the EVs. In other words, even if there were higher peaks and energy available in the car batteries to be discharged to the network, the power supply restrictions from the vehicles would limit the maximum discharging power. The lowest curve combined with the topmost curve illustrates the powers without EVs and storages.

When applying the day-specific analysis presented in Fig. 8 to the annual base load data (Fig. 2), the annual decrease in peak levels can be determined. For the case feeder, the original peak power (3.6 MW) decreases by 900 kW to 2.7 MW after implementing V2G properties to the vehicles. This means that the end condition (Fig. 3.) for peak cutting comes from the maximum discharging power, which is in this case 3.6 kW per EV, and 900 kW in total for 250 EVs (ΔP_{Peak} in Fig. 8.). It has to be borne in mind that the peak cut value is more or less a theoretical one because not all the EVs are available at the same time for V2G operation in practice. However, from the methodological perspective, it is nevertheless advisable to define the maximum theoretical situation for this assumption. Moreover, possible practical restrictions can be taken into account with a better understanding of the technical properties and behavior of EVs.

On the case feeder, at the moment without any EVs, the load exceeds the new peak (2.7 MW) for 300 h. In other words, to be able to limit this peak, energy storages have to be used and the power has to be decreased at least for 300 h per year. The total

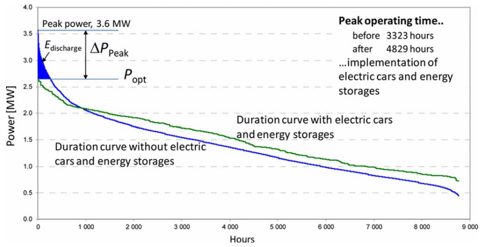


Fig. 10. One-year duration curves of the medium voltage feeder based on load curves presented in Fig. 9.

amount of energy needed to be discharged during the load peaks ($E_{\mathrm{discharge}}$) is 65 MWh/a (per annum). This is about 0.5% of the total distributed energy on the feeder. The calculation does not include charging and discharging losses, which are estimated to be approx. 10%–20% of the total energy.

In Fig. 10, one-year duration curves based on load curves of Fig. 9 are illustrated. It can be seen that the duration curve with the optimal use of EVs and energy storages is lower than the present situation (the curve without EVs and energy storages).

The results show that the peak loads could be significantly decreased on the case feeder depending on the number and type of EVs, charging and discharging arrangements, their driving distances, and the shape of the base load curve. In this case, the base load of the network was so spiky (i.e., short peak-operating times) that the limitation for the peak cutting came from the inadequate discharging capacity (kW), not from the actual size of the energy storage (kWh).

V. Economic Effects of Storages

Depending on the EV penetration scenarios and EV charging methods, the peak load may increase considerably on the distribution network. This calls for additional investments in larger cross sections of underground cables and overhead lines, and more transformer capacity. On the other hand, utilization of energy storages may cut the peak loads and release network capacity for future loads.

The feasibility of the idea to utilize energy storages in electricity distribution has to be assessed from an economic perspective before wide-scale implementation. The economic feasibility can be estimated by comparing the reduced reinforcement needs and the value of batteries used in the charging and discharging processes.

A. Average Marginal Cost and Reinforcement Needs

The amount of required or delayed investments can be estimated by defining the transmission- or distribution-capacity-related average marginal cost of the network (€/kW). This reflects the fact that the utility must have capacity available to serve the customer, and encourages to reduce the electricity use during peak periods (especially load shifting) [37], [38]. The average marginal cost is based on the network replacement value and the maximum load of the year, and it describes how much the network capacity costs for the distribution company per each peak load kilowatt. For instance, if the network replacement value is 1 M€ and the distribution capacity of the network is 1 MW, the average marginal cost is 1 €/W or 1000 €/kW. To be able to allocate costs more accurately in the distribution system, the analysis is performed for each part of the network (400 V low-voltage networks, 20 kV medium-voltage networks, and 110/20 kV primary substations). At the medium-voltage and primary substation level, a statistical approach of an additional load can be taken because the load is well balanced. In the low-voltage network, it is more likely that different loads overlap each other. A typical peak operating time in the low-voltage networks is 2000 h per year, in the medium-voltage networks 3500–4500 h per year, and at the primary substation level 4500–5000 h per year. In the low-voltage networks, it is difficult to adjust an additional load to those time periods when the load level is low. On the other hand, there are numerous reasons for the present individual peak loads, such as saunas, electric space heating, air conditioning, and car electric pre-heating systems, which can be adjusted thereby avoiding the overlapping of peak loads.

When information of the marginal cost is combined with the capacity increase, an estimate of reinforcement needs can be determined

$$\mathrm{Reinforcement} = \mathrm{Average\ marginal\ cost} \cdot \Delta P. \tag{11}$$

B. Effect of the Peak on the Distribution Fee

From the electricity end-user perspective, it is interesting to investigate how much an increase in the peak and capacity affect the distribution fee (cent/kWh). The additional network investments will eventually be paid by the end-customers. This can be determined when the annuity of reinforcement costs (€ per year) is compared with the annual delivered energy in the network.

$$\mathrm{Network\ value\ per\ delivered\ energy} = \frac{\mathrm{Reinforcement}}{\mathrm{Annual\ energy}}. \tag{12}$$

The methodology is demonstrated in Fig. 11, where the situation before and after utilization of EVs is presented. The replacement value of the case network is 50 M€ and the annual delivered energy in the distribution company is 200 GWh. By (12), the network value per delivered energy is 1.46 cent/kWh. The network value with EVs is based on a scenario where all the traditional cars are replaced with electric ones. Depending on the charging method and the level of intelligence in the charging, a rough estimation of the investments required in a new transformer and the distribution capacity in the whole network would be 0–20 M€. When comparing the reinforcement needs and the delivered energy, the network cost (distribution fee) would be between 1.18 and 1.66 cent/kWh.

Even though these case-specific values are not important from the methodological perspective, the fee range shows that when the peak power of the network increases more than the delivered energy, the distribution fee will increase. If the additional charging load has only a slight effect on the peak power, it is possible to cut the distribution fees.

	Without EVs	With EVs
Network value:	50 M€ = 2.9 M€ per year*	50–70 M€ = 2.9–4.0 M€ per year*
Delivered energy:	200 GWh per year	246 GWh per year**
→ network cost per delivered energy:	1.46 cent/kWh	1.18–1.66 cent/kWh

* annual cost calculated by interest rate p = 5 % and life-time t = 40 years

** charging energy 46 GWh comes from 11 000 cars, 20 900 km/car per year and 0.2 kWh/km per car

The network value compared with the peak load is 320 €/kW in the low-voltage networks, 300 €/kW in the medium-voltage networks, and 100 €/kW at the primary substation level (110/20 kV)

Fig. 11. Effects of EVs on the network value and distribution fee.

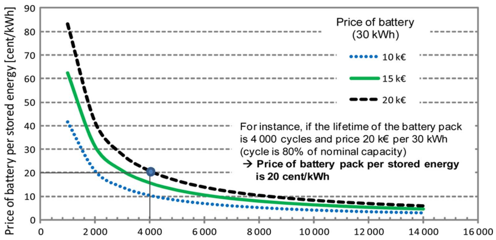


Fig. 12. Price of batteries (30 kWh) compared with their lifetime (number of charging and recharging cycles).

C. Economy of Energy Storages

At the moment, the price of batteries compared with their lifetime (number of charging and recharging cycles) is quite high. A simplified economic analysis shows that the battery technology has still to be developed further. If the price of a battery is 300–700 €/kWh and the lifetime is 2000–4000 cycles, the investment price per discharged energy is 10–40 cent/kWh (Fig. 12). When the number of cycles is increased by the battery technology improvement, the investment price per stored energy will be lower. The battery lifetime also depends strongly on the depth of discharging. In this study, the battery lifetime is based on an assumption that the cycle is 80% of the nominal capacity of the battery.

Because of the present high price of batteries, there are incentives to use batteries rather as power sources than as energy storages. Targets where the peak operating time is short provide the most feasible circumstances for battery storage. This is often the situation in low-voltage networks.

To sum up, energy storages are the more profitable, the less charging-discharging cycles there are and the higher is the load peak to be cut with the stored energy. The limit value for the economic feasibility can be determined by

$$\text{Savings} = \text{costs of the use of storages} \tag{13}$$

$$\Delta P_{\text{Peak}} \cdot C_{\text{inv}} = C_{\text{e-storage}} \cdot \Delta P_{\text{Peak}} \cdot t_{\text{peak}} \tag{14}$$

$$\rightarrow t_{\text{peak}} = \frac{C_{\text{inv}}}{C_{\text{e-storage}}} \tag{15}$$

where:

Savings the saved network reinforcement costs;

C_{inv} the average marginal cost on the feeder per year;

$C_{\text{e-storage}}$ the battery price per discharged energy;

t_{peak} the peak operating time of charging power.

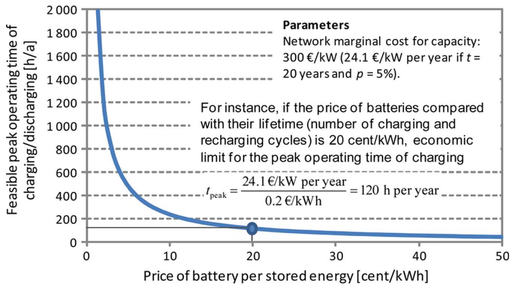


Fig. 13. The maximum economically feasible peak operating time of charging/discharging when price of batteries compared with their lifetime (number of cycles) varies between 0 and 50 cent/kWh.

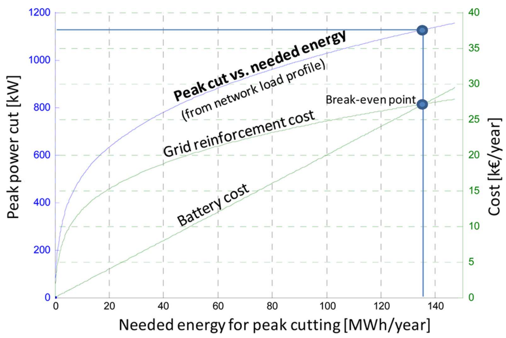


Fig. 14. Economic limit for peak cut in the case feeder. Grid reinforcement is 24.1 €/a multiplied by peak cut and battery cost is 0.2 €/kWh multiplied by stored energy. The example is related to the feeder of Fig. 9.

The maximum economically feasible peak operating time of charging/discharging depends on the battery price per discharged energy as presented in (15). In Fig. 13, the price per discharged energy is varied between 0 and 50 cent/kWh. The average marginal cost on the feeder is 300 €/kW (24.1 €/kW per year if $t = 20$ years and $p = 5\%$).

In Fig. 14, the total amount of stored energy used in the storages vs. the achieved peak cut and the economic limit for the peak cut are presented. In the break-even point, the costs of the batteries are equal to the savings from the avoided/delayed network reinforcement costs (14). The reinforcement costs depend on the amount of peak cut and the marginal price of the network, whereas the battery costs are based on the battery unit cost (price of battery per stored energy) and the amount of stored energy.

It can be seen in Fig. 14 that the cost from batteries are equal to the savings from network reinforcement costs when the stored energy is 135 MWh and the peak cut is 1130 kW. If the target is to cut the peak more than that, the energy that has to be charged/discharged to the batteries will reduce the lifetime and economic value of the batteries more than the value of savings obtainable from the released network capacity.

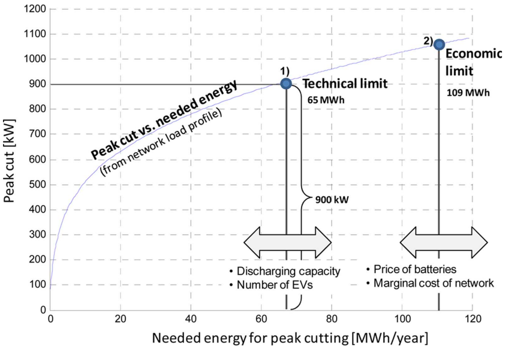


Fig. 15. Technical and economic limit for peak cut in the case feeder. Maximum technical limit (point 1) comes from the discharging power restrictions and the economic limit (point 2) comes from (16). The example is related to the annual load curve of the feeder of Fig. 9.

In the case of Fig. 9, the peak decrease is 900 kW. Here, the technical limitation for the use of batteries comes from the maximum discharging power, which is 3.6 kW per EV, and 900 kW in total for 250 EVs. With (11), the saved life-time reinforcement costs are 270 000 €. The annual value is 21 700 € per year (if $t = 20$ years and $p = 5\%$). The economic limit for charged and discharged energy for 900 kW cutting is

$$\begin{aligned} E_{\mathrm{peak,limit}} &= \frac{\mathrm{Savings}}{C_{\mathrm{e-storage}}} \\ &= \frac{21\,700\,€\mathrm{per\ year}}{0.2\,€/\mathrm{kWh}} = 109\,\mathrm{MWh\ per\ year.} \end{aligned} \quad (16)$$

For the case feeder, the total amount of energy needed to be discharged during the load peaks ($E_{\mathrm{discharge}}$) is 65 MWh per year when the peak cut is 900 kW. This is below the economic limit calculated in (16). This means that from an economic point of view, batteries could be used for the peak cutting more than they are now used. In other words, savings coming from an avoided/delayed network reinforcement are higher than the reduction in the lifetime and financial value of the batteries. As presented in Fig. 15, the technical and economic limits depend on A) the present load curve of the network (shape of the peaks), B) the discharging capacity and C) the price of batteries and the financial value of the network (marginal cost).

If the maximum discharging power were for instance 5 kW per EV (1250 kW for 250 EVs) and the target for peak cutting were the same 1250 kW, the savings from the network reinforcement would be 375 000 € (300 €/kW × 1250 kW) which is 30.1 k€ per year and it would be less than the reduction in the financial value of the batteries. The peak cut of 1250 kW would require charging and discharging energy of 194 MWh per year, which would reduce the value of the batteries by 38.8 k€ per year (194 MWh × 0.2 €/kWh).

In Fig. 16, savings are presented from the viewpoint of stored energy. It can be seen that the maximum savings can be reached with a relatively low amount of stored energy.

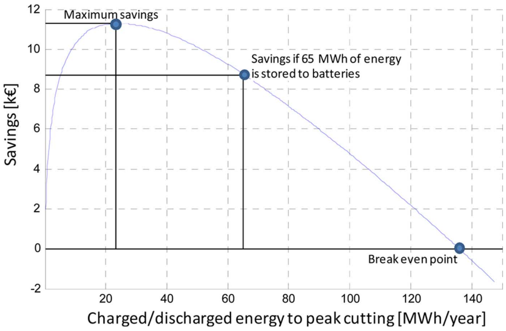


Fig. 16. Savings vs. needed battery capacity (charging/discharging).

The results show that the need for a peak cut arises rather from the power than energy point of view (for instance Figs. 6, 15, and 16). The economic feasibility is at best when the maximum peak cut can be achieved with the minimum energy stored to the battery. It has to be borne in mind that these results are only demonstrative. The results are case-specific and they depend on electricity consumption in the area (load curve), the value and capacity of the network (marginal cost), and the properties of the storage system.

The effects of storage losses can be taken into account by considering the situation from the distribution company's perspective. In (17) it is presented which way losses effects to the price of operation of batteries.

$$C_{\mathrm{Opex}} = \frac{C_{\mathrm{e-storage}} \cdot E_{\mathrm{charge}}}{\eta} + (1-\eta) \cdot E_{\mathrm{charge}} \cdot c_{\mathrm{w-electricity}} \quad (17)$$

where:

E_{charge} the amount of electricity stored to battery;

$c_{\mathrm{w-electricity}}$ the price of electricity.

In the present situation, the price of losses does not play a significant role in battery storage studies. This is because of the relatively high price of batteries compared with the price of electricity. For instance, if the energy stored to the battery is 1 MWh, the price of battery per stored energy is 0.2 €/kWh (Fig. 12), the price of electricity is 10 cent/kWh and the efficiency 90%, we get 23.2 € per each stored MWh, of which the loss costs are 4.3%. However, when the price of batteries decreases substantially, the significance of losses in the process will increase. This has to be taken into account in the service agreement between the customer and the network operator.

When the battery price is compared with the typical electricity market spot price, 3–7 cent/kWh in the Nordic markets, the feasibility of the idea is highly questionable at least for the time being. However, the situation will change as the battery technology will be improved (for instance the lifetime) and the price of batteries will decrease.

The methodology presented here can be used also in low-voltage networks. In low-voltage networks, the peak operating times are typically shorter, which creates stronger incentives to apply energy storages. However, random variation in the available energy storages (EVs) is larger in the low-voltage than in the medium-voltage networks.

VI. Conclusions and Discussion

Energy storages will be part of the future smart grids. So far, the prices of storage systems (e.g., battery systems) have been so high that there has been no economic justification for energy storages in distribution networks. However, the prices are decreasing and the technological properties of batteries are improving. The role of energy storages will be significant in the peak shaving and in smoothing of the load curves. The first results show that the need for a peak cut arises rather from the power than energy point of view. The economic feasibility is at best when the maximum peak cut can be achieved with the minimum energy stored to the battery.

Although the calculations and parameters involve many assumptions and uncertainty, the study shows how important it is to understand the correlation between the distribution network value, network capacity, and energy storage systems. If the issue can be reasonably taken into account in the system planning, it will be possible to cut the distribution fees charged to the electricity end-users during the large-scale adoption of EVs. Correspondingly, if the system planning requirements are neglected, huge reinforcement investments will have to be made in the distribution infrastructure. This will significantly increase the distribution fees.

Although this study has been made in the Nordic environment, the methodology presented in this paper can be adopted in any other circumstances. Only the calculation parameters have to be reconsidered according to the environment in question.

The main outcomes of this paper are:

1. Description of the overall energy storing methodology in distribution networks; what background information is required and how it is used to determine the need for electric vehicle charging and discharging energy and to analyze the associated economic effects.
2. The results verify the feasibility of the peak cutting function in a distribution system. There are economic incentives to use EVs as energy storages. Peak loads could be decreased significantly depending on the number and type of EVs, charging and discharging arrangements, their daily driving distances, and the shape of the base load curve. However, information used in the analyses has to be further specified.
3. The base load of the network can be so spiky (i.e., short peak-operating times) that the limitation for the peak cutting may come rather from the inadequate discharging capacity (kW) than the actual size of the energy storage (kWh).
4. The shape of the base load curve and the peak operating time affects strongly to the feasibility of energy storages. The feasibility of storages is the better the more seldom storing is needed; in other words, storages are more profitable the less charging-discharging cycles there are and the higher is the load peak to be cut with the stored energy.
5. It is possible to cut the distribution fees charged to the electricity end-users during the large-scale adoption of EVs, if the charging system is well planned and enough intelligence is included in it.
6. The major challenges will be faced in those low-voltage networks where load overlapping is more probable. However, there is a lot of experience of the transfer of loads (air condition, sauna ovens, electric space heating, water heaters, block heaters).
7. In the present situation, the price of losses does not play a significant role in energy storage studies. This is because of the relatively high price of batteries compared with the price of electricity. However, when the price of batteries decreases substantially, the significance of losses in the process will increase. This has to be taken into account in the service agreement between the customer and the network operator.

The study has been written assuming that the customer owns the energy storage (battery). However, if the network operator owns the storage instead, several uncertainty factors related to the operation of storages will disappear. Nevertheless, EVs have to be equipped with intelligence even if they did not have a V2G property built in them.

The use of EVs as distributed energy resources makes it possible to decrease the above-presented estimated additional charging peak loads. However, this kind of an arrangement is very complicated and will require significant technological development in EV control systems.

References

[1] M. Ehsani, Y. Gao, and A. Emadi, *Modern Electric, Hybrid Electric and Fuel Cell Vehicles*, 2nd ed. Boca Raton, FL: Taylor & Francis, 2010, p. 534.

[2] L. Guzzella and A. Sciarretta, *Vehicle Propulsion Systems*. Berlin, Germany: Springer-Verlag, 2007.

[3] J. M. Miller, *Propulsion Systems for Hybrid Vehicles*. London, U.K.: Inst. Electr. Eng., 2004, p. 455.

[4] J. Larminie and J. Lowry, *Electric Vehicle Technology Explained*. West Sussex, U.K.: Wiley, 2003, p. 296.

[5] F. Koyanagi and Y. Uriu, "A strategy of load leveling by charging and discharging time control of electric vehicles," *IEEE Trans. Power Syst.*, vol. 13, no. 3, pp. 1179–1184, Aug. 1998.

[6] L. Liu, M. Eisenreich, G. Balzer, and A. Kessler, "Evaluation of absorption capacity of distribution grids for electric vehicle integration in rural areas," in *Proc. Eur. Conf. SmartGrids E-Mobility*, Brussels, Belgium, 2010, pp. 77–84.

[7] V. Pop, P. Regtien, P. Notten, D. Danilov, and H. Bergveld, *Battery Management Systems*. Dordrecht, The Netherlands: Springer Science, 2008.

[8] Y. Ota, H. Taniguchi, T. Nakajima, K. M. Liyanage, and A. Yokoyama, "An autonomous distributed vehicle-to-grid control of grid-connected electric vehicle," in *Proc. Conf. Ind. Inf. Syst. (ICIIS)*, 2009, pp. 414–418.

[9] HCAdeMO Association, "Desirable characteristics of public quick charger," 2010. Tokyo, Japan [Online]. Available: www.emc-mec.ca/phev/Presentations_en/S12/PHEV09-S12-3_TakafumiAnegawa.pdf, accessed Apr. 29, 2010

[10] P. Ponticel, "SAE standard on EV charging connector approved," *Automotive Eng. Online*, Jan. 15, 2010 [Online]. Available: http://www.sae.org/mags/AEI/7479

[11] J. Lassila, T. Kaipia, J. Haakana, J. Partanen, P. Järventausta, A. Rautiainen, M. Marttila, and O. Auvinen, "Electric cars—Challenge or opportunity for the electricity distribution infrastructure?," in *Proc. Eur. Conf. Smart Grids Mobility*, Wurzburg, Germany, 2009.

[12] W. Kempton and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *J. Power Sources*, vol. 144, no. 1, pp. 280–294, Jun. 2005.

[13] L. Fernández, T. San Román, R. Cossent, C. M. Domingo, and P. Frías, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 206–213, Feb. 2011.

[14] J. Balcells and J. Garcia, "Impact of plug-in electric vehicles on the supply grid," in *Proc. Veh. Power Propulsion Conf. (VPPC)*, 2010, pp. 1–4.

[15] S. Blumsack, C. Samaras, and P. Hines, "Long-term electric system investments to support plug-in hybrid electric vehicles," in *Proc. IEEE Power Energy Soc. Gen. Meet.—Conversion and Delivery of Electrical Energy in the 21st Century*, Jul. 2008, pp. 1–6.

[16] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 371–380, Feb. 2010.

[17] I. Cvetkovic, T. Thackerm, D. Dong, G. Francis, V. Podosinov, D. Boroyevich, F. Wang, R. Burgos, G. Skutt, and J. Lesko, "Future home uninterruptible renewable energy system with vehicle-to-grid technology," in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Sep. 2009, pp. 2675–2681.

[18] K. J. Dyke, N. Schofield, and M. Barnes, "The impact of transport electrification on electrical networks," *IEEE Trans. Ind. Electron.*, vol. 57, no. 12, pp. 3917–3926, Dec. 2010.

[19] W. Kempton and J. Tomic, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *J. Power Sources*, vol. 144, no. 1, pp. 268–279, Jun. 2005.

[20] T. K. Kristoffersen, K. Capion, and P. Meibom, "Optimal charging of electric drive vehicles in a market environment," *Appl. Energy*, vol. 88, no. 5, pp. 1940–1948, May 2011.

[21] K. Mets, T. Verschueren, W. Haerick, C. Develder, and F. De Turck, "Optimizing smart energy control strategies for plug-in hybrid electric vehicle charging," in *Proc. IEEE/IFIP Netw. Oper. Manage. Symp. Workshops*, Apr. 2010, pp. 293–299.

[22] P. S. Moses, S. Deilami, A. S. Masoum, and M. A. S. Masoum, "Power quality of smart grids with plug-in electric vehicles considering battery charging profile," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Eur.*, Oct. 2010, pp. 1–7.

[23] J. A. P. Lopes, S. A. Polenz, C. L. Moreira, and R. Cherkaoui, "Identification of control and management strategies for LV unbalanced microgrids with plugged-in electric vehicles," *Elect. Power Syst. Res.*, vol. 80, no. 8, pp. 898–906, Aug. 2010.

[24] J. R. Pillai and B. Bak-Jensen, "Impacts of electric vehicle loads on power distribution systems," in *Proc. IEEE Veh. Power Propulsion Conf. (VPPC)*, Sep. 2010, pp. 1–6.

[25] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011.

[26] S. Rahman and G. B. Shrestha, "An investigation into the impact of electric vehicle load on the electric utility distribution system," *IEEE Trans. Power Del.*, vol. 8, no. 2, pp. 591–597, Apr. 1993.

[27] A. Rautiainen, S. Repo, and P. Järventausta, "Intelligent charging of plug-in vehicles," in *Proc. Nordic Electr. Asset Manage. Conf. (NORDAC)*, Aalborg, Denmark, 2010.

[28] D. Rua, D. Issicaba, F. J. Soares, P. M. R. Almeida, R. J. Rei, and J. A. P. Lopes, "Advanced metering infrastructure functionalities for electric mobility," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Eur. (ISGT Eur.)*, Oct. 2010, pp. 1–7.

[29] A. Y. Saber and G. K. Venayagamoorthy, "Plug-in vehicles and renewable energy sources for cost and emission reductions," *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1229–1238, Apr. 2011.

[30] H. Sekyung, H. Soohee, and K. Sezaki, "Development of an optimal vehicle-to-grid aggregator for frequency regulation," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 65–72, Jun. 2010.

[31] E. Sortomme, M. M. Hindi, S. D. J. MacPherson, and S. S. Venkata, "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 198–205, Mar. 2011.

[32] A. N. Brooks, "Vehicle-to-grid demonstration project: Grid regulation ancillary service with a battery electric vehicle," Dec. 2002, prepared for the California Air Resources Board and the California Environmental Protection Agency.

[33] S. Rusitschka, S. Merk, H. Kirchauer, and M. Sturn, "Meter data management—From the smarter grid to future market platforms in liberalized energy markets," in *Proc. 21st Int. Conf. Electr. Distrib.*, Frankfurt, Germany, Jun. 2011.

[34] S. Käbisch, A. Schmitt, M. Winter, and J. Heuer, "Interconnections and communications of electric vehicles and smart grids," in *Proc. 1st IEEE Int. Conf. Smart Grid Commun.*, Oct. 2010.

[35] D. Rua, D. Issicaba, F. J. Soares, P. M. R. Almeida, R. J. Rei, and J. A. P. Lopes, "Advanced metering infrastructure functionalities for electric mobility," in *Proc. IEEE PES Int. Conf. Innov. Smart Grid Technol. Conf. Eur. (ISGT Eur.)*, Oct. 2010.

