Lappeenranta
University of Technology

Jussi Tuunanen

MODELLING OF CHANGES IN ELECTRICITY END-USE AND THEIR IMPACTS ON ELECTRICITY DISTRIBUTION

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Supervisors Professor Jarmo Partanen
Electrical Engineering
LUT School of Energy Systems
Lappeenranta University of Technology
Finland

Dr. Samuli Honkapuro
Electrical Engineering
LUT School of Energy Systems
Lappeenranta University of Technology
Finland

Reviewers Professor Pekka Verho
Department of Electrical Engineering
Tampere University of Technology
Finland

Dr. Pirjo Heine
Research and development manager
Helen Electricity Network Ltd
Finland

Opponent Professor Pekka Verho
Department of Electrical Engineering
Tampere University of Technology
Finland

Dr. Pirjo Heine
Research and development manager
Helen Electricity Network Ltd
Finland

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Abstract

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The electricity distribution sector will face significant changes in the future. Increasing reliability demands will call for major network investments. At the same time, electricity end-use is undergoing profound changes. The changes include future energy technologies and other advances in the field. New technologies such as microgeneration and electric vehicles will have different kinds of impacts on electricity distribution network loads. In addition, smart metering provides more accurate electricity consumption data and opportunities to develop sophisticated load modelling and forecasting approaches. Thus, there are both demands and opportunities to develop a new type of long-term forecasting methodology for electricity distribution.

The work concentrates on the technical and economic perspectives of electricity distribution. The doctoral dissertation proposes a methodology to forecast electricity consumption in the distribution networks. The forecasting process consists of a spatial analysis, clustering, end-use modelling, scenarios and simulation methods, and the load forecasts are based on the application of automatic meter reading (AMR) data. The developed long-term forecasting process produces power-based load forecasts. By applying these results, it is possible to forecast the impacts of changes on electrical energy in the network, and further, on the distribution system operator's revenue. These results are applicable to distribution network and business planning.

This doctoral dissertation includes a case study, which tests the forecasting process in practice. For the case study, the most prominent future energy technologies are chosen, and their impacts on the electrical energy and power on the network are analysed. The most relevant topics related to changes in the operating environment, namely energy efficiency, microgeneration, electric vehicles, energy storages and demand response, are discussed in more detail.

The study shows that changes in electricity end-use may have radical impacts both on electrical energy and power in the distribution networks and on the distribution revenue. These changes will probably pose challenges for distribution system operators. The study suggests solutions for the distribution system operators on how they can prepare for the changing conditions. It is concluded that a new type of load forecasting methodology is needed, because the previous methods are no longer able to produce adequate forecasts.

Keywords: Electricity end-use, electricity distribution, electricity distribution business, electricity distribution pricing, future technologies, load forecasting, long-term planning, power-based tariff

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The work was carried out at the Laboratory of the Electricity Markets and Power Systems at Lappeenranta University of Technology, Finland, between 2011 and 2015. The results of this doctoral dissertation are based on the following research programs: Smart Grids and Energy Markets (SGEM) coordinated by CLEEN Ltd and Tariff scheme options for distribution system operators, and Demand response – Practical solutions and impacts for DSOs in Finland. These projects were funded by the Finnish Funding Agency for Technology and Innovation (Tekes), Finnish Energy (Energiateollisuus), the Finnish Electricity Research Pool (Sähkötutkimuspooli), and several companies in the field.

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Abstract

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Nomenclature

Latin alphabet

a	year	
C	cost	€
E	expectation value	
h	hour	
I	insulation	
K	starting value	
k	coefficient	
L	levelling coefficient	
n	number	
P	active power	kW
Q	two-week index	
R	hourly index	
q	electricity end-use	
T	outdoor temperature	ºC
t	time	
W	energy	kWh
x	variable	
y	variable	
z	normal distribution	

Greek alphabet

α	temperature dependence parameter
β	coefficient of the outdoor temperature
η	efficiency factor
σ	standard deviation

Subscripts

a	coefficient
ave	average
COP	coefficient of performance
DR	demand response
eh	electric heating
ES	energy storage
EV	electric vehicle
ev	profile of electric vehicle
h	hour
HP	heat pump
i	time
in	investment

k	customer
L	lighting
l	indoor-lighting-dependent proportion
lo	losses
MG	microgeneration
mg	profile of microgeneration
max	maximum
min	minimum
o	interruption
off	off
on	on
om	operation and maintenance
pc	peak cutting
pro	proportion
r	customer group
sv	set value
tod	measured
tot	total

Abbreviations

AAHP	Air to air heat pump
AMI	Advanced metering infrastructure
AMR	Automatic meter reading
ANN	Artificial neural network
ASHP	Air source heat pump
ATOTEX	Allowed efficiency costs in the regulatory model
CCA	Curvilinear component analysis
CHP	Combined heat and power
CI	Computational intelligence
CIS	Customer information system
COP	Coefficient of performance
DC	Direct current
DER	Distributed energy resources
DES	Distributed energy storages
DG	Distributed generation
DR	Demand response
DSM	Demand-side management
DSO	Distribution system operator
EA	Energy Authority of Finland
EC	European Comission
EMA	Energy Market Authority of Finland
EU	European Union
EV	Electric vehicle
FL	Fuzzy logic

FMI	Finnish Meteorological Institute
GDP	Gross domestic product
GSHP	Ground source heat pump
HP	Heat pump
HS	Heating system
IBP	Incentive-based programs
ICT	Information and communications system technology
IRP	Integrated resource planning
ISODATA	Iterative self-organizing data-analysis technique algorithm
LF	Load forecasting
LIS	Land information system
LTLF	Long-term load forecasting
MG	Microgeneration
MDMS	Meter data management system
MTLF	Medium-term load forecasting
NIS	Network information system
PBP	Price-based programs
PCA	Principal component analysis
PHEV	Plug-in electric vehicle
PIS	Population information system
PV	Photovoltaic(s)
SLY	Suomen Sähkölaitosyhdistys, the former Association of Finnish Electricity Utilities
SOM	Self-organizing map
SPF	Seasonal performance factor
STLF	Short-term load forecasting
StoNED	Stochastic Non-Smooth Envelopment of Data
TOTEX	Total expenses
ToU	Time of use tariff
WACC	Weighted average cost of capital

1 Introduction

The energy evolution transforms the traditional energy system into the future energy system. The future energy system may include for instance new types of power production, energy end-use, and energy technologies such as energy storages, electric vehicles, and microgeneration. All in all, these changes will be very significant for the energy sector. The changes in the energy system will also have impacts on the electricity distribution. These effects may lead to new and challenging issues in the operating environment of the electricity distribution in the future. One example of these challenges can be customers' microgeneration; the customers may produce more electricity than they consume. However, the overall impacts of the future challenges on electricity distribution have received little attention in the literature so far. The main focus of this doctoral dissertation is on investigating what kinds of changes are taking place in the electricity distribution environment, how the future energy consumption and powers in electricity distribution networks can be forecasted, and what their effects are on the electricity distribution business.

1.1 Overview of electricity distribution

The main function of electricity distribution is to transmit electricity from the transmission networks to the customers everywhere with an adequate quality of supply (Willis, 2004). Over the past few decades, the end-customers of electricity distribution companies have become more and more dependent on electricity, and their electricity consumption has typically increased.

Electricity distribution is a large-scale operation, which generally involves many issues such as network planning, construction, and maintenance. In principle, the distribution business can be divided into two parts; operation and planning. The focus of this doctoral dissertation is on network planning. Electricity distribution network planning is a long-term planning task, which requires information from many data systems. Data on the present state of the network, including loads, losses, and voltage drops are needed. Further, the trends and guidelines for the long-term network development are of importance for the network planning (Lassila, 2009). Figure 1.1 introduces long-term planning and information flows in the electricity distribution.

Figure 1.1. Long-term planning of electricity distribution (Lassila, 2009).

Long-term network planning establishes the basis for the long-term distribution business. The network investments are made over a long period of time, and the lifetimes are typically 30–40 years. The cost structure of the distribution business requires the distribution business environment to be stable and predictable. It is important for the distribution system operator (DSO) to anticipate how electricity consumption will develop in the future, because consumption impacts directly on the network planning and business. Forecasting energy consumption for years ahead provides valuable information for business planning and development of pricing models. Moreover, forecasting distribution network powers decades ahead is an important tool in the distribution network planning. The importance of forecasting will grow in the future, if the operating environment changes. Appropriate development of the future electricity distribution networks calls for identification of challenges, and it is also necessary to be able to prepare for future changes in the distribution networks (Lohjala, 2005).

The oldest parts of the present electricity distribution networks in Finland have been built over 50 years ago. In practice, this means that renovation needs in electricity distribution networks are high. In addition to the renovation needs, the new Electricity Market Act defines the limits on the reliability of electricity distribution in Finland. The law requires that the electricity distribution operators have to develop their networks such that the maximum blackout duration is 36 hours in rural areas and six hours in population centres by 2028 (Electricity Market Act, 2013). The ageing distribution network and reliability requirements make the network planning and load forecasting a critical and current research topic. In addition, society is more and more dependent on electricity, and challenges may be raised by high expectations of the quality of supply and cost efficiency of the electricity distribution in Finland. There are also other unstable factors, which may have an indirect influence on the distribution business environment. An example of this kind of a challenge is possible modifications in the electricity market model.

A solution to the challenges raised by the changing operating environment could be an advanced distribution network, smart grid, which can achieve a higher energy efficiency and reliability than the current networks. The distribution networks will very likely develop as smart grids in the future. Smart grids may involve different kinds of new loads and power production such as microgeneration, energy storages, and various measurements and load controls. Smart grids are considered to have potential to save energy, promote demand response and new innovations, and enhance the reliability of electricity distribution (Rahimi and Ipakchi, 2010). Ultimately, the effects and changes in the energy system can be detected only years later.

Nowadays, more detailed data of the end-customers' electricity usage are available. Smart meters will provide more data on customers' consumption and other related issues. This will revolutionize information of the customers' electricity usage. In Finland, the majority of automatic meter reading (AMR) installations were made by the end of 2013. Hence, there is already some evidence that changes in the energy sector are in progress. New technologies will have different effects on the DSOs' operation and networks. For instance, some devices and technologies like electric vehicles (EVs) will increase the amount of electrical energy transmitted through the distribution network. On the other hand, some other solutions such as microgeneration will decrease the amount of electrical energy transmitted through the distribution network.

The key elements for the DSOs are the total electrical energy consumption, peak powers, costs, security of supply, and revenue. Energy consumption is an informative indicator of the business development in the electricity distribution. The highest peak loads in the electricity networks are the most essential element in the dimensioning of the network. Similarly, peak loads are a major aspect in the network construction and renovation. Further, it is emphasized that the electricity distribution business is a capital-intensive trade. A majority of the expenses are comprised of network investments. Investments of this kind typically require significant economic resources, and they are made in the long term. The major part of the distribution costs depend on powers on the distribution network. The higher are the loads, the higher are the costs. The majority of the electricity distribution revenues, on the other hand, come from distribution tariffs. Distribution tariffs and the DSO's revenue, again, typically depend on energy consumption.

This doctoral dissertation aims at developing methodology to forecast changes in energy and power volumes. This way, we can produce more information for distribution planning and business management. Up-to-date knowledge is highly important because of the efforts put into planning and huge investments made both at the moment and in the future. Despite the considerable changes, people will still be dependent on electricity distribution for many years ahead. However, the evolving operating environment poses certain challenges, and new information of the future trends is urgently needed. If wrong decisions and investments are made now, they may prove very costly and difficult to rectify. Therefore, information and approximations of the future electricity use and operational changes in the electricity distribution network are required. This research will introduce new tools to enhance and facilitate DSOs' operations and planning work. The doctoral dissertation also provides new options for DSOs to plan their future strategies.

1.2 Objectives and research questions of the work

The main objective of this doctoral dissertation is to develop methodology to forecast future electrical loads in electricity distribution networks in the long term. The objective can be divided into the following tasks:

- Identifying the main future energy evolution factors and recognizing the effects of future energy technologies
- Developing the long-term load forecasting process for electricity distribution, which can be used to analyse energy and power in electricity distribution networks in the future
- Analysing the effects and results of the future energy technologies on electrical energy and power on the electricity distribution networks 10 to 40 years ahead
- Investigating how to manage the impacts of energy technologies on the electricity distribution networks and business

The work aims at promoting knowledge of the main factors in energy evolution and recognizing the effects of future energy technologies on electricity consumption. The work identifies changes that will probably take place in the electricity distribution operating environment. In addition, the target is to propose solutions on how DSOs can survive from the challenges. Changes in the operating environment are already on the way; for instance, electricity consumption patterns may be radically different in the future, and it is important to recognize the challenges involved in the process. The role of energy and power will grow essentially in the future, which further emphasizes the significance of load forecasting for DSOs.

The results of this work can be applied to distribution network planning, and distribution networks can be analysed by this methodology over a long-term period. Moreover, DSOs achieve valuable knowledge of their future business environment and also obtain new tools to develop their business models. However, also other operators such as electricity retailers could exploit the methodology of this work in their own businesses.

The analysis includes all types of customers, which are connected to a low-voltage network. The work concentrates on the Nordic operating environment with a specific reference to rural networks. The focus of the work is based on the fact that the DSOs may face difficulties in the future: consumption patterns may change, the revenues may decrease, and there will be a significant need for investments. The calculations are dependent on the geographical location of the network, which means that each network area has to be studied individually. Mean hourly powers are used in the power calculations. Further, it is pointed out that the dissertation takes into account peak powers at an hourly level in the distribution networks.

The focus of the work is solely on the estimation of electrical energy and power in the future distribution networks. Network losses or other network-related issues are not addressed in detail. Further, all customer types cannot be studied separately, because there is a large variation in customer types and electricity consumptions. For instance, the characteristics between service sector customers or the consumption patterns between customers of a same type may vary considerably. As to the future energy technologies, only the ones that are anticipated to be in common use in the future are taken into consideration. Again, the energy efficiency actions are limited to main devices such as lighting, heating systems, and insulation of the buildings.

The research questions in this study are mainly associated with DSOs. The main research questions are related to the background of the challenges that the DSOs face in their operating environment, the effects of the future technologies, and the approaches to manage the changing business environment. In addition, the doctoral dissertation answers the following main research questions:

- How can the future electrical energy and power be forecasted in the distribution networks?
- Which methodologies can be applied to the long-term electricity load forecasting in electricity distribution?
- How will the energy consumption and powers change in the distribution networks 10 to 40 years forward?
- What are the effects of the changes on the electricity distribution business?
- How can the DSOs adapt to the changing operating environment?

In the dissertation, answers to the research questions are sought by analysing the results of the case studies. However, it is emphasized that the topic is extensive, and thus, all the research questions related to the theme cannot be included in the dissertation.

The dissertation shows that major changes will occur in the electricity distribution in Finland. The contribution of this dissertation is the new methodology for the long-term load forecasting in electricity distribution. Finland is one of the first countries in the world that has launched AMR meters at electricity end-customers. Almost all meters have been installed by the end of 2013 (Government Decree 66/2009, 2009). The metering data can be applied to the load forecasting. Currently, AMR data are not yet widely used globally, and thus, these data have not been used extensively in the long-term load forecasting. In addition to the new forecasting methodology with an AMR data analysis, the methodology also observes some future energy technologies.

The future energy technologies will have significant effects on energy consumption. Further, the dissertation includes the key technologies in the long-term load forecasting. Typically, new technologies are forecasted in certain conditions at the electricity distribution level. The analysis of the effects of the new technologies on electricity distribution adds to the novelty value of the dissertation.