[36] S. K. Mullen, "Plug-in hybrid electric vehicles as a source of distributed frequency regulation," Ph.D. dissertation, Univ. Minnesota , Minneapolis, MN, 2009.

[37] A. Bishop, "Tariff Development II: Rate Design," The Georgian National Energy Regulatory Commission and the Vermont Public Service Board, Jun. 2008, accessed Jun. 29, 2011 [Online]. Available: http://www.narucpartnerships.org/Documents/Session3%20Rate%20design.ppt

[38] CER and NERA, "Marginal cost of electricity service study," Rep., Jul. 2004.

Jukka Lassila was born in Ilomantsi, Finland, in February 1975. He received the M.Sc. and D.Sc. (Tech.) degrees in electrical engineering from Lappeenranta University of Technology (LUT), Lappeenranta, Finland, in 2000 and 2009, respectively.

He is a Postdoctoral Researcher at LUT and is also Director of Asset Vision Ltd., a consultant company. His main area of interest is electricity distribution systems, especially strategic planning of networks and network effects of electric vehicles.

Juha Haakana was born in Ruokolahti, Finland, in December 1984. He received the M.Sc. degree from Lappeenranta University of Technology (LUT), Lappeenranta, Finland, in 2008. He is currently working toward the Ph.D. degree at LUT.

His main area of interest is strategic developing of electricity distribution systems.

Ville Tikka was born in Savitaipale, Finland, in March 1984. He received his M.Sc. degree from LUT in 2010.

Since then he has been a Doctoral Student at LUT. His main area of interest is modeling of the grid effects of electric mobility.

Jarmo Partanen (M'88) received the D.Sc. (Tech.) degree in electrical engineering from Tampere University of Technology, Tampere, Finland, in 1991.

He has been a Professor at Lappeenranta University of Technology (LUT), Lappeenranta, Finland, since 1994. He is currently the Head of the Institute of Energy Technology at LUT. His main fields of interest are smart grids, electricity market, RES, and regulation of electricity distribution business. He has been a member of IEEE since the 1980s.

Publication IV

Lassila, J., Tikka, V., Haakana, J., and Partanen, J.
Electric cars as part of electricity distribution—who pays, who benefits?

Reprinted with permission from
IET Electrical Systems in Transportation
2.4, pp. 186–194, 2012

www.ietdl.org

Published in IET Electrical Systems in Transportation
Received on 24th February 2011
Revised on 6th February 2012
doi: 10.1049/iet-est.2011.0015

ISSN 2042-9738

Electric cars as part of electricity distribution – who pays, who benefits?

J. Lassila V. Tikka J. Haakana J. Partanen

Lappeenranta University of Technology, P.O. Box 20, 53851 Lappeenranta, Finland
E-mail: jukka.lassila@lut.fi

Abstract: The nature of transport and energy use is radically changing along with the upward trend of electric vehicles (EVs). This poses a challenge for the existing electricity distribution infrastructure. Key questions are: what efforts are required to guarantee that the network infrastructure has sufficient capability to deliver energy and power to the customers, and how does this development affect the network value and distribution fees? In this study, this challenge is approached from the economic perspective of an electricity distribution company. In this study, a generic model to analyse the network effects of EVs is presented. One significant result is that depending on the EV charging methods, the power demand (peak load) may increase dramatically or remain almost at the present level. Correspondingly, the required network reinforcements and distribution fees can be tens of percents lower than today or they can be higher, depending on how much intelligence is integrated into the charging process.

1 Introduction

The question of the effects of electric vehicles (EVs) on electric power networks is challenging in many ways. Although there are already numerous analyses (e.g. an overview of the EV technology is given in [1–4], load levelling is addressed in [5, 6], batteries are discussed in [7, 8] and charging interfaces (outlets) are studied in [9, 10]), the economic network effects of EVs [11–13] have mostly been neglected. From the electricity distribution business and electricity end-user perspectives, there is a great interest in the development of distribution fees. Does the revolution in transportation lead to a pressure to increase investments and raise distribution fees paid by the customers? Several analyses all over the world show already that an incontrollable way of vehicle charging leads to the overloading of the electricity distribution system. As a result and solution, a controllable smart charging alternative has been presented. However, these studies lack a definition of the economic drawbacks and benefits of different charging alternatives. This paper aims to fill this gap. The target is on developing process knowledge and setting up a methodological framework by which key issues related to the network economic effects of EVs can be addressed. The effects of different kinds of EV charging profiles on the distribution system and distribution fees paid by electricity end-users are defined. Even though the results are based on information of actual distribution companies, the main focus of the paper is on the methodological development work. However, the results are interesting and they show that there are economic incentives for controlled charging through the distribution fee.

The preparation of forecasts for charging energy and power is based on nationwide passenger transport statistics, local traffic flow measurements, different penetration schedules, estimation of the electricity consumption of EVs and several charging profiles. The effect of charging profiles is analysed by using data from an actual distribution company. Determination of charging effects on the networks is based on load flow calculations that apply charging profiles and information of the required charging energies. Finally, the economic effects of EVs on the distribution fees are defined and discussed. The origins and accuracy of the background data used in the economic analyses are case-specific. However, from the procedural perspective, the main structure of analyses follows the same principles. Hence, the model presented in the paper is flexible and adaptive to different electricity distribution business environments.

2 Problem description

The focus in the paper is on the methodology development for the economic feasibility studies on the distribution network capacity. The key is to find out whether there are incentives for controllable charging and what the economic effects of charging are on the distribution fees paid by the electricity end-customers. Another question is whether we have to make reinforcements to ensure the charging process at any time or whether it is possible to adjust the charging load to a moment when the overall load of the network is low, thereby avoiding overlapping of the charging load and the existing peak load.

The target is to establish a generic model by which the grid effects on the distribution business can be detected at an EV penetration level determined by the network analyser. Even though this paper presents some results by a case network, the objective is not to give any exact values for the network analysis, but to present the required information and the method in general. Thus, this paper provides tools for an analyser to determine the effects in different cases.

The main steps of the developed methodology are presented in Fig. 1. In the first phase, information for the analyses was collected from numerous different sources. In the second phase, charging profiles were defined based on the data collected earlier. The third phase dealt with the technical network effects of EVs, and in the last phase, the economic perspective on the network effects was analysed and discussed.

As described in the previous section, there is a lack of analyses on the economic drawbacks and benefits of EV charging from the electricity distribution business and end-customer perspective. This can also be seen from Table 1, where a literature review considering EVs and distribution networks is presented. It has to be borne in mind that the publications presented in the table do not fully cover the research area of EVs. Nevertheless, the literature samples show that although several scientific papers have been published on EVs over the past few years, the economic effects of EVs on the distribution business have mostly been neglected.

3 Background information

To analyse the network effects of EVs, comprehensive information is required about the penetration and usage of EVs as well as distribution network components and actual load flows. In our case, the penetration levels are varied from 25 to 100%. In this paper, the probability of different scenarios has not been analysed. The network lifetimes are usually long (40–50 years), which prepares the way for high EV penetration levels in the network. Even though the probability of the 100% penetration scenario is not realistic, the analyses show the ultimate situation for the network planner.

3.1 Transport statistics and traffic measurements

Nationwide passenger transport statistics can be used to determine how, when and how often cars are nowadays used, what are the travel distances driven, and in which way the environment influences the car use. In Finland, the latest National travel survey was carried out between 2004 and 2005; the survey was conducted for the Ministry of Transport and Communications, the Finnish National Road Administration and the Finnish Rail Administration [28]. According to the survey, in the geographical area where the case network of this paper is located, the average driving distance is 20 900 km/car per year, which makes ~57 km/car per day. This simplified average value approach is taken in this study also. The accuracy of the analyses can be improved by gathering street- or block-specific information on the number of registered cars. This kind of information is usually provided by local authorities. In this study, the accuracy is improved by traffic flow measurements carried out for a residential area. The main idea in the measurement is to count the vehicles passing the control point close to the residential area. Thus, it is possible to obtain more exact information about the moment when the customers are leaving and arriving home, in other words, the place where the vehicles are charged. When the size of the residential area is reasonable and the measurement point is close to the area, the time required for the car to pass the measurement point and arrive home is short enough to be able to estimate the exact moment when the charging of the car will start. The measurement period has to be long enough to be able to define daily deviations in the traffic flows and later in the charging curves. For instance, weekdays and weekends, similarly as summer and wintertime differ from each other. With a smaller time window, the traffic flow measurement gives a more accurate distribution in the time axis, but at the same time, each data point has a larger deviation if the sample rate is too low. Public transportation, taxis, service traffic and pass-by traffic have to be filtered out from the case area data in order to provide reliable traffic flow measurement results. Therefore it is essential to have an appropriate measurement device with a capability to identify different vehicle types and pedestrians or bikers. With the best possible device, the results may be more accurate, yet manual verification should not be neglected. Fig. 2 shows an example result of the traffic measurement.

3.2 Properties of EVs

The energy consumption (kWh/km) of an individual EV depends on many factors. These include the efficiency of the charging–discharging cycle (including the efficiencies of the charger and the battery), the efficiency of the regenerative braking system, the energy needed for heating and air-conditioning, the drag coefficient, the rolling resistance, the total mass of the vehicle and the driving cycle. A Nordic company has recently measured the energy

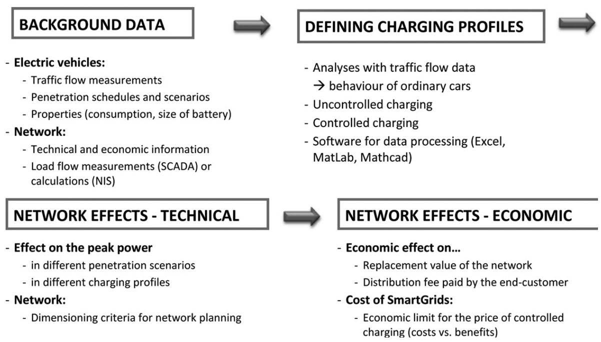


Fig. 1 *Main steps of the methodology*

doi: 10.1049/iet-est.2011.0015

Table 1 Literature review on EVs and electricity distribution

Publication	Theoretical	Simulation + case	Case (measurements)	G2 V	V2G, V2H	Network efects	EVs as part of Smart Grids	Load modelling and forecasting	Load levelling (peak cutting)	Power quality	Ev charging standards	Control of charging	Communication and data interface	Distribution business	Electricity markets	Costs, cost optimisation	Penetration perspective	EV and battery technology	Simulations and statistical analysis	Environmental effects
	Content					Energy flow			Grid perspective				Charging and control			Business			Other	
Balcells and Garcia [14]		o	o	o		+ +		+		+++	+ +	+						+	+ +	
Blumsack *et al.* [15]	o			o		+ +		+ +	+ +							+			+ +	+++
Clement-Nyns *et al.* [16]	o			o		+++	+	+ +	+	+ +			+	+	+		+		+++	
Cvetkovic *et al.* [17]		o	o	o	o	+	+ +			+ +		+++	+ +		+			+ +	+	
Dyke *et al.* [18]		o	o	o	o	+ +	+	+++	+	+		+			+		+	+ +	+ +	+
Fernández *et al.* [13]		o		o		+++	+	+ +	+		+ +	+		+ +		+ +	+ +	+	+ +	+
Koyanagi and Uriu [5]	o	o		o	o	+ +		+ +	+++								+		+ +	
Kristoffersen *et al.* [19]	o	o		o	o		+	+ +				+			+++		+	+	+ +	+
Mets *et al.* [20]	o			o	o	+ +	+	+++	+ +	+		+ +	+						+ +	
Moses *et al.* [21]	o	o		o		+ +	+ +	+		+++	+ +	+					+		+ +	
Pecas Lopes *et al.* [22]	o			o	o	+ +	+ +	+	+	+ +	+	+++	+						+ +	
Pillai and Bak-Jensen [23]		o		o		+++	+	+ +		+ +	+	+					+ +		+	+
Qian *et al.* [24]	o			o		+ +	+	+++			+	+			+		+	+ +	+ +	
Rahman and Shrestha [25]	o	o		o		+++		+++	+ +			+					+		+ +	
Saber and Venayagamoorthy *et al.* [26]	o			o	o	+	+ +	+++	+ +						+	+++			+ +	+++
Sortomme *et al.* [27]	o			o		+++		+ +	+ +	+	+	+		+			+		+ +	+

+++ = main theme in the publication, ++ = in an important role in the publication, + = mentioned in the publication

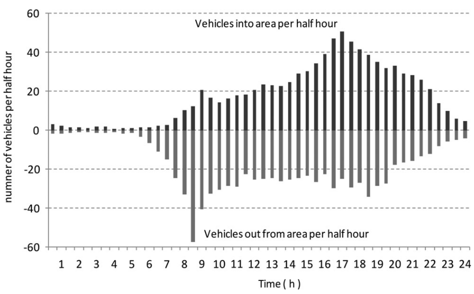


Fig. 2 *Results of the traffic flow measurement in a residential area*

consumption of an EV in wintertime in Finland, and obtained average values of 0.20–0.25 kWh/km. However, energy consumption could be cut by technological improvements. For instance, the energy required for heating could be reduced by improving the thermal insulation of vehicles and by developing heat pump systems for vehicle purpose. Some car models soon coming to the market include solar panels, which decrease the need for energy taken from the grid. The weight of the cars could also be reduced by advanced materials and structures.

Fast charging and battery replacement are not considered in this work, and the maximum charging power is set to 3.6 kW/car. The limit comes from the present electric pre-heating systems used for cars in the Nordic countries in wintertime. The pre-heating system is based on one-phase voltage (230 V) and 16 A limited current (by fuses).

3.3 Distribution network data

Definition of the network effects requires both technical and economic data from the distribution company. The network area to be analysed has to be large enough to ensure the reliability of the analysis. On the other hand, the area to be analysed has to be small enough so that the effects of parameter variation can be detected fast and easily. It is also of utmost importance to find such a network section that adequately describes the operating environment and the structure of the distribution system and thereby makes it possible to bring the results to a more general, company level. In this paper, the required data are demonstrated by the case network where there are around 20 000 inhabitants, 10 800 electricity customers and 11 000 cars. The network key figures are presented in Table 2. In this study, the focus has been set on two medium-voltage (20 kV) feeders. Feeder 1 represents a densely populated area (a small city) and Feeder 2 represents a rural area. Both feeders describe well the operating environment and structure of the distribution system. The peak load occurs in the winter season because of the cold weather and a high rate of electric heating. In the area, the peak load in winter is 50 MW and the energy 200 GWh/a.

In this study, the focus is on the winter period because of the more critical load flows compared with other seasons. The peak load in winter can be five times as high as that of a low-load moment in summertime. The load level varies considerably not only by season, but also between weekdays. Considering EV loads, the additional load depends greatly on the number of vehicles during the day and night in the area supplied by the feeder.

4 Charging profiles

One of the main challenges in the analysis of the grid effects is a paucity of information required to define reliable charging profiles (load curves). This is because of the relatively small number of EVs presently in use and the charging measurements available. However, from a methodological point of view, the lack of actual EV measurement data does not prevent from developing a generic model by which the grid effects can be analysed. Later on, when the EV penetration level is higher and EVs are used in households as primary cars, the input data used previously can be replaced with actual EV charging data in the model.

4.1 Charging curves based on intuitive behaviour of citizens

In this study, EV charging is modelled both by the intuitive behaviour of citizens and actual traffic flow measurements. In the intuitive option, four different charging curves are presented in Fig. 3. The curves are based on nation-wide information (statistics) on the behaviour of citizens, for instance, on how traditional cars are used in different areas at different times of the day. Part of this information is obtained from the travel survey discussed in the previous section. The curves differ significantly from each other, which makes it easy to demonstrate the grid effects in different situations.

In ‘direct night-time charging’, it is assumed that almost all the customers on the feeder start charging their cars at the same time in the evening. In ‘split-level night-time charging’, car charging loads are distributed between the night hours. In ‘working-hour and time-off charging’, customers concentrate their car charging on working hours and time-off hours after coming back to home. In ‘optimised charging’, the focus is on low-load moments on the feeder. It is a more or less theoretical perspective, but it gives an overview of what is the possible distribution of car charging (between hours). In each option, the charging energy is the same. The total amount of energy is based on the number of EVs on the feeder. The load on the medium-voltage feeder depends significantly on the charging arrangements; whether it is a simple direct charging system or there is some intelligence included in the system.

4.2 Charging curves based on traffic flow measurements

In this option, charging curves are curves produced based on actual traffic flow measurements in the case area. The measurements are carried out in a residential area as described in the previous section. The traffic flow measurement is used as a discrete probability distribution. Cars cannot be identified in the measurement (only the number of EVs and the time of passing), the driving lengths (need for energy) have to be evaluated somehow. To solve this, the length of the trip is randomised based on the probability density derived from the national travel survey. The simulation is repeated until a sufficient end

Table 2 Key figures of the network

	Feeder 1	Feeder 2	Whole company
110/20 kV primary substations	—	—	4
20 kV feeders	—	—	22
inhabitants	4171	1037	19 470
end-customers	2278	444	11 000
workplaces	1577	84	5333
houses			
detached houses	659	372	5992
terraced houses	266	0	525
apartment houses and others	888	0	1415
20/0.4 kV distribution substations	39	27	470
peak load	8 MW	2 MW	50 MW
annual energy	36 GWh	6 GWh	200 GWh
20 kV lines and cables	21 km	31 km	433 km
20 kV underground cabling rate	33%	6%	16%

Feeder 1 is located in a densely populated area and Feeder 2 in a rural area

doi: 10.1049/iet-est.2011.0015

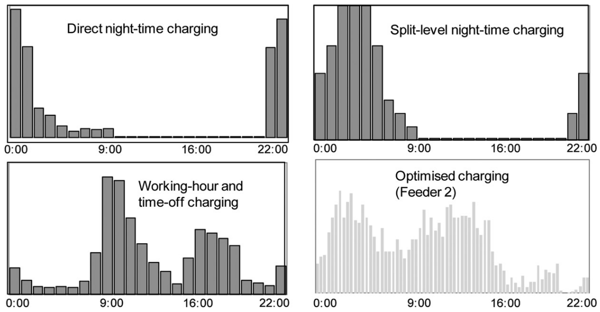


Fig. 3 *Four charging alternatives of EVs*
In each alternative, the total charging energy is the same

criterion is met. The example simulated load curve for the residential area with a 100% EV penetration level is presented in Fig. 4. The charging curve is based on the traffic flow measurement in Fig. 2. The penetration levels are varied later in Fig. 5.

5 Technical network effects

5.1 Background for power flow simulations

Power flow simulations have a long history in electricity distribution systems. Power flow calculations were carried out by applying network and customer information systems (NIS and CIS) already in the 1970s [29, 30]. The link between the NIS and the CIS has been intensively used since the 1960s [31]. As the restrictions related to the large number of customers (individual load points) and computer processing power, the calculations were mainly based on customer annual energy and load profiles of customer groups.

In these studies, the load flow analyses are mainly based on commercial power flow software. The main challenge is to define reasonable charging curves for the EVs. The groups of EV users are not yet large enough to allow the definition of EV charging profiles for power flow calculations. To make the studies possible, the analyses are supplemented by load profiles defined in the previous section. In principle, the charging curves are obtained based on the feeder-specific base load as presented in

$$P(t) = P_{\text{base}}(t) + n_{\text{EV}}(t)P_{\text{supply}} \tag{1}$$

where P_{base} is the base load of the feeder without EVs, P_{supply} is the maximum charging power of the EVs and n_{EV} is the number of EVs. The base load is defined by traditional power calculations, which are specified by actual power flow measurements. In this study, the base load is from winter season, when the consumption is at highest (electric heating of houses, saunas etc.) in the case network. The maximum charging power of the EV depends on the charging arrangements; in this study, the charging type is slow charging from a household-type socket-outlet (IEC 61851-1), where the maximum power is limited to one-phase voltage (230 V) and 16 A current.

Deviation plays a key role in power flow analyses. This is the case also with EV charging load analyses. The fewer vehicles there are, the larger is the relative variation. The sum of charging load can be considered as a probabilistic maximum value at a certain time. In other words, a confidence level should be determined based on the simulated load curve values and the deviation. In these studies, a 95% confidence level is used.

5.2 Network effects

Fig. 5 presents the load curves before (base load) and after the implementation of the EV charging on Feeder 2 in each charging alternative. The first four alternatives are defined for the 100% penetration level of EVs. In the bottom figure (in Fig. 5*e*), the charging curves are based on actual traffic flow measurements with four different penetration scenarios

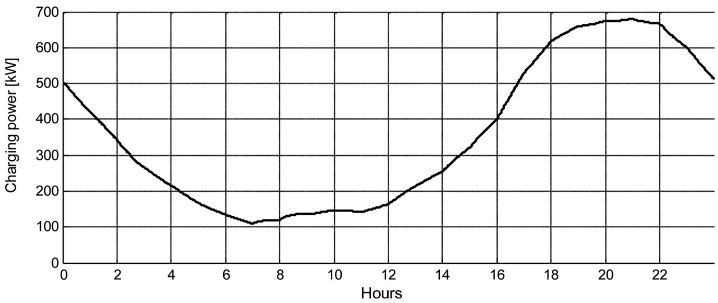


Fig. 4 *Charging alternative of EVs based on actual traffic flow*

doi: 10.1049/iet-est.2011.0015

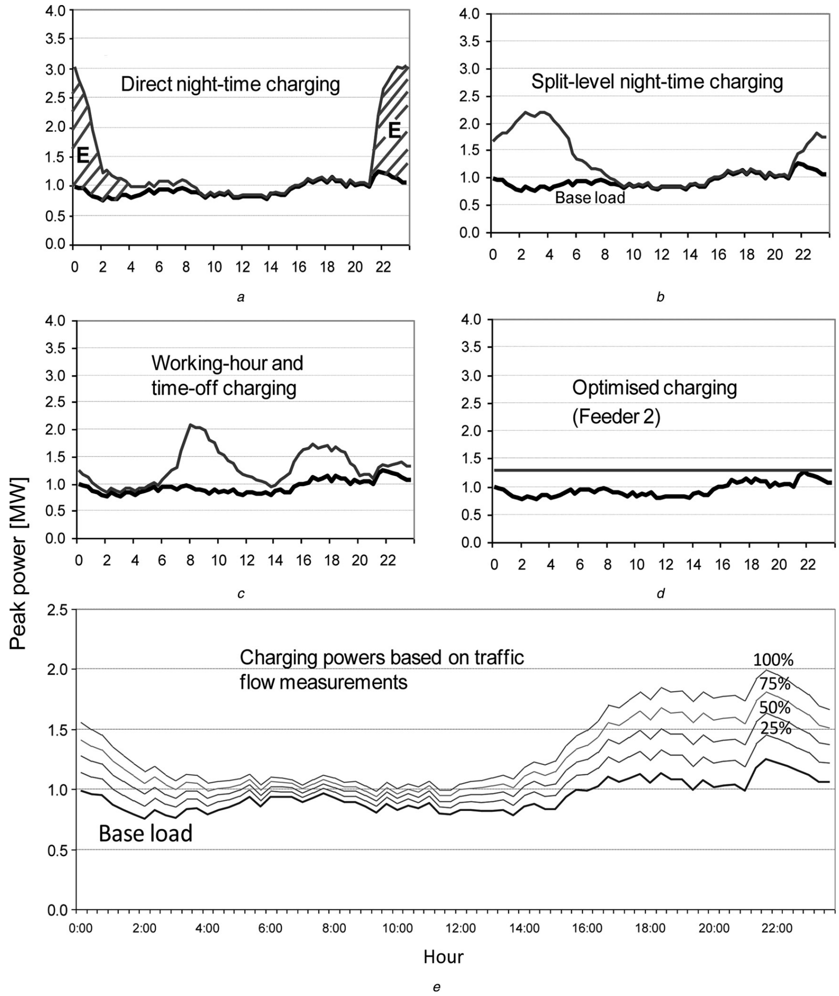


Fig. 5 *Five charging models of EVs on a feeder in a rural area*

In each figure, the lower curves represent the existing peak load (base load), whereas the upper curves represent the load when the charging power is taken into account. The charging energy is equal in each alternative. In the bottom figure (Fig. 5*e*), four different EV implementation scenarios (25, 50, 75 and 100%) are presented

(25, 50, 75 and 100%). In the 100% scenario, all 750 traditional passenger cars are replaced by electric ones.

In a rural area (Fig. 5), the relative increase in the peak load in ‘direct night-time charging’ is about 250% compared with the situation without EVs. The high growth can be explained by the low-base load level in the rural area; electrification of transportation increases the total consumption of electricity relatively more in a rural area than in a densely populated area. The rural area feeder alternatives ‘direct night-time charging’ and ‘split-level night-time charging’ are the most probable options because of the high proportion of residential customers and a low number of workplaces on the feeder (Table 2).

The traffic flow measurement based curves in Fig. 5 show that the peak charging load is scheduled on evening hours when residential customers are coming back from work. Working-hour charging is rather minimal because of the low number of workplaces in the rural area fed by the case feeder. Compared with intuitive-behaviour-based charging profiles, the load growth is lower being about 160% higher than the peak power in the present situation without EVs.

Fig. 6 summarises the effects of EV charging on the peak power in different charging alternatives and in different EV penetration scenarios for a rural area feeder.

It can be seen from Fig. 6 that ‘direct night-time charging’ has clearly the highest effect on the peak power at all penetration levels. ‘Split-level night-time charging, working-hour charging and traffic flow measurement based’ charging have a rather similar effect on the peak power.

IET Electr. Syst. Transp., pp. 1–8
doi: 10.1049/iet-est.2011.0015

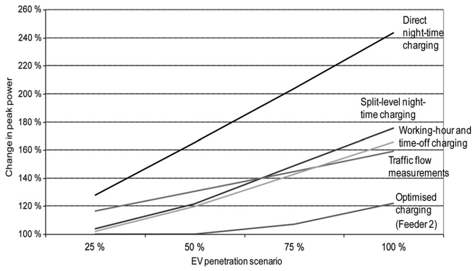


Fig. 6 *Effects of charging on the peak power on the feeder with different charging profiles in different penetration scenarios*

In the 'optimised charging', the peak load starts to increase after the penetration level of EVs is more than 50%.

6 Economical network effects

Overall, the analyses of the effects of EVs have mostly focused on the technical perspective as shown in Table 1. In this paper, the methodology to analyse the economic effects of EVs on the electricity distribution business is in a key role. Next, the effects of EVs on the replacement value (RV) and electricity distribution fee are defined.

6.1 Effects on the RV

The definition of wide-scale economic effects of EVs on the distribution business requires simplification of the analyses. Case-specific studies at the low-voltage and end-customer level could provide accurate information for the network planning process. However, resource- and time-consuming studies of this kind would not serve the network development in a reasonable way at the asset management level.

To obtain the first estimations for the business planning, the amount of required investments can be estimated by defining the average additional investment cost of the network [32, 33]. It is based on the network RV and the maximum load of the year, and it describes how much the network capacity costs for the distribution company per each peak load kilowatt. For instance, if the network value is 1 M€ and the distribution capacity of the network is 1 MW, the average investment cost is 1 €/W or 1000 €/kW. For instance, in the case network, the RV of the whole network is 50 M€ and the peak power 50 MW.

To be able to allocate costs more accurately to the distribution system, the analysis is performed for each part of the network (400 V low-voltage networks, 20 kV medium-voltage networks and 110/20 kV primary substations). In this case, the network value compared with the peak load is 500 €/kW in the low-voltage networks, 450 €/kW in the medium-voltage networks and 50 €/kW at the primary substation level (110/20 kV). These values depend strongly on the network structure (e.g. urban area against city area network). The accuracy and opportunity to use voltage-level-specific cost information depends on the network information system used in the distribution company. At the medium-voltage and primary substation level, a statistical approach of an additional load can be taken because the load is usually well balanced. In the low-voltage network, it is more likely that different loads overlap each other. A typical peak operating time in the low-voltage networks is 2000 h/year, in the medium-voltage networks 3500–4500 h/year and at the primary substation level 4500–5000 h/year. In the low-voltage networks, it is difficult to adjust an additional load to those time periods when the load level is low. On the other hand, there are numerous reasons for the present individual peak loads, such as saunas, electric space heating and car electric pre-heating systems, which can be adjusted thereby avoiding the overlapping of peak loads.

The idea of average additional investment cost in the reinforcement cost definition on a medium-voltage feeder is demonstrated in Fig. 7. In the scenario, the present peak load increases by 1.8 MW ($=\Delta P$) from 1.2 to 3.0 MW because of EVs. When the average additional investment cost for the case area is 450 €/kW, the peak growth requires new network capacity worth of 810 000 €. The direct night-time charging curve from Fig. 5 is used in the example.

The same principle of average additional investment cost can be used also in the case where some network capacity is released by the decreasing peak. Even though the decrease in the peak does not bring direct return for the distribution company, it leaves space for the normal load growth in the network and that way, delays network capacity investments. In general, the change in the RV of the network can be defined by the average additional investment cost and the change in the peak power (ΔP) as presented in

$$\text{Change in RV} = \text{Average additional investment cost}\,\Delta P \tag{2}$$

The presented principle is applied to all those scenarios that are realistic or interesting for the case distribution company. Fig. 8 presents the effects of EV charging on the RV of the feeder with different charging profiles in different penetration scenarios. The example of the effects of direct night-time charging presented in Fig. 7 is illustrated by a black dot in Fig. 8.

As it is seen in Fig. 8, it is not insignificant which kinds of scenarios and charging methods are chosen to be used in the network analyses. Even though the results are case-specific, there are clear incentives to avoid dumb charging and to study opportunities to adopt intelligence to the control of EV charging (optimised charging).

6.2 Effects on distribution fee

In addition to the effects on the network capacity, principles to define the effects on the distribution fee have to be

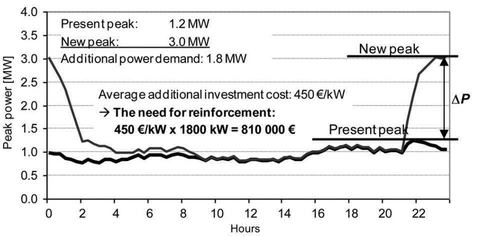


Fig. 7 *Estimation of the reinforcement costs on a medium-voltage feeder as a result of an increase in peak power*

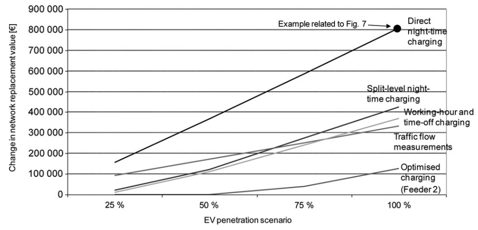


Fig. 8 *Effects of EV charging on the RV of the feeder with different charging profiles in different penetration scenarios*

The price of additional network capacity (average additional investment cost) is 450 €/kW

determined. From the electricity end-user perspective, it is interesting to investigate how much an increase in the peak and capacity affects the distribution fee (cent/kWh).

The additional network investments will eventually be paid by the end-customers. This can be determined when the straight-line depreciation of the RV and lifetime of the network (€ per year) is compared with the annual delivered energy in the network. In other words, the equation below determines the proportion of the network asset value in the distribution fee

$$\text{Network value per delivered energy} = \frac{\text{Straight line depreciation}}{\text{Annual energy}} \quad (3)$$

In the case of EVs, it is not obvious whether the increasing penetration of EVs will finally have a positive or negative effect on the distribution fee. This depends on the relation of the change in the delivered energy to the change in the power peak. As (3) illustrates, lower reinforcement needs (a minor change in the replacement value) and a growing amount of delivered energy (a growing number of EVs) may lead to lower network unit costs finally paid by the end-customer. The methodology is demonstrated in Fig. 9, where the situation before and after adoption of EVs is presented with different charging types in different penetration scenarios. The RV of the rural area feeder is 1.4 M€ and the annual delivered energy on the feeder is 6 GWh/year. By (3), the network value per delivered

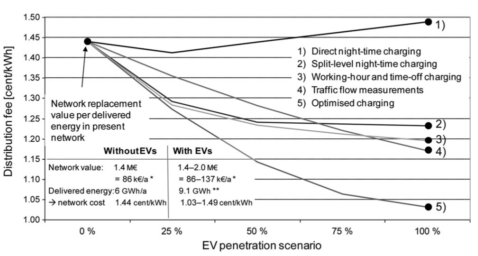


Fig. 9 *Effects of charging on the distribution fee with different charging profiles in different penetration scenarios*

*in the annual value
p is 5% and the life-time
t is 35 a, **the charging energy 3.1 GWh comes from 750 cars, 20 900 km/car per year and 0.2 kWh/km per car

energy is 1.44 cent/kWh in the present situation. Depending on the charging method and the level of intelligence in the charging, a rough estimation of the additional investments (2) required in a new transformer and the distribution capacity in the feeder would be 0–0.6 M€. When comparing the reinforcement needs and the delivered energy, the network cost (distribution fee) would be between 1.03 and 1.49 cent/kWh. This means that in the optimum situation, the network-value-related distribution fee could be about 28% lower after the full-scale penetration of EVs and the implementation of the intelligent control of charging.

Even though these case-specific values are not important from the methodological perspective, the fee range shows that when the peak power of the network increases more than the delivered energy, the distribution fee will increase. If the additional charging load has only a slight effect on the peak power, it is possible to cut the distribution fees.

7 Conclusions and discussion

In this paper, a methodological study of the charging effects of EVs on the network value and the distribution fees was presented. In the technical part of the paper, the focus was on the peak load growth in different charging profiles and penetration levels in a medium-voltage network. In this study, intuitive-behaviour-based charging profiles were compared with profiles based on actual traffic flow measurements. The results show that the type of the charging profile and the penetration level have a strong influence on the resulting peak power. In addition, different base load profiles (for instance a densely populated area against a rural area) lead to different resulting powers with a certain charging type. These issues have to be taken into account when the network effect analyses are made in electricity distribution companies.

The second part of the study concentrated on the definition of the economic effects of EVs in an electricity distribution system. This research area has been mostly neglected, as was discussed at the beginning of this paper. In this task, the objective was to define both the effects on the RV of the network and the effect on the electricity distribution fee paid by the electricity end-customer. Based on the results related to the case network, there is potential to cut the distribution fees after the adoption of EVs. Depending on the charging profile and penetration level of EVs, the prices could be lowered by tens of percents. However, this requires intelligent control of EV charging. From the end-customer perspective, the most positive effect is reached when the efficiency of the operation of the existing electricity distribution capacity is improved, which provides opportunities to reduce the distribution fees.

By the methodology and principles presented in the paper, it should be possible to define both the technical and economical network effects in any environment. The quality of the results depends on the quality of the background data; how well the number and behaviour of the future EVs are known, what is the situation with the present distribution network infrastructure and which economic parameters best describe the distribution business. The results are strongly dependent on the parameters, and therefore sensitivity analyses in different phases of the process need to be made. It has also to be borne in mind that the method of the average additional investment cost applies best to situations where the analyses are made for

doi: 10.1049/iet-est.2011.0015

an area that is wide enough; the smaller the case area is, the more uncertainty is included in the analyses.

One of main targets of the paper was to define and demonstrate the relationship between additional network investments and the distribution fee paid by the electricity end-user in the case where the network capacity changes because of EVs. The results show that when the peak power of the network increases more than the delivered energy, the distribution fee will increase. If the additional charging load has only a slight effect on the peak power, it is possible to cut the distribution fees. This creates economic incentives to the intelligent control of EVs.

Although this study has been made in the Nordic environment, the methodology presented in this paper can be adopted to any other circumstances. Only the calculation parameters have to be reconsidered according to the environment in question.

8 References

1 Ehsani, M., Gao, Y., Emadi, A.: 'Modern electric, hybrid electric and fuel cell vehicles' (Taylor and Francis Group, Boca Raton, Florida, USA, 2010, 2nd edn.), p. 534

2 Guzzella, L., Sciarretta, A.: 'Vehicle propulsion systems' (Springer-Verlag Berlin Heidelberg, 2007)

3 Miller, J.M.: 'Propulsion systems for hybrid vehicles' (Institution of Electrical Engineers, 2004), p. 455

4 Larminie, J., Lowry, J.: 'Electric vehicle technology explained' (John Wiley, 2003), p. 296

5 Koyanagi, F., Uriu, Y.: 'A strategy of load leveling by charging and discharging time control of electric vehicles', *IEEE Trans. Power Syst.*, 1998, **13**, (3), pp. 1179–1184

6 Liu, L., Eisenreich, M., Balzer, G., Kessler, A.: 'Evaluation of absorption capacity of distribution grids for electric vehicle integration in rural areas'. European Conf. SmartGrids and E-Mobility, Brussels, 2010, pp. 77–84

7 Pop, V., Regtien, P., Notten, P., Danilov, D., Bergveld, H.: 'Battery management systems' (Springer Science, 2008)

8 Ota, Y., Taniguchi, H., Nakajima, T., Liyanage, K.M., Yokoyama, A.: 'An autonomous distributed vehicle-to-grid control of grid-connected electric vehicle'. Conf. on Industrial and Information Systems (ICIIS), 2009, pp. 414–418

9 HCAdeMO Association, Desirable characteristics of public quick charger, 2010, Tokyo, Accessed 29 April 2010. Available at www.emc-mec.ca/phev/Presentations_en/S12/PHEV09-S12-3_TakafumiAnegawa.pdf

10 Ponticel, P.: 'SAE standard on EV charging connector approved', Automotive engineering online, Accessed 15 April 2010. Available at www.sae.org/mags/AEI/7479

11 Lassila, J., Kaipia, T., Haakana, J., *et al.*: 'Electric cars – challenge or opportunity for the electricity distribution infrastructure?'. European Conf. on Smart Grids and Mobility, Wurzburg, 2009

12 Kempton, W., Tomic, J.: 'Vehicle-to-grid power implementation: from stabilizing the grid to supporting large-scale renewable energy', *J. Power Sources*, 2005, **144**, (1), pp. 280–294

13 Fernández, L., San Román, T., Cossent, R., Domingo, C.M., Frías, P.: 'Assessment of the impact of plug-in electric vehicles on distribution networks', *IEEE Trans. Power Syst.*, 2011, **26**, (1), pp. 206–213

14 Balcells, J., Garcia, J.: 'Impact of plug-in electric vehicles on the supply grid'. Vehicle Power and Propulsion Conf. (VPPC), 2010, pp. 1–4

15 Blumsack, S., Samaras, C., Hines, P.: 'Long-term electric system investments to support plug-in hybrid electric vehicles'. Power and Energy Society General Meeting – Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE, July 2008, pp. 1–6

16 Clement-Nyns, K., Haesen, E., Driesen, J.: 'The impact of charging plug-in hybrid electric vehicles on a residential distribution grid', *IEEE Trans. Power Syst.*, 2010, **25**, (1), pp. 371–380

17 Cvetkovic, I., Thackerm, T., Dong, D., *et al.*: 'Future home uninterruptible renewable energy system with vehicle-to-grid technology'. Energy Conversion Congress and Exposition, 2009. ECCE 2009. IEEE, September 2009, pp. 2675–2681

18 Dyke, K.J., Schofield, N., Barnes, M.: 'The impact of transport electrification on electrical networks', *IEEE Trans. Ind. Electron.*, 2010, **57**, (12), pp. 3917–3926

19 Kristoffersen, T.K., Capion, K., Meibom, P.: 'Optimal charging of electric drive vehicles in a market environment', *Appl. Energy*, 2011, **88**, (5), pp. 1940–1948

20 Mets, K., Verschueren, T., Haerick, W., Develder, C., De Turck, F.: 'Optimizing smart energy control strategies for plug-in hybrid electric vehicle charging'. Network Operations and Management Symp. Workshops, 2010 IEEE/IFIP, April 2010, pp. 293–299

21 Moses, P.S., Deilami, S., Masoum, A.S., Masoum, M.A.S.: 'Power quality of smart grids with plug-in electric vehicles considering battery charging profile'. Innovative Smart Grid Technologies Conf. Europe, 2010 IEEE PES, October 2010, pp. 1–7

22 Pecas Lopes, J.A., Polenz, S.A., Moreira, C.L., Cherkaoui, R.: 'Identification of control and management strategies for LV unbalanced microgrids with plugged-in electric vehicles', *Electr. Power Syst. Res.*, 2010, **80**, (8), pp. 898–906

23 Pillai, J.R., Bak-Jensen, B.: 'Impacts of electric vehicle loads on power distribution systems'. Vehicle Power and Propulsion Conf. (VPPC), 2010 IEEE, September 2010, pp. 1–6

24 Qian, K., Zhou, C., Allan, M., Yuan, Y.: 'Modeling of load demand due to EV battery charging in distribution systems', *IEEE Trans. Power Syst.*, 2011, **26**, (2), pp. 802–810

25 Rahman, S., Shrestha, G.B.: 'An investigation into the impact of electric vehicle load on the electric utility distribution system', *IEEE Trans. Power Deliv.*, 1993, **8**, (2), pp. 591–597

26 Saber, A.Y., Venayagamoorthy, G.K.: 'Plug-in vehicles and renewable energy sources for cost and emission reductions', *IEEE Trans. Ind. Electron.*, 2011, **58**, (4), pp. 1229–1238

27 Sortomme, E., Hindi, M.M., MacPherson, S.D.J., Venkata, S.S.: 'Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses', *IEEE Trans. Smart Grid*, 2011, **2**, (1), pp. 198–205

28 The National Passenger Transport Survey 2004–2005. Finland. ISBN 951-803-682-9. Paino Dark Oy 2006. Available at www.hlt.fi/HTL04_loppuraportti.pdf [In Finnish]

29 Adams, R., Laughton, M.: 'Dynamic programming/network flow procedure for distribution system planning'. Power Industry Computer Applications Conf., 1973, pp. 348–354

30 Backlund, Y., Bubenko, J.A.: 'Distribution system design using computer graphics technique'. Power Industry Computer Applications Conf., IEEE, 1979, pp. 382–388

31 Lakervi, E., Nurmi, M.: 'Present status in applying mathematical planning methods in AM/FM-GIS systems'. Proc. CIRED 97, 1997, No. 438, IEE, **6**, pp. 24/1–24/5

32 Bishop, A.: 'Tariff development II: rate design' (The Georgian National Energy Regulatory Commission and The Vermont Public Service Board, 2008), Accessed 29 June 2011. Available at www.narucpartnerships.org

33 CER and NERA: 'Marginal cost of electricity service study', report, July 2004

Publication V

Tikka, V., Makkonen, H., Lassila, J., and Partanen, J.
Case Study: Smart Charging Plug-In Hybrid Vehicle Test Environment with Vehicle-To-Grid Ability

Reprinted with permission from
2014 16th European Conference on Power Electronics and Applications
Lappeenranta, Finland, 2014

Case Study: Smart Charging Plug-In Hybrid Vehicle Test Environment with Vehicle-To-Grid Ability

Ville Tikka, Henri Makkonen, Jukka Lassila, Jarmo Partanen
LAPEENRANTA UNIVERSITY OF TECHNOLOGY
P.O.BOX 20, FI-53851 Lappeenranta
Lappeenranta, Finland
Tel.: +358 503 373 685.
Fax: +358 5 411 7201.
E-Mail: ville.tikka@lut.fi
URL: http://www.lut.fi

Acknowledgements

This work was carried out in the Smart Grids and Energy Markets (SGEM) research program coordinated by CLEEN Ltd. and the EVE – Electric Vehicle Systems program with funding from the Finnish Funding Agency for Technology and Innovation, Tekes.

Keywords

«Electric Vehicle», «Hybrid Electric Vehicle (HEV)», «Charging Infrastructure for EV's», «Energy system management», «Smart Grid»

Abstract

The aim of the paper is to describe and introduce smart charging test environment and plug-in hybrid vehicle capable of smart charging and vehicle to grid functionality. Furthermore, the paper aims at demonstrating simple smart charging strategy in operation on smart charging test bed. The demonstration utilizes commercially available components and open source programming solutions. Charging strategy demonstration is a combination of actual hardware operations and stochastic sampling to synthetize driving cycles of the electric vehicle. Driving behavior synthetizing is based on national travel survey data to ensure reasonable driving behavior in testing of the smart charging strategy. The main outcome of the paper is the description of an actual smart charging test environment. The results also suggest that the charging strategy targeting to minimization of the charging costs may not be feasible for a single customer or single end user. However it must borne in mind that the electricity retailer (or market aggregator) may see some feasible incentives in smart charging strategies based on market price control.

Introduction

The number of electric vehicles (EV) is slowly increasing while also the green ideology seems to be gaining a stronger foothold in the political field in Finland. Based on the scenarios presented in [1], a substantial number of EVs will be on the road by 2020, in Finland. Moreover, the emissions targets of the European Union are driving towards less polluting society. In the field of transportation, EVs are among the most promising alternatives to strive towards CO_2 free transportation. As the previous studies [2] and [3] suggest, the grid effects of the EV charging will have a substantial impact on grid loads, and therefore, all alternative charging schemes have to be studied. The main concern is simultaneous charging of a large number of EVs which may pose a considerable threat to the electricity distribution networks. Among the most discussed charging strategies, the strategy aiming at lowest charging cost from socio-economic perspective is the preferable choice. Such a strategy can be understood simply aiming at minimizing the cost of electricity or with more sophisticated manner, aiming at total cost minimization. The total cost minimization covers elements such as loss power cost, electricity cost, grid (capacity) cost and charging equipment cost. In the paper the aim is to describe and verify the functionality of the charging strategy aiming at the lowest electricity cost, because, the main aim of the paper is verify functionality of smart charging test bed, rather than demonstrate highly sophisticated charging strategies.

Some special cases such as spot price controlled charging may result in undesirable effects to the grid, such as peak load growth. For instance, if a large group of electric vehicles are controlled based on the price signal, it could result into a case in which the majority of the charging loads become concentrated on the same hour. Furthermore some of the smart meter functions may enable even more flexible loads that may behave similar as EV charging load, in the near future. Thus, it is essential to investigate the effects of such charging control algorithms. Furthermore, it is essential to develop pilot systems that can support testing of such control systems. Pilot systems also produce user experience data that can also be seen valuable as smart charging may and will need some input parameters from the user. For instance, typically the car is used only an hour per day. However, when usage occurs the car has to be ready for use. Therefore the car user should have the possibility to give the system an initial estimation of the usage time instances or requirement on the state-of-charge (SoC). Real-life demonstrations are needed to validate the theoretical charging strategies.

Testing of the charging strategies on test bed neither solves, nor gives answers for all of the questions posed. For instance, controllable loads are capable of posing unpredictable load behavior in the distribution grids. At least load may seem to behave unpredictably if observed from other than market aggregators' perspective. For instance, if electricity retailer has control privilege of some of the loads, electricity distribution system operator (DSO) may see the load vary unpredictably or unnaturally. Issue becomes even more difficult if DSO is given control privileges of the load, as it ruins the electricity retailer's balance between forecasted and realizing electricity demand, resulting in higher balance settlement cost.

From the DSO's perspective market price controlled charging may appear as a treat to the grid, because loads might overlap more than natural behavior would suggest. For instance, grids are typically dimensioned based on some confidence level, so that the line sections are not selected to withstand theoretical maximum loads (sum of maximum loads of each individual customer). In a LV transformer circuit of 30 household customers, the dimensioning load may be only fifth of the theoretical load. It has to be borne in mind that the dimensioning power is not only technical dimensioning, but a techno-economical compromise. In practice this, means that the grids are not that likely to be overloaded. Load over dimensioning criteria cause loss power to increase, and when loss power increases also loss power cost increases. Equation guiding the dimensioning of the grid is be presented as follows:

$$\min \int_{t_0}^{t_1} (C_{\text{investm}}(t) + C_{\text{loss}}(t) + C_{\text{intr}}(t) + C_{\text{oper}}(t))dt, \tag{1}$$

where,

C_{investm} = investment cost
C_{loss} = cost of losses
C_{intr} = cost of interruptions
C_{oper} = cost of operation
Δt = planning period.

According to the equation, grid development is dependent of the expected load behavior that should be known as well as possible. The typical planning period of the distribution grid is tens of years. Therefore the pilot projects are in crucial role in the strategic planning of the distribution grids.

In the paper, the charging load is optimized based on the electricity price information and demonstrated with the real-life case on actual test setup. The electricity cost minimized charging does not solve problems of increasing grid load but could still be an option for the end customer. It is likely that electricity price controlled charging appears as a conflict of interest between distribution system operator and electricity retailer. This conflict of interest is discussed briefly in the case of smart charging of EVs. The conflict of interest in a demand response application is studied in [4]. Grid effects and modeling of EV charging is discussed in [6]-[11].

The key elements of the study are:

- Demonstration of smart charging test bed in action
- Demonstration of electricity cost minimized charging
- Definition of data requirements for smart charging scheme considered
- Studying of the conflict of interests between the DSO and the electricity retailer

Simulation Setup

Pilot demonstration aims at providing a platform for testing of the smart charging strategies. Furthermore, the vehicle to grid (V2G) functionality is considered as part of the smart charging properties. In other words the test platform has capability of feeding electricity back to the grid. Pilot demonstration is based on modified Toyota Prius Plug-in-Hybrid Vehicle (PHEV). The vehicle has been updated with an additional LiFePo battery pack the capacity of which is 4.6 kWh . The battery pack is connected to the hybrid drive battery with a 13 kW DC/DC converter which provides power for highway cruising. In addition, the vehicle is equipped with two 500 W inverters to achieve vehicle-to-grid functionality with maximum in-feed power of 1 kW. The nominal power of the on-board battery charger is 3 kW and it is controlled by the battery management system of the additional LiFePo battery pack. The battery charger is only used to charge the additional LiFePo battery, not hybrid system battery.

The smart charging management is conducted with an industrial PC running Linux operating system. The physical control is handled by the relay control board connected to the on-board PC. The on-board PC has CAN bus interface for the car, and thus, it is capable to poll values from the information system of the vehicle. The on-board PC is also used to maintain the automatic driving diary as vehicle is driven. Charger management connects to a charging pole via power line carrier (PLC) modem. The charging pole has simple Linux based interface operating as a proxy between the pole and the vehicle. The charging pole routes communication requests directly to a Linux server running the energy management system (EMS). The EMS server maintains MySQL database where data of each event is stored. For instance, when car plugs in, the EMS server updates database item flag to active. Vehicle's driving history is stored on the server also. The communication from the car's on-board PC to EMS server is operated via Ethernet by TCP/IP protocol.

The main purpose of the smart charging pilot has been to develop test bed for the functionality testing rather than develop fine tuned product for the end user, and thus, the communication between units has been conducted by robust TCP/IP commands that could be send directly to the desired unit. For instance, the charging management could set the EV to discharge. It is possible to develop and run different smart charging schemes on the test setup.

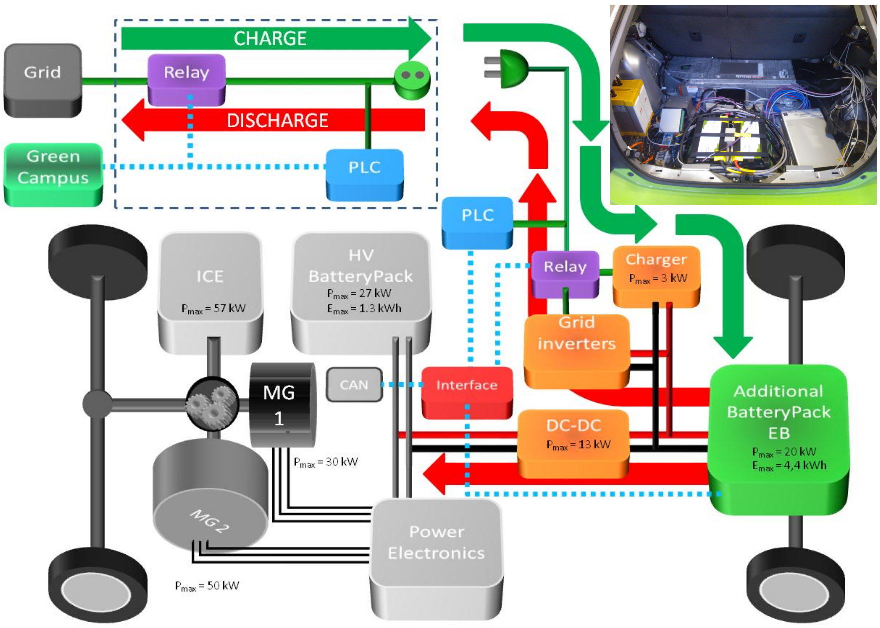


Fig. 1: Test setup, batteries, BMS, charger and inverters.

The aim of the paper is to demonstrate the operation of the price signal controlled charging . Driven mileage and availability (duration the car is connected to the charging point) of the car is synthetized by sampling the departure time, arrival time and average daily mileage from the distributions acquired from the National Travel Survey (NTS) of Finland [5].

Required Data for the Smart Charging Interface

The smart charging scheme needs data from several different sources to operate efficiently. Depending of the charging strategy, requirements on the data sources and time criticality vary. For instance, some of the grid support functions may need almost real-time data, while market price strategies can operate with delays ranging up to hours. In the paper, the electricity price optimized charging is considered, and therefore, the management of the charging necessitates hourly electricity tariff from the Nord Pool Spot.

The working environment in the paper is Nordic area, and therefore, Nord Pool Spot is considered as a source of the price signal. The Nord Pool market consists of two physical electricity trades; day-ahead and intraday markets. The day-ahead market for the next day, and the bids must be submitted before 1 pm in Finnish time (+3h GMT) [12]. After the bids have been submitted the market is closed and day-ahead prices are published based on crossing point of supply and demand of the each hour. The intraday market begins after the day-ahead market is closed. The operation is similar to day-ahead market, but intraday market closes for each hour just before delivery. The Nordic market is divided into the different price areas. For example, the area price in Finland may differ from the Nordic system price in the case of power flow congestions.