1.3 Scientific contribution

The main contribution of the doctoral dissertation is the definition of the changes in the operating environment and development of modelling methodologies for the long-term planning. The scientific contributions are concentrated on the methodology to forecast energy and power over a long-term period, and a method to manage the effects of changing consumption patterns on the electricity distribution business in the Finnish operating conditions is proposed. The contributions of the work can be listed as follows:

- The work defines the factors that have major impacts on electricity consumption and the electricity distribution business.
- Methodology is proposed for forecasting electricity use in the electricity distribution environment in the long term.
- The work shows the kinds of network load changes that the DSOs have to be prepared for. Energy and power may change considerably in the electricity distribution networks. This is presented by a new forecasting process. The case results show that in the future, network powers will increase and electrical energy may even decrease.
- The work introduces new models for the DSOs to develop their business operations and options to manage challenges. For instance, power-based electricity distribution pricing is suggested to prevent an increase in network loads.

A new load forecasting process is required, which can take into account the future changes. This kind of a forecasting process will include several methods, which are applied in different phases of the forecasting process. Some of the most critical challenges in the forecasting process are related to the acquisition of information and application of different data systems. The forecasting process requires a lot of information from several sources, which may be challenging and laborious to make suitable for the process. In addition, selection of appropriate parameters and scenarios is a key element in the forecasting process.

1.4 Outline of the work

This doctoral dissertation is organized as follows. Chapter 2 addresses electricity distribution. The chapter begins with a review of electricity distribution and describes the future operating environment of electricity distribution. Furthermore, the chapter presents a regulation model, pricing principles, the role of load forecasting, and the benefits of smart meters and smart grids. Moreover, the significance of energy and power for the distribution sector is analysed.

Chapter 3 focuses on the history of electricity consumption. Basically, this includes traditional electricity usage ranging from an individual customer to the national level. Electricity usage trends are also studied; in addition, the chapter researches into the drivers for changing electricity consumption. The chapter is concluded with the most significant energy technologies and scenarios of the related equipment.

Chapter 4 provides a literature review and different methodologies to forecast electrical loads. It introduces typical long-term load and energy forecasting methodologies and describes the most important characteristics of load forecasting in electricity distribution networks. The technical part is divided into sections comprising load modelling and load forecasting methodologies.

In Chapter 5, the methodology for long-term electricity load forecasting is investigated further. The first part elaborates on the structure of the forecasting methodology. In the second phase, the requirements for the data, AMR data processing, and customer clustering are demonstrated. Moreover, volume and consumption forecasts and future energy technologies are modelled and the forecasting system is described.

Chapter 6 presents the case studies and their analysis. The chapter evaluates the impacts of future energy technologies on the electrical energy and powers at different network levels. The impacts of each future energy technology are presented separately. The effects on the distribution business are also dealt with. The chapter analyses the DSOs' opportunities to manage the impacts of changes in the electricity distribution business environment. The chapter suggests solutions for DSOs to develop their distribution system operation and business. It is concluded that load management can be a solution to network load challenges. From the economic perspective, new distribution tariff models are proposed to manage the electricity distribution business more effectively. Finally, conclusions are made and future research questions are considered in Chapter 7.

1.5 Research activities related to the doctoral dissertation

In addition to this doctoral dissertation, which is a monograph, the author has written publications that are related to the topic of the dissertation but are not included in the work. In these publications, the present author wrote and modelled most parts of the articles. The co-authors provided comments on the manuscripts. The most relevant of these publications are listed below.

Tuunanen, J., Honkapuro, S. and Partanen J. (2015), "A novel long-term forecasting process for electricity distribution business," in *CIRED 2015, International Conference and exhibition on electricity distribution*, Lyon, France.

Tuunanen, J., Honkapuro, S. and Partanen J. (2013), "Effects of residential customers' energy efficiency on electricity distribution," in *CIRED 2013, International Conference and exhibition on electricity distribution*, Stockholm, Sweden.

Tuunanen, J., Honkapuro, S. and Partanen J. (2012), "Managing impacts of distributed energy resources and demand response by tariff planning," in *NORDAC 2012, Nordic Conference on Electricity Distribution System Management and Development*, Helsinki, Finland.

Tuunanen, J., Honkapuro, S. and Partanen J. (2010), "Energy efficiency from the perspective of electricity distribution business, in *NORDAC 2010*," in *Nordic Conference on Electricity Distribution System Management and Development*, Aalborg, Denmark.

In addition, the present author has been co-author in other publications. As a co-author, he provided comments on the manuscripts. The most relevant of these publications are listed below.

Honkapuro, S., Valtonen, P., Tuunanen, J., and Partanen J. (2015), "Demand side management in open electricity markets from retailer viewpoint," in *EEM 2015*, 12*th International Conference on the European Energy Market*, Lisbon, Portugal.

Honkapuro, S., Tuunanen, J., Valtonen, P., Partanen J., and Järventausta P. (2015), "Practical implementation of demand response in Finland," in *CIRED 2015, International Conference and exhibition on electricity distribution*, Lyon, France.

Honkapuro, S., Tuunanen, J., Valtonen, P., and Partanen, J. (2014), "DSO tariff structures – development options from stakeholders' viewpoint," *International Journal of Energy Sector Management*, Vol. 8, Iss. 3, pp. 263–282.

Honkapuro, S., Tuunanen, J., Valtonen, P., Partanen J., Järventausta, P., and Harsia, P. (2014), "Demand response in Finland – Potential obstacles in practical implementation," in *NORDAC 2014, Nordic Conference on Electricity Distribution System Management and Development*, Stockholm, Sweden.

Annala, S. Viljainen, S., Tuunanen, J., and Honkapuro, S. (2014), "Does knowledge contribute to the acceptance of demand response?" *Journal of*

Sustainable Development of Energy, Water and Environment Systems, Vol. 2, No. 1, pp. 51–60.

Annala, S., Viljainen, S., and Tuunanen, J. (2013), "Rationality of supplier switching in retail electricity markets," *International Journal of Energy Sector Management*, Vol. 7, No. 4, pp. 459–477.

Annala, S., Viljainen, S., Hukki, K., and Tuunanen, J., (2013), "Smart use of electricity – How to get consumers involved?" in *IECON 2013, Annual Conference of the IEEE Industrial Electronics Society*, Vienna, Austria.

Belonogova, N., Valtonen, P., Tuunanen, J., Honkapuro, S. and Partanen J. (2013), "Impacts of market-based residential load control on the distribution network business," in *CIRED 2013, International Conference and exhibition on electricity distribution*, Stockholm, Sweden.

Annala, S., Viljainen, S., and Tuunanen, J. (2012), "Demand response from residential customers' perspective," in *EEM 12, 9th International Conference on the European Energy Market*, Florence, Italy.

Moreover, there are other publications in the preparation of which the present author has been involved. Publications and research results are mainly based on the following research programs: Smart Grids and Energy Markets (SGEM) coordinated by CLEEN Ltd., Tariff scheme options for distribution system operators, and Demand response – Practical solutions and impacts for DSOs in Finland. The results were produced by a research team at Lappeenranta University of Technology. The present author studied end-use profiles of different new technologies, load modelling, electricity distribution business models, and distribution pricing.

2 Electricity distribution operating environment

The Finnish Electricity Market Act (386/1995) reformed and opened the electricity markets to competition in 1995. Consequently, the DSOs' role changed, and since 1998, small-scale consumers have had an opportunity to switch their electricity supplier. In the European electricity markets, the operations are commonly divided into electricity generation, sales, transmission, and distribution. The markets are open for electricity generation and sales, but the transmission and distribution networks have typically been natural monopolies (Viljainen, 2005). A basic model of the electricity markets in most of the EU countries is presented in Figure 2.1.

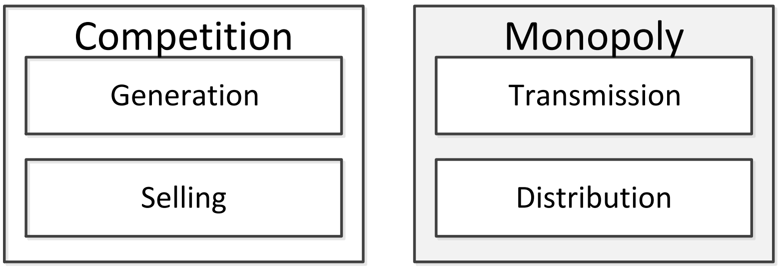

Figure 2.1. Typical structure of the electricity markets (Viljainen, 2005).

Traditionally, the DSO's function has been to transmit electricity reliably through the distribution network to the customers while ensuring an adequate quality of supply and reasonable prices (Willis, 2004) and (Haakana, 2013). Over the years, the DSOs' duties have evolved, and also the operating environment has changed in Finland. DSOs have developed their services significantly; for instance, some DSOs now offer energy consumption information services. However, more services can be developed also in the future. DSOs have also developed their business strategies, and some companies have outsourced their services such as network construction and maintenance (Brådd et al., 2006), (Tahvanainen, 2010). This chapter elaborates, for instance, on the importance of energy and power, the role of load forecasting, and distribution pricing. Further, the chapter describes how the operating environment of electricity distribution has evolved, and what kinds of challenges will arise in the future.

2.1 Electricity distribution business

There are a total of 81 electricity distribution companies in Finland, and the DSOs have over 3 million electricity customers. The Finnish electricity distribution system consists of 140 000 km of medium-voltage network lines and 235 000 km of low-voltage lines (EA, 2014a). The DSOs operate in varying conditions; there are differences for instance in customer structures, distribution networks, and operating environments (Hyvärinen, 2008). However, the basic elements of distribution business operation are quite similar in every company.

Electricity distribution business encompasses many elements, which are illustrated in Figure 2.2. The figure demonstrates the core and auxiliary functions of the business, which are grouped also according to their functionalities. The core operations of the DSO are asset management, which covers business operation planning and implementation tasks, planning of network development, network construction, and customer service (Lakervi and Partanen, 2008).

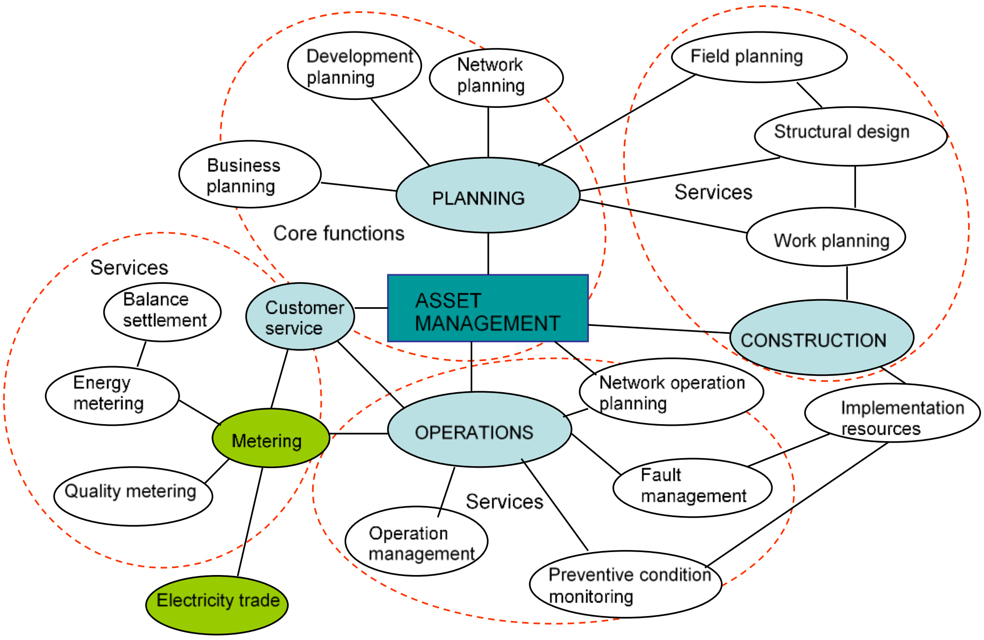

Figure 2.2. Core and auxiliary functions of the DSO (Lakervi and Partanen, 2008).

Electricity distribution business determines the wherewithal for the operating environment of a distribution system. Moreover, the distribution business is in a monopoly position, and the business is regulated by the Energy Authority (EA). The authority sets limits on the operation and controls the business. Because investments are expensive and the life spans long, the distribution business should be predictable and stable in the long term. Figure 2.3 presents a typical cost structure of a DSO. Over half of the costs come from financing and investments, which are capital costs. This indicates how strongly electricity distribution companies have developed and invested in their distribution networks. Only 6 % of the total costs are due to losses. Load losses and transmission tariffs to Fingrid are energy-based costs only, whereas other distribution costs are mainly dependent on power. Investments and financing costs are based on power demand. This can be explained by dimensioning of the grid components, which is based on peak loads. The majority of the DSOs' costs are based on the power demand in the electricity distribution.

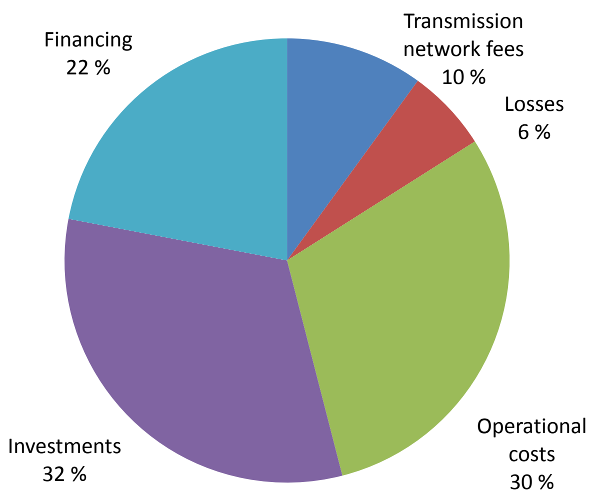

Figure 2.3. Typical cost structure of a DSO (Partanen, Honkapuro, and Tuunanen, 2012).

Generally, cost minimization is an essential element of business planning. However, DSOs' options to influence certain overall DSO's costs such as transmission network tariffs, losses or financing are slight. In addition to the minimization of the overall costs of the distribution business, the role of network cost minimization is significant. Electricity distribution design aims at minimizing the total costs of the distribution network over the total lifetime of the network. This can be presented as follows (Kivikko, 2010):

$$C_{tot} = \sum (C_{in} + C_{lo} + C_{om} + C_o) \qquad (2.1)$$

where

C_{tot}	total costs of the distribution network
C_{in}	investment costs
C_{lo}	cost of losses
C_{om}	operating and maintenance costs
C_o	interruption costs

The DSO can typically achieve the highest benefits in the network cost minimization from investment costs and operating and maintenance costs. However, it may be difficult to decrease the investment costs; because of the reliability requirements, the amount of investments has to be at a high level in the future. On the other hand, DSOs may take various approaches to decision-making with respect to investments. Opportunities to achieve savings in investment costs are to dimension the network components smaller or to find optional ways to build the network. Other options to minimize costs are to decrease the operating and maintenance costs, costs of losses, and outage (interruption) costs. Here, operating and maintenance costs play the major role.

The greatest benefits of the DSO's overall cost reduction can be obtained if investment, operating, and maintenance costs can be reduced. Minimizing costs in the long run is one of the challenging tasks in the distribution network design. As it was mentioned above, DSOs will have to make extensive investments in the near future. Therefore, cost reduction is a highly important and current topic. The costs may increase considerably, if wrong decisions are now made in the strategic planning.