Spot price for the next day is public information and can be obtained directly from the Nord Pool website with a scheduled script and stored on the EMS server's database. In the simulation Finnish area price is used.

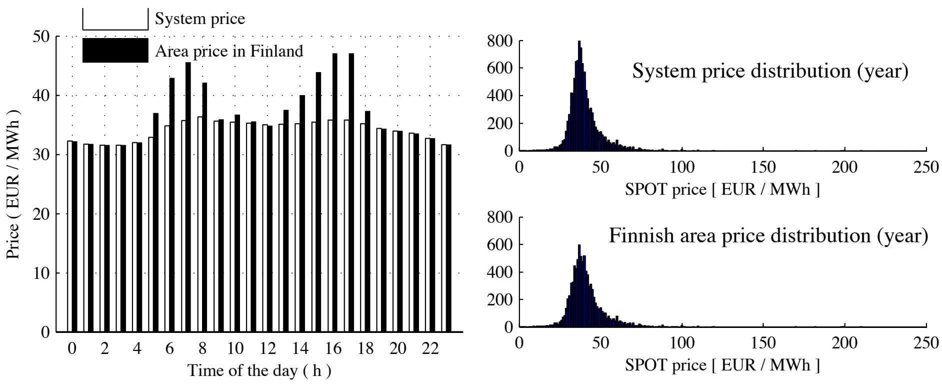


Fig. 2: Example of SPOT price over a day and price distribution over a year 2013.

The smart charging strategy needs also data concerning the vehicle to be charged. For instance, it is vital to know the duration of the charging and restrictions that user may have set. In the paper, one case deals with the case in which the user of the vehicle has option to set the time when the charging event should be finished. In that case, the user of the vehicle is considered to have standard daily working hours from 8.00 am to 16.00 pm and the charging is set to be finished at 7.00 am.

Vehicle also delivers nominal values of the charger to the EMS server so that the charging management is capable of estimating the required charging time for fully charged battery pack. Vehicle can also deliver SOC value and nominal charging power for more sophisticated optimization strategies such as demand management and grid support applications. In the case demonstrated, the nominal charger power is set to 3 kW, even though the charging power may vary during the charging event. Typically the charging current of the LiFePo batteries may vary quite heavily as a function of temperature, to maintain the performance of the battery. In Nordic environment, heating of the battery may also be necessary before the charging begins. Therefore, LiFePo -cells cannot be charged on sub-zero temperatures. Vehicle also delivers other miscellaneous values for the EMS server. More specific description can be found in [13], where demonstration environment is presented in more detail.

Smart charging algorithm

In the paper the smart charging is considered as electricity price minimization. Optimization goal can be simplified as follows:

$$\min c_{\text{tot}} = \int c_{\text{e}}(t)dt \tag{1}$$

where

t = time

c_{e} = cost of electricity

The cost of the charging energy is minimized over time $t_1 \ldots t_2$. The t_1 is defined by the arrival time or current time. The t_2 is defined by the availability of the Nord Pool Spot price data or user defined "ready time" (set by the user/driver). For instance if cost optimization algorithm runs at noon, the Δt is limited to

12 hours ahead or to the user set time earlier. In the case optimization runs at 6 pm, the day-ahead SPOT market data should be available and minimization window could reach 24 + 6 h ahead (unless user has set earlier "ready time"). The actual charging management algorithm runs on MATLAB platform. Management algorithm runs inside infinite loop and refreshes values to be stored every minute. Charging strategy algorithm gathers all the necessary data from the EMS MySQL database by using Perl-functions. Charging control is conducted with robust TCP messages to EMS server. Message includes ID of the desired vehicle or other unit connected to the EMS and status to be set to the unit. Status can be set to idle, charging and discharging in the case of the PHEV test setup. The algorithm can be described by simplified block diagram format as Fig. 3 illustrates.

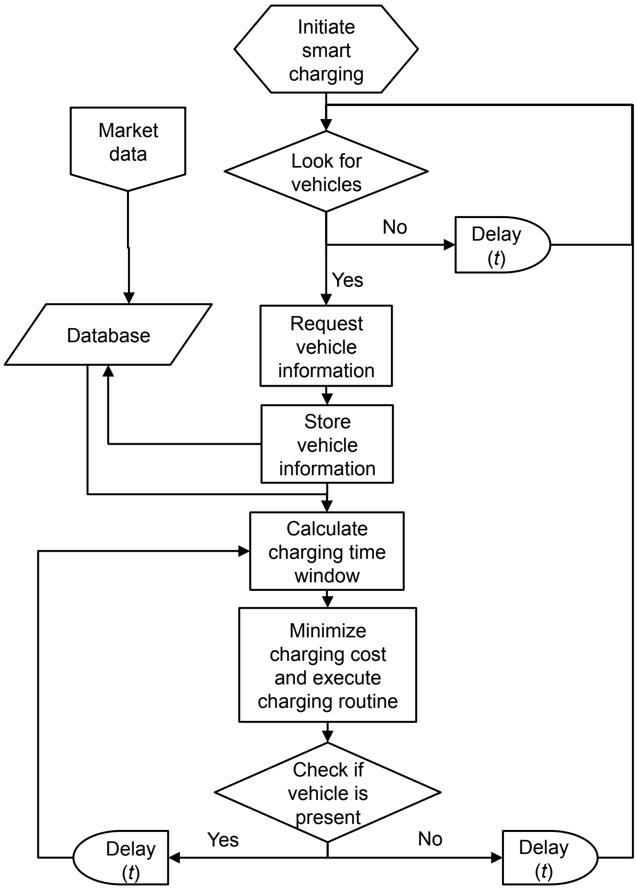


Fig. 3: Basic principle of the smart charging algorithm.

The charging control diagram does not describe the whole test procedure, as there are some stochastic sampling involved as well. The driving behavior is modeled rather than actually conducted by driving the vehicle. The actual vehicle usage could have lead to behavior that does not present average vehicle user. The more suitable solution is to synthetize driving behavior by sampling random events from the distributions acquired from the National Travel Survey conducted in Finland.

The travel survey can provide distribution for departures from certain typical trips such as from homes to working places or grocery stores. The daily driving distribution can be acquired as a sum of all the trips during a day. The data consist of thousands events collected during years 2010 –2011. Fig. 4 illustrates cumulative distribution of trip lengths used in synthetizing driving cycles.

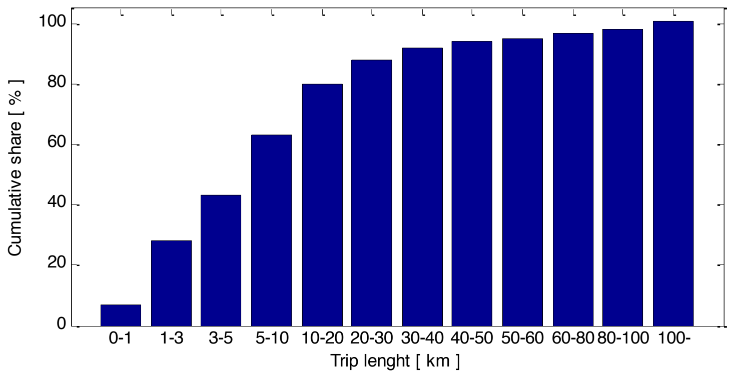


Fig. 4: Cumulative distribution of trip lengths driven in Finland. 80% of daily trips are less than 20 km.

Pilot system in the operation

The system has been in operation for a week. The main purpose of the demonstration was to test algorithm and communication, in practice. The vehicle was not driven during the test period so that the battery could be discharged at any time by the V2G function. In addition, the vehicle was held in controlled environment to ensure safe operation of the charging system. The driving does not give any surplus value for the test. In addition, the synthetized driving cycles can be assumed to represent average driver better than researcher driving the car. The driven mileage was randomized based on the NTS data by extracting distributions of average behavior and then sampling event from the distribution. The average daily total mileage in Finland is around 50 km/d per car, but for persons driving a car average total mileage is about 29 km/day/person. There are more than 4 million persons whom are considered in NTS study and about 2 million cars in Finland, thus mileage for the car is higher than average mileage per person driving a car.

The charging window was set to be randomly sampled, similarly as the mileage. Distributions were acquired from the NTS data and time of return was then randomly sampled. The “ready time” was set to 7 am to ensure that the car is fully charged when departure should happen.

Table I: The charging assumption.

Vehicle user type	Average workign person (defined due to random sampling)
Charging place	Home
Charging power	3 kW (nomimal)
Charging 'ready time'	7 am
Charing scheme	Electricty cost minimization
Price signal	Finnish area price (Nord Pool Spot)

The charging control algorithm was executed on MATLAB workstation that was operating as centralized control for the vehicles. The smart charging test was conducted over a week test period and data was collected during that time. Fig. 5 shows charging power over the week test period.

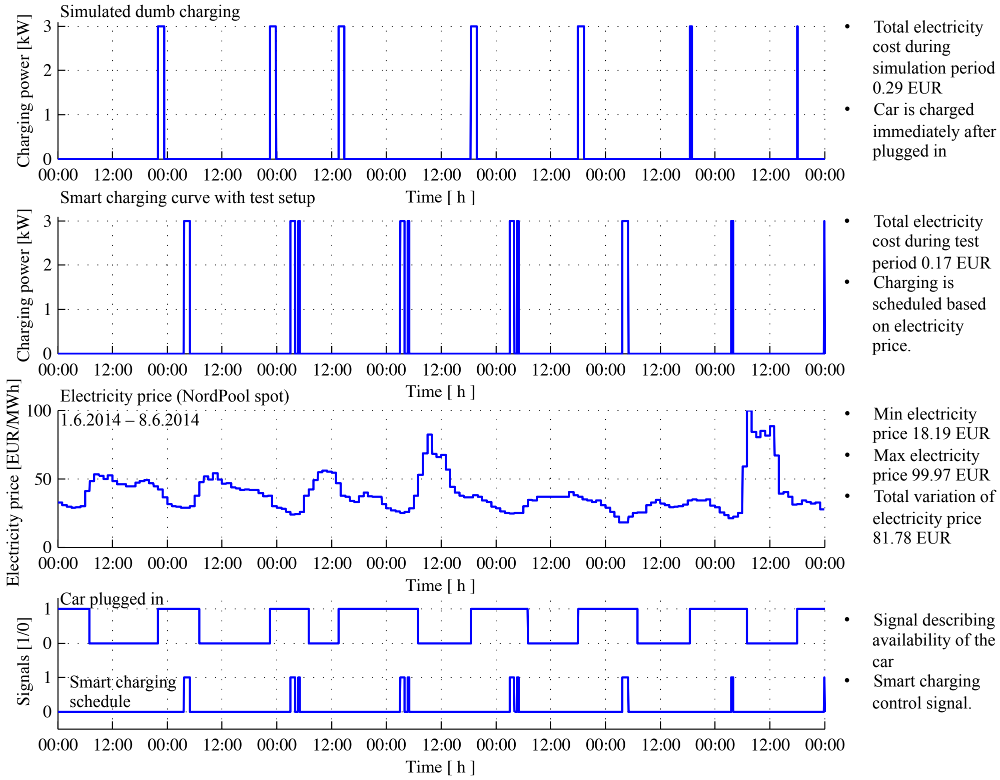


Fig. 5: EV charging curve over test period of a week.

In the first graph of the Figure 5 is shown simulated dumb charging strategy as a reference. The actual smart charging strategy conducted on the test bed is shown on second graph from top. It can be noticed that in the dumb charging scheme it is assumed that car is charged immediately after plugging in by nominal power of 3 kW. The total electricity cost in the case of the simulated dumb charging is 0.29 € per week. The actual smart charging scheme tested on the test setup resulted total electricity cost of 0.17 € per week.

In the smart charging strategy it is assumed, that the charging takes place when the Nord Pool Spot price is at the lowest and charging window is met. If demand of the charging energy is higher that can be charged during an hour, the second charging event takes place when the Nord Pool Spot price is at the second lowest level, and charging window is met. The length of the charging event changes as the charging demand is different for each day.

The total saving potential can be estimated based on the assumption that EV would have been charged right after arrival to the charging pole. The total saving of the test period is 0.11 €/week, equaling 6 €/a. It must be borne in mind that the saving potential is highly dependent on the electricity cost variation, and such a generalization of the annual saving potential should not be interpreted as the one and only truth, but more like guideline showing roughly what the saving potential could be. The more relevant result is the validation of the control strategy, which has been shown to operate over test period. Initial testing before the week test period showed, that communication and error handling is of great importance in the smart charging applications. For instance, the communication system and applications must be capable of handling short disturbances in the communication network. The latency of the communication line was not in critical role in the case test, but should be investigated more carefully for the applications that are more time critical.

Brief Discussion of the Conflict of Interests

There exists a conflict of interest between the DSO and the electricity retailer. In the Nordic countries, the DSOs operate in a monopoly position under a national regulation model, but the electricity retail market is liberalized since 1995 in Finland. It is in the DSO's interest to aim at the highest possible peak operating time, and thus, the grid should be exploited as effectively as possible, even though the reformed structure of the wholesale market has decreased the incentive to directly control loads [14]. On the other hand, electricity retailers probably have different goals depending on the product they are offering. For instance, balance settlement would create an incentive to control some of the loads to find a balance between the estimated and realized consumption or end users electricity cost minimization many cause high peak load to distribution grid. These goals are not usually in line with the DSO's load control targets that are based on the grid load.

The electricity retailer could have an incentive to control loads in the case of some unusual or unpredicted change in the consumption. The electricity retailers operate in a day-ahead market, and thus, the load has to be forecasted a day before the consumption takes place. The load forecast accuracy may be affected by several factors; for instance, adverse weather or an accident may cause traffic jams, and thus, people may arrive home later than expected. There has to be a balance between the consumption and the forecast to maximize the retailer's profit; to this end, the load control of the EVs would provide an ideal opportunity to shift loads to meet the forecasted load as closely as possible. Or in case cost minimization load forecast problem might even vanish. If the base load is shifted several hours later, probably there are few EVs already in the area waiting to be charged. On the other hand, the electricity retailer might aim at a positive error if the power balance in the grid requires down-regulation. If excess power is bid into the regulation market, the profit may be higher than the matching consumption forecast would have delivered. The described control scheme could be seen as a demand response power resource. The paper focuses on investigating a control scheme that aims at the lowest spot price of electricity, but in future, the actual control might be dependent in several other factors also. The question of further studies is: what are products electricity retailer can offer for the end user?

Results

The main result of the paper is the description of the fully operating smart charging system in laboratory environment. The results also show that the smart charging strategy tested in the paper can be implemented with only a few data sources. Operation of the charging strategy aiming at lowest electricity is proven to be functional. However, feasibility of the charging strategy cannot be well justified. The overall saving in the charging cost over a week test period was 0.11 €. In comparison to system cost savings are nearly irrelevant and highly dependent on electricity price.

Conclusion

The paper describes charging strategy aiming at electricity cost minimization conducted on smart charging test bed.
As a main result, the smart charging strategy is shown to be operating on actual test vehicle. Furthermore, the results suggest that savings earned by using the charging strategy aiming at lowest electricity price are negligible. But if considered in larger scale, also the electricity retailer may have interest into controlling of the charging. For instance, demand response applications may emerge as new opportunities in field of

smart charging. The system described in the paper could be operated based on the aggregator's commands, but also working on its own. To conclude, the paper delivered early stage description of the smart charging test bed and described simple smart charging strategy in operation. It is question of further studies, what kind of control strategies should be tested and what communication should exist between EVs (or energy storages, in general) and related data sources. The testing period emerged question of charging power estimation, because charging power is highly dependent on environment condition. In the case presented in the paper, tests were conducted in well-controlled environment. In practice ambient temperature may vary, and therefore, result decreased charging power due to restrictions posed by the LiFePo cells. It is question in the further studies: how charging power should be estimated and could heating be used to compensate ambient temperature changes?

References

[1] Electric Vehicles In Finland - Report (Sähköajoneuvot Suomessa –selvitys) 6 Aug.2009, Biomeri Oy, Ministry of Transport and Communications, [Online]. Available: http://www.tem.fi/files/24099/ Sahkoajoneuvot_ Suomessa-selvitys.pdf, (In Finnish).

[2] V. Tikka, J. Lassila, J. Haakana, J. Partanen, "Case study of the effects of electric vehicle charging on grid loads in an urban area," in *Proc. Innovative Smart Grid Technologies (ISGT Europe), 2011 2nd IEEE PES International Conference and Exhibition on*, pp.1–7.

[3] V. Tikka, J. Lassila, H. Makkonen, J. Partanen, "Case study of the Load Demand of Electric Vehicle Charging and optimal Charging Schemes in an urban area," *Innovative Smart Grid Technologies (ISGT Europe), 2012 3nd IEEE PES International Conference and Exhibition on*, pp.1-7.

[4] N. Belonogova, T. Kaipia, J. Lassila, J. Partanen, Demand response: conflict between distribution system operator and retailer, *21nd International Conference on Electricity Distribution (CIRED),* Frankfurt, 6-9 June 2011

[5] National Travel Survey 2010-2011, (Henkilöliikennetutkimus 2010–2011), Finnish Transport Agency, Transport Planning. Helsinki 2012, ISBN 978-952-255-102-3,(In Finnish).

[6] R.A. Verzijlbergh, M.O.W. Grond, Z. Lukszo, J.G. Slootweg, M.D. Ilic, "Network Impacts and Cost Savings of Controlled EV Charging," *Smart Grid, IEEE Transactions on* , vol.3, no.3, pp.1203,1212, Sept. 2012

[7] A, Rautiainen, S. Repo, P. Järventausta, A. Mutanen, Statistical charging load modelling of PHEVs in electricity distribution networks using National Travel Survey data, Rep., 2011, Tampere University of Technology.

[8] J. Lassila, T. Kaipia, J. Haakana, J. Partanen, P. Järventausta, A. Rautiainen, M. Marttila, and O. Auvinen, "Electric Cars – Challenge or Opportunity for the Electricity Distribution Infrastructure?" *European Conference on Smart Grids and Mobility*, Würzburg, Germany, 2009.

[9] J. Lassila, J. Haakana, V. Tikka, J. Partanen, "Methodology to Analyze the Economic Effects of Electric Cars as Energy Storages," *Smart Grid, IEEE Transactions on* , vol.3, no.1, pp.506,516, March 2012

[10] Xing Yuhui, Zhu Guiping, "Charging power forecasting for electric vehicle based on statistical model," *Electricity Distribution (CICED), 2012 China International Conference on*, 10-14 Sept. 2012

[11] F.J. Soares, J.A. Peas Lopes, P.M.R. Almeida, "A Monte Carlo method to evaluate electric vehicles impacts in distribution networks," *Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES), 2010 IEEE Conference on*, 27-29 Sept. 2010

[12] NordPoolSpot, "Nord Pool Spot," 15.5.2014. [Online]. Available: http://www.nordpoolspot.com/How-does-it-work/Day-ahead-market-Elspot-/. [Accessed 15.5.2014].

[13] H. Makkonen, V. Tikka, J. Lassila, J. Partanen, P. Silventoinen, "Demonstration of smart charging interface in LUT Green Campus", The 16th European Conference on Power Electronics and Applications (EPE 14), Lappeenranta, Finland, 26-28 August 2014

[14] N. Belonogova, P. Valtonen, J. Tuunanen, H. Honkapuro, J. Partanen, Impact of market-based residential load control on the distribution network business, *22nd International Conference on Electricity Distribution (CIRED),* Stockholm, 10-13 June 2013

Publication VI

Markkula, J., Tikka, V., and Järventausta, P.
Local versus centralized control of flexible loads in power grid

Reprinted with permission from
CIRED 2021—The 26th International Conference and Exhibition on Electricity Distribution
Online conference, 2021

LOCAL VERSUS CENTRALIZED CONTROL OF FLEXBILE LOADS IN POWER GRID

Joni Markkula[1], Ville Tikka[2], Pertti Järventausta[1]

[1]*Faculty of Information Technology and Communication Sciences, Tampere University, Tampere, Finland*
[2]*Laboratory of Electricity Market and Power systems, School of Energy Systems, Lappeenranta-Lahti University of Technology LUT, Lappeenranta, Finland*
**joni.markkula@tuni.fi*

Keywords: ELECTRIC VEHICLE, BATTERY, FREQUENCY, RESERVE, DEMAND RESPONSE

Abstract

Electric vehicle (EV) charging and their batteries are recognized as a future solution for power system demand flexibility but also a potential source of problems for the network due to increasing power requirements in new locations. In either case the amount of EVs will grow and the amount of available energy storage with them. EV batteries can provide the necessary energy storage in distributed, variable power generation networks where wind and solar power are used in larger scale and increase grid's ability to handle higher share of variable renewable energy (VRE) production. Operating EV batteries as controllable storages without major downsides has it challenges. In this study three different strategies of controlling EV charging power based on grid frequency are compared: 1. utilizing distribution system operator's (DSO) existing metering infrastructure, 2. using centralized measurement with dedicated flexibility server, and 3. using local measurement and control. In our testing, operating through the DSO infrastructure caused significant delays and prevents EV's batteries to be offered on the primary reserve markets with given conditions. The dedicated systems built for EV charging power control offers faster response, more reliability and control.

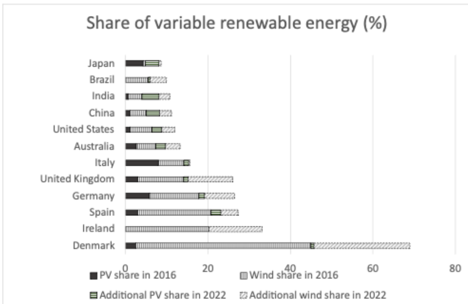
1. Introduction

In 2019, the total number of plug-in hybrids and full electric vehicles was over 7 million [1], and scenarios expect the number to grow somewhere between 150 and 250 million by 2030. This will be one of the main drivers to increase lithium-ion battery production from 300 GWh to 2000 GWh per year [2]. The production ramp up in the past decade has already reduced the prices of batteries at an incredible speed dropping from 668 \$/kWh to 137 \$/kWh during 2013-2020 which is on average 20% price decrease per year and the development is continuing, pushing battery prices below 100\$/kWh [3]. This development makes battery energy storages (BESS) suitable for new applications. Dedicated BESS systems and EV batteries together are creating new energy storage capacity for the power grid. *How much energy storages now in the world? How much wind and solar? How much storage is needed for them?*

At the same time variable renewable energy (VRE) production is growing quickly and thus power system will require flexible consumption, energy storages or in best case both. In some cases, VRE might account for over half of the annual energy production, and more often there will be growing number of hours during the year where VRE portion is significant (see picture 1) [4]. This added to the EV charging that is projected to require up to 6-9% of peak electricity demand [5].

To avoid the foreseeable problem different flexibility options and energy storages have been proposed [maybe source]. The advancements in telecommunication and remotely controlled systems can provide cost-effective way of tackling the future problems.

Finland's power system has a well-developed Supervisory control and data acquisition (SCADA), automatic meter reading (AMR) and mobile telecommunication infrastructure. These together provide a test platform where different kinds of remote-control mechanisms can be examined within real, operational systems.



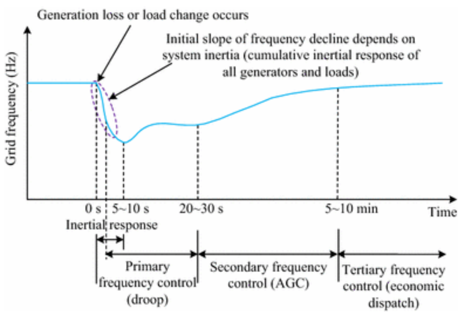
Picture 1: Variable renewable energy in power system in selected countries [4]

2. Demand response markets

Demand side flexibility and energy storages provide value for several actors in the power system: customers can limit their connection power, size of fuses or their energy bill, energy retailers can keep their hourly balances in check, distribution system operators (DSO) can avoid investment costs and interruptions, and transmission system operators (TSO) can maintain the power balance in the grid even in rapid, unexpected changes. This study concentrates on TSO frequency containment markets as it currently has the highest financial value. Finnish TSO, Fingrid, has open frequency containment markets and large, unified markets under construction for Central Europe [6,7].

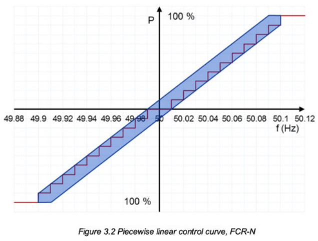
2.1. TSO frequency containment markets

Power system frequency indicates the balance between electricity consumption and production. When there is more consumption in the system than production, the grid frequency decreases. In the same way, if there is more production than consumption, the frequency increases. The frequency is essentially the same in all points of the grid and every generator and load contributes to the frequency.
What is special about frequency containment reserves, is that the first response to frequency changes must be fast and accurate in order to prevent further frequency deviation and restore the system power balance. The grid frequency is always changing as production and consumption vary and normally this deviation is small (+/- 0.05 Hz). The grid frequency is kept close to nominal by adjusting production capacity and the final responsible party is TSO for maintaining the system frequency. The different response times and classification of inertial, primary, secondary and tertiary control is found in picture 2.



Picture 2: Power system reaction to changes in grid frequency [8]

Finnish and also European frequency reserve markets consist of three categories: 1. Fast Frequency reserves FFR (e.g. 0.7-1.3s activation time), 2. Frequency Containment Reserves for Normal operation (FCR-N) that are meant to keep the frequency close to nominal value (activation in seconds), and 3. Frequency Containment Reserve for Disturbances (FCR-D), which is meant to be used to when frequency has deviated too far from nominal value and larger actions need to be taken (activation during 3-30 s). All of these Frequency Containment Reserves act automatically based on preset rules and contracts.
Automatic frequency reserves are activated on daily basis and the volumes for the markets are in the scale of hundreds of megawatts per reserve type in the Nordics. Picture 3 shows in graphical form the ramp up/down curve that is required from systems participating in automatic frequency containment market. Relay controlled loads can have stepwise sloping when it stays within required limits. FCR-D has dead-band area between 49.9-50.1 Hz and FCR-N deadband of +/- 0.01 Hz.



Picture 3: FCR-N frequency [9]

The value of yearly contract for the FCR markets is presented in table 1.

Table 1: frequency reserve yearly market [10]

	FCR-N volume (MW)	FCR-N price (€/MW,h)	FCR-D volume (MW)	FCR-D price (€/MW,h)
2017	55	13,00	455,7	4,70
2018	72,6	14,00	435,0	2,80
2019	79	13,50	445,6	2,40
2020	87,1	13,20	458,3	1,90
2021	105,8	12,50	425,0	1,80

Also the hourly market for both exists and the average hourly market value of FCR-N during 2020 in Finland was 20,83 €/MW,h and average volume was 34,6 MW. Thus providing +/- 1kW of flexibility for every hour of the year to the FCR-N market would yield ca. 180 € income for provider. EV controllable power could be much higher than 1 kW but on the other hand it wouldn't be all the time available. This extra income is the motivator for EV charging control as it technically feasible to implement.

3. Methodology

3.1. Vehicles

Measurements were conducted with commercially available equipment. To measure the charging power behaviour in real life, four different passenger EVs were tested in first two cases: Tesla Model S (3x16 A), Nissan Leaf (1x16A), Opel Ampera (1x16A), Mitsubishi Outlander (1x16A). All vehicle batteries were depleted to 30-70% state of charge so that the batteries wouldn't limit the charging current. The temperature outside was about +5°C and it was not limiting the charging current which was tested before testing started. All vehicles had IEC 61851 compliant chargers. In the last test Volvo V60 plugin hybrid was used.

3.2. Electric Vehicle Supply Equipment (EVSE)

The EVSE in use was Ensto ECV100, which has IEC61851 compliant proprietary controller and RS-485 interface for external load management signals. Requirements for passenger EV chargers are defined in IEC 61851 (communication protocols) and ISO 62196-2 (plugs and sockets) standard. IEC 61851 standard describes the analog sequence which is needed to initiate the charging process and the PWM modulation that enables the charger's controller to give maximum current limit instructions to EV charger. The IEC 61851 defines the following values for dynamic power regulation events during the charging:

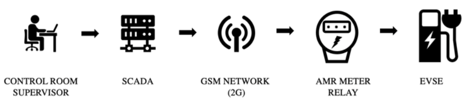
- External system to EVSE PWM max duration: 10 s
- EVSE PWM to vehicle on board charger current change: max 5 s
- Termination of energy supply when pilot contact is opened: 100ms
- Stop charger current draw: 3 s

The standard leaves quite much flexibility for EVSE and EV manufacturers to make their own decisions on the ramp up/down times, expect when pilot contact is lost which is a safety related feature. [11].

3.3. Test setups

Tests were conducted with three different setups: 1. DSO's AMR infrastructure with GPRS modem connection, 2. Centralized frequency measurement and control with dedicated service, and 3. With fully local control.

Test 1 - Distribution System Operator infrastructure: First tests were run through the DSO provided SCADA and AMR infrastructure, where AMR meter remote controllable relay would be used as input to computer IO pin and transformed into RS-485 message for EVSE controller, which outputs required PWM signal.



Picture 4: DSO's control infrastructure

Test 2 - Centralized measurement and control over internet:
Custom made electronics was created in order to consider, how local frequency measurement could be done cost effectively for a large number of devices. Electronics bill of materials cost for this was ca. 3 euros. Power system frequency was verified with a Fluke 83 multimeter that provides 0.01 Hz frequency accuracy which would be sufficient for actual use also.

Test 3 - Local measurement and control: Third testing was using Siemens Sentron PAC 3200 frequency measurement device and power limitation signal was fed directly to the charger controller which provided the PWM for EV.

3.4. Locally controlled vs remote system

The benefits of locally operating systems are that it is not dependent on remote data connections and response times are faster. The disadvantages are the cost of implementing frequency measurements on every device and creating the direct connection to EVSE controller instead of back office service. These add up costs, but also provide speed and independence, which adds resilience to the system.

4. Results

4.1. Charging power control with DSO's infrastructure

First test with DSO's AMR infrastructure showed that GPRS network and SCADA systems create delays that are documented in tables 2 and 3. "DSO delay" means the duration, how long it took from the manual triggering on DSO control room to AMR relay state change, "Start of ramp" means when charging power has changed over 10% from existing value, and "Power final" means when power is within 10% of the new, given setpoint (i.e. 6A or "max").

Table 2: Decrease charging power

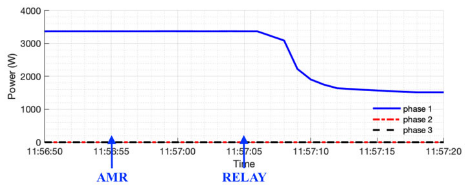
	Ampera	Leaf	Outlander	Tesla
DSO delay	10 s	6 s	12 s	13 s
Start of ramp	4 s	3 s	4 s	4 s
Final power	2 s	1 s	2 s	2 s
TOTAL	**16 s**	**10 s**	**18 s**	**19 s**

Table 3: Increase charging power

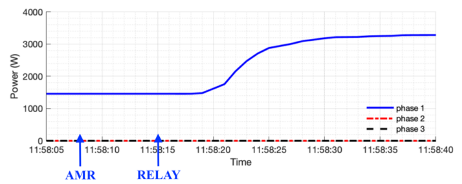
	Ampera	Leaf	Outlander	Tesla
DSO delay	7 s	10 s	13 s	11 s
Start of ramp	6 s	4 s	4 s	8 s
Final power	5 s	2 s	2 s	12 s*
TOTAL	**18 s**	**16 s**	**19 s**	**31 s**

** charger's three phases were not in sync, see picture 12*

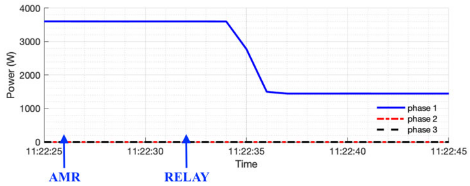
Vehicle specific charging power curves are presented in pictures 5-12. Manual trigger signal is marked as "AMR" text, and relay activation as "RELAY" text in the picture.



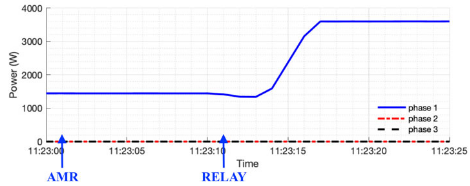
Picture 5: Opel Ampera down



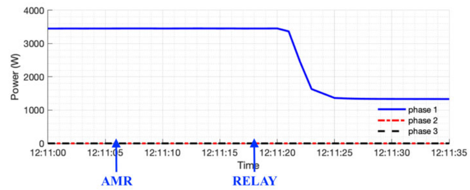
Picture 6: Opel Ampera up



Picture 7: Nissan Leaf down

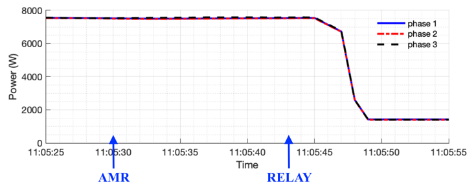


Picture 8: Nissan Leaf up

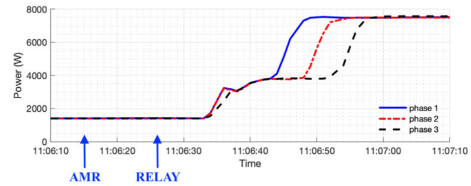


Picture 9: Mitsubishi Outlander down

Picture 10: Mitsubishi Outlander up



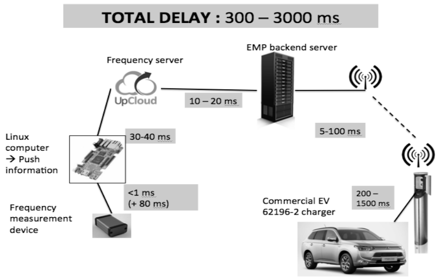
Picture 11: Tesla Model S down



Picture 12: Tesla Model S up

4.2. Centralized frequency measurement, dedicated EV power control server

Second tests were done with frequency monitoring hardware and micro-service built for EV load management. Test setup with delays is shown in picture 13.

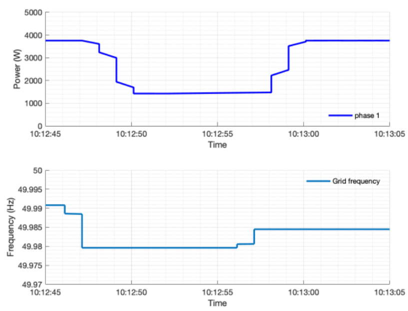


Picture 13: From frequency measurement to EV power control on dedicated platform

Compared to previous test, the DSO delay was replaced by delay from dedicated flexibility system, and was cut from 6-13s to ca. 2s. The delay from frequency measurement to PWM control signal was varying between 0.3 and 3 seconds. This change alone, with the added controllability and possibility to get feedback from EVSE meets the criteria of primary frequency reserve markets.

4.3. Control with local measurement and local control

Last test was done with Volvo V60 plugin hybrid. Frequency limit was set to be 49.98 Hz for signal automation for testing purposes. The response pattern is show in picture 14.



Picture 14: Volvo V60 plug-in hybrid

Response from observed frequency deviation to start of ramp was only 1 second and final value was achieved in 3 seconds on power down and 4 seconds in power up events. Also it is noteworthy that in local setup the delays do not change based on internet traffic duration.

5. CONCLUSION

The flexibility market is open for new service providers and market model offers quite easy access to reserve markets. In present situation investments to EV batteries and the charger infrastructure are made, independent of possible smart charging cash flows. Thus, the income from demand response provides additional value to charging service users and providers. Demand response financial value is at its highest on the primary market, where power adjustment speed requirement is measured in seconds.
Electric vehicles battery response times were benchmarked against two Frequency Containment Reserves: FCR-N, where reserves must be in use within 3 minutes and follow the change of frequency linearly or stepwise linearly, and FCR-D where reserves must activate within 5 seconds and provide full power in 30 seconds.
This study showed that EVs can be used as part of primary reserves (FCR markets) in power system when used with local control, and in some cases with dedicated demand response infrastructure (measurement, servers, services, telecom). Using existing AMR infrastructure from DSO created delays that currently do not allow providing EV batteries' flexibility on primary reserve markets.
What is needed is a socket based, constantly open, communication path if EV demand response is controlled by a central system. GSM network latencies vary greatly and the limited reliability of GSM connections must be taken into account when planning the system. Varying latencies do bring some benefits in the form of unintended randomization of up and down regulations, but the latencies must be well understood when designing the system for real use.

6. DISCUSSION

In the future we expect better network connections, e.g. 5G, to help with real time control of demand response resources. Also the EVSE and EV manufacturers presumably will shave off seconds from the delays where it is easy. DSOs could be helping with providing easy access to customer's equipment with their existing infrastructure, but that would require interfaces to give control of the customer devices to third parties. These interfaces don't exist at the moment but are in development.

7. References

[1] IEA (2020), Global EV Outlook 2020, IEA, Paris

[2] Bloomberg article: "Global Demand for Batteries Multiplies" fetched 19.12.2020 from https://www.bloomberg.com/news/articles/2018-12-21/global-demand-for-batteries-multiplies

[3] BNEF, https://about.bnef.com/blog/battery-pack-prices-cited-below-100-kwh-for-the-first-time-in-2020-while-market-average-sits-at-137-kwh/

[4] IEA, VRE share in annual electricity generation in selected countries, 2016-2022, IEA, Paris https://www.iea.org/data-and-statistics/charts/vre-share-in-annual-electricity-generation-in-selected-countries-2016-2022

[5] IEA, Contribution of electric vehicles to hourly peak demand by country and region in the evening and night charging cases in the Sustainable Development Scenario, 2030, IEA, Paris https://www.iea.org/data-and-statistics/charts/contribution-of-electric-vehicles-to-hourly-peak-demand-by-country-and-region-in-the-evening-and-night-charging-cases-in-the-sustainable-development-scenario-2030

[6] Commission Regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing

[7] Entso-E. Frequency Containment Reserves (FCR). Retrieved on 15.2.2021 from https://www.entsoe.eu/network_codes/eb/fcr/

[8] WU, Z., GAO, W., GAO, T. et al. State-of-the-art review on frequency response of wind power plants in power systems. J. Mod. Power Syst. Clean Energy 6, 1–16 (2018). https://doi.org/10.1007/s40565-017-0315-y

[9] Fingrid FCR, Appendix 2 to the Yearly Market Agreement: The technical requirements and the prequalification process of Frequency Containment Reserves (FCR)

[10] Fingrid. Frequency containment reserves (FCR-N, FCR-D), transactions in the hourly and yearly markets. 2021. fetched 25.1.2021 from https://www.fingrid.fi/en/electricity-market/electricity-market-information/reserve-market-information/frequency-controlled-disturbance-reserve/

[11] IEC61851 Electric Vehicle Conductive Charging System part 1. 2017

Publication VII

Tikka, V., Haapaniemi, J., Räisänen, O., and Honkapuro, S.
Convolutional neural networks in estimating the spatial distribution of electric vehicles to support electricity grid planning

Reprinted with permission from
Applied Energy
328, pp. 120–124, 2022

Applied Energy 328 (2022) 120124

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Convolutional neural networks in estimating the spatial distribution of electric vehicles to support electricity grid planning

Ville Tikka *, Jouni Haapaniemi, Otto Räisänen, Samuli Honkapuro

LUT School of Energy Systems, Yliopistonkatu 34, Lappeenranta, 53850, Finland

ARTICLE INFO

MSC:
0000
1111

Keywords:
Electric vehicle
Deep learning
Electricity distribution
Convolutional neural network
Socioeconomics

ABSTRACT

From the perspective of electricity distribution networks and the energy system, the increasing numbers of electric vehicles are among the most topical and challenging problems. The paper investigates a novel approach of a convolutional neural network-based modeling method for estimating the spatial distribution of electric vehicles. The proposed model extracts features from multilayer socioeconomic input raster data that are sequenced in strides and outputs a spatial estimation of EV distribution. Spatial forecasting or area forecasting is at the core of the distribution system operators' planning and development process as it provides a solid foundation for stochastic load modeling and load development analysis. Present models mostly focus on stochastic load modeling, lacking the spatial forecasting aspect of EV distribution. The proposed model aims to enhance EV load modeling by providing a more accurate spatial approach to the models. The study uses large actual socioeconomic and vehicle registration data sets to tackle the modeling challenge. In comparison with previous studies on similar topics, the present study benefits from more samples resulting from an increase in the adoption of electric vehicles. The proposed model architecture performs adequately in predicting a spatial electric vehicle distribution; the CNN model reached a weighted average precision score of 0.91. The proposed methodology greatly enhances stochastic EV load modeling by providing a good spatial forecast of the initial EV locations, and the results can be further aggregated to support the electricity distribution system planning process. An energy-, material-, and cost-efficient electricity distribution system is the backbone of the modern energy system.

1. Introduction

There is a growing global awareness of climate change, and technological advances to mitigate global warming are becoming widely available. Climate change, the key driver of the changing operational environment, has triggered energy policy actions such as the Paris Agreement [1] and the EU net zero greenhouse gas emission target by 2050 [2]. From the perspective of electricity distribution networks, the increasing numbers of EVs are among the most topical and challenging problems. The effects of EVs on the power system and especially on the electricity distribution are known to cause major renovation needs [3, 4]. In order to manage and optimize grid reinforcement investments, it is essential to be aware of the spatial distribution of EVs. EVs are also known to be able to provide substantial amounts of flexibility if their market entry is made possible [5], but without accurate spatial distribution estimates, this flexibility resource may not be utilized in full. European EV sales have doubled for several years in a row. Fig. 1 shows the rapid increase in Finnish EV sales over the past few years. The spatial distribution of EVs is heavily centered on the capital region and a few other larger cities in Finland. Furthermore, many governments and public bodies have set their own targets for electric traffic. For example, the Finnish target is 700 000 EVs on the road by 2030 [6] (the total number of cars registered in Finland was 2.7 million at the end of 2020). According to the International Energy Agency (IEA), approximately 3 million EVs were sold globally in 2020, and it is estimated that there will be 145 million EVs on the road by 2030 [7].

1.1. Modeling challenge

As the number of EVs is growing, it will be increasingly important to be able to accurately model distribution grids with EV charging loads included. The charging load of an EV has numerous similarities with loads presently connected to the grid, but the behavior of an EV load is very different as the load can connect to the grid at different locations and times. In order to properly model the effects of such loads on the distribution grid, it is essential to be aware of the home location or region of the EV. The planning process of a distribution system operator

* Corresponding author.
E-mail address: ville.tikka@lut.fi (V. Tikka).

https://doi.org/10.1016/j.apenergy.2022.120124
Received 22 June 2022; Received in revised form 21 September 2022; Accepted 6 October 2022
Available online 22 October 2022

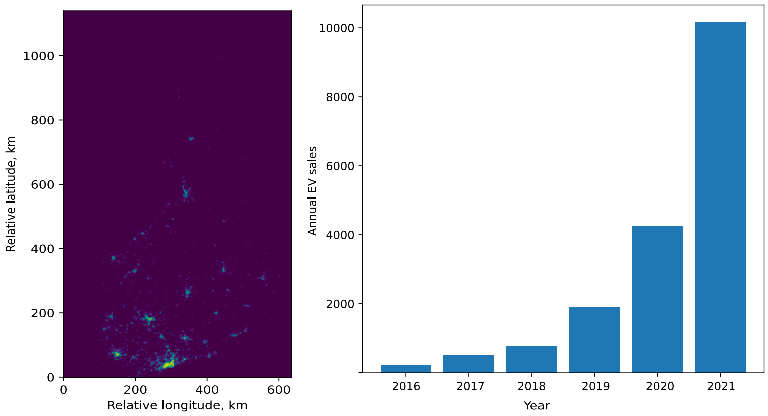


Fig. 1. Spatial distribution of the registered EVs at the end of 2020 and annual EV sales (2016–2021).

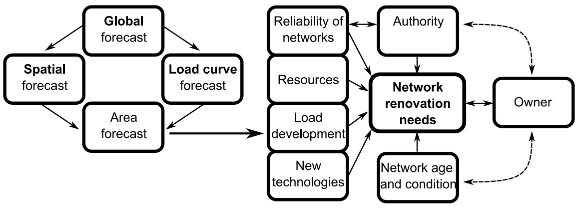


Fig. 2. Simplified illustration of the DSO network renovation drivers and spatial load forecasting.
Source: Adapted from [8,9].

(DSO) relies strongly on several data resources from different entities. Data mining and data processing are at the core of an efficient asset management process in the current and future operational environments. Fig. 2 illustrates the main drivers of the DSO network planning operation. A distinctive characteristic of the process is that it is fed with a lot of data that are processed with stochastic processing methods, other probabilistic methods, and time series analysis. As the role of EV charging loads is growing, it is reasonable to investigate which tools can be used to maintain the network planning process as efficient as possible.

There are resources for estimating the current spatial distribution of EVs, such as national statistics or surveys dedicated to specific case areas. Approaches of this kind require access to data resources that are often difficult to reach outside academic institutions, creating barriers to making efficient estimations and models for distribution grid development. In [10,11], it is suggested that the spatial distribution of EVs or plug-in hybrid electric vehicles (PHEVs) can be estimated based on socioeconomic raster data from public data, which can be available as open or semiopen data (e.g., available for a charge, or the availability is restricted only to educational institutions). The proposed methods rely on self-organizing maps [12] employed in regression models. A regression-model-based method results in fairly good outcomes in forecasting, but it disregards relations that the geographically neighboring features may have. The presence of the ‘‘neighborhood effect’’ was shown in a study using a spatio-temporal approach [13]. In practice, regression models build regression factors node by node or based on more sophisticated methods, such as clustering. An approach of this kind is not capable of including features of nearby areas that may have an impact on the area under observation. Regardless of the performance of the models presented previously for instance in [10,11], and [13], it is worthwhile to study the performance of the latest tools and methods available to grasp the issue. Studies in other fields of science have shown promising results on very similar problem sets that can be seen to have an analogy to the modeling of the spatial distribution of EVs based on multivariate input features. Geographical patterns or other spatially distributed features can be used to build models that are capable of weighting properties beyond a single local observation point. For instance, a study on species distribution modeling shows the benefits of a CNN in spatial distribution modeling [14]. The CNN is a deep learning technique, which is a subclass of the more general artificial neural network (ANN). There are many resources and frameworks, such as Keras [15], Tensorflow [16], or PyTorch, [17], which make the use of deep learning tools easy and efficient. CNNs are typically used to analyze visual imagery [18] or to build machine learning models related to visually perceivable features [19].

1.2. Hypothesis

The main hypothesis of the study is that by training a neural network by limited-access proprietary data, it could be later used to forecast the spatial distribution of EVs using up-to-date open data resources. Furthermore, a data resource offers more accurate spatial granularity in comparison with open data sources. The study also reveals the overall performance of the CNN model in such a problem set. The novelty of the study lies in introducing a CNN-based modeling method for estimating the spatial distribution of EVs. The study also shows the benefits of maintaining a well-covered national socioeconomic raster data set. Compared with previous studies in the same

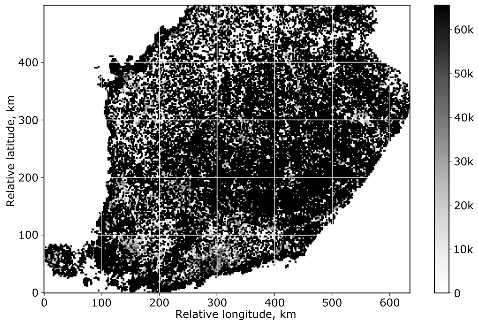


Fig. 3. Sample of spatially distributed socioeconomic data in southern Finland. The colormap in the figure represents households' median annual income.

geographical region in [10,11], the present study benefits from more samples as a result of further developed EV adoption.

1.3. Focus and outcomes

The study focuses on Finland and uses an open data set maintained by Statistics Finland [20] and proprietary access data from Traficom [21] and Statistics Finland. The primary dataset used for training the model includes geographical location information and properties of vehicles registered in Finland. The data intended for forecasting the spatial distribution of EVs in Finland include 109 socioeconomic features of Finnish households and population in a raster data format. Fig. 3 shows a sample of the spatially distributed data set in the capital region of Finland. The feature map shows clearly the areas where population is denser if only the sample number per node is drawn on the map.

As the main outcome, the study shows that the CNN model can be used to estimate and further forecast the spatial distribution of EVs in a case where large amounts of training data are available. The model performance with the present data set is acceptable, and based on the results, it seems to benefit from the information about the neighboring area. A direct comparison with other similar studies is not straightforward because of the different practices related to result outputs and model precision indicators. In addition, the studies [10,11] made several years ago did not have access to sufficient data resources as EV adoption was yet to begin, the novelty of the present study being thus in the data set applied. As the main result, the study shows that the CNN can extract spatial features from a large socioeconomic data set. The study does not, however, provide many tools for estimating the stochastic features of the spatially distributed output data as the data lack samples in history. Moreover, it still remains unknown if the model can be developed further to produce a better understanding of the stochastic properties of spatially distributed output data. The study focuses solely on spatial EV distribution forecasting, which provides a good starting point for the further stochastic analysis of EV charging loads. The outcomes of the study can be summarized as follows:

- The study demonstrates how the proposed CNN model can be applied to spatial EV distribution estimation.
- The proposed CNN model employs large actual national data sets for training and validation of the model.
- As the main outcome, the study shows that the proposed model can be used to extract beneficial features from socioeconomic raster data.

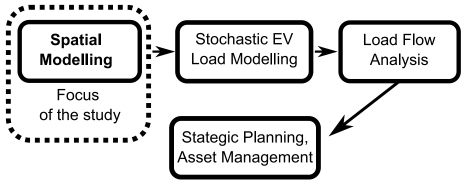


Fig. 4. Modeling process of incorporating the EV charging load in the strategic planning and asset management.

2. Background and source data

Modeling of the spatial distribution provides a solid foundation for more advanced EV charging load modeling and eventually, for the asset management of distribution grids. To fully grasp the rationale behind spatial modeling, one must understand the process of modeling load development that supports further decision-making in the distribution grids. Asset management is a complex process involving several inputs; nevertheless, load formation and load development are the key aspects in the process. Fig. 4 shows the simplified process flow of load modeling and highlights the main focus of the study.

Spatial modeling often gives a first estimation of how grid-connected loads are distributed in the case area. Estimations are typically based on multiple data streams, such as information on changes in socioeconomic factors, area development plans, and surveys of the geographical target area. The spatial information is used to develop area-specific load profiles further or to estimate changes in existing load curves. The load curve data are then used for the load flow analysis of the grid in its present state and for a prognosis for its future development, which can be exploited in grid development plans.

EV charging loads have unique characteristics, as they can connect to the grid in various locations. The proposed model provides a tool to estimate the initial locations or home locations of EVs. If the home locations of loads are known, they can be modeled based on the distributions of arrival and departure times and trip lengths of the EVs, and the technical boundaries of the connection point and the vehicle. Actual load profile modeling can be based, for instance, on simple stochastic models [22,23], neural network models [24], or agent-based models [25]. There are also various studies into EV charging modeling based on real measurement data, or studies that apply, for example, data provided by automatic meter reading (AMR) infrastructure [26] or measurements from EV charging stations [27]; moreover, a travel survey has been used as a basis for a modeling approach in [28]. The present study proposes a spatial modeling approach that could be combined with load profile modeling to further enhance area-specific estimations and forecasts related to EV charging.

2.1. Socioeconomic data

The study uses data sets describing the spatial distribution of population and households' socioeconomic features [20], as well as vehicle registration data maintained by the Finnish Transport and Communication Agency Traficom [21]. The study is geographically constrained by the national borders of Finland and uses an open data set maintained and provided by Statistics Finland [20] and proprietary access data from Traficom [21] and Statistics Finland. The study employs data resources that are specific to Finland as in that case, the data availability for academia is very smooth. The proposed method is, however, applicable to any other location as long as similar data resources are available. It is also noteworthy that in densely populated areas, the data might be even a better fit to train neural networks.

The raster data database is a large set of data describing the socioeconomic features of the Finnish population and households. The

Table 1
Socioeconomic data classes used in the study.

Data class	Variables in the data class
General variables, metadata	7
Population structure	24
Education structure	7
Inhabitants' disposable monetary income	7
Size and stage of life of a household	15
Households' disposable monetary income	7
Building and dwelling	8
Workplace structure	26
Main type of activity	7

data are available in 250 × 250 m, 1 × 1 km, and 5 × 5 km formats. For privacy reasons, the raster nodes including fewer than three or ten data points (depending on the data group) are filtered out. Finland is a sparsely populated country, averaging 18 people per square kilometer [20], whereas elsewhere in Europe, for instance, the average population density is 109 people per square kilometer [29]. Selecting too small a raster size results in a major data loss, as data nodes in the data set having fewer than ten occupants or five household registers are omitted from the data set for privacy reasons. In the present study, a 1 × 1 km data format was selected as it was considered reasonably accurate without a major data loss. The socioeconomic data used in the study can be divided into nine main classes as illustrated in Table 1.

The initial assumptions based on other studies suggest that the strongest correlation between the vehicle type and the willingness to invest in clean technology is evident in the variables describing the wealth and age structure of an area. For instance, according to [11], it is likely that a higher average income and a larger living space are among the variables that contribute to higher hybrid electric vehicle (HEV) adoption rates. This observation is supported also in other studies [30]. The input data set was analyzed by running a variance inflation factor (VIF) test on the data. The analysis showed that 99 out of 101 variables have a cross-correlation (VIF > 10).

The data set is organized in a raster format so that each node contains the number of items per variable or statistical parameter, such as the mean value or the median of the data points. The raster node is identified by a node ID and (x, y) axis values tied to the ETRS89-TMFIN35 coordinate system. Fig. 5 shows an example of data points in the data set.