2.1.1 Regulatory model

The main targets for the companies are usually profit-making and growth. However, electrical power networks are in a special position, because they operate in a natural monopoly environment. The electricity market reform in the 1990s gave rise to the electricity distribution regulation in Finland, which meant new requirements for the distribution business. Now, the DSOs have to operate within the limits set by the EA (Energy Authority). The regulation is twofold; both technical and economic. Technical regulation gives instructions for the building and operation of the power system. Economic regulation, again, aims at preventing the misuse of the monopoly position by prohibiting companies from overcharging their customers, and ensuring an adequate level of service quality (Honkapuro, 2008).

A DSOs' maximum allowed profit is determined by the Energy Authority (EA). The EA controls the quality of transmitted electricity, and also the profit of electricity distribution has to be within certain limits. The EA does not regulate the distribution tariffs, but it monitors certain components of the revenue. The target of the regulation is to make the monopoly business environment more efficient. The present economic regulatory period 2012–2015 is the third in Finland. The inputs in the allowed revenue have remained almost unchanged between the different periods, but some of the calculation details within the scheme have changed. The scheme includes for instance general and individual efficiency requirements determined by the efficiency benchmarking for the company. The current efficiency benchmarking applies a StoNED (Stochastic Non-Smooth Envelopment of Data) model. The efficiency benchmarking generates a reference value for actual efficiency expenses. Total expenses (TOTEX) and allowed total expenses (ATOTEX) constitute the efficiency bonus in the scheme. Other essential factors having an impact on the allowed revenue are the quality bonus, the allowed depreciations, and the reasonable return on capital. Figure 2.4 introduces the Finnish regulatory model for the years 2012–2015 (EA, 2014c).

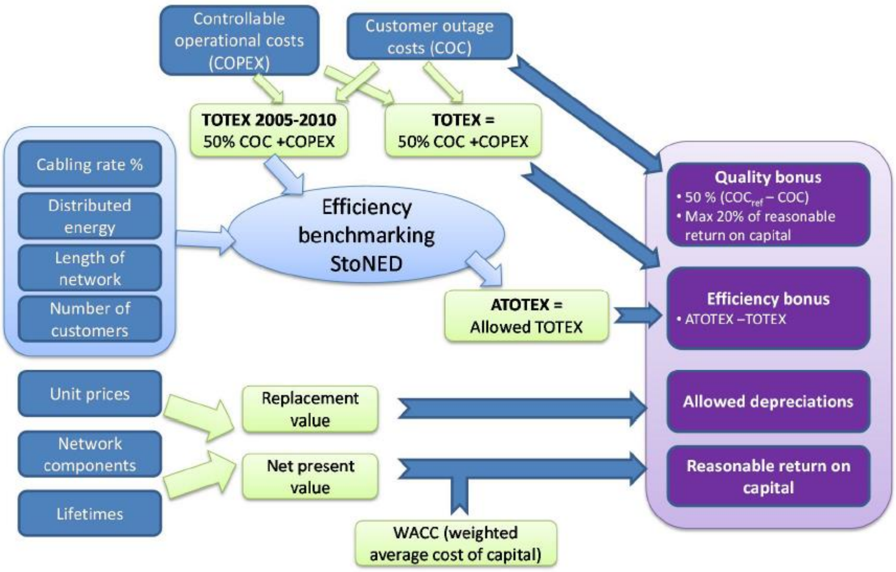

Figure 2.4. Finnish regulatory model 2012–2015 (EA, 2014c), reproduced from (Haakana, 2013).

The replacement value and the net present value can be determined by unit prices, network components, lifetimes, and ages. The reasonable return on capital can be calculated from the net present value and the weighted average cost of capital (WACC). In the Finnish regulatory model, customer outage costs determine a quality bonus or a sanction for the DSO for exceeding or failing to meet the performance criteria. The outage costs are calculated from interruptions and unit costs (EA, 2014c).

There is also an investment incentive in the present regulatory model, which aims at spurring DSOs to develop their distribution networks and ensure adequate investments in the network. The investment incentive comprises two parts: a depreciation method and monitoring of the DSO's adequate investment level. The depreciation method of the investment incentive takes into account the straight-line depreciations from the replacement value of the DSO's electricity network. In addition, it takes into consideration the planned depreciation on the electricity network assets and value adjustments in the DSO's unbundled profit and loss account (EA, 2014c).

Over the past few years, the DSOs have encountered challenges both from the technical and economic perspectives. In spite of the challenges, the DSOs' economic preconditions for operation have remained adequate in Finland (EA, 2014b). However, distributed energy resources (DER) will cause significant changes in the planning and operation of power systems. These changes will pose challenges also for the regulation of power systems (Pérez-Arriaga et al., 2013). Therefore, new regulatory aspects will have to be taken into consideration in the future.

2.1.2 Distribution pricing

Electricity pricing can be divided into distribution charges, retail prices, and taxes. Figure 2.5 shows the distribution of residential customers' total electricity costs. The proportion of taxes is 34 %, sales 37 %, and transmission 29 %. The total price is 15.57 cent/kWh in January 2015 (EA, 2015a).

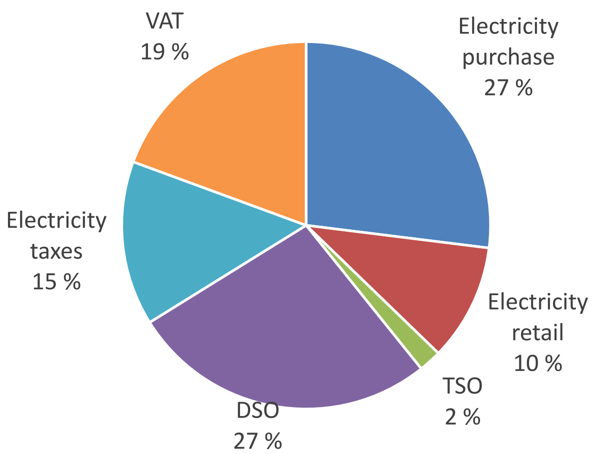

Figure 2.5. Distribution of residential customers' total electricity costs (consumption 5000 kWh, a) in January 2015 (EA, 2015a).

A typical characteristic of electricity pricing is spot pricing. This means that distribution prices are equal for the same type of customers everywhere in the network area. Distribution pricing can be based on a fixed tariff (the size of the main fuses), an energy tariff (day/night, winter/summer), or active power or reactive power tariffs. For instance, residential customers' total distribution charges consist of fixed and energy tariffs. Figure 2.6 shows the distribution of the electricity bill of a residential customer into fixed and energy-based charges.

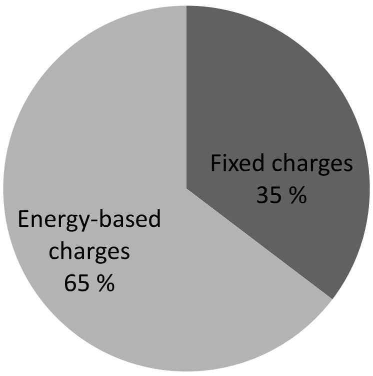

Figure 2.6. Distribution of residential customers' distribution charge divided into energy-based and fixed charges, adapted from (EMA, 2013b).

Distribution pricing scheme has to ensure predictable and reasonable revenue, and encourage the customers to use electricity in a way that is useful for the distribution networks. Moreover, a distribution pricing has to be cost reflective to ensure that changes in electricity end-use affect the revenues and costs as equally as possible. Interests of different stakeholders such as customers, retailers and transmission system operator, have to be taken consideration in distribution tariff design. Thus, a distribution and retail tariff do not generate signals that conflict with each other (Partanen, Honkapuro, and Tuunanen, 2012).

2.1.3 Planning of the electricity distribution network

Strategic planning of electricity distribution networks plays an important role in the asset management of DSOs. The long-term operations and the capital-intensive nature of the DSOs emphasize the significance of strategic planning. An appropriate strategy increases awareness of the challenges involved in the operating environment and the future targets of the DSO. The role and interdependences of strategic planning are illustrated in Figure 2.7. An efficient and workable strategy takes into consideration the requirements and opportunities arising from the business environment, owners, and economic regulation. Moreover, the strategy has to provide valuable knowledge for the management (Lassila et al., 2011).

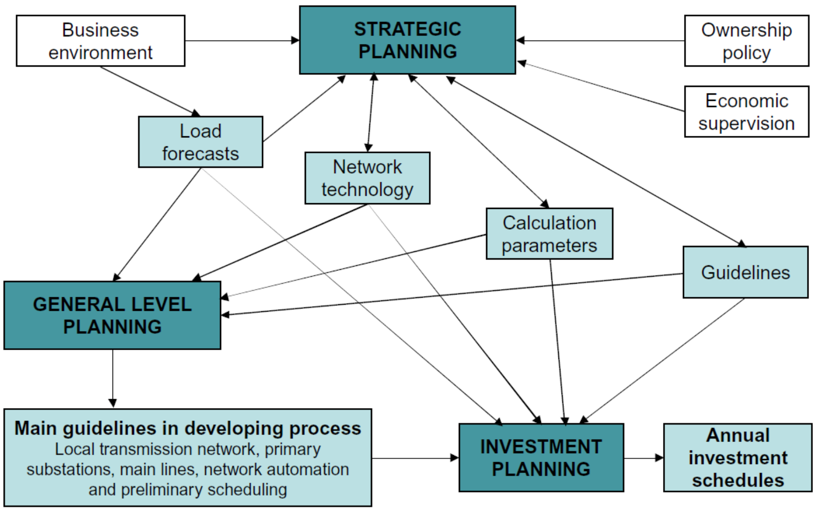

Figure 2.7. Role of strategic planning (Lassila et al., 2011).

Annual investment schedules are part of strategic planning. These schedules are based on investment planning, which is an essential element of strategic planning. Among the key inputs of investment and general plans are load forecasts. Especially, long-term load forecasts generate important knowledge of the changes and development in the business environment.

2.1.4 Importance of energy and power

A DSO's target is to transmit electrical energy through the distribution network constantly. As mentioned above, electrical energy consumption and power are important distribution network and business planning criteria. Knowledge of the electrical energy consumption and powers in a certain area 10 to 40 years forward would prove very useful information from this perspective. The power loads are of significance from the perspective of distribution network planning, because network dimensioning is based on powers. Thus, power loads are considered from the primary substation level to the customer points. Typically, customer interfaces are almost always dimensioned by the same type of approaches, which means that power forecasting in customer points is not an issue. Figure 2.8 shows a typical rural electricity distribution network from the primary substation to the customer points.

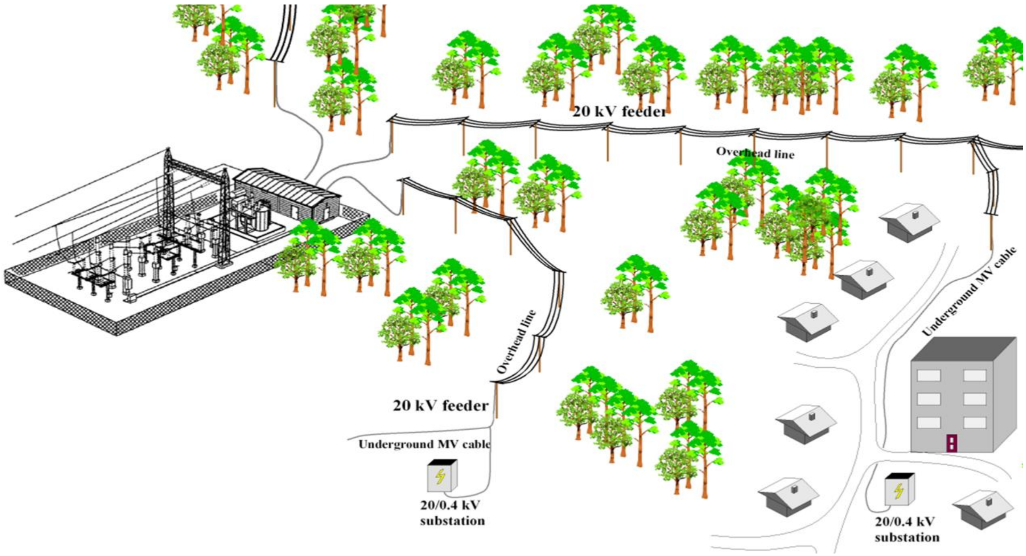

Figure 2.8. Example of a DSO's medium-voltage (MV) distribution network.

The highest mean hourly power is not of such significance at the DSO level. The power load depends on location, and power is important in the distribution networks. Instead, electrical energy consumption plays a decisive role at the DSO level as it has direct impacts on the distribution business. Energy consumption is also a key factor at the customer level as it has impacts on the distribution charges. At the DSO level, the variation in the total energy consumption is reflected in the distribution revenue. Figure 2.9 depicts the total transmitted electrical energy in 0.4 kV networks and the DSOs' revenues in Finland.

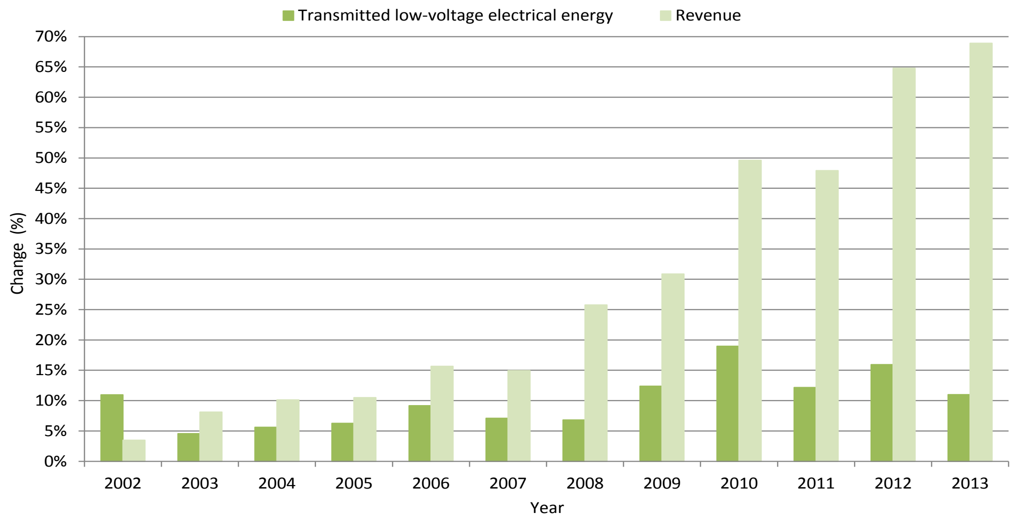

Figure 2.9. Transmitted low-voltage electrical energy and the DSOs' revenues in Finland between 2001 and 2013 (EA, 2015b). The change describes how energy and revenue have developed in different years compared with the reference year 2001.

Electricity consumption in low-voltage networks has grown by about 15 % between 2001 and 2013 in Finland. The DSOs' revenues, again, have increased by about 70 % over the past ten years. Energy consumption in the low-voltage networks decreased for example in 2011, which also had a decreasing impact on the revenues. Naturally, energy consumption concerns the whole DSO. Energy and power are at the core of the electricity distribution business; consequently, forecasting of the electrical energy and power is important in the long term for the DSO.

2.1.5 Electrical loads in distribution networks

Electricity consumption in distribution networks depends on many factors such as the number of population, number of customers and buildings, customer types, geographical location, outdoor temperature, and presence of electrical devices. The load data can be categorized in many ways. The most significant elements for load data are system location, customer class, time, dimension (A or kW), and time resolution of load recording (Seppälä, 1996). Here, location may refer for instance to a customer, a low-voltage network, or a medium-voltage network. Different load types are typically divided into groups: residential, agriculture, industrial, private, and public services (SLY, 1992). The loads vary according to the time of year, the day of week, and the time of day. The dimensions of the load data can be amperes or kilowatts. The time resolution of the load recording is system dependent, and it can vary for instance from minutes to hours (Seppälä, 1996). Energy consumption and mean hourly powers are based on load factors. There are several factors that generally influence the customers' electric loads. Perhaps the most relevant factors are listed and divided as follows (Seppälä, 1996):

- Customer factors
- Time factors
- Climate factors
- Other electric loads
- Previous load values and load curve patterns

Customer factors are often related for instance to the type of consumption, type of electric space heating, building size, and electric devices. The primary factors are the number, type, and size of the electrical devices of the customer. Even if the customers' electrical devices and installations are dissimilar, it is possible to identify certain customer types with similar properties (Seppälä, 1996).

There are significant standard deviation in customers' electricity consumption and electrical loads in the distribution networks. Different kinds of customers in different locations of the distribution network cause varying peak operating times. The peak operating time typically increases from the low-voltage network to the primary substation. Table 2.1 lists some peak operating times for losses. The role of random variation is further emphasized if the number of electricity end-users is low and the standard deviation is high. These aspects have to be taken account in the power forecasts in the electricity distribution networks.

Table 2.1. Peak load times at different network levels (Lakervi and Partanen, 2008).

Network level	**Peak operation time of losses t_{lo}, h/a**
Low-voltage network	700–1000
Medium-voltage line	2000–2500
Primary substation	3000–3500
Idle losses	8760

In addition to the load type, there are other factors that have a direct impact on electrical loads and that have thus to be taken into consideration. All information is not always directly available, and therefore, data from different sources have to be applied (Grip, 2013). Time factors have to be taken into account when analysing the loads. The estimations in the load analysis are based on the hour of the day, the day of the week, and the time of the year. In the daytime, electricity consumption is typically higher than at night-time, unless there is energy storage capacity available such as electric storage heating. Electricity consumption varies also according to the day of the week and special days like Christmas and Easter days (Seppälä, 1996).

Loads are also influenced by weather factors: outdoor temperature, wind speed, and solar radiation. Outdoor temperature is the main factor affecting the customers with electric space heating. In practice, considering climate-related load factors, only the outdoor temperature is typically taken into account (Seppälä, 1996). Occasionally, electric loads have an impact on each other. For instance, the use of other electrical appliances may reduce the electric heating demand. Electric loads often involve periodic elements, which usually makes them relatively easy to predict (Seppälä, 1996).

2.1.6 Load forecasting in the long-term planning

The delivery of electric power is a capital intensive business. Electricity distribution facilities need land for power line paths and substation sites, power equipment for distribution, protection, and control, and labour. The arrangements and plans for new or extended infrastructure may require several years. Network planning is a decision-making process that aims at identifying the best schedule of future resources and actions. Financial aspects, in other words, minimizing cost and maximizing profit, service quality and reliability, environmental impacts, public image, and future flexibility are common objectives in network planning. The objective of the planning process is to meet the future electric demand with an acceptable level of reliability. Basically, this includes determining the sizes, locations, interconnections, and timing of future grid extensions, and commitment to DER such as distributed generation (Willis, 1996).

Energy consumption and power forecasts play a crucial role in electricity distribution. Energy and power forecasts yield information about the development of the future electricity distribution environment. Thus, the DSOs can also prepare for the future challenges in advance. If the energy forecasts are erroneous, the effects on the distribution revenue can be detected swiftly, at least in the profit and loss account. In the long term, an incorrect energy forecast can cause problems in the management of the distribution business.

One of the main objectives of the electricity distribution planning is to make distribution networks work in the most efficient way. Load forecasting provides important information for the electricity network planning, and it essential for the electricity system development. The objective is to produce information of the required primary substation capacity, information for planning of feeders, distribution transformer areas, and preliminary information for field planning. New electricity distribution networks are being built and existing networks are renovated. Furthermore, there has to be a plan in which order and within which time period these network investments will be carried out (Willis, 1996). In practice, this means that there is a need for power and energy forecasts. If the power forecasts fail, this will result in either over- or underdimensioning of the network. From the planning perspective, the network should not be over- or underdimensioned; overdimensioning will cause extra costs in the investment phase while underdimensioning will lead to extra costs afterwards. A need for forecasting does not disappear even if loads do not grow in a certain region. This kind of an area can yield information of the network capacity to be released. Network loads have one of the greatest impacts on network planning. Figure 2.10 presents long-term load forecasting objectives.

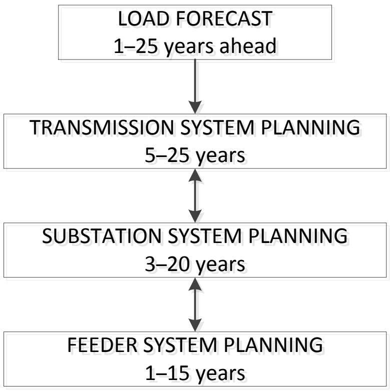

Figure 2.10. Simplified transmission and distribution planning process. All steps are based on forecasts of future loads (Willis, 1996).

Electricity load forecasting is dissimilar in different operating environments. For instance, national electricity consumption is typically forecasted by applying different methods compared with electricity distribution. Load forecasting can be divided into small- and large-area load forecasting in distribution systems. A small area typically refers to local distribution levels while a large region covers the whole capacity in a regional system (Willis, 1996).

Electrical load forecasts have traditionally been based on the DSO's own historical information of the electricity consumption obtained by trending and simulating. The DSO's external data such as land-use plans have also been taken into consideration (Rimali et al., 2011). Annual energy consumption has traditionally been the basis for the long-term load forecasting in electricity distribution. In this context, regional forecasts have been a prerequisite for the electricity distribution. A starting point for forecasting has been the information of the present building stock and customers' electricity consumption data. In general planning, quite a rough distribution of geographical areas has been made. In rural areas, a municipal region has typically been a suitable unit for planning while town districts have served the same purpose in urban areas.

In region-specific forecasts, the sizes of customer groups and characteristic consumptions are the most essential elements. The size of the customer group can be determined, for example, by the number of customers and employees in industries or the building area. The characteristic consumptions are typically given as MWh/dwelling/a or MWh/place of work/a. By multiplying the number of customers by the characteristic consumptions, the total consumption in a customer group can be determined. Summing up the consumptions of all customer groups, the total consumption in the area can be calculated (Lakervi and Partanen, 2008). Table 2.2 shows an example of a regional consumption forecast.

Table 2.2. Example of a forecasting process where the electricity consumption has been forecasted by adopting a regional and customer-group-based electricity consumption approach (adapted from Lakervi and Partanen, 2008).

Year	**0**	**10**	**20**
Population	**11 700**	**11 900**	**12 200**
Number of the residential customers	4 135	4 540	5 080
Characteristic consumption MWh/dwelling/year	4.2	4.7	5.2
Consumption of residential customers, MWh/year	**17 400**	**21 300**	**26 400**
Number of customers with electric space heating	650	1 000	1 750
Characteristic consumption MWh/year	17.1	17.6	18.1
Consumption of electric space heating, MWh/year	**11 100**	**17 600**	**31 700**
Number of farms	415	400	370
Characteristic consumption MWh/farm/year	5.6	6.7	8.0
Consumption of farms, MWh/year	**2 300**	**2 700**	**3 000**
Number of employees in industries	1 350	1 400	1 475
Characteristic consumption MWh/employee/year	6.1	7.0	8.2
Consumption, MWh/year	**8 200**	**9 800**	**12 100**
Total consumption MWh/year	**39 000**	**51 400**	**73 200**

The forecasts of these volumes can be based for example on analyses by Statistics Finland. For instance, the number of building types or the level of livelihood can be estimated; municipal registers also provide valuable information for the purpose. These forecasts can include, for instance, plans for new buildings and employment (Lakervi and Partanen, 2008).

Region-specific forecasts have traditionally been made by the DSOs while national forecasts are typically used as a basis for spatial forecasts. Spatial characteristics have been taken into account in annual energy consumptions of the each customer group and by using the spatial population and employment forecasts in the case area. In network planning, the spatial energy forecasts have to correspond to the present or planned supply areas. Energy forecasts can be transformed into power forecasts by applying load models (Lakervi and Partanen, 2008). The above-presented methodology is quite widely used in the Finnish distribution environment. However, the long-term load forecasting process may vary significantly between different DSOs in Finland. To sum up, the basic concept has been to first prepare the electrical energy consumption forecasts, which have then been transformed into load forecasts by applying load models.

Forecasting typically involves many uncertainties, which make forecasts inaccurate. Nevertheless, load forecasts are needed for network planning and operation of distribution networks. Electricity distribution networks are different from each other. Some distribution networks may consist of a large number of customers in urban areas while others may have a small number of customers, for instance in rural areas. Therefore, forecasts and analyses have to be made for each case individually. An electricity distribution network consists of different levels: customers, low-voltage nodes, distribution substation service areas, medium-voltage nodes, distribution feeders, and primary substations.

Load forecasts are needed all the way in the distribution networks, and the long-term load forecasting has to be able to analyse different distribution network levels. The forecasting can be divided into subcategories: specific methodologies are needed for large and small distribution network areas. Large distribution network areas may cover network levels from the primary substation to feeder levels and distribution substation service areas. Again, small distribution network areas may include network levels from the distribution substation service area to the customer level. Figure 2.11 presents an example of the distribution network levels and the large and small distribution network areas. The highest mean hourly power is the most interesting factor, because peak powers determine the dimensioning of the network in the long term.

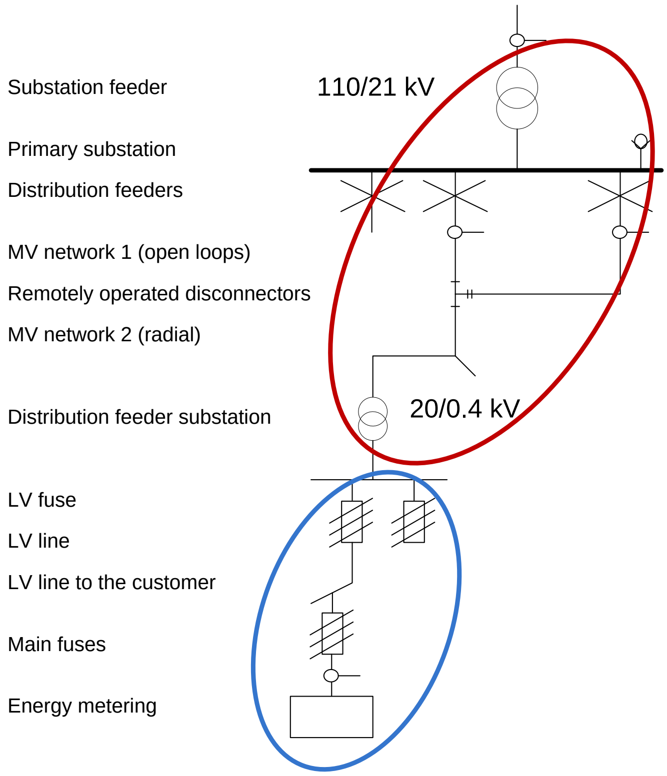

Figure 2.11. Distribution network levels. The red circle indicates a large distribution network area and the blue circle a small distribution network area. Adapted from (Seppälä, 1996).

The amount of data, and the number of customers vary markedly between different areas and network levels. A DSOs' networks typically consist of primary substations, which have one to three main transformers. Some DSOs have only a few substations while larger DSOs may have over a hundred substations in Finland. A substation may supply 1 000–10 000 customers, and the customer structure may vary a lot in the Finnish power systems. The power demand at primary substations may typically be 10–40 MW, and there may be three to ten feeders in one primary substation. The number of customers can diverge considerably between the feeders. In addition, the electrical energy consumption and power can vary greatly between different feeders. Major differences can also be detected at the lower network levels. The number of customers is typically quite small at these levels; for example, a service area of a distribution substation may include 50–500 customers in a population centre but only one to five customers in sparsely populated areas.

2.2 Future distribution grids

Technical requirements for distribution networks have increased dramatically from the level of the past decades. Previously, the requirements were related to the distribution network development and construction. However, the operating environment of electricity distribution has changed essentially over the past ten years. Economic regulation, enhanced reliability of electric power distribution, an increase in distribution automation, adoption of underground cabling, and other technologies are examples of elements that have altered the present environment (Haakana, 2013). This development is likely to continue, and changes may bring new characteristics to the distribution business. Electricity distribution is facing changes because of growing service markets, customer demand, and new technologies in the Nordic countries. Driving forces for the network changes may also be due to ageing networks, customer requirements, climatic changes, and developments in the competitive structure and network technology (Brådd et al., 2006).

The future of the distribution systems has been discussed exhaustively for instance in (Oosterkamp et al., 2014) and (Clastres, 2011). The terms 'smart grids' and 'distribution system of the future' have been introduced in the literature to describe the future electricity distribution systems. The future distribution grids are anticipated to provide new functionalities such as self-healing, high reliability, and energy management. In addition, demand response (DR), distributed generation (DG), and distributed energy storages (DES) play a paramount role in the upcoming smart grid (Brown, 2008) and (Rahimi and Ipakchi, 2010).

2.2.1 Technical aspects

Over the past few years, reliability has become one of the key issues in the electricity distribution sector. One of the reasons for this was the severe storms that caused long-lasting faults and interruptions in electricity distribution networks between 2010 and

2012. The Finnish Government decided to develop the electricity markets and passed the (Electricity Market Act 588/2013, 2013). The new act sets limits on the reliability of supply in the distribution networks. In practice, in order to meet the new limits, for example, extensive underground cabling projects are required from some DSOs. The target is to get rid of long-lasting blackouts. As a consequence, major investments have to be made to improve the reliability of the electricity distribution. This will be the next major challenge, and it will take a lot of time and money.

One of the current electricity distribution topics is the application of smart meter data. Smart meters have mainly been installed by the end of 2013 in Finland. Smart meters and automatic meter reading (AMR) represent quite a new technology, which introduces an entirely new operating environment to the market parties. AMR measurements produce an increasing amount of data for the market parties.

In the future, electricity distribution may be different from the present situation. Technical challenges will put extra pressure on the network planning and development. The future requirements may be challenging for the DSOs, but they have to be taken into consideration in the strategic plans. The reforms will have impacts on the operating environment of electricity distribution.

2.2.2 Business aspects

The electricity distribution business model has remained basically the same over the past years. Suitable market models for small customers have been considered ever since the electricity market was opened to competition. The present market model is a customer-based model, where the customer is in focus. Nevertheless, this model has raised discussion about the conflicts of interest between the DSO and the retailer (Belonogova et al., 2010). Figure 2.12 illustrates two market models. Model I is the present model while model II is an optional model for the future. In model II, the retailer is the market operator. In general, the question of the market model is crucial for the DSOs, because it has influences on the future operating environment.

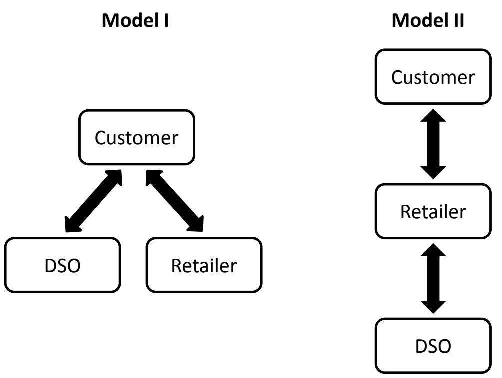

Figure 2.12. Two market models; the left-hand model is in use in Finland at present.