Even though Finland is a sparsely populated country, the data set still has enough data points to present an outline of Finland in the map image. The data shown in the image also include data nodes that are omitted to ensure the privacy of the individuals. In the data set, the privacy-filtered items are labeled with a constant −1. In the modeling phase, the privacy filtering data marker is replaced by zero to avoid unwanted bias in the model.

2.2. Vehicle registration data

The vehicle registration data in Finland are available as open data without spatial identification information. In this study, the data set was generated by request by the Finnish Transport and Communication Agency Traficom [21]. The data set consists of all the same variables available in the open data from Traficom, but in addition, the data are aggregated into a 1 × 1 km grid raster data set defined by the ETRS89-TMFIN35 coordinate system. Fig. 6 shows a sample of the vehicle registration data in Finland.

The vehicle registration data cover the whole country. From the image, it is easy to observe the location of the main highway regions and larger cities. By browsing data with different zoom levels, layers, and combinations, it soon starts to seem obvious for the human eye that the data hold a lot of spatial information that is linked to other data layers. The sheer amount of data and information makes a further analysis impossible without sophisticated data mining methods. It is well known that CNNs have a superior performance in managing spatial data connecting features of several spatial data layers.

2.3. Theoretical background of the model

CNNs are often used for complex images or spatial data analysis because of the superior performance in spatial data handling. Variations of CNNs are used widely in research in multiple disciplines of science; for instance, machine vision applications employ CNN methods to recognize objects from raw images [31,32]. CNNs are also often applied in image classification systems [33], medical image analysis [34], image feature segmentation [35], data mining financial data series [36], and species distribution studies [14].

The CNN model structure can be divided into a convolution layer, a pooling layer, and a fully connected layer. Fig. 7 shows a simplified illustration of the CNN model that can be considered a reference model or a traditional model architecture. The model architecture often varies based on the application; for instance, the model can be enhanced with additional layers [37].

The model can also be considered to involve data engineering before convolution is applied to the input data. In the convolution layer, filters or kernels are applied to the input data, and the convolution layer may sometimes be termed as filtering. In practice, the convolution operation can reveal features such as edges, corners, or some other recognizable forms from the spatial image input data. In general, convolution can be defined as follows:

$$g(x, y) = \omega \times f(x, y) = \sum_{dx=-a}^{a} \sum_{dy=-b}^{b} \omega(dx, dy) f(x - dx, y - dy) \tag{1}$$

where $g(x, y)$ is the filtered image, $f(x, y)$ is the original image, and ω is the filter kernel. Every element of the filter kernel is considered by $-a \leq dx \leq a$ and $-b \leq dx \leq b$. Then, the convoluted feature maps are reduced in size in the pooling layer with nonlinear down-sampling, which can be formulated for instance as:

$$f(x, y)(S) = \max_{a,b=0}^{1} S_{2X+a,2Y+b}, \tag{2}$$

where S corresponds to the filter applied to the feature matrix f. The above-mentioned pooling function is max pooling, which is the most commonly used pooling method.

Finally, the pooling layers are flattened to a two-dimensional (2-D) form by fully connected layers and put through the activation functions to formulate a one-dimensional (1-D) output vector:

$$\mathbf{x}^l = g(\mathbf{w}^l \mathbf{x}^{l-1} \mathbf{b}^l), \tag{3}$$

where $\mathbf{w}^1$ and $\mathbf{b}^l$ denote the weight matrix and the bias vector, respectively.

3. Modeling

Similar to many other data mining studies, the validity of the input data plays a key role in the modeling. The data resources used in the present study are all validated by public organizations. For the model sanity check, also an ablation analysis is performed. The selected CNN model architecture presented in the study is very close to the standard or traditional CNN model.

3.1. Data preprocessing and feature engineering

The vehicle registration data are a list of registered vehicles with the vehicle properties presented as numerical and textual string values. The data are categorized by the EUREF-FIN coordinate system so that each data row has (x, y) coordinates. The raw data are reclassified into a raster data format, and thus, the data are presented as a matrix $\mathbf{Y} = (y_{n,m}) \in \mathbb{R}^{636\times1140}$.

The source data consist of information about the vehicle primary energy source, which can be used to categorize vehicles into internal combustion engine (ICE) vehicles, HEVs, PHEVs, and EVs. Each primary energy class of the vehicle is identified respectively by a variable

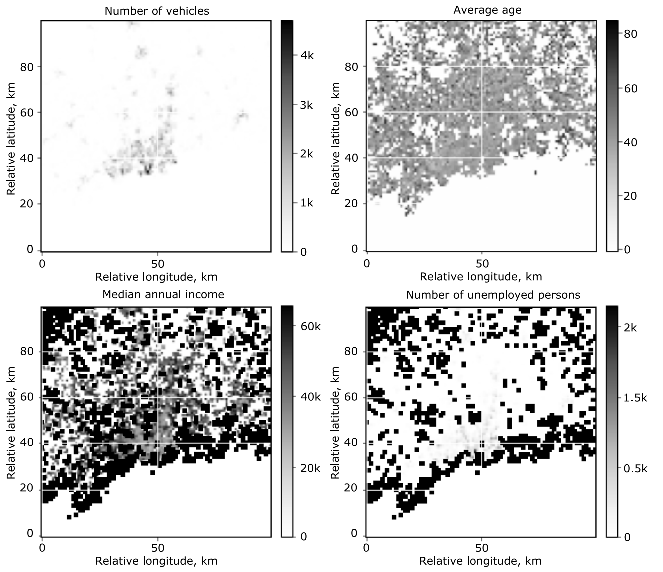


Fig. 5. Spatially distributed socioeconomic data in Finland. The top-left subfigure shows the total number of cars registered per node, the top-right subfigure the average age of the persons per node, the bottom-left subfigure the annual median income of the households, and the bottom-right subfigure the number of unemployed persons per raster node.

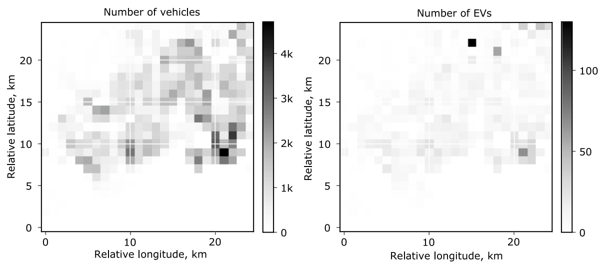


Fig. 6. Vehicle registration data. On the left, a feature map of the registered cars per node. On the right, the number of registered EVs per node.

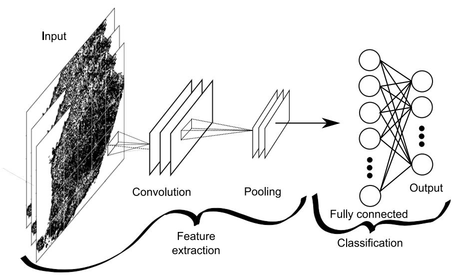


Fig. 7. Simplified illustration of a CNN.

$c_{\text{energy}} \in \{1 \ldots 5\}$. Data rows are filtered to match only occasions with an electric primary energy source $c_{\text{energy}} = 3$. The data are then categorized into a raster map $\mathbf{Y}$. Each node $y(i,j)$ of $\mathbf{Y}$ contains a sum of the EVs in the raster map matrix node.

The socioeconomic data are denoted by a three-dimensional matrix $\mathbf{X} = (x_{ijk}) \in \mathbb{R}^{636\times1140\times101}$. The matrix dimensions are matched with the vehicle registration raster data matrix, and thus, each node in either matrix corresponds with the same geographical location. The raster map $\mathbf{X}$ layers are defined as $k \in 1 \ldots 101$. Each layer of the raster map $\mathbf{X}$ may contain mean values of initial observations or statistics $\overline{x}(m,n,j) \in \mathbb{R} : j \in (1 \ldots 99)$, median values $\tilde{x}(m,n,j) \in \mathbb{R} : j \in (1 \ldots 99)$, Boolean $x(m,n,j) \in (0|1) : j \in (1 \ldots 99)$, or the sum of the observations $x(m,n,j) \in \mathbb{R} : j \in (1 \ldots 99)$.

3.2. Managing the class bias of the data set

The data have very few samples of positive EV occurrences because of the very early stage of the adoption of EVs. The vehicle registration raster data have 3537 nodes containing one or more EV registration samples. The total number of nodes having vehicle registration items is 98 393. When the data are classified for the model, zero occurrence nodes are heavily overrepresented in the classification, and thus, actions are taken to even out the class bias. The node containing EVs is oversampled by 300% to increase the proportion of the EV occurrence classes in the modeling. Oversampling often comes with the downside of overfitting the model. In this particular case, however, the lack of samples is a far larger issue than the downsides of oversampling, and thus, it was decided to oversample the minority classes. Even though the minority classes are oversampled, the training classes remain heavily overbiased, and thus, it was decided to undersample 20% of the nodes containing zero EV occurrences. The undersampling was performed by randomly dropping 20% of the samples. The undersampling is re-initialized each time the model is re-executed, as it gives tools to evaluate if valuable information is lost in undersampling.

3.3. Serialization of the input data

The input data are serialized so that the model will get an input shape of $\hat{v} \times 25 \times 25 \times k$, where k is the number of selected input feature layers and $\hat{v}$ is the count of serialized input raster maps. The socioeconomic input data are selected from the countrywide data by selecting matrices $x_{m+(25+1)/2,n+(25+1)/2,j,k}$ by the vehicle registration data nodes $y_{m,n}$. The data nodes are organized as a sequence $x_{\text{train}} \in \mathbb{R}^{\hat{v},25,25,101}$ and $y_{\text{train}} \in \mathbb{R}^{\hat{v}}$. The input then consists of socioeconomic data from around each node that has at least one vehicle registration data event. The target dataset y_{train} is further classified into three classes describing the number of EVs in the node:

$$y_{\text{classes}}(v) = \begin{cases} 0: y_{\text{train}}(v) = 0, \\ 1: 0 < y_{\text{train}}(v) \leq 2, \\ 2: y_{\text{train}}(v) > 2 \end{cases} \tag{4}$$

3.4. Normalization of the serialized data

The input data are normalized to avoid any bias caused by absolute values of the input data. The normalization is executed for the serialized data by layers by applying MinMaxScaler. The data are also checked for outliers to ensure the best possible input data for the model. The scaled values can be formulated as:

$$x_{\text{scaled}} = \frac{x - \min x}{\max x - \min x} * (\max x - \min x) + \min x, \tag{5}$$

where x represents the matrix to be normalized, and x_{scaled} denotes the normalized output.

The input raster data consist of sea areas and parts of countries sharing the same borderline with Finland, and therefore, the data consist of a large proportion of null nodes, which are also transferred into a serialized input format. During the normalization process, the null matrices are also dropped from the data set.

3.5. Training and testing data

The serialized data set is divided into training and testing data sets. To avoid sampling bias in the training, it was decided to randomly select a set of data for testing and training. Then, the ratio between the training and testing data is $20:80$. The data set randomization is re-executed each time the model is retrained to double-check the sanity of the model.

Randomization was performed by using Python's pseudo-random uniform distribution $\mathcal{U}_{0,1}$ random number generator. Randomization was used to generate unique index numbers to carry out testing data set selection of 17 808 frames from the whole serialized data set of 89 544 frames.

3.6. CNN model parameters

The CNN model is a sequential model available in Python Tensoflow Keras API. The model can be built with several options. For the purpose, it was decided to use a 2D convolution layer with 256 filters, 3×3 kernels, and rectilinear activation functions. In the second convolution layer, the number of filters was reduced to 128 and to 64 for the third convolution layer. Pooling was performed with 2D max pooling after each convolution layer. In practice, this can be considered a layer downsampling operation, which takes the maximum value over an input window (of the size defined by pool size) for each channel of the input. The window is shifted by strides along each dimension. 2D convolution and pooling layers were applied before flattening the input data. Finally, the input was passed to the softmax activation function for the elementwise activation.

3.7. Ablation analysis

Ablation analysis was performed for the model to ensure the sanity of the black-box-like model. The initial input data were considered to include valuable knowledge and information for the model, and thus, the model was tested with rotated input raster data to make sure that the training result is not a coincidence. The model performance did not change even though the input matrices were rotated. The model was also fed with randomly permuted input matrices and a fully randomized input with uniformly distributed random data. The model training was not able to pick any useful data out of the permuted original data or from the fully randomized input.

4. Results

The selected approach shows promising results for predicting the spatial EV distribution. Even though the data are rather sparse and there are some dense concentrations in the larger city areas, the model is able to learn features from the input data. The CNN are known to be sensitive to sparse input data sets. The model easily fails to validate itself with the validation data if the validation split contains very few meaningful samples. In the present study, the model was able to learn features with a low number of iterations. After about ten epochs, the model started to overfit the input data. Fig. 8 shows the model loss over training iterations in the case of three output classes.

The performance of the chosen architecture was sufficient especially in the high occurrence classes. Minority classes with one to two car occurrences and more than two car occurrences suffer from a lower accuracy and often mix detection between two minority classes.

The model performance can be estimated by the receiver operating characteristic (ROC) curve. The curve describes the ratio of true and false positive predictions. Figs. 9(a) and 9(b) show the ROC curves and area under the ROC curve (AUC) scores of the two models. It can be seen that the two-class model performs with a higher accuracy, but also the three-class model shows a good performance on the ROC curve and the AUC scores.

The ROC curve of the three-class model suggests that the model is capable of fitting the first class very well; however, it is noteworthy that the number of samples in the first class was significantly higher than in the second and third classes. Similar observations can be made from the model performance scores presented in Tables 2 and 3. In the three-class model, the F1 score of the first class is relatively high, 0.94, but in the second and third classes, the score is significantly lower. Table 2 shows the results in detail.

If only observing the whole model accuracy, the result may seem misleadingly good. A closer look at the classification confusion matrix and per class results reveal the true nature of the model performance (see Fig. 10). The model is able to identify if the node contains EVs, but the lack of data makes a more accurate analysis very challenging.

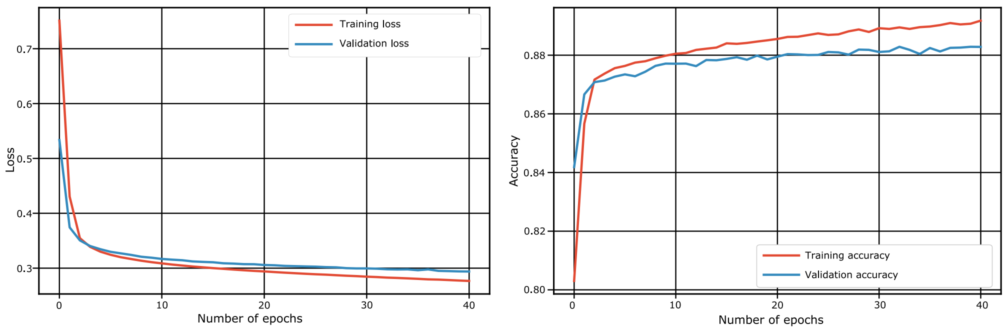
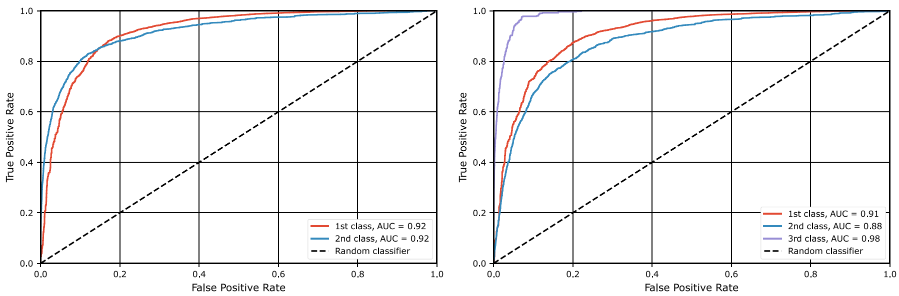


Fig. 8. On the left, training and validation losses over the model iterations. On the right, training and validation accuracy over the model iterations.



(a) Two-class model.

(b) Three-class model.

Fig. 9. ROC curves of the two-class and three-class models. The figure legend indicates the AUC. The first class represents the case of zero EV occurrences.

Table 2
Model accuracy indices with the three-class output model.

Class	Precision	Recall	F1 score	Support
0	0.92	0.97	0.94	15 050
[1...2[	0.63	0.41	0.50	2 400
[2...	0.80	0.054	0.65	458
Macro avg	0.78	0.64	0.70	17 908
Weighted avg	0.88	0.88	0.88	17 908
Samples avg	0.89	0.88	0.88	17 908

Table 3
Model accuracy indices with the two-class output model.

Class	Precision	Recall	F1 score	Support
0	0.93	0.97	0.95	15 116
[1...	0.80	0.61	0.69	3 005
Macro avg	0.86	0.79	0.82	18 121
Weighted avg	0.91	0.91	0.91	18 121
Samples avg	0.91	0.91	0.91	18 121

The results by class in Table 2 and the confusion matrix show that the amount of EVs is difficult to predict.

Model variation of two input classes was also implemented. Reducing the number of classes increased the number of samples and made the model perform better. The lack of data is a major issue in the study. The model clearly indicates that there are features that are beneficial for the model and can be learned, but the lack of samples in the validation data set makes the model training a challenging task. Fig. 8 shows the model accuracy over the training epochs.

The two-class output model performed much better and achieved a total accuracy score of 0.91, which is 0.03 higher compared with the three-class model. Table 3 summarizes the model results. The model class scores are also much higher, and it is clear that the model is able to predict EV occurrences rather accurately.

The model performance was also tested with a partial data set from the Finnish capital region. Fig. 11 shows an example of the prediction results in the raw format. The illustration shows high occurrence probabilities in the third class prediction in the more densely populated areas. The real vehicle registration data support the model prediction. The first and second prediction classes also show clear patterns well aligned with the real data set.

The example illustration reveals a weakness of the model in detecting single frame hot spots in EV occurrences. The graph of the real data set shows many small areas with a high EV density, but the third class prediction shows only slightly increased probabilities. The second class prediction performs much better under visual inspection of the results. It will be a question of further studies how the density-related hot spot accuracy can be improved.

4.1. Computational cost

The computational cost of the model is relatively low even with off-the-shelf hardware. The simulations were executed on hardware with Intel® Core™ i7 9700K CPU, 32 GB DDR4 RAM of memory, and NVIDIA® GeForce® RTX 3070 graphics card with 5888 NVIDIA® CUDA® Cores and 8 GB GDDR6 VRAM of memory. The data preprocessing is mainly a CPU- and memory-intensive task. The whole

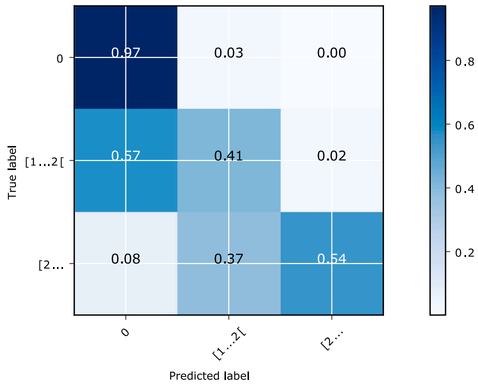


Fig. 10. Confusion matrix of the three-class output model.

reprocessing task takes less than half an hour, and it must be executed only when the initial input data change. Compiling and training the proposed model on the described hardware takes approximately 10 min, depending on the training stop criteria. The calculation cost is not a very relevant factor in such an analysis, as area distributions are typically used to feed other models used in the long-term planning of electricity distribution systems. A typical planning horizon may be several tens of years. Even though the actual planning process is more or less a constant process, there is no need to retrain the model very often. The input socioeconomic data can be updated yearly, or in the case of case area development planning, socioeconomic forecasts are made on demand.

5. Discussion

The study shows that it is possible to build a CNN model to estimate the spatial distribution of EVs. The lack of positive samples makes the model development and testing challenging, but regardless of the many issues with the current model, there are multiple applications where such a model could be beneficial. At the time of the study, however, the data resources available were still limited. Nevertheless, the early stage of the global and national EV adoption and statistical data gave a good starting point for the study. There are several topics that remain to be examined as soon as more data will be available. A similar modeling approach could also be adopted to generate an up-to-date prognosis of the spatial EV adoption rates as there seems to be a subtle correlation between socioeconomic data and vehicle properties. In addition, supporting data sources could be used to improve the model accuracy. There are many spatial data sets, such as road maps in a vector format, area characteristics describing area types, and many more. The hypothesis is that infrastructure types correlate somehow with the registration data. It is also likely that the model performance can be tuned to vary the model architecture or parameters. In the present study, the architecture and parameters were tuned by trial and error; automated hyperparameter tuning would probably improve the model performance. More sophisticated tuning methods incorporated with larger training data sets could make such a model highly interesting for many applications. The presented approach is novel in the field, and so far, there are not many studies available on the estimation of spatial distribution of EVs; thus, the paper is dedicated to introducing a CNN-based method for spatial distribution estimation. A comparison with other algorithms and methods would, indeed, bring added value, but as the proposed methodology has still untapped potential, a comparison with other algorithms would be unfair.

The model results provide a valuable input for the DSO network planning process as the spatial distribution of the EVs allows a more accurate load allocation to be conducted in the network simulation. Accurate load allocation makes strategic decision-making more reliable as the input drivers are based on well-founded analysis. Furthermore, the analysis makes it possible to investigate a developing area where socioeconomic factors are changing, or the area is expanding rapidly. Spatial analysis tools are often used in network management tools and software. Investigating software integration with the presented analysis is also a highly interesting prospect as there is already growing interest in software solutions where open data are utilized.

6. Conclusion

The scientific contribution of the paper lies in describing the application of the CNN model in spatial EV distribution modeling. The model is based on an exceptionally large actual countrywide data set covering socioeconomic aspects and vehicle registration statistics. The study investigated the applicability of the CNN in the spatial distribution modeling of EVs. The model architecture followed a very basic CNN architecture, and the CNN model parameters were tuned by trial and error. Considering the early stage of the EV adoption and the limited data resources, the model was able to pick up enough features out of the learning data to successfully predict the spatial EV distribution. The model was also validated with actual vehicle registration data. The model achieved a weighted accuracy of 0.88 in the case of the three-class output, whereas the class-specific accuracy scores were lower in the minority classes. The model also suffered from the biased output classes because of the limited number of positive data samples. The model was also executed with two-class output classification to quantify the performance in a simple EV occurrence prediction task. The model performed better when the positive sample number was slightly increased. The model results are sufficient to support DSO network planning as the model is clearly capable of indicating an increased EV occurrence probability. Because of the current data sets' lack of minority class samples, it is uncertain how much added value the model can provide for the network planning with the present data set. By fine-tuning the model architecture and parameters, it is likely that the performance can be further improved. To conclude, the CNN shows a high potential for the spatial EV distribution modeling.

It is a question of future studies how the model could be improved and if additional input data could enhance the model performance. In the present study, the model parameters were selected by trial and error, and thus, the model performance could be improved by hyperparameter optimization. The data set was also limited to socioeconomic factors and vehicle registration statistics, and therefore, further development of the model could benefit from information of the land use, road network, and other infrastructure. In addition, it would be important to test the model against other algorithms and models that are considered standard approaches, like the regression analysis. Moreover, as the model showed promising potential for applicability to spatial analysis, there are many other cases where a similar approach could be employed. Customer loss in rural areas is often explained by changing socioeconomic factors and infrastructure, thereby making it an interesting use case for the proposed model.

CRediT authorship contribution statement

Ville Tikka: Conceptualization, Methodology, Software, Data curation, Visualization, Writing – original draft. **Jouni Haapaniemi:** Conceptualization, Methodology, Writing – review & editing. **Otto Räisänen:** Conceptualization, Methodology, Data curation, Software, Writing – review & editing. **Samuli Honkapuro:** Supervision, Writing – review & editing.

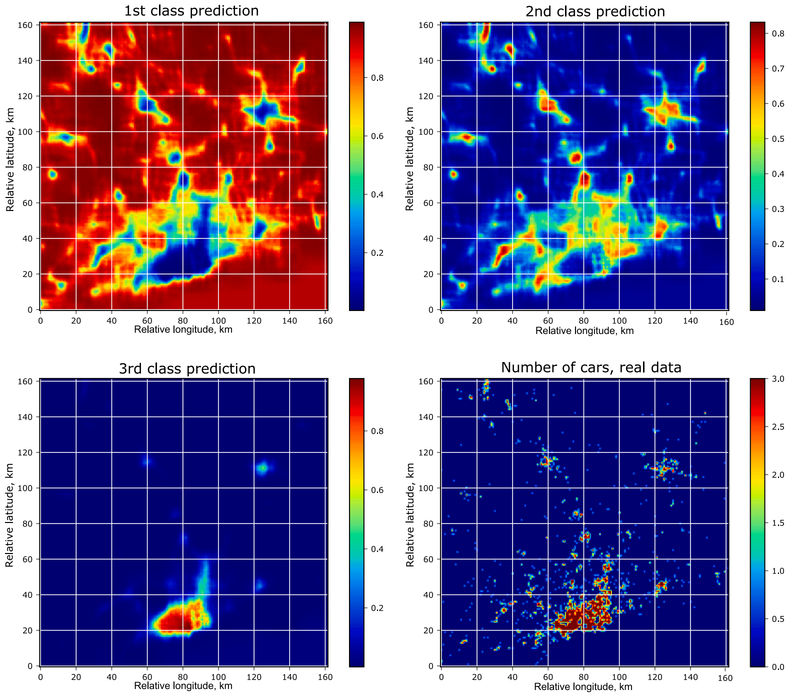


Fig. 11. Three-class model prediction example from the Finnish capital region. The first three subfigures show the model prediction results as probabilities, and the fourth subfigure illustrates real data for comparison. The real data are saturated to a maximum of three cars per node for illustrative reasons.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

References

[1] Paris agreement. United Nations Treaty Series Online, I-54113, United Nations; 2015, URL https://treaties.un.org/doc/Publication/UNTS/No Volume/54113/Part/I-54113-0800000280458f37.pdf.

[2] Stepping up Europe's 2030 climate ambition, Investing in a climate-neutral future for the benefit of our people. Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions, COM(2020) 562 final, European Commission; 2020, URL https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0562.

[3] Jenn A, Highleyman J. Distribution grid impacts of electric vehicles: A california case study. IScience 2022;25(1). http://dx.doi.org/10.1016/j.isci.2021.103686.

[4] Stiasny J, Zufferey T, Pareschi G, Toffanin D, Hug G, Boulouchos K. Sensitivity analysis of electric vehicle impact on low-voltage distribution grids. Electr Power Syst Res 2021;191. http://dx.doi.org/10.1016/j.epsr.2020.106696.

[5] Gonzalez Venegas F, Petit M, Perez Y. Active integration of electric vehicles into distribution grids: Barriers and frameworks for flexibility services. Renew Sustain Energy Rev 2021;145. http://dx.doi.org/10.1016/j.rser.2021.111060.

[6] Andersson A, Jääskeläinen S, Saarinen N, Mänttäri J, Hokkannen E. Road map for fossil-free transport – Working group final report. Liikenne- ja viestintäministeriön julkaisuja 2020:17, Helsinki: Ministry of Transport and Communications; 2020, URL http://urn.fi/URN:ISBN:978-952-243-598-9.

[7] Global EV Outlook 2021. Accelerating ambitions despite the pandemic, International Energy Agency; 2021, URL https://www.iea.org/reports/global-ev-outlook-2021.

[8] Lassila J. Strategic development of electricity distribution networks - Concept and methods (Ph.D. thesis), Lappeenranta: Lappeenranta teknillinen yliopisto / Lappeenranta University of Technology; 2009.

[9] Willis HL. Spatial electric load forecasting. CRC Press; 2002, http://dx.doi.org/10.1201/9780203910764.

[10] Saarenpää J, Kolehmainen M, Niska H. Geodemographic analysis and estimation of early plug-in hybrid electric vehicle adoption. Appl Energy 2013;107:456–64. http://dx.doi.org/10.1016/j.apenergy.2013.02.066.

[11] Saarenpää J, Kolehmainen M, Niska H. Identifying socio-demographically favourable area types for early hybrid electric vehicle adoption through mining of public sector data. Intell Data Anal 2016;20(2):339–55. http://dx.doi.org/10.3233/IDA-160808.

[12] Kohonen T. The self-organizing map. Proc IEEE 1990;78(9):1464–80. http://dx.doi.org/10.1109/5.58325.

[13] Selena Sheng M, Wen L, Sharp B, Du B, Ranjitkar P, Wilson D. A spatio-temporal approach to electric vehicle uptake: Evidence from New Zealand. Transp Res Part D 2022;105:103256. http://dx.doi.org/10.1016/J.TRD.2022.103256.

[14] Deneu B, Servajean M, Bonnet P, Botella C, Munoz F, Joly A. Convolutional neural networks improve species distribution modelling by capturing the spatial structure of the environment. PLoS Comput Biol 2021;17(4). http://dx.doi.org/10.1371/journal.pcbi.1008856.

[15] Keras. 2022, URL https://keras.io.

[16] TensorFlow. 2022, URL https://www.tensorflow.org.

[17] PyTorch. 2022, URL https://pytorch.org/features/.

[18] Zhang J, Shao K, Luo X. Small sample image recognition using improved convolutional neural network. J Vis Commun Image Represent 2018;55:640–7. http://dx.doi.org/10.1016/j.jvcir.2018.07.011.

[19] Sarikan SS, Ozbayoglu AM, Zilci O. Automated vehicle classification with image processing and computational intelligence. In: Procedia computer science, vol. 114. Elsevier B.V.; 2017, p. 515–22. http://dx.doi.org/10.1016/j.procs.2017.09.022.

[20] Statistics Finland – about the site. 2022, URL https://www.stat.fi/org/tietoa{_}sivustosta{_}en.html.

[21] Traficom – The finnish transport and communications agency. 2022, URL https://www.traficom.fi/en/traficom/about-traficom.

[22] Tikka V, Lassila J, Haakana J, Partanen J. Case study of the effects of electric vehicle charging on grid loads in an urban area. In: IEEE PES innovative smart grid technologies conference europe. 2011, http://dx.doi.org/10.1109/ISGTEUROPE.2011.6162667.

[23] Tikka V, Lassila J, Makkonen H, Partanen J. Case study of the load demand of electric vehicle charging and optimal charging schemes in an urban area. In: IEEE PES innovative smart grid technologies conference europe. 2012, http://dx.doi.org/10.1109/ISGTEUROPE.2012.6465687.

[24] Jamali Jahromi A, Mohammadi M, Afrasiabi S, Afrasiabi M, Aghaei J. Probability density function forecasting of residential electric vehicles charging profile. Appl Energy 2022;323:119616. http://dx.doi.org/10.1016/J.APENERGY.2022.119616.

[25] Lee R, Yazbeck S, Brown S. Validation and application of agent-based electric vehicle charging model. Energy Rep 2020;6:53–62. http://dx.doi.org/10.1016/J.EGYR.2020.02.027.

[26] Kim JD. Insights into residential EV charging behavior using energy meter data. Energy Policy 2019;129:610–8. http://dx.doi.org/10.1016/J.ENPOL.2019.02.049.

[27] Siddique C, Afifah F, Guo Z, Zhou Y. Data mining of plug-in electric vehicles charging behavior using supply-side data. Energy Policy 2022;161:112710. http://dx.doi.org/10.1016/J.ENPOL.2021.112710.

[28] Pareschi G, Küng L, Georges G, Boulouchos K. Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data. Appl Energy 2020;275:115318. http://dx.doi.org/10.1016/J.APENERGY.2020.115318.

[29] Statistics — Eurostat. 2022, URL https://ec.europa.eu/eurostat/databrowser/view/tps00003/default/table.

[30] Erdem C, Sentürk I, Simsek T. Identifying the factors affecting the willingness to pay for fuel-efficient vehicles in Turkey: A case of hybrids. Energy Policy 2010;38(6):3038–43. http://dx.doi.org/10.1016/j.enpol.2010.01.043.

[31] Xiao B, Yin X, Kang SC. Vision-based method of automatically detecting construction video highlights by integrating machine tracking and CNN feature extraction. Autom Constr 2021;129. http://dx.doi.org/10.1016/j.autcon.2021.103817.

[32] Hosseini A, Hashemzadeh M, Farajzadeh N. UFS-net: A unified flame and smoke detection method for early detection of fire in video surveillance applications using CNNs. J Comput Sci 2022;61:101638. http://dx.doi.org/10.1016/J.JOCS.2022.101638.

[33] Gill HS, Khehra BS. An integrated approach using CNN-RNN-LSTM for classification of fruit images. Mater Today: Proc 2022;51:591–5. http://dx.doi.org/10.1016/J.MATPR.2021.06.016.

[34] Chen S, Sedghi Gamechi Z, Dubost F, van Tulder G, de Bruijne M. An end-to-end approach to segmentation in medical images with CNN and posterior-CRF. Med Image Anal 2022;76:102311. http://dx.doi.org/10.1016/J.MEDIA.2021.102311.

[35] Gonçalves DN, Weber VAdM, Pistori JGB, Gomes RdC, de Araujo AV, Pereira MF, Gonçalves WN, Pistori H. Carcass image segmentation using CNN-based methods. Inform Process Agricult 2021;8(4):560–72. http://dx.doi.org/10.1016/J.INPA.2020.11.004.

[36] Cavalli S, Amoretti M. CNN-based multivariate data analysis for bitcoin trend prediction. Appl Soft Comput 2021;101:107065. http://dx.doi.org/10.1016/J.ASOC.2020.107065.

[37] Khan A, Sohail A, Zahoora U, Qureshi AS. A survey of the recent architectures of deep convolutional neural networks. Artif Intell Rev 2020;53(8):5455–516. http://dx.doi.org/10.1007/S10462-020-09825-6, arXiv:1901.06032.

Publication VIII

Tikka, V., Haapaniemi, J., Räisänen, O., Mendes, G., Lassila, J., and Honkapuro, S.
Electric vehicle charging measurements in the Nordic environment—Charging profile dependence on ambient temperature

Reprinted with permission from
CIRED 2023—The 27th International Conference and Exhibition on Electricity Distribution
Rome, Italy, 2023

ELECTRIC VEHICLE CHARGING MEASUREMENTS IN THE NORDIC ENVIRONMENT—CHARGING PROFILE DEPENDENCE ON AMBIENT TEMPERATURE

Ville TIKKA
School of Energy Systems
LUT University - Finland
ville.tikka@lut.fi

Otto RÄISÄNEN
School of Energy Systems
LUT University - Finland
otto.raisanen@lut.fi

Jouni HAAPANIEMI
School of Energy Systems
LUT University - Finland
jouni.haapaniemi@lut.fi

Gonçalo MENDES
School of Energy Systems
LUT University - Finland
goncalo.mendes@lut.fi

Jukka LASSILA
School of Energy Systems
LUT University - Finland
jukka.lassila@lut.fi

Samuli HONKAPURO
School of Energy Systems
LUT University - Finland
samuli.honkapuro@lut.fi

ABSTRACT

This paper aims at providing further understanding of electric vehicle (EV) charging in a cold environment by providing an overview of laboratory tests conducted for several EVs. The paper describes the laboratory test process and the main findings of the laboratory measurements. The measurement results and stochastic load modeling show that the energy demand increases significantly over wintertime charging sessions. The increased energy demand also increases peak loads in the distribution networks. In Nordic distribution grids, EV charging peak loads often overlap baseload peaks, creating incentives to manage charging in a smart way. The increased energy content and additional preheating power cause a need to rethink smart charging applications. As the main outcome of the paper, the laboratory routine is described with the measurement results of four EVs and one plug-in hybrid electric vehicle (PHEV). As the main result, the study shows that the temperature dependence is among the key variables to be added to the stochastic EV charging load modeling in cold environment areas.

INTRODUCTION

Electric mobility is taking an increasing role in the private and public transportation. EU directives, national legislation, and energy policy are the key driving forces behind the rapid change of the private transportation sector. An attitude change can also be seen in the press releases of many car manufacturers, indicating a greater focus on full electric powertrains. While the public attitude toward EVs is also changing, EV sales are rapidly increasing in pace in the Nordic countries and all over the world. In practice, this means that scenarios are about to become reality, and distribution grids are already facing new loads. Countries with cold climate conditions need to pay special attention to the temperature dependence of EV charging loads as it is likely to cause additional needs for distribution grid reinforcement. The measurement results and stochastic load modeling show that the energy demand increases significantly over wintertime charging sessions. The increased energy also increases peak loads in distribution networks. In Nordic distribution grids, charging peak loads often overlap baseload peaks, creating incentives to manage charging in a smart way. The increased energy content and additional preheating power cause a need to rethink smart charging applications. Cutting the charging power too low is likely to compromise the charging event as charging energy per heating energy ratio leans strongly on heating energy, and as a result, the charging time window may run out.

The strategic planning of the electricity distribution is a multivariable optimization problem, which involves masses of variables describing various technical properties, economic aspects, and forecasts. Many of the variables related to EVs, such as kilometers driven per day or arrival time, can be estimated based on national traffic surveys or site-specific surveys. Vehicle stack or fleet properties can be queried from public or semipublic registers. In the Nordic climate conditions, the energy consumption and charging capabilities of vehicles in a cold climate play a significant role in the electricity system planning. Thus, it is important to study how a charging event changes when the ambient temperature drops below zero. Some studies [1, 2] have raised similar issues and partially answered these questions. In addition, efforts have been made by the press [3, 4] and associations in the field [5], but more research and measurement of the real-life operating conditions are needed.

This paper aims at providing further understanding of electric vehicle (EV) charging in a cold environment by giving an overview of laboratory tests conducted for several EVs, but also by showing how to apply results to stochastic load modeling. The paper describes the laboratory test process and the main findings of the laboratory measurements.

As the main outcome of the paper, a brief summary of the laboratory routine is provided with the measurement results of four EVs and one plug-in hybrid electric vehicle (PHEV). All cars were tested at temperatures of 20°C, 0°C, -10°C, and -20°C, reflecting typical outdoor temperatures in the Nordic countries. The measurement report describes the test setup, the measuring routine, and results

Fig. 1: Cold environment vehicle testing laboratory with the test subject car attached to a four-wheel dynamometer

in detail [6], and the raw data are also publicly available [7]. The measurements were conducted in a large temperature-controlled vehicle technology laboratory (Fig. 1), and the charging measurements were logged from a three-phase power analyzer. In the worst-case scenario, the charging energy demand may even double compared with charging in standard conditions (+20°C). In the testing, all the cars equipped with a battery heater showed an increasing energy demand. The car without an auxiliary battery heater was not able to charge fully when the temperature was decreased below -10°C. The results benefit EV charging modeling and EV uptake scenario analysis of the distribution grids in cold climate countries.

BACKGROUND INFORMATION

The main motivation for the further testing of electric vehicle (EV) charging was to acquire more detailed knowledge of how the charging power and energy can vary under different climate conditions, especially in the cold Nordic climate. The hypothesis based on the public discussion and basic physics is that EVs consume more energy when operating in cold climate conditions. The increase in the consumption can mainly be explained by the additional heating energy required to maintain a comfortable cabin temperature while driving. In reality, it is obvious that there are multiple factors that impact the total energy demand. Several scientific publications support the hypothesis, yet not many focus on the effect that the increased demand may cause on the distribution grid infrastructure.

The main interest of the measurements lies in low-temperature charging events as they set the parameters for the worst-case scenario in the Nordic climate conditions. The worst-case scenarios cannot be overlooked when designing and dimensioning the EV charging infrastructure. The rationale behind the time-consuming laboratory testing is that there is clear evidence that lithium-ion-based battery technologies face challenges in cold climate conditions. Issues are related, for instance, to accelerated battery degradation [8], cold climate fast charging capabilities [9], or cold climate charging capabilities in general [10]. The root cause for challenges in lithium-ion battery charging at subambient (below 20°C ambient temperature) temperatures is often dendrite growth [11] that potentially causes an internal short-circuit. Therefore, it is required to maintain a certain operating temperature during the charging event. Active temperature control requires energy, which is then shown as an additional demand on the distribution grid side. The cold climate charging power curve is often very different compared with charging events executed in close proximity of the battery manufacturer's recommended nominal operating temperature. Real-world laboratory or field tests can be seen to bring high added value, because modeling the car operation in varying conditions is likely to require many simplifications and contain a large number of very uncertain input variables, which affects the modeling results. Moreover, charging tests can be used to validate charging models to enhance the reliability of the results and even further encourage engineers to exploit the modeled results.

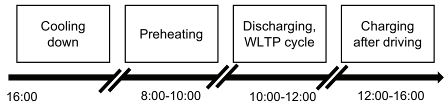


Fig. 2: Full-day testing routine divided into four main parts.

TEST SETUP AND ROUTINE

In the design process of the testing routine, the main challenges are related to the selection of the cars and setting up a sufficient charging routine. The car selection can be considered to have a major impact on the results, as car manufacturers use distinct technologies for the powertrains and batteries of the cars. Often, models that fall into the premium full-size class are better equipped. A premium car can, for instance, be equipped with better battery temperature management to ensure a good charging experience regardless of the ambient temperature. The current sales figures in Finland were used as a guideline in the selection of the test cars; a detailed description is available in the measurement report [6]. The main goal of the test routine was to mimic a typical or average car usage. Fig. 2 illustrates the four stages of the charging routine. First, the car is cooled to the target temperature. The cooling cycle continues over night to ensure that also the battery has reached the target temperature. Secondly, in the morning, the discharge cycle begins with preheating of the car cabin. The preheating mimics typical operation of cars in winter conditions in the Nordic countries. The car is operated at the test bed according to the worldwide harmonized light vehicle test procedure (WLTP) test cycle to mimic the real-world driving as closely as possible. The operation continues until the battery state-of-charge (SoC) has discharged to 70%. The fourth and last stage is the charging stage. After the driving stage, the car is immediately plugged into the charger and charged to the full SoC.

The testing took place in the laboratory of Metropolia University of Applied Sciences in Helsinki, Finland. The test cycles were monitored and logged in data logs to be

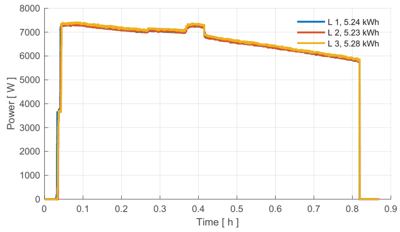


Fig. 3: Power curve of three phases at 20°C ambient temperature in the car A charging test.

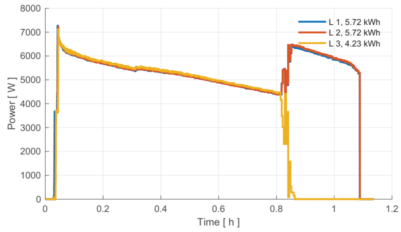


Fig. 4: Power curve of the three phases at -10°C ambient temperature in the car A charging test.

examined later. An Ensto EVF100W-BSAC [12] charging pole was used to provide mode 3 charging support. The charging power was measured by using a Carlo Gavazzi EM340 [13] power analyzer. Data were then logged by using the Modbus interface of the power analyzer by a Modbus logger [14] and further uploaded to a long-term storage [7].

LABORATORY MEASUREMENT RESULTS

The tests conducted in the laboratory revealed substantial changes in the power and energy demand of the EVs. In the following, highlights of the power curves recorded at the testing event are provided, and changes in the total charging energy demand are summarized. The testing of the cars was highly time consuming, taking a full working week per a car tested. The first test for each car was a reference test, where the car charging was tested at the ambient temperature of 20°C. Fig. 3 shows that the total energy of the charging event is 15.7 kWh. The charging begins with the rated power and continues at the full power for a few minutes before the battery cell voltages begin to limit the charging current.

The second test at 0°C showed a similar power curve compared with the +20°C testing case. All cars followed a similar pattern between the first two tests. The reference and 0°C curves varied slightly between the cars depending on how close to the actual full capacity the battery was reaching at the 100% SoC observed by the user. The cars with smaller safety tolerances showed a typical lithium-ion charging curve, where the end of the charging period has a concave-shaped end caused by the decreasing charging current (to not exceed the maximum allowed cell voltage).

The third test at -10°C changes the setting dramatically with the test conducted to car A (Fig. 4). The total energy of the charging event stays almost the same as in the reference case. The charging event begins with the rated power and quickly drops by about 1 kW per phase. The charging continues at a steadily decreasing charging current until the car reduces the third-phase power to zero and increases the power of the two other phases. The total charging time increased by about 35%, and the shape of the power curve changed slightly. Furthermore, it is noteworthy that in the last part of the charging event, the three-phase load

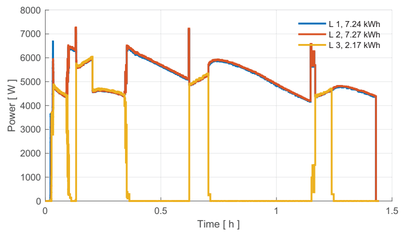


Fig. 5: Power curve of the three phases at -20 °C ambient temperature in the car A charging test.

is asymmetrical as the car has dropped the power of one phase to zero.

The fourth test at -20°C shows major changes in the shape of the charging load power curve and in the total energy. The total energy increased by about 1 kWh, but the power demand was very intermittent and the car switched multiple times between two-phase and three-phase charging. The charging curve shows clearly that the car uses the battery heating element to reach temperature levels where charging can be continued. Fig. 5 demonstrates the intermittence of the charging curve characteristics. The total charging time was also prolonged significantly compared with the reference test, by almost 80%.

Tables 1 and 2 summarize the total preheating and charging energies of each car under test. Absolute values are car-specific and should not be compared, as the reference charging energy varies according to the car under test. The relative change in the charging energy varies between a 100 % increase and a -36 % decrease. The cars that showed a decreasing energy content were not equipped with battery heaters, and thus, the total energy charged to the battery was lower than it would have been in the reference operating temperature. In low (below 0°C) temperatures, it is possible that battery is not capable of storing the full energy capacity (see car B in Table 1). The cars that showed an increasing total energy in low-temperature charging were equipped with battery heaters. Most of the additional charging energy was due to battery heating.

Table 1: Total charging energy of the tested cars. *Battery charging was terminated before reaching the 100% SOC. **Worst-case scenario, the car parked overnight with a discharged battery. Preheating energy not included.

Car	Testing temperature				
	20°C	0°C	-10°C	-20°C	-20°C**
	kWh	kWh	kWh	kWh	kWh
Car A	15.7	15.6	15.7	16.7	23.6
Car B	20.3	17.8	18.3	15.3	15.6*
Car C	13.0	12.4	12.6	12.6	15.0
Car D	23.3	23.0	25.5	24.3	27.5
Car F	10.3	10.2	10.0	9.7	7.6*

Table 2: Total preheating energy of the tested cars.

Car	Testing temperature		
	0°C	-10°C	-20°C
	kWh	kWh	kWh
Car A	5.5	7.9	12.3
Car B	0.7	3.1	3.1
Car C	1.6	2.9	2.4
Car D	1.4	0.5	2.5
Car F	0.3	0.5	0.4

In addition to charging tests, the cars were preheated before driving, and the data were recorded. The total energy content of preheating is highly dependent on the ambient conditions, technical boundaries, and most importantly, also on the user preferences. Table 2 shows that the total energy content of preheating can be compared with the total charging energy content. The cars equipped with heat pumps had a much lower energy impact.

NETWORK EFFECTS

The results of the cold climate charging tests were applied to stochastic EV charging load modeling to reveal the dependence of the peak load and the stochastic load curve on the ambient temperature. The stochastic model used in the analysis is described in more detail in [15]. To obtain the overall effect of the ambient temperature in the modeling, the relation of the car's energy consumption to the ambient temperature has to be incorporated in the model. Fig. 6 shows how the consumption depends on the ambient temperature. The data are gathered from various sources and include tens of cars in different car sizes and type classes [3–5]. When the temperature drops below 0°C, the consumption starts to increase dramatically. It is pointed out that the tests are not conducted scientifically, but can still be used to build a good starting ground for the stochastic model. It is also important to note that driving cycles, the driver's driving style, and other personal preferences have a major impact on the EV's energy consumption in cold climate conditions.

The stochastic model is a relatively simple Monte Carlo simulation, but the parameter tuning requires skill, experience, and fine-tuning. The model is fed with distributions

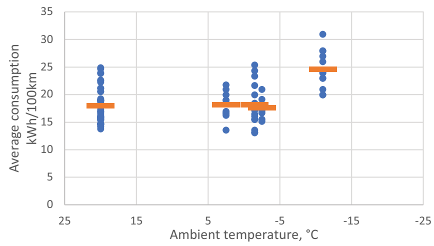


Fig. 6: Car power consumption estimates in different temperatures. Data compiled from various sources.[3–5, 15]

of arrival time, departure time, number of trips, total kilometers driven, vehicle consumption, battery size area efficiency, and user preferences. In addition, there is a large number of parameters that allow to adapt the model for various environmental conditions. Fig. 7 shows an example of the model results in the case of an apartment house parking area with a total of 20 charging spots equipped with 11 kW chargers. The effect of cold ambient temperature can be seen as an increased peak load, but also as a secondary consumption peak in the morning hours. The secondary peak is caused solely by the preheating of the cars, and it is typically very difficult to estimate accurately. The primary peak power increases by approximately 25%, which is a substantial increase considering the grid planning. The model captures the stochastic properties of the EV charging load, because even a low number of cars often results in a peak power, which is a product of the charger power and the number of cars. Fig. 8 illustrates the model properties as a function of the number of cars. The model also provides a capability to estimate smart charging, which aims at the lowest possible peak power by shifting individual charging events to a later time. Dynamic charging coordination or peak shifting can be very beneficial especially in cold climate conditions, where peak loads are likely to increase when the ambient temperature drops below zero. Based on the simulation, uncontrolled charging at +20°C ambient temperature results in high peak loads as does the dynamically controlled charging at -20°C ambient temperature.

CONCLUSION

The study summarized testing of four EVs and one plug-in hybrid electric vehicle (PHEV). The results show that the subambient temperature has a substantial effect on the EV charging power, energy, and total charging time. The absolute magnitude of changes is highly dependent on multiple variables, such as battery temperature, battery heating equipment, the car manufacturer's preferences for cold climate operation, battery chemistry, and probably also battery age. As the main result, it is shown that EV charging has a significant temperature dependence. In respect of grid planning, it is recognized that cold climate

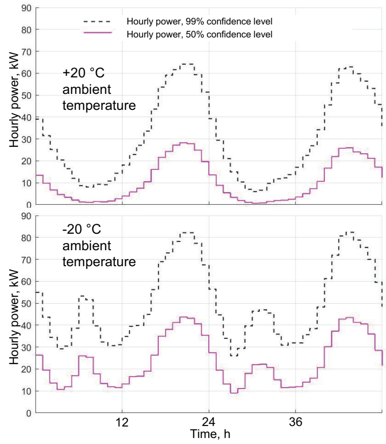


Fig. 7: Comparison of +20°C and -20°C ambient temperature charging events. The upper graph shows the charging load profile simulated for +20°C ambient temperature and the lower graph the same result graph when the temperature parameter is changed to -20°C.

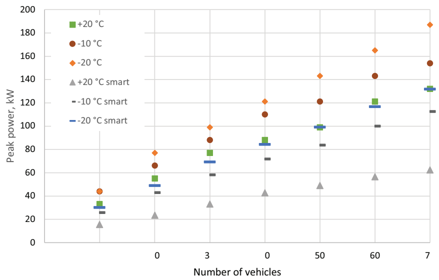


Fig. 8: EV charging peak power as a function of the number of cars. In the legend, "smart" refers to dynamic load control (peak shifting or valley filling). Peak powers are presented at a 99% confidence level.

not only increases the peak power of the EV charging but also impacts the energy demand and the shape of the charging profile. When charging takes place at a below-zero temperature, the load curve is introduced with a secondary power peak, which is mainly caused by preheating of the cars. The primary peak of the load curve increases by 25–30%. The energy demand in the winter season also increases significantly, up to double.

REFERENCES

[1] P. Huang, S. Liu, Y. Zhang, Y. Ou, G. Zeng, J. Zhou, and Z. Bai. Assessment of Electric Vehicle Charging Scenarios in China Under Different-temperature Conditions. Journal of Energy Storage, 41:102859, 2021.

[2] X. Hao, H. Wang, Z. Lin, and M. Ouyang. Seasonal effects on electric vehicle energy consumption and driving range: A case study on personal, taxi, and ridesharing vehicles. Journal of Cleaner Production, 249:119403, 2020.

[3] Talvisähköauto 2019 [in Finnish]. Tekniikan Maailma (TM), 5:23–40, 2019.

[4] Talviauto 2021 [in Finnish]. Tekniikan Maailma (TM), 5:26–50, 2021.

[5] Norges Automobil-Forbund. 20 popular EVs tested in Norwegian winter conditions. URL: https://www.naf.no/elbil/aktuelt/elbiltest/ev-winter-range-test-2020, 2020.

[6] V. Tikka, J. Kalenius, O. Raisanen, and J. Lassila. Technical report: Measurements of cold climate EV charging. Technical report, LUT University, Lappeenranta, Finland, 2021.

[7] V. Tikka and T. Laine. Measurements of cold climate EV charging. URL: http://urn.fi/urn:nbn:fi:att:1ac935ce-fbb9-422e-9081-9a8db3c53399, 2021.

[8] K. Darcovich, S. Recoskie, H. Ribberink, and C. Michelet. The impact of V2X service under local climatic conditions within Canada on EV durability. eTransportation, 9:100124, 2021.

[9] Y. Motoaki, W. Yi, and S. Salisbury. Empirical analysis of electric vehicle fast charging under cold temperatures. Energy Policy, 122:162–168, 2018.

[10] J. Jaguemont, L. Boulon, and Y. Dubé. A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures. Applied Energy, 164:99–114, 2016.

[11] R. Akolkar. Modeling dendrite growth during lithium electrodeposition at sub-ambient temperature. Journal of Power Sources, 246:84–89, 2014.