In the electricity distribution business, the whole company's business environment is typically considered for one year at a time. To this end, various economic analyses are required, and there are many ways to analyse business-related parameters. Relevant business parameters are return on capital, equity ratio, income financing of investments, revenue growth, investment rate of the network, and return on investment. However, the main economic key figures are revenue, profit, and investments; these three parameters are the most commonly used ones in economic reviews. The future requirements for electricity distribution will increase pressure to make more investments in the distribution system. Hence, it is quite obvious that network investments will generally increase in the future.

In the electricity distribution business, a DSO's revenue depends on energy consumption. Energy consumption and revenue may vary much as a result of changes in the electricity usage. In particular, in network areas with a lot of electrically heated buildings, the electricity consumption is highly dependent on outdoor temperatures. Varying energy consumption may cause notable fluctuations in a DSO's incomes with the present business model. Nevertheless, in the Finnish electricity distribution companies, electricity distribution prices have risen in some customer groups even by 90 % over the past five years. Figure 2.13 shows the changes in the electricity distribution prices between May 2008 and May 2013 in K1 customer group among the Finnish DSOs.

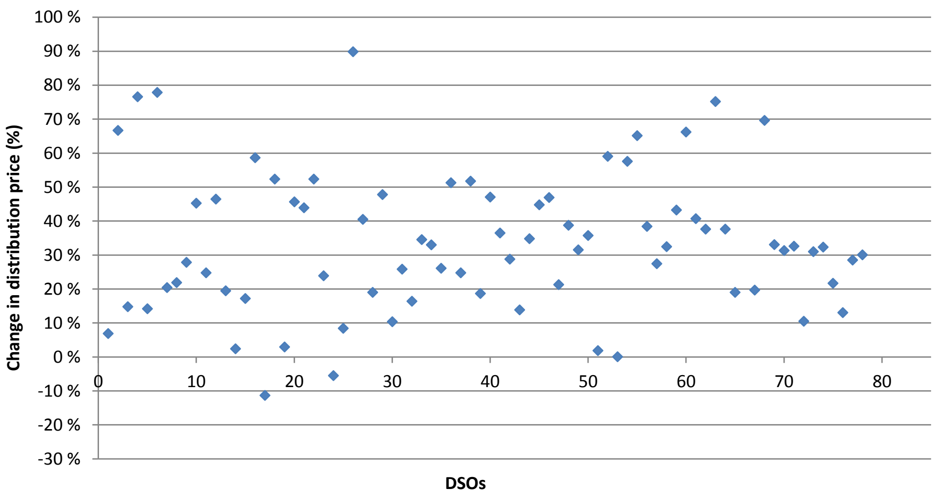

Figure 2.13. Change in electricity distribution prices from 2008 to 2013 for K1 customers (EMA, 2013a).

Electricity distribution prices have risen significantly in some parts of the country, especially in rural areas. The proportion of fixed charges in distribution pricing has increased over the past few years (EMA, 2013b). At the same time, customers' opportunities to affect their distribution charges have decreased.

2.2.3 Smart grids

There are diverse definitions of the term ‘smart grid environment’ in use (Farhangi, 2010) and (Clastres, 2011). Basically, a smart grid must provide visibility and pervasive control over the DSOs’ assets and services. Self-healing and immunity to system departures are requirements that a smart grid should meet. Expanding control and monitoring options in the smart grid will call for a convergence of information and communication technologies with the power system. Thus, investing in electricity distribution automation will make it possible to enhance capabilities in the future, which will intensify the role of communication and data management (Farhangi, 2010).

Smart grids may bring several benefits for different operators; for instance, consumers are more efficiently integrated into the electricity system, renewables are better incorporated into electricity networks, the quality of energy supply is enhanced, and the use of electrical assets is optimized (Clastres, 2011). Typically in Finland, smart grids comprise different elements such as generation, energy storages, loads, signals, and controls. The basic idea behind the smart grid environment is presented in Figure 2.14. The figure illustrates the perspective of the interactive customer gateway; however, the grid automation receives less attention in the illustration.

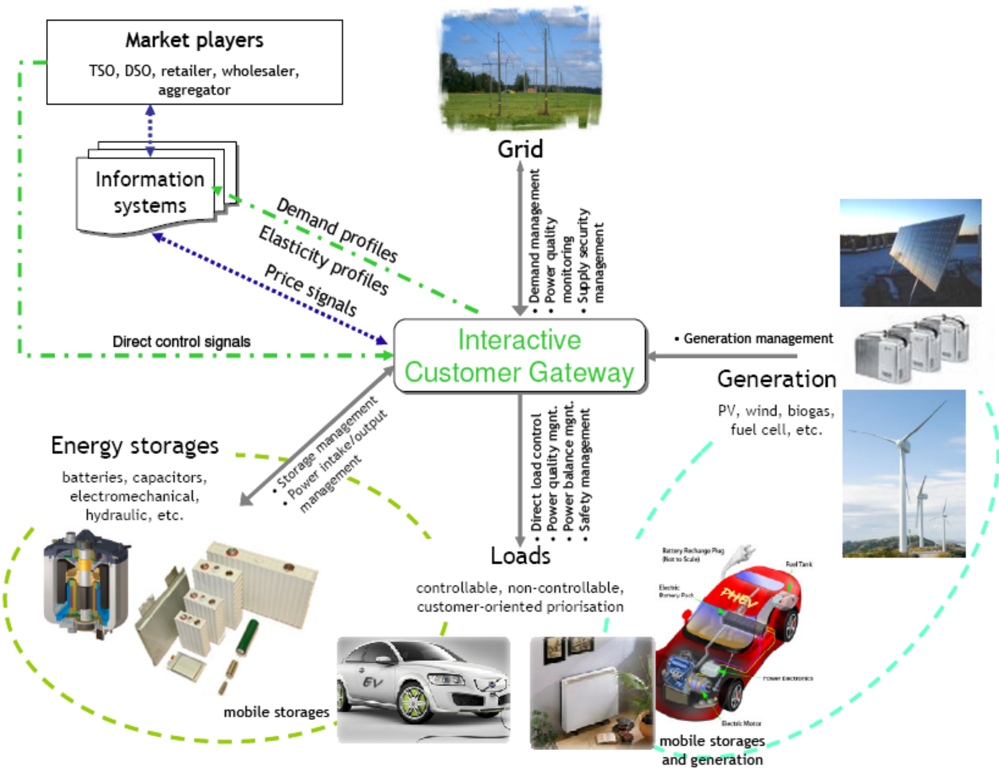

Figure 2.14. Example of the interactive customer gateway (Kaipia et al, 2010).

The smart grid concept introduces new solutions like power electronics and direct current (DC) systems for the future power distribution infrastructure. The traditional and passive distribution network will be reformed to a new and active system with energy resources including distributed generation and storages. Furthermore, new ICT solutions for network operation and asset management may provide intelligence to active networks (Järventausta et al., 2011).

Already at present, automation and ICT systems are at the core of network operation. This development will accelerate in the smart grid environment. The development of smart grids raises the demands and opportunities for the LV network automation, the role of which has typically been minor. Advanced metering infrastructure, distributed generation, and charging of EVs are examples of the significance of LV automation. The number of data and information systems will also grow in the future; further, new data can be integrated into different data systems. For instance, an AMR system can be applied to many functions of the DSO; for instance to support network operation and planning. New communication interfaces and software applications will be in a key element of smart grids (Järventausta et al., 2011).

2.2.4 Smart metering

Smart meters open up an entirely new range of opportunities (Farhangi, 2010) and (Depuru et al., 2011). The introduction of smart meters has taken place in the context of energy efficiency and electricity retail market targets; for instance, the energy efficiency targets of the EU have boosted smart metering. The EU has mandated that 80 % of residential customers have smart meters by 2020, and a Finnish Government Decree states that at least 80 % of customers shall have smart meters by the end of 2013. Distribution system operators (DSO) play a key role in smart metering installations.

Previously, actual consumption information was very difficult to obtain and estimate without smart meters. Nowadays, accurate information of individual customers' electricity consumption is an important element in the analyses on electricity usage. Consequently, more accurate analyses can be made at the electricity primary substation, feeder, distribution substation service areas, and customer levels. The amount of data is constantly increasing as a consequence of the AMR, and more accurate results can be obtained from the customers' consumption curves by applying these smart metering data. By combining the customer data it is possible to obtain results from areas of different sizes such as distribution substation service areas. Figure 2.15 presents features associated with smart metering. As a result, we may state that smart metering can bring significant benefits from the customers' and DSOs' perspective. Further, smart metering can also bring benefits for retailers and society. Finally, we may also anticipate that smart metering promotes sustainable energy usage. Consumption data can provide customers with detailed information about their electricity use and decrease inefficient energy consumption.

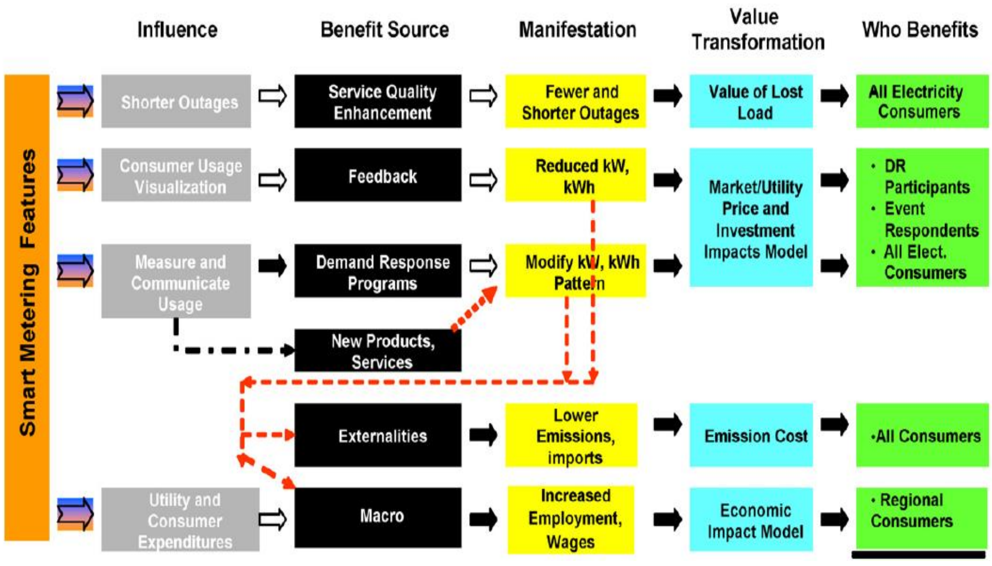

Figure 2.15. Features of smart meters (Neenan and Hemphill, 2008).

The benefits of the smart meters are wide-ranging for the DSOs. The main benefits for DSOs derive from cost savings, greater efficiency in metering and customer service, and higher metering accuracy. The quality of data about electricity distribution and electricity end-use will essentially improve (Sarvaranta, 2010). (Räsänen et al., 2010) has shown that monitoring the electricity end-use provides a new view to develop electricity distribution systems, customer-specific services, and to increase energy efficiency. Electricity distribution companies receive a lot of information about the low-voltage distribution network and the customers by smart meters. AMR enables and facilitates various functionalities such as meter reading, follow-up consumption, and low-voltage fault detection. One of the most important advantages is that smart metering can efficiently indicate changes in the electricity use in a certain network area. In addition, customers can apply home-in-displays to monitor changes in their electricity end-use. More accurate consumption information could be deployed in various ways; for instance, DSOs could obtain useful information of loads.

Previously, electricity metering was carried out once or couple of times a year. Electricity charges were based on estimated and actual metering data. Customers were not necessarily aware of how much electricity they consumed and how much they paid for it. Thus, customers did not have motivation or understanding to impact on their electricity consumption. Today, information of customers' electricity consumption can be delivered effectively to the customers. This should enhance customers' awareness of their electricity use and motivate to save energy and decrease peak loads.

The benefits of the AMRs for DSOs are indisputable. In practice, smart meters provide an opportunity to revolutionize the whole electricity distribution system. Automatic meter reading is the first step towards the future distribution network. AMR systems have been in the focus of recent infrastructure investments in the distribution networks. The DSOs are able to remotely read consumption records and alarms, for instance, on customers' premises. However, AMR is a communication system, which is primarily designed for reading of meter information. Advanced metering infrastructure (AMI), again, will serve as a two-way communication system for the meters. Thus, this may be a significant step towards smart grids as the DSOs could, for instance, manage the loads with this technology (Farhangi, 2010).

3 Electricity usage

The enormous challenges such as environmental issues and climate change have raised a lot of discussion about the energy sector and its development. There seems to be a common agreement that the consumption of energy should be cut and more renewable energy sources should be brought into production (European Commission 109/4, 2011). Today, the end-customers have a wide variety of opportunities for energy saving, for example, the selection of lighting options has increased. Lately, interest in energy saving and energy efficiency has risen considerably. Introduction of electricity metering services and consumption data may produce additional value for the customers. Among other things, incentive-based electricity pricing, microgeneration, and electric vehicles can radically change electricity consumption patterns. Recognizing the relevant load factors would be useful for the future electricity distribution development.

3.1 History of electricity usage

Electricity consumption has typically increased over the past decades (Statistics Finland, 2014a). There have been many reasons for this such as the growing population, the increasing industrial sector, and electric space heating. Again, the electricity use of small-scale customers has increased significantly. This can be explained, for instance, by the increasing number of electrical appliances and household items. Hence, the customers' dependence on electricity and requirements for the reliability of electricity distribution has increased. However, the consumption may also decrease. A typical load growth curve follows an S curve. When the consumption stops to grow, it is considered to have reached a saturation point (Figure 3.1) (Lakervi and Holmes, 1995).

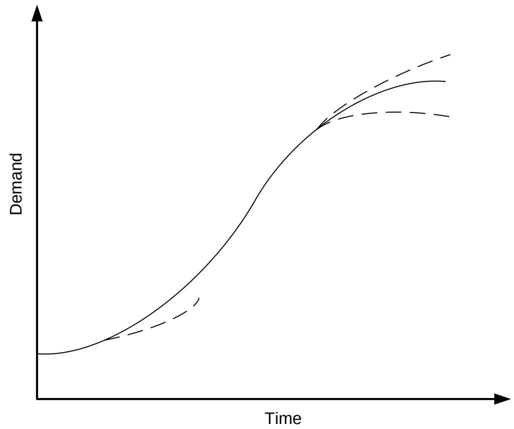

Figure 3.1. Electricity demand and a typical load-growth curve is often based on the S curve model (Lakervi and Holmes, 1995).

The saturation point demonstrates how the traditional residential electricity usage reaches the maximum level. After reaching the saturation point, the electricity consumption may even decrease (Lakervi and Holmes, 1995).

3.1.1 Electricity consumption in Finland

In Finland, the first connection to the electricity network took place at the end of the 19th century, when electricity was used for the first time for lighting. Gradually, electricity consumption started to increase, and later on, the first electricity distribution company was founded. In Finland, the total electricity consumption has increased approximately ninefold over the period of 1960–2010. Over that time, the whole of Finland has been electrified; the electrification of the countryside has been a significant effort, and the decades before 2000 have witnessed a boom in the total electricity consumption. There have been various factors contributing to the increase in the electricity consumption such as an industrial and international financial boom, which have had an impact on the electricity demand. Electricity consumption has constantly increased at the national level until 2007. Figure 3.2 presents total electricity consumption for the period of 1980–2014 in Finland (Statistics Finland, 2014a).

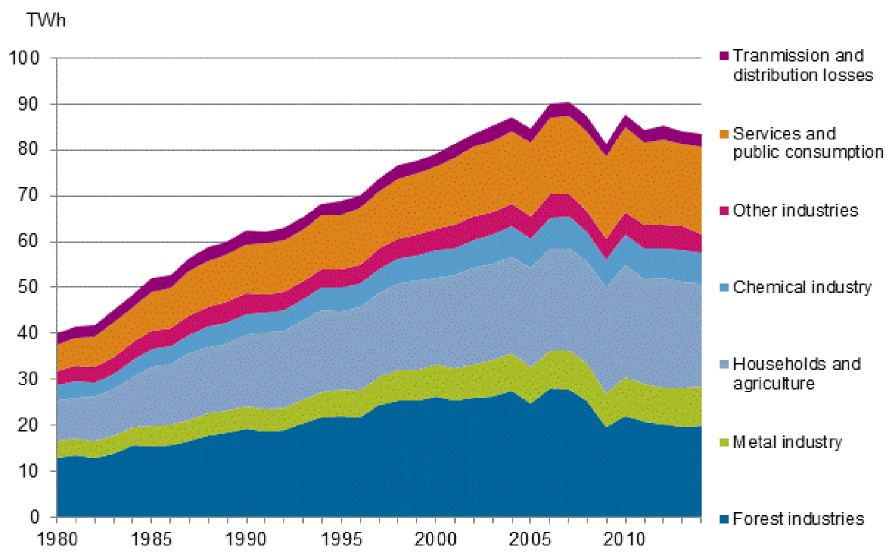

Figure 3.2. Total electricity consumption by sector in 1980–2014 in Finland (Statistics Finland, 2014a).

The Finnish peak annual consumption, 90 TWh, was reached in 2007. Since then, the total electricity consumption has varied between 80 and 90 TWh between the years 2007–2014. Recently, the electricity consumption has gradually slowed down. This is the first time in the Finnish history of electricity consumption when the consumption has not significantly increased. In Figure 3.2, a possible saturation point can also be detected in the total electricity consumption. The first radical change took place in 2008 and 2009, when the total electricity consumption clearly decreased compared with the previous year. This may be explained by various structural changes in Finland at that time. The proportion of heavy industry has decreased in Finland, which has probably been one of the major contributors to the massive and rapid change.

Over the last few years, the total electricity consumption has been about 85 TWh a year on average in Finland. In 2014, the consumption was 83.3 TWh. A more accurate analysis can be made based on Figure 3.3; about half of the electricity was consumed in the industrial sector while housing and agriculture accounted for 28 %, services and building 22 %, and losses 3 % of the total electricity consumption (Finnish Energy Industries, 2015). A typical characteristic of the Finnish electricity demand is the high proportion of electric space heating and lighting (World Energy Council, 2014). The DSOs transmitted 49.5 TWh of electricity in 2013, and 35.7 TWh in low-voltage networks.

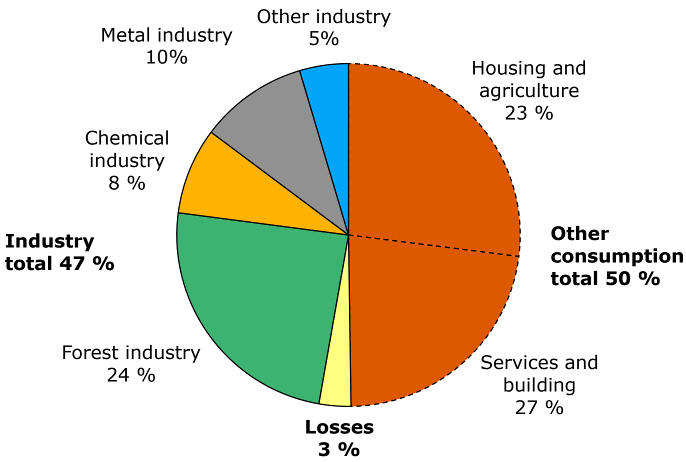

Figure 3.3. Electricity consumption in Finland (Finnish Energy Industries, 2015).

Peak loads determine for instance the need for national power generation and national self-sufficiency. The highest peak load has been about 15 000 MW in Finland (Finnish Energy Industries, 2015).

3.1.2 Electricity consumption at the DSO level

The national electricity consumption has increased by some per cents per year on average. Consequently, the overall assumption has traditionally been that electricity consumption increases by about 1–2 % a year. However, the total annual electricity consumption fluctuates at each DSO. This can be explained for instance by outdoor temperature. Electricity consumption also varies markedly between different areas of the electricity distribution networks. Typically, electrical energy consumption has increased by 0.5–2 % a year on average at the DSO level. Figure 3.4 illustrates the average change in the electrical energy consumption between 2005 and 2012.

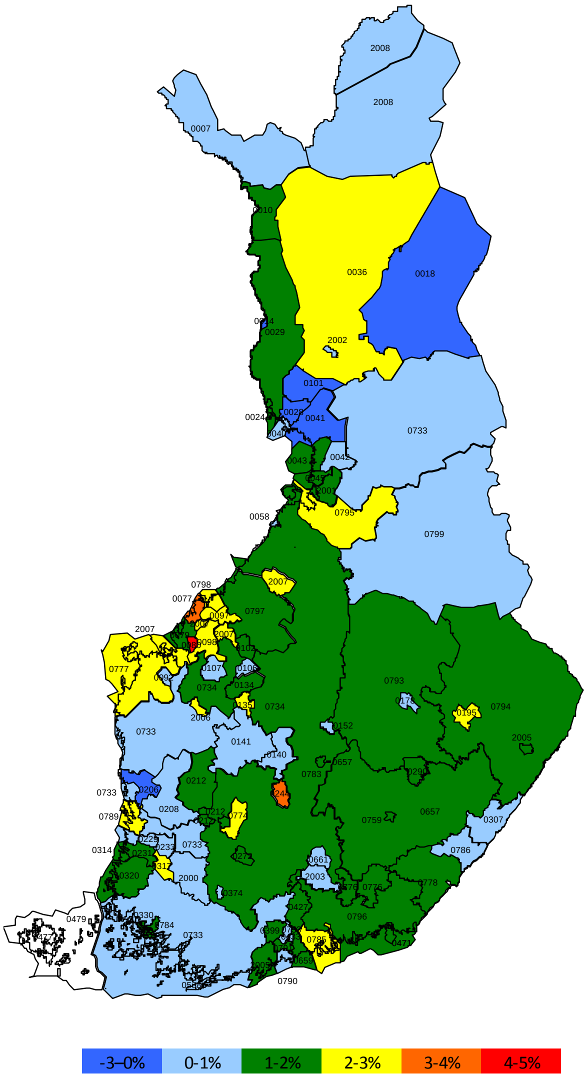

Figure 3.4. Change in the annual electrical energy consumption between 2005 and 2012 by DSOs.

The energy use has increased by 0–2 % for most of the DSOs. In addition, there are cases in which the energy consumption has increased even by 4–5 % a year. For some DSOs, the energy consumption has not changed or has actually decreased. These companies are typically small companies in rural areas. The map illustrates the different kinds of operating environments in which the DSOs are operating in Finland. Structural changes and other factors will probably maintain this development also in the future. In the long term, this will bring challenges especially for the business in smaller companies.

3.1.3 Electricity end-use

This dissertation focuses on customers connected to the low-voltage electricity distribution network. Low-voltage customers can be classified in several different ways (SLY, 1992). Low-voltage customers may include for instance residential, agriculture, service (public and private), and small-scale industrial sector customers. Residential customers, again, may live in detached houses, attached houses, and blocks of flats. The buildings may be either non-electric-heated ones or equipped with electric space heating (direct, partial storage, storage heating). Often, the consumption varies markedly between industrial, agricultural, and service customer groups. The electricity consumption may vary considerably within a customer group. For instance, the service sector customers' electricity usage may be very heterogeneous (Larinkari, 2012). Customer grouping can be useful in many ways, because it makes possible to compare for instance the electricity consumption and pricing between DSOs. However, there are noticeable differences in the DSOs' customer structure and customer types (EA, 2015b).

Electricity consumption varies considerably between different buildings. For instance, in detached houses, more electricity is usually consumed compared with flats. The consumption devices can also be dissimilar. Thus, electricity consumption in different buildings has to be analysed case by case. In addition to electricity consumption, information are needed of the buildings; building and heating system types have a major effect on the electricity end-use. Table 3.1 shows the building stock in Finland. The number of people in residential houses and the living standards of people vary greatly; in city centres many people live in blocks of flats, whereas in the countryside people typically live in detached houses (Adato Energy, 2013).

Table 3.1. Building stock in Finland (Statistics Finland, 2014c).

	Number of buildings	**Gross floor area (m^2)**	**% of total m^2**
Detached houses	1 139 290	160 058 577	35 %
Attached houses	79 362	33 798 205	7 %
Blocks of flats	59 047	95 304 584	21 %
Commercial buildings	42 868	29 167 513	6 %
Office buildings	10 846	19 408 091	4 %
Traffic buildings	56 363	12 574 580	3 %
Institutional buildings	8 606	12 069 488	3 %
Buildings for assembly	13 977	9 524 670	2 %
Educational buildings	8 867	18 327 907	4 %
Industrial buildings	42 799	48 846 199	11 %
Warehouses	29 833	19 720 737	4 %
Other buildings	5 676	1 912 120	0 %
Buildings total	**1 497 534**	**460 712 671**	**100 %**

Electricity end-uses are associated for instance with heating, lighting, cooking, water heating, running water, and electrical appliances. Traditionally, energy consumption has increased together with the increasing number of electrical devices and higher requirements for the comfort of living. Modern conveniences like electric saunas, dishwashers and indirect electric heating such as underfloor heating have become more popular in apartments, and have increased electricity consumption (Adato Energy, 2013). Figure 3.5 shows an example of residential customers' electricity end-use. In Finland, electricity consumption is clearly higher than on average in Europe. This can be seen especially in residential customers' consumption figures (World Energy Council, 2014).

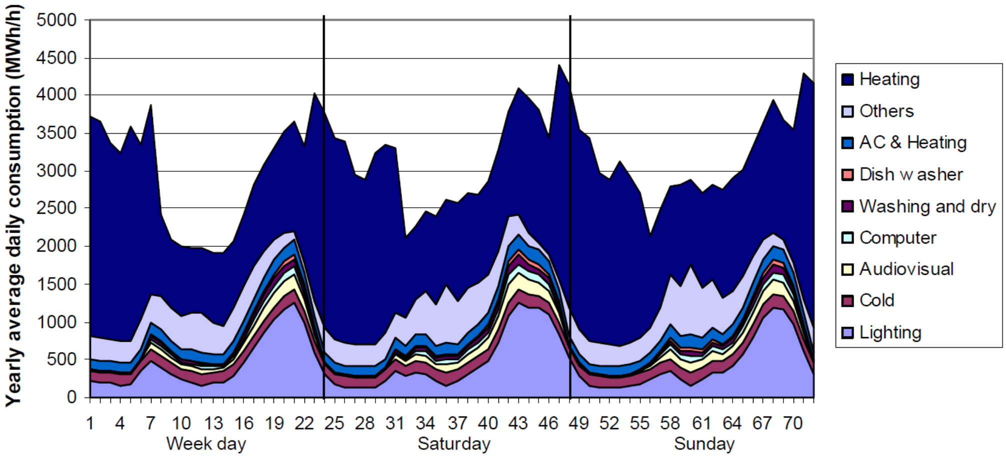

Figure 3.5. Example of electricity end-use of a residential customer (Corentin et al., 2010).

There is no information available of device group measurements, which would give more detailed information of the electricity end-use at various customers. AMR measurements only include mean hourly powers for each hour in a year. For instance, information of the electricity consumed in lighting within a certain customer group would be very useful. Data of this kind are not widely available.

3.2 Future changes in electricity demand and end-use

Sustainable development of energy usage is naturally the target in the energy sector (European Commission (2011), 109/4). There are a lot of drivers that promote the adoption of future energy technologies. The energy sector has globally faced numerous challenges, including global warming and CO_2 emissions, over the past years. However, these challenges can promote development in the energy sector and make electricity consumption more efficient. Some solutions have already been found for these challenges; for instance energy efficiency, renewable energies, emissions targets, and emissions trading. Awareness of climate change, CO_2 emissions, and pollution may have had an influence on customers' thinking, and thereby, on electricity consumption. Again, regulations have been issued on certain customer appliances both at the national and EU level. One example of the EU energy efficiency targets is the Ecodesign Directive (Implementing Directive 2005/32/EC of the European Parliament and of the Council with regard to ecodesign requirements for non-directrional household lamps) (European Commission, 2009).

As stated above, there may be technologies and modifications that may have significant impacts on the electricity end-use. Consequently, these changes influence the electricity distribution. For instance, energy efficiency actions and microgeneration may decrease the transmitted electrical energy in distribution networks. Hence, future technologies such as energy storages may have wide-ranging effects on the energy sector. Individual devices may not have a significant impact on electricity distribution, but a large number of future energy technologies can have major effects on electricity consumption. In addition, decreasing population and other structural changes may alter the volume of delivered energy.

In the following sections, structural changes and different technologies are discussed. The primary research question is how electrical energy consumption and power will change because of the new devices. As it was stated above, some technologies will increase electricity consumption while others may have an opposite effect. The most significant technologies are studied in more detail in the following. The future scenarios for these technologies are also relevant to the research.

3.2.1 Structural changes in electricity demand

Structural changes in society, for instance changes in the number of population, labour market and occupational transitions, and developments in building structures and heating systems will have impacts on the electricity demand in distribution networks. At the time when the population increased notably in Finland, also energy consumption grew substantially. The population has still grown in Finland, although the birth rate has decreased compared with previous decades (Statistics Finland, 2014b). In particular, the situation may be challenging in rural areas because of the decreasing number of people. Both a decrease and an increase in population can be considered to have a direct impact on the electricity demand in electricity distribution networks. The population forecasts of two different areas are illustrated in Figure 3.6. The population forecast shows the total number of people in two areas. In the first example case, the population will decrease by more than 10 % in 2020 and by 20 % in 2040 compared with the present situation. In the second example, the population will increase by 10 % by 2020 and by 20 % by 2040 of the present situation.

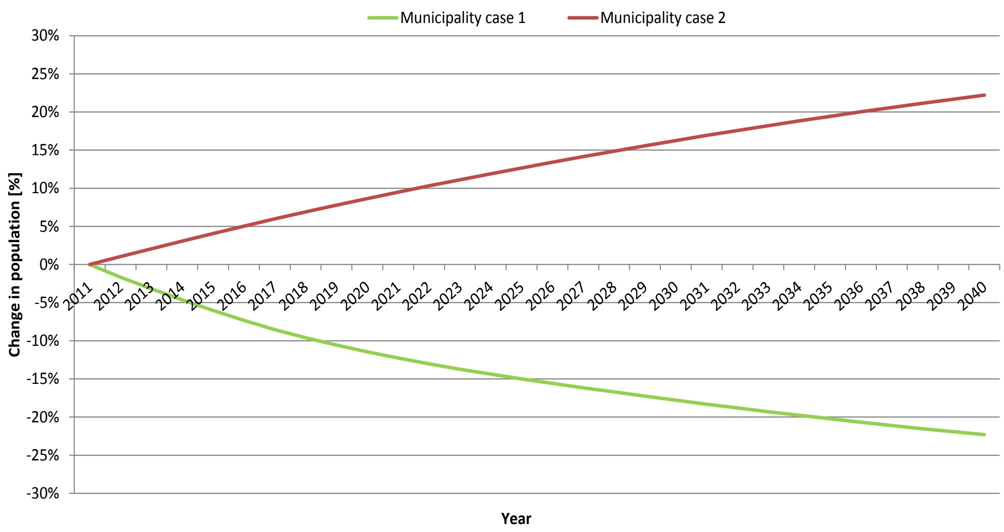

Figure 3.6. Population forecasts for two municipalities in Finland (Statistics Finland, 2014b).