[12] Charging station EVF100W-B4B. URL: https://www.ensto.com/fi/tuotteet/sahkoauton-lataus/julkinen-lataus/pro/evf100w-b4b/, 2021.

[13] Carlo Gavazzi EM340. URL: https://carlogavazzi.com, 2020.

[14] CAN Bus and CAN FD Interfaces and Analyzers. URL: https://dewesoft.com/products/interfaces-and-sensors/can-interfaces, 2020.

[15] V. Tikka, J. Kalenius, O. Raisanen, and J. Lassila. Loppuraportti: Sähköautojen latauksen muodostama kuormitus- ja mitoitusteho erilaisissa toimintaympäristöissä [in Finnish]. Technical report, LUT University, Lappeenranta, Finland, 2021.

Publication IX

Mendes, G., Tikka, V., Vahidinasab, V., and Aghaei, J.
Review of Emerging Advanced Smart Charging Flexibility Business Models

Reprinted with permission from
CIRED 2023—The 27th International Conference and Exhibition on Electricity Distribution
Rome, Italy, 2023

REVIEW OF EMERGING ADVANCED SMART CHARGING FLEXIBILITY BUSINESS MODELS

Gonçalo MENDES, Ville TIKKA
LUT University – Finland

Vahid VAHIDINASAB
Nottingham Trent University – UK

Jamshid AGHAEI
LUT University – Finland

ABSTRACT

Electric vehicle sales across all transport modes have had a steady growth over the last decade, and mass electric mobility will soon become a reality. In Europe, this represents an opportunity to introduce higher shares of variable renewable energy into the generation mix. However, a shift to mass electromobility needs to be accompanied by extensive integration of advanced smart electric vehicle charging, which could serve growing mobility needs while supporting the power system through a series of possible flexibility services. Such services need yet to mature, and its synergistic business models to be better understood in terms of value streams they will deliver and to whom. This paper investigates a group of such business models, particularly linking EV and/or homeowners, building managers, and network operators.

INTRODUCTION

Global electric vehicle (EV) sales have grown steadily over the last decade. Sales of electric cars doubled in 2021 to reach a new record of 6.6 million, and by the end of the year, there were over 16 million EVs on the road, triple the amount of 2018 [1]. A leader segment among these increases has been passenger light duty vehicles (e-PLDVs). In 2020 only, there has been a 41% increase in e-PLDVs registrations, despite the COVID-19 pandemic, multiple supply chain disruptions, and a resulting 16% drop in overall car sales during that period [2]. In Europe, mass EV deployment carries a game-changing decarbonization potential, due to the opportunity to introduce higher shares of variable renewable energy (VRE) sources into the generation mix [3,2]. This is aligned with ambitious European Union policies aimed at reducing greenhouse gases (GHG) emissions in half by 2030, and at reaching climate neutrality by 2050 [4,5,6]. However, the forthcoming mass EV deployment is not without challenges; if scaled up to mass-market levels, the mainstream approaches to EV charging, dominated by uncontrolled or time-of-use pricing-driven on/off control, are likely to create an unsustainable upsurge in power system peak demand [3,7,8,9]. Depending on context, this could either be deemed technically unfeasible or lead to prohibitive grid infrastructure upgrade requirements [3]. Thus, an effective shift to mass electromobility needs to be accompanied by advanced, bidirectional, "smarter" EV charging, characterized by vehicle-to-building (V2B), vehicle-to-home (V2H), and vehicle-to-grid (V2G) strategies, which could unlock unprecedented levels of flexibility in future VRE-rich power systems [3]. As a result, bidirectional charging is often colloquially termed "vehicle-to-everything", or simply "V2X".

V2X flexibility services

It is estimated that by 2050, around 14 TWh of flexible EV battery capacity would be available to provide grid-supportive services [11]. If properly exploited, this flexibility could minimize the need for costly grid infrastructural upgrades. Yet, it remains paramount to consolidate the market instruments and the business cases that incentivize the synergistic cooperation between EV users and the power system, while enabling stacking of various grid services and their value streams [3]. The technical flexibility service potential from V2X ranges from higher-level participation in electricity markets to balancing and system-level services to transmission and distribution network operators. Because the development of V2X business models needs to be supported by more than one revenue stream, it is imperative that its value proposition is clarified. This paper investigates a triangle of commercial interactions between EV owners (or prosumer-EV owners), building managers and network operators. It reviews and individually depicts six families of emerging V2X business models deemed to be dominant based on project surveys and literature research

The V2X marketplace

Bidirectional charging is part of an overarching marketplace concept where EV users and prosumers/homeowners, building managers, and distribution network operator entities (which could be traditional DSOs or other types of operators, such as energy communities) can interact and openly trade EV charging flexibility under different contexts (Figure 1). The marketplace incorporates various "scenarios" of EV user participation in the market, namely:

- A *V2G scenario*, where EVs connect directly to network operators through public charging stations (BM1, public charging case).
- A *V2B scenario*, where EVs connect to building parking lots and lend their battery capacity to the building manager's control (BM2, BM4, BM5).
- A *V2H scenario*, where EVs are connected within the distribution board of individual homes (BM1, home charging case, and BM3).

ADVANCED SMART CHARGING BUSINESS MODELS

The following section will depict the bidirectional charging business models BM1-BM6, by visually highlighting stakeholder roles and their interactions, and clarifying the unlocked value streams in each case.

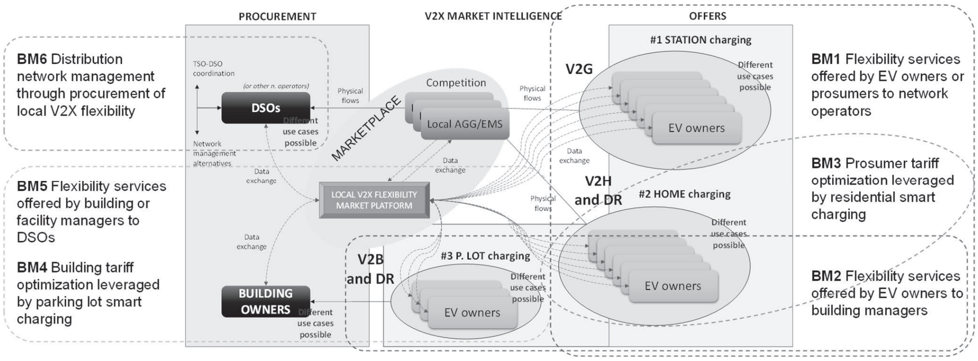


Figure 1 – Overarching bidirectional charging flexibility marketplace concept and respective portfolio of possible business models.

Flexibility services offered by EV owners or prosumers to network operators (BM1)

This business model covers possible commercial arrangements based on which individual EV owners contribute to providing some level of grid support services to formal distribution system operators or other eligible network operators managing specific branches of the distribution grid. Such services could be aimed at maintaining power quality parameters related to frequency and voltage under specific limits, or at improving the technical and economic operation of the grid by increasing renewable energy integration (avoiding curtailment), providing demand and supply balancing support, or offering congestion relief. Due to the small scale of the EV assets, this activity must take place through the involvement of intermediary aggregator agents.

This business model could possibly materialize under two distinct scenarios:

1) **Home charging**, through demand response (Figure 2): In this scenario, flexible EV charging is handled by a home energy management system (HEMS) along other connected assets the EV owner/electricity customer/prosumer may have at its disposal. The HEMS also coordinates customer participation in the balancing markets through demand response events.

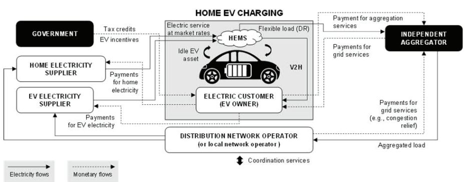


Figure 2 – Representation of financial and commodity flows in flexible services provided by EV owners to network operators, mapped in overarching marketplace as BM1 (home charging).

2) **Station/public charging**, directly through charging point management activities (Figure 3): In this scenario, the flexibility services to network operators are intermediated by charging point operators (CPOs), who can act as aggregators due to their direct connection and control of large portfolios of individual EV charging sessions. CPOs can also outsource that activity to other aggregator entities in the market.

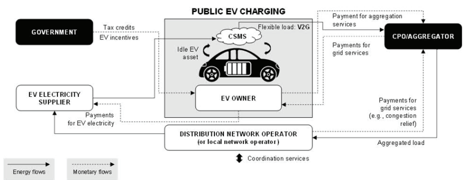


Figure 3 – Representation of financial and commodity flows in flexible services provided by EV owners to network operators, mapped in overarching marketplace as BM1 (station charging).

The different circumstances of the above scenarios result in that EV owners are positioned as direct flexibility service providers when in public charging stations, but not when connected at home. In home charging, the EVs are one additional flexible asset controlled by the HEMS, which manages demand response events on behalf of the residential electricity customer – the flexibility service provider in that case, being the EV role here an indirect one. Regardless of who receives it, service compensation from network operators is due in both models through the aggregator/CPO intermediaries. However, aggregation activities are also remunerated, and as a result EV owners/electricity customers must give up part of their revenue, as a condition for accessing these services. In context of HEMS, EV assets can also be optimally managed for capturing energy savings from V2H, which could compete with the revenues from demand response. Lastly, depending on the regulatory context in question, various capital subsidies and/or tax credits may be available to new EV owners, which could help offset some of the running costs and stack up with other value streams.

Flexibility services offered by EV owners to building managers (BM2)

If rather than at home or along the public way EVs are parked inside large commercial building facilities, they become idle energy assets that can be made available for performing V2B in context of energy management contracts established between EV owners and building managers (Figure 4). If efficiently managed with BEMS, the collective battery capacity of parked EVs can offer benefits to facility energy management, such as reduction of time-of-use electricity and power costs through peak shaving and energy arbitrage, in addition to intelligent and safe charging through dynamic load balancing.

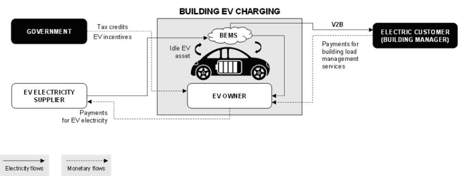


Figure 4 – Representation of financial and commodity flows in flexible services provided by EV owners to building managers, mapped in overarching marketplace as BM2.

This type of arrangements could pertain to short-term (e.g., supermarkets) or long-term charging (e.g., employee parking in offices, passenger parking in airports…), which will influence the constraints and contractual conditions of the energy service. Through digital identifiers at the connection point, an integrated BEMS could recognize the EV unit and contracted service possibilities before acquiring the available capacity, whereas connection/disconnection times would be introduced manually each time by the EV owner/driver. The BEMS ensures that the EVs are ready to drive at the designated exit times, by liaising with EV electricity suppliers. The building manager will then provide EV owners with compensation or charging credit for the service of accessing their idle battery capacity for energy management purposes. That compensation may suffer some level of penalties in case the EV owner fails to comply with the planned connection/disconnection times. As with other EV owner-centric business models, certain government subsidies and tax credits could help EV owners in making financial sense of EV investments. As to the building managers, they have the additional chance of participating in demand response markets, whose revenues can be appropriately balanced and/or stacked with savings from V2B-leveraged energy management.

Prosumer tariff optimization leveraged by residential smart charging (BM3)

When the EV is connected at home and is being controlled by a HEMS alongside other distributed flexible assets, such as heat pumps, electric boilers, and air conditioning units, potentially together with some type of renewable energy generation, it can support the optimization of residential energy costs via V2H (Figure 5). Inevitably, that ability will depend substantially on individual working and driving habits and must be studied at a case by case basis. For example, in a remote working situation, the EV battery could be charged with solar PV during peak-sun hours, virtually at no cost for the EV/homeowner. In another possible case, a fully charged EV battery could support home electricity demand during expensive evening "shoulder hours" and be recharged along the early morning hours, when electricity is cheap. In other words, V2H does not necessarily require renewable energy integration to deliver monetary value, due to the price difference between the peak and off-peak periods of time-of-use (TOU) electricity tariffs. Furthermore, the coupling of V2H with stationary electric storage can enhance flexibility even further, since EV energy injected to the home's distribution board can be appropriately stored for later internal distribution, if the HEMS optimization so dictates.

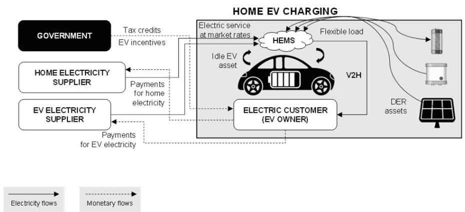


Figure 5 – Representation of financial and commodity flows in prosumer tariff optimization leveraged by residential smart charging, mapped in overarching marketplace as BM3.

Government subsidies and tax credits are often available to strengthen the value proposition of pure-V2H business models for EV owners. However, just like with the commercial buildings, potential revenue streams from involvement in balancing markets could also be accessible and considered under a stacked value logic by the HEMS.

Building tariff optimization leveraged by parking lot smart charging (BM4)

This business model mirrors the scenario of collective EV charging in building parking lots from BM2, being however established from the point of view of the building manager and/or large electricity customer. Here, building management facilitates EV charging services in the building's premises in exchange for provisional access to idle battery capacity through a V2B setup (Figure 6). Such large customers are often plagued by not only extensive electricity consumption during peak tariff periods, but also by high monthly power usage bills. The ability of a BEMS to connect dynamically to each individual EV charging session allows for balancing of charging needs and optimizing of the collective power draw at each instant, which effectively results in peak shaving and helps reduce overall demand charging costs.

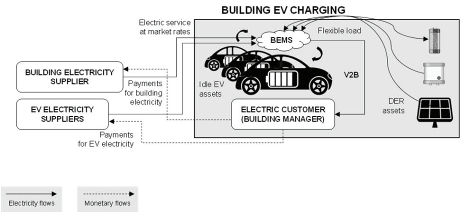


Figure 6 – Representation of financial and commodity flows in building tariff optimization leveraged by parking lot smart charging, mapped in overarching marketplace as BM4.

In addition to this, the BEMS will operate the aggregated mobile storage capacity of idled EVs a "virtual battery", optimally combining its use with the flexible use of other distributed heat and power assets of the facility, such as HVAC units, renewable energy, and stationary storage. In conditions of time-of-use electricity pricing, this joint asset optimization could be geared towards capturing as much cheap and/or green electricity as possible and direct it for consumption during price-peak periods, resulting in substantial reductions of electricity costs for the building. While performing these operations, the BEMS also needs to ensure that the requirements of each individual EV charging session (e.g., disconnection times and minimum SOC at exit) are strictly complied with. According to contracting rules between the building manager and the EV owners, monetary compensation is due for the temporary use of the idle mobile storage capacity (to cover for proportional battery degradation and ensure a profit margin for EV owners), which in absence of any service revenues, and otherwise subsidies or incentives could hinder the viability of this business model alone. As mentioned earlier, to fully capture and maximize value, building managers may have to consider combining V2B energy management savings with revenues from participation in the balancing markets (BM5).

Flexibility services offered by building/facility managers to DSOs (BM5)

While BM4 envisions the case when a portfolio of building distributed energy assets (notably including portfolios of parked EVs) is managed for electricity tariff optimization (i.e., for the purpose of *minimizing energy costs*) this business model contemplates the case when the same assets are managed for electricity market participation optimization (i.e., for the purpose of *maximizing flexibility service revenues*). Large building customers can engage with intermediary agents to allocate their load flexibility to the grid balancing markets, known as explicit demand response. In fact, due to still prevalent high minimum bids required for participation in these types of markets across various European countries, it is in principle easier to do so for these customers than it is for smaller residential prosumers (BM1). Yet, regardless of scale, aggregator parties will play the part of capturing the individual loads and operate with collective grid support services towards distribution system operators or others (Figure 7).

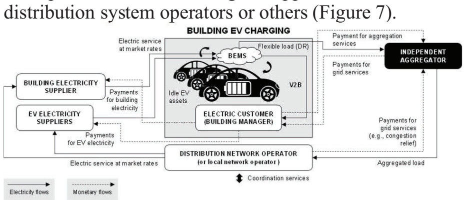


Figure 7 – Representation of financial and commodity flows in flexibility services offered by building/facility managers to DSOs, mapped in overarching marketplace as BM5.

Similar to BM1, the aggregators will channel the payments for technical grid support services from the DSOs to the building managers, after aggregation service fees have been appropriately factored in. Please note that just like in the "home charging" scenario for BM1, the EV assets take the role of mere enablers and have here an indirect involvement in the flexibility services since both the BEMS operations and the demand response are technologically neutral. Yet, as explained before, building managers have to follow their contractual obligations with EV owners and take in the operational costs of monetary compensations for use of idle EV battery capacity. Lastly, this business model focuses on generation of service revenues, but in a realistic situation where the building manager may wish to capitalize on multiple value creation opportunities, it could be combined with energy management of the flexible assets, including the idle EVs, for capturing tariff-related savings, as in BM4.

Distribution network management through procurement of local V2X flexibility (BM6)

This business model is markedly different from other business models studied in this paper in that it focuses exclusively on the perspective of distribution network operators accessing local flexibility to solve technical grid constraints and/or energy balancing issues (Figure 8).

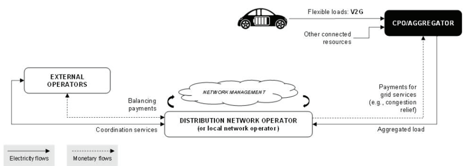


Figure 8 – Representation of financial and commodity flows in distribution network management through procurement of local V2X flexibility, mapped in overarching marketplace as BM6.

Traditionally, day-to-day problems in electric distribution would be handled by using network management infrastructure and through the coordination with external network operators, most notably the TSO. The emergence of aggregator agents with the ability to gather flexible load contributions from large amounts of dispersed assets and deliver it to the distribution system operators changed this paradigm, most notably reducing their dependency from external agents. As the previous models have shown, regardless of charging scenario circumstances, bidirectional charging flexibility is among the distributed resources that operators can access and/or procure locally, either directly or indirectly (via demand response), through aggregation intermediaries (which could be independent aggregators or CPOs). The procurement of localized resources allows for a more cost-effective handling of grid constraints and balancing challenges, which results in savings benefits for distribution system operators.

BUSINESS MODEL COMBINATION AND VALIE STACKING

While the analysis of possible bidirectional charging flexibility business models is facilitated by their discrete consideration and analysis, it is likely that in realistic conditions and whenever possible they could be combined and/or their value streams could be stacked (or both), in order to best recover mobility or infrastructure investments. None of the two options is possible for all the business models studied in this paper. For example, it is unlikely that BM6 could be combined with other bidirectional charging-based models, even though this is possible for other flexibility exploitation models available to DSOs (e.g., linked to different sources of local flexibility). As a rule-of-thumb, business models centered on delivering value to the same stakeholder (e.g., EV owner-centric models) could be combined. On the other hand, value stacking requires that for the considered business models, the charging scenarios are maintained. Table 1 describes the different possible combinations and value stacking possibilities among the six studied models.

Table 1 - Possible business model combinations and value stream stacking possibilities among the studied business models.

	EV owner-centric	Building manager-centric
Models' combination	BM1 home and station charging, BM2, and BM3	BM4 and BM5
Value stream stacking	BM1 home charging and BM3	BM4 and BM5

As Table 1 suggests, nothing prevents EV owners from adopting different types of business models in different contexts, in that way tapping different value creation opportunities brought by bidirectional charging. Because mobility is an individual and uncertain phenomenon with many possible driving and charging patterns possible at home, public charging stations, and inside buildings, this combination is expected to take place in a realist context. As to value stream stacking, it is fully dependent on the charging scenario, and for that reason, for EV owners, only the revenues from BM1 in home charging environment and the home energy savings from BM3 could be stacked for maximum capturing of bidirectional charging value. Such stacking is only made possible through real-time techno-economic optimization performed by the HEMS and is not necessarily always concurrently triggered. For building managers, the business model combination and value stacking possibilities resemble those for EV owners. In a building charging environment, BM4 and BM5 could be combined and the value streams they deliver pertaining to building energy savings and flexibility service revenues, respectively, could also be stacked with the expert decision support from BEMS optimization.

CONCLUSIONS

Mass electric mobility will soon become a reality and it is paramount to deepen the knowledge of bidirectional charging strategies and the grid support services they enable. This paper reviewed six bidirectional charging flexibility business models, studying also potential model combinations and its value stream stacking opportunities.

ACKNOWLEDGMENTS

The authors are thankful for the European Commission funding from project DriVe2X, grant No. 101056934.

REFERENCES

[1] IEA, "Global electric car sales have continued their strong growth in 2022 after breaking records last year", Press release, 23 May 2022

[2] IEA, "Global EV Outlook 2021 – Accelerating ambitions despite the pandemic" Paris, 2021

[3] IRENA, "Innovation Outlook – Smart Charging for Electric Vehicles", Abu Dhabi, 2019.

[4] European Commission, "Clean Energy for All Europeans", Website, Accessed in June 2021.

[5] European Commission, "A European Green Deal: Striving to be the first climate-neutral continent", Website, Accessed in May 2021.

[6] European Commission, "CO2 emission performance standards for cars and vans (2020 onwards)", Website, Accessed in July 2021.

[7] Nogueira, T., Sousa, E., Alves, G., "Electric vehicles growth until 2030: Impact on the distribution network power", Energy Reports, Vol. 8, Supplement 3, Pages 145-152, 2022.

[8] Chen, L., Wu, Z., "Study on effects of EV charging to global load characteristics via charging aggregators". Energy Procedia, Vol. 145, Pages 175-180, 2018.

[9] Taljegard, M., "The impact of an Electrification of Road Transportation on the Electricity system in Scandinavia", Lic. Thesis, Chalmers University of Technology, Sweden, 2017.

[11] IRENA, "Global energy transformation: A roadmap to 2050", Abu Dhabi, 2019.

ACTA UNIVERSITATIS LAPPEENRANTAENSIS

1086. CARILLO MELGAREJO, DICK. Improving the design of cellular networks beyond 5G for smart grids. 2023. Diss.

1087. MALACINA, IRYNA. Zooming in and out: The strategic management of innovation across multiple levels of complex supply networks. 2023. Diss.

1088. SORE, SARISEELIA. Impact of information system capabilities on business value creation: Aspects of IT-producing and IT-consuming companies. 2023. Diss.

1089. IMMONEN, EERO. Advances in optimal design of shapes and processes by computational fluid dynamics. 2023. Diss.

1090. LAVOYE, VIRGINIE. Augmented reality in consumer retail: a presence theory approach. 2023. Diss.

1091. HÄRKÖNEN, KALEVI. Smart buildings in the green energy transition. 2023. Diss.

1092. TSYTSYNA, EVGENIYA. Motives, uncertainties, and imbalances in the evolution of a sustainable business ecosystem. 2023. Diss.

1093. JÄÄSKELÄINEN, ATTE. Business model innovation opportunities when news has become a public good. 2023. Diss.

1094. ADEDIPE, TAIWO. Atmospheric boundary-layer characteristics and their significance in wind energy and urban air quality assessment. 2023. Diss.

1095. SOSUNOVA, INNA. Model and guidelines for designing Internet-of-Things-enabled smart waste management system in smart cities. 2023. Diss.

1096. VUORELA, JYRI. Operative business development through system model and changing business structures. 2023. Diss.

1097. TRIAPITCIN, ILIA. Knowledge injection method for real-time decision support. 2023. Diss.

1098. RÄISÄNEN, OTTO. Open data in distribution network asset management. 2023. Diss.

1099. MATELA, MIKA. Procurement improvement in the public agency. 2023. Diss.

1100. SHAH, DIPAL. Quantification of synchronization. 2023. Diss.

1101. GHAFOURI, MEHRAN. Thermomechanical finite element simulation of welding, and elevated-temperature mechanical behaviour of high and ultra-high strength steels. 2023. Diss.

1102. NEUVONEN, RIKU. Numerical ductile fracture assessment of weldments in direct-quenched, ultra-high-strength steel. 2023. Diss.

1103. HUPPONEN, MARI. Long-term evolution of greenhouse gas emissions from municipal solid waste management. 2023. Diss.

1104. WANG, QI. Dynamic analysis and parameter identification for robotic manipulators. 2023. Diss.

1105. KIMPIMÄKI, JAAN-PAULI. From observation to insight: Computational abduction and its applications in sustainable strategy research. 2023. Diss.

1106. YIN, RUOCHEN. Research on key technologies for lightweight maintenance operations of the remote handling system for a fusion reactor. 2023. Diss.

1107. MUNIR, QAISAR. Designing printing parameters for geopolymer concrete prepared from construction and demolition waste and industrial side streams. 2023. Diss.

1108. ROHANI RAFTAR, HAMIDREZA. Assessment of weld root fatigue strength of load-carrying fillet welded joints using notch stress approaches and finite element analysis. 2023. Diss.

1109. SADIQA, AYESHA. Sustainable energy transition for Pakistan: Assessing the role of energy, water supply, social and gender equity dimensions. 2023. Diss.

1110. GHOREISHI, MALAHAT. The role of artificial intelligence in circular value creation: A conceptual framework and evidence from case studies. 2023. Diss.

1111. SUURONEN, JARKKO. On numerical implementation of α-stable priors in Bayesian inversion. 2023. Diss.

1112. PIILI, HEIDI. A conceptual, holistic framework to overcome limitations and constraints of design in laser based powder bed fusion of metals: Case novel separation and purification units. 2023. Diss.

1113. LOPATINA, ANASTASIIA. From alternative sources of cellulose to ultrafiltration membranes. 2023. Diss.

1114. MARTTINEN, KATI. Toward more sustainable supply management: Practices, determinants, and enablers for ensuring sustainability across multiple supply chain tiers. 2023. Diss.

1115. HU, HAO. Development of hybrid microdevices composed of Ni-Mn-Ga and silicon layers: fabrication and metrology. 2023. Diss.

1116. MARAIA, RAMONA. Bayesian likelihood for intractable data. 2023. Diss.

1117. ULLAH, MEHAR. Framework for digitalizing different industrial sectors via the internet of things. 2023. Diss.

1118. SIHVONEN, TUOMAS. Adaptive binning and spatial profile partial least squares methods in scanning electron microscopy energy-dispersive X-ray spectroscopy and satellite hyperspectral pansharpening. 2023. Diss.

1119. VOIPIO, VILLE. The role of radio-frequency identification in the sustainable digital transformation of the supply chain. 2023. Diss.

1120. WICKER, REBECCA. Bioprospecting for Nordic photosynthetic consortia for wastewater treatment, carbon capture, and value creation. 2023. Diss.

1121. SAUD, ALI. Sustainable recovery of nitrogen from sewage sludge. 2023. Diss.

1122. SHABBOUEI HAGH, YASHAR. Sigma-point Kalman filtering in physics-based digital twin applications: Synchronization between simulation and real world. 2023. Diss.

1123. KALITEEVSKII, VASILII. Artificial Inventiveness: Towards AI supported model-driven systematic conceptual design.

ISBN 978-952-412-046-3
ISBN 978-952-412-047-0 (PDF)
ISSN 1456-4491 (Print)
ISSN 2814-5518 (Online)
Lappeenranta 2024