Moreover, changes in the economic structure of society play a significant role in the electricity end-use. Changes in the numbers of customers in service, industrial, and agricultural sectors will probably indicate changes also in the electricity consumption. In addition, the energy consumption of service and industrial sectors may be sensitive to economic fluctuations. The extent of structural changes will probably increase in the future because of urbanization and other changes in society.

3.2.2 Energy efficiency

Energy efficiency plays a central role in the EU's 2020 strategy for smart, sustainable, and inclusive growth. Energy efficiency has a cost-effective potential to increase the security of energy supply and to reduce emissions. Consequently, energy efficiency can be estimated to be the most significant European energy resource. The EU has set a target to reduce the primary energy consumption by 20 % compared with projections for 2020. This target was set as a key step towards long-term energy and climate goals (European Commission 109/4, 2011). In electricity distribution, energy efficiency may have various effects on electrical energy and power. For instance, air source heat pumps in detached houses with electric space heating decrease energy consumption, but they can even increase peak loads in wintertime (Tuunanen et al., 2013). Effects of energy efficiency actions on electrical energy consumption can already be detected. Changes in the electricity usage in certain device groups and the development of total residential electricity consumption in Finland are presented in Table 3.2.

Table 3.2. Electricity end-use of household appliances in 1993, 2006, and 2011 (Adato Energy, 2013).

	1993	%	2006	%	2011	%
Cooking	GWh		GWh		GWh	
Cookers and other cooking	796	6 %	653	4 %	632	3 %
Home electric appliances						
Dish washing machine	125	1 %	261	1 %	367	2 %
Washing and drying	316	2 %	391	2 %	373	2 %
Refrigeration equipment	2 215	15 %	1 461	8 %	1 410	7 %
TV and accessories	537	4 %	834	5 %	564	3 %
Computers and accessories	(-)		407	2 %	848	4 %
Car heating	226	2 %	215	1 %	571	3 %
Other	623	4 %	1 468	8 %	1 649	9 %
Indoor lighting	1 541	11 %	2 427	14 %	1 230	6 %
Outdoor lighting	(-)		85	0 %	290	2 %
Total	**6 379**	**44 %**	**8 201**	**46 %**	**7 935**	**41 %**

In households, the total electricity consumption has increased between 1993 and 2006, whereas during the period of 2006–2011, the consumption has decreased. The electricity consumption of cooking and refrigeration equipment and indoor lighting has decreased considerably. The energy efficiency directive of electrical appliances (European Parliament 2005/32, 2005) has probably been a key factor in this development. For instance, certain types of incandescent bulbs are no more available in the markets, and they have typically been replaced by more energy-efficient lamps. On the other hand, the electricity consumption of computers and accessories, other consumption and outdoor lighting have grown significantly. Furthermore, air conditioning in summertime has increased in Finland (Adato Energy, 2013). Enhancing energy efficiency has become an overall trend, and there is no evidence why the same development would not continue in the future.

Another example of changes in electricity consumption can be seen in Figure 3.7, which represents the electricity usage of a flat of three people with an ordinary set of equipment. The figure shows that energy efficiency regulations and agreements have had effects on the electricity consumption of appliances. For instance, residential customers' refrigeration equipment has consumed far less electricity in 2011 compared with the year 1993. Energy efficiency directives have forced manufacturers and service providers to enhance the energy efficiency of their devices and systems (European Commission regulation (EC) No 244, 2009).

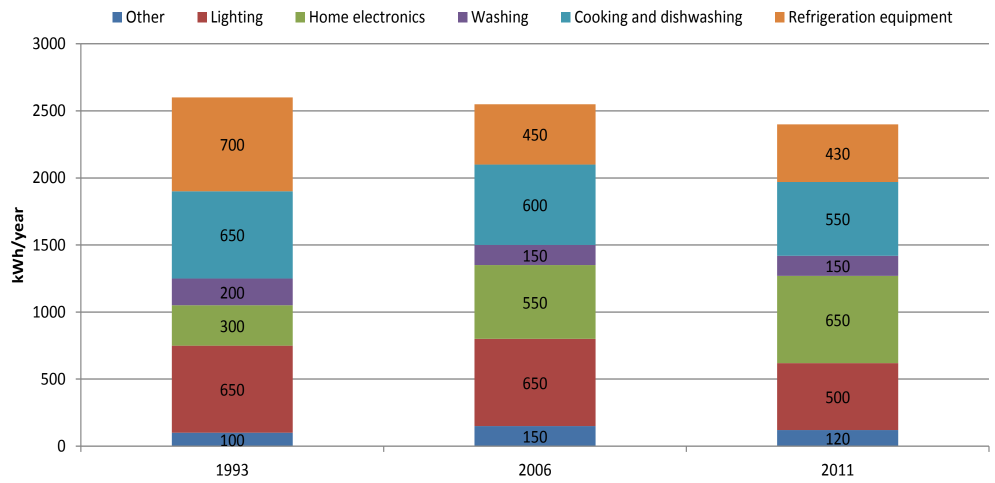

Figure 3.7. Total electricity usage of three people in a flat in 1993, 2006, and 2011 (Adato Energy, 2013).

The greatest energy efficiency potential is available in buildings (European Commission 109/4, 2011). Energy efficiency actions in heating and insulation systems will have different kinds of effects on electricity consumption. In heating systems, heat pumps have become a key contributor to energy efficiency. Hence, heat pumps will have an influence on electrical demand: energy and power; for instance, if a heat pump is installed in a building with electric space heating, it will typically decrease electrical energy consumption in the building. On the other hand, if a heat pump is installed in non-electric heated buildings, it will increase electricity consumption (Tuunanen, 2009) and (Hellman, 2013). The main parameter in heat pump efficiency calculations is the seasonal performance factor (SPF), which describes the ratio of the heat output to the electricity used over the heating season. SPFs vary between different heat pump types.

Heat pumps have become popular in Finland; they have been chosen as heating solutions both in existing and new buildings. Figure 3.8 shows that over 40 % of the new detached houses have chosen a ground source heat pump (GSHP) as a heating system in Finland in 2011. Again, the proportion of electric space heating has decreased in new detached houses, and also the number of oil heating systems in new houses is low.

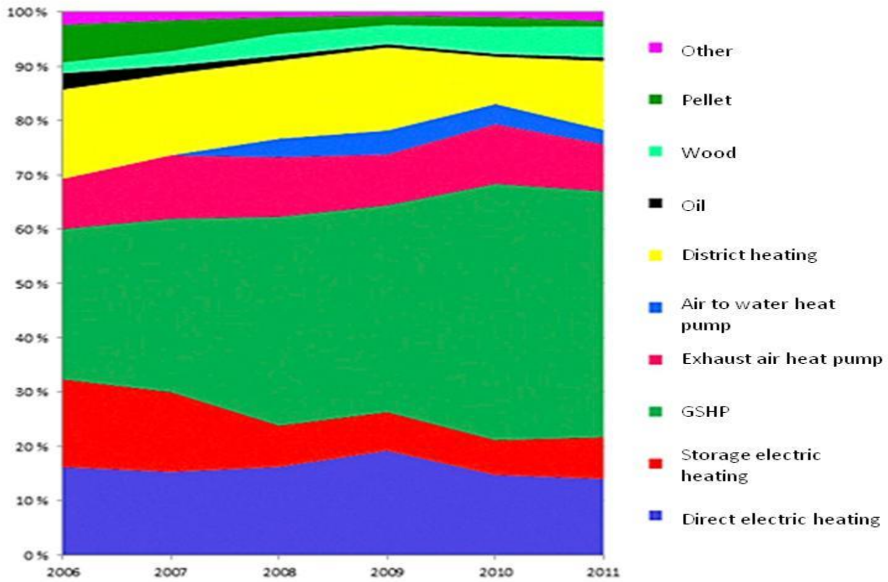

Figure 3.8. Heating systems in new detached houses in Finland, 2006–2011 (Motiva, 2014a).

Figure 3.9 shows the development of the total number of heat pumps between 1996 and 2012 in Finland; the majority of heat pumps are air source heat pumps. The number of ground source heat pumps is increasing, especially in large buildings. GSHP can be used as the main heating system in buildings, which makes it a rational and profitable heating system.

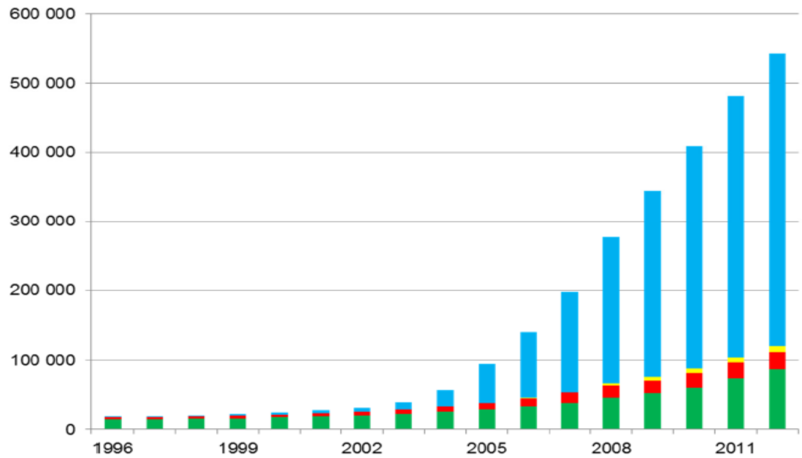

Figure 3.9. Total number of heat pumps in Finland, 1996–2012 (Sulpu, 2014). The blue bar indicates air-to-air heat pumps, yellow air-to-water heat pumps, red exhaust-air heat pumps, and green ground source heat pumps.

Changes in heating systems (e.g. an increasing number of heat pumps) will have major impacts on electrical loads. Different scenarios of the total number of heat pumps in Finland have been presented for instance by (Laitinen et al., 2011) and (Sulpu, 2014). Figure 3.10 demonstrates one scenario of the total number of heat pumps in Finland by 2020 (Sulpu, 2014).

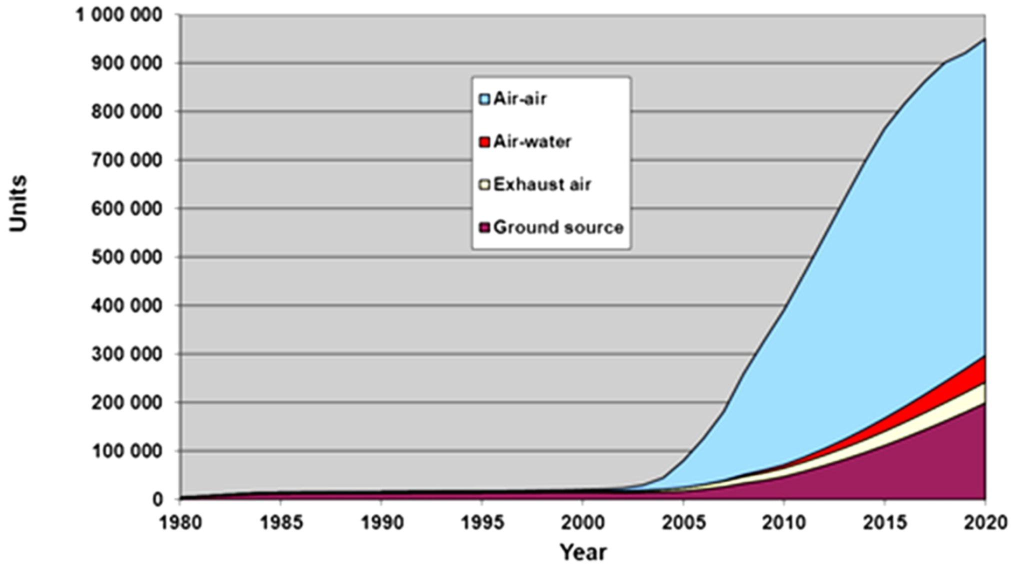

Figure 3.10. Scenario of the total number of heat pumps in Finland by 2020 (Sulpu, 2014).

A potential distribution of heat pumps in different types of buildings and heating systems has been introduced in (Laitinen et al., 2011) and (Tuunanen, 2009). The distribution of installed heat pumps in different buildings and heating systems is essential information as it has multifaceted impacts on electricity consumption.

The energy performance and thermal insulation of buildings will gain significance in the future. The Decree of the Ministry of the Environment on the energy efficiency of buildings 2/11 (*Ympäristöministeriön asetus rakennusten energiatehokkuudesta*), which took effect in June 2012, sets limits on the thermal insulation in new buildings. This should decrease the amount of electricity used in heating in the future. Energy-efficient insulation materials in external walls, ground floors, roofs, windows, and entrance doors will reduce the energy consumption. Table 3.3 gives forecasts for the average heating demand in different building types for the years 2020 and 2050.

Table 3.3. Estimated heating demand in different types of buildings in Finland in 2020 and 2050 (Honkapuro et al., 2009).

	Estimated heating demand of the average building compared with demand in year 2010, (kWh/m^2, a)		
Building type	**2010**	**2020**	**2050**
Detached houses	148	134 (91 %)	88–110 (59–74 %)
Attached houses	145	136 (94 %)	93–116 (64–80 %)
Apartment houses	151	142 (94 %)	99–124 (66–82 %)
Shop buildings	286	272 (95 %)	195–244 (68–85 %)
Office buildings	227	205 (90 %)	136–170 (60–75 %)
Traffic buildings	207	187 (90 %)	131–164 (63–79 %)
Institutional buildings	272	241 (89 %)	152–190 (56–70 %)
Buildings for assembly	193	186 (96 %)	138–172 (72–89 %)
Educational buildings	158	146 (92 %)	98–122 (62–77 %)
Industrial buildings	353	338 (96 %)	241–301 (68–85 %)
Warehouses	166	153 (92 %)	103–129 (62–78 %)

The new buildings will be low-energy houses in the future. A low-energy house should consume less than 60 kWh/brm^2 in a year in Southern Finland. In the future, there will be passive houses, which could require only 20 kWh/brm^2 energy in a year (Motiva, 2014b). In addition, there can be zero-energy houses and energy-plus houses. There are various definitions of zero-energy houses (Marszal et al., 2011); a zero energy building may refer to a building whose net energy consumption is zero over a normal year (Wang et al., 2009). According to (Motiva, 2014b), a zero-energy house produces at least an amount of renewable energy equal to the amount of non-renewable energy it consumes. An energy-plus house produces more energy than it consumes at a year level (Motiva, 2014b). The European Parliament has defined that new buildings occupied and owned by public authorities shall be nearly zero-energy buildings by 31 December 2018 (Directive 2010/31/EU of the European Parliament and of the Council).

Energy saving in lighting has been significant. The results of energy saving can be observed from the national statistics in Finland, as was presented above. The results may partly be explained by the decreasing usage of incandescent light bulbs in Europe. However, there is still great potential to save energy in lighting, for instance by energy-efficient lights and control and automation systems. These methods are introduced for example in (Lehtonen et al., 2007) and (Wall and Crosbie, 2009).

Considering energy saving actions, thermal insulation, heating systems, and lighting are assumed to have the most significant impacts on electrical loads and electricity consumption. The effects of different energy efficiency actions and technologies are diverse, and thus, they have to be assessed for each customer group individually, as there are significant differences between building types and customer groups. Data required for the analysis include for instance the proportion of buildings with electric space heating, approximations of space and water heating and cooling energy, an estimate of the seasonal performance factor (SPF) and distribution of heat pumps in different kinds of buildings. In addition, energy saving in other electrical appliances and systems will have an influence on electrical loads. However, this is beyond the scope of this doctoral dissertation, and furthermore, the above-mentioned technologies are predicted to be the most important ones from the perspective of this work.

3.2.3 Microgeneration

Microgeneration will be one of the major changes in electricity distribution in the long term. There are several microgeneration resources such as solar, wind, hydro, and biomass (Ackermann et al., 2001). At present, solar power seems to be the most popular microgeneration method (Masson et al., 2014). Solar power is becoming the most important microgeneration type as the volume of solar power installations has exploded globally over the last few years. Figure 3.11 depicts the European cumulative installed photovoltaic (PV) capacity between 2000 and 2013. In Europe, 17.7 GW of PV capacity was connected to the gird in 2012, and almost 11 GW in 2013 (Masson et al., 2014). In some European countries, as for example in Italy and Germany, PV technologies have increased considerably (Masson et al., 2014) and (Grau et al., 2012). This is the main reason why solar power is in a special position in microgeneration studies. However, other microgeneration alternatives and micro combined heat and power (µCHP) technologies may play an important role in future energy systems.

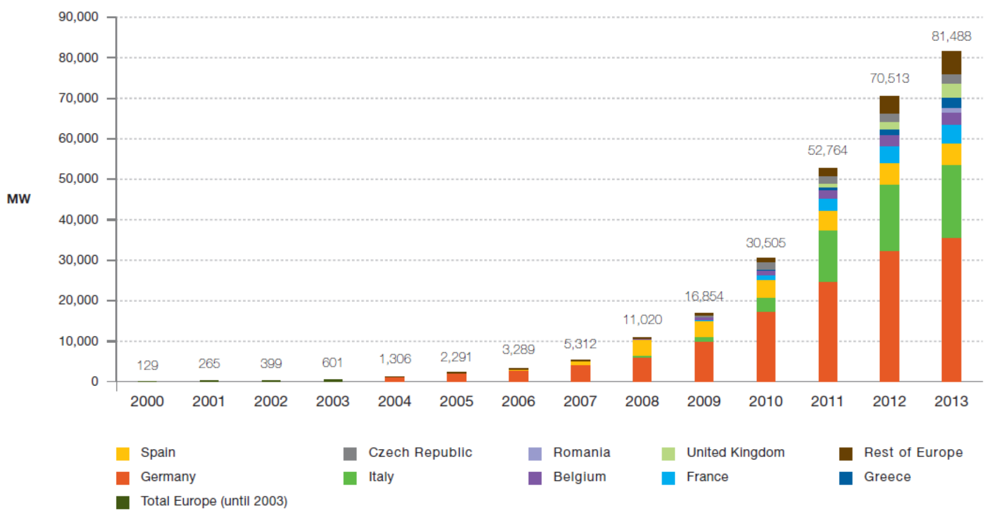

Figure 3.11. Cumulative installed PV capacity in Europe between 2000 and 2013 (Masson et al., 2014).

The term 'microgeneration' may refer to various production capacities (Ackermann et al., 2001), (Infield, 2008) and (Richardson and Keane, 2009). The size of solar panels may vary significantly: the largest microgeneration power plant may be several dozens of kW, the smallest ones being less than 1 kW.

In Finland instead, the role of solar power generation is minor at the moment. There are no exact statistics available of the number of PV systems in Finland. Microgeneration will probably be adopted slower in Finland compared with some other European countries, because there are no feed-in-tariffs or other incentives for customers to install microgeneration at the moment. However, the amount of microgeneration will probably increase a lot in the future. Here, a key factor will be the price of the PV systems. Figure 3.12 shows the price development of the PV systems in Germany. As we can see, the prices have come down, which makes PV systems more profitable.

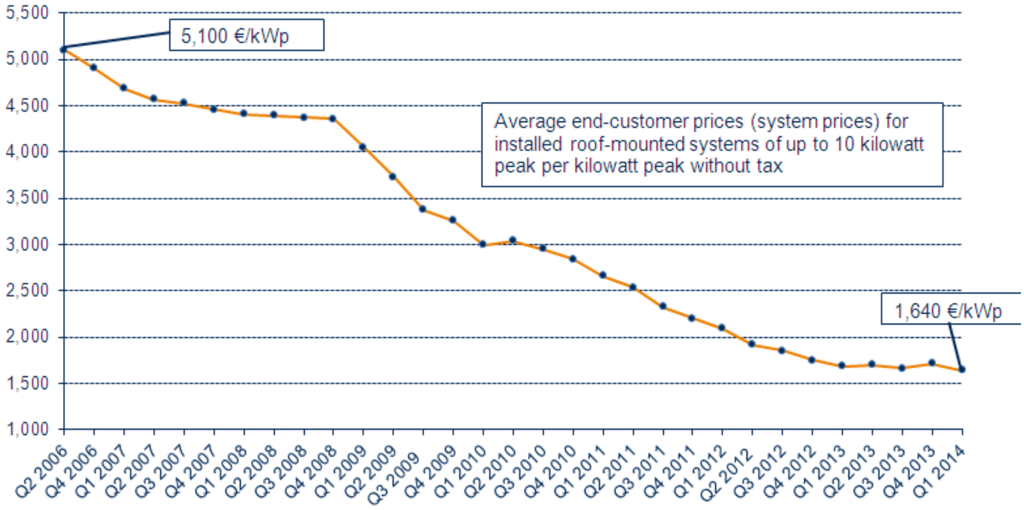

Figure 3.12. PV system price development (BSW-Solar, 2014).

For DSOs, microgeneration is mainly a challenge. If customers consume the electricity that they have produced by themselves, energy distributed in the networks will decrease. This means that the DSOs' incomes will decrease. In addition, customers may be interested to sell their surplus electricity to the retailer, and transmit electricity into the distribution network. Typically, PV does not impact on the peak electricity demand in wintertime, when the electricity production by PV is often at lowest in the Nordic conditions. However, PV may have significant impacts on distribution networks in summertime. A load profile of one distribution transformer substation in a rural area in Germany is presented in Figure 3.13. In the example, surplus PV production is supplied into the distribution network, which has a significant impact on the loads. Customers generate more electricity to the distribution network than they consume from the network. This may change the criteria for network dimensioning.

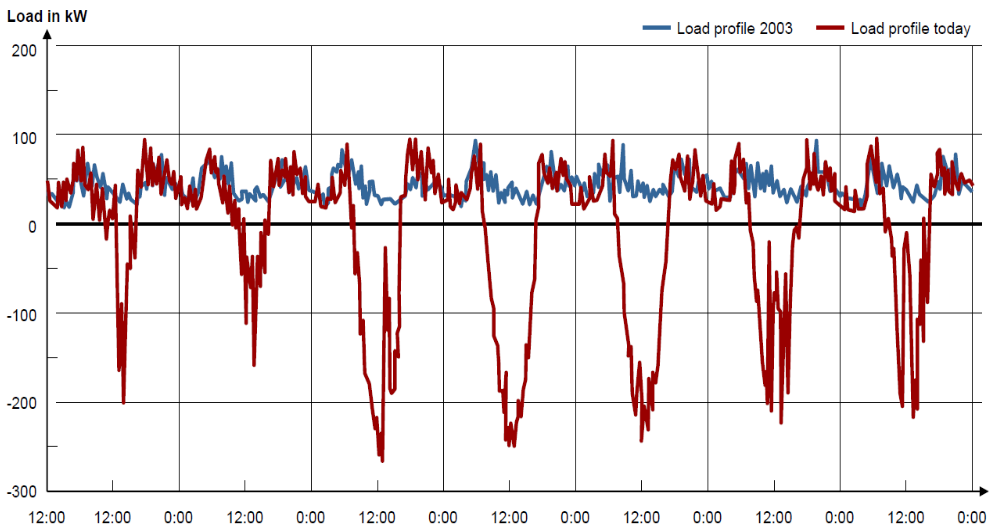

Figure 3.13. Solar power production curve at the distribution transformer level (Koch, 2013).

Solar power production can be analysed from the measurement and production curves. Typically, production curves are similar in shape, the maximum production capacity occurring at midday. Figure 3.14 shows a typical solar power production curve. The maximum production capacity is 5 kW.

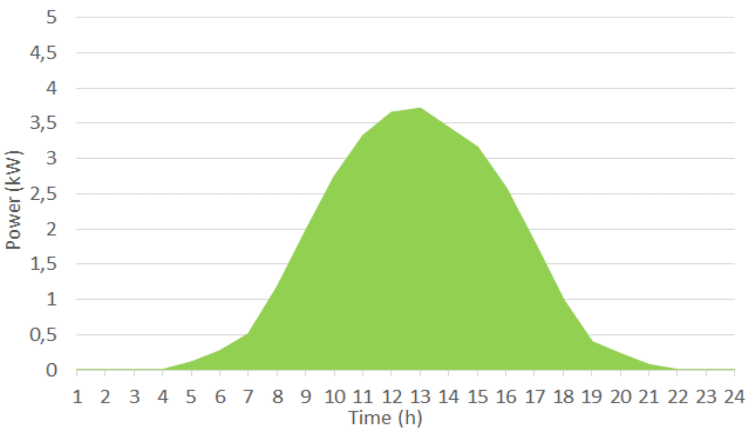

Figure 3.14. Modelled solar power production curve (National Renewable Energy Laboratory, 2015).

The impacts of PVs on electricity distribution depend on the amount of microgeneration and the production capacity of generation. The worst case from the grid perspective is that solar panels are producing the maximum capacity in summertime, when the electricity consumption is low. This is one of the issues in microgeneration that have to be analysed in the long-term load forecasting analysis.

3.2.4 Electric vehicles

Electric vehicles (EV) will probably penetrate the markets on a large scale in the future. Table 3.4 presents the scenario of the number of electric vehicles and plug-in hybrid electric vehicles in Finland. Three different scenarios have been made: a slow, basic, and fast scenario.

Table 3.4. Scenario of the electric vehicles in Finland, adapted from (Biomeri Oy, 2009).

		The number of cars		**The proportion of the new cars**	
Scenario	**Year**	**PHEV**	**EV**	**PHEV**	**EV**
Slow scenario	2020	38 000	12 000	5 %	2 %
	2030	207 000	92 000	20 %	10 %
Basic scenario	2020	66 000	13 000	10 %	3 %
	2030	480 000	160 000	50 %	20 %
Fast scenario	2020	190 000	26 000	40 %	6 %
	2030	960 000	450 000	60 %	40 %

At the moment, electric cars have been adopted slowly by consumers; this is demonstrated in Figure 3.15. The figure shows the registered plug-in and electric vehicles in Finland. The total number of plug-in and electric vehicles was 1 282 in August, 2015. In this light, a slow scenario could be the most realistic one. The most typical EV users will be the service sector and residential customers (Pastinen et al., 2012).

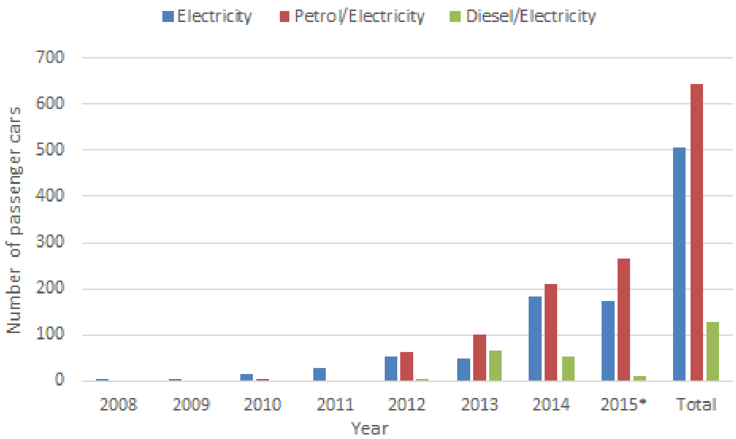

Figure 3.15. First registrations of passenger cars in Finland. *) Situation in August 2015 (Trafi, 2015).

Electric vehicles will increase the energy consumption in electricity distribution networks (Rautiainen et al., 2012). EV charging can be done simultaneously with dump charging; another option is to use smart charging. With smart charging, electric loads do not necessarily grow in electricity distribution networks. A study has been made on the network impacts with a 25 % penetration level of electric vehicles. In that case, the transferred energy increased by 12 % and the peak load by 34 % with dump charging (Tikka et al., 2011).

The most relevant factors for electric vehicle analysis are the number of electric vehicles in the case area, the mode of charging, and the charging spans and times. Charging types can be categorized into slow, basic, and fast charging. The majority of charging may follow some kind of a pattern, but a single charging event can be difficult to forecast. The charging mode has a great impact on the distribution loads. Slow charging may have a smaller influence on the network than fast charging (Tikka et al., 2012). Customers can charge their EVs in ordinary charging places by slow and basic charging. Separate charging stations may apply fast charging systems.

The main questions are whether there will be electric vehicles, where those cars will be found, and how many vehicles will be in use ten or forty years ahead. Individual vehicles do not necessarily have negative effects on the network, but if there are many electric vehicles, and the vehicles are charged simultaneously, they will have very significant impacts on loads (Lassila et al., 2009).

3.2.5 Energy storages

Electric energy storages are assumed to be an important element of the electricity infrastructure of the future (Eyer and Corey, 2010). Energy storages can be, for instance, battery solutions, thermal storages, super capacitors, or fuel cells. Table 3.5 lists some of the numerous functions and benefits of energy storages. The most essential energy storage applications will probably be associated with microgeneration, backup power solutions, or saving potential in electricity costs. The number of energy storages can increase, if customers have an incentive to purchase energy storages.

Table 3.5. Different benefits of energy storages (Eyer and Corey, 2010).

Application-specific Benefits
1. Electric Energy Time-shift
2. Electric Supply Capacity
3. Load Following
4. Area Regulation
5. Electric Supply Reserve Capacity
6. Voltage Support
7. Transmission Support
8. Transmission Congestion Relief
9. Transmission and Distribution (T&D) Upgrade Deferral
10. Substation On-site Power
11. Time-of-use (TOU) Energy Cost Management
12. Demand Charge Management
13. Electric Service Reliability
14. Electric Service Power Quality
15. Renewables Energy Time-shift
16. Renewables Capacity Firming
17. Wind Generation Grid Integration
Incidental Benefits
18. Increased Asset Utilization
19. Avoided Transmission and Distribution Energy Losses
20. Avoided Transmission Access Charges
21. Reduced Transmission and Distribution Investment Risk
22. Dynamic Operating Benefits
23. Power Factor Correction
24. Reduced Generation Fossil Fuel Use
25. Reduced Air Emissions from Generation
26. Flexibility

From the DSO’s perspective, the main benefits of energy storages may be peak cutting and the use of energy storages with microgeneration. Energy storages can also be batteries used in EVs (Lassila et al., 2012). However, the network impacts of energy storages are highly dependent on the way the storages are used. For instance, different energy storage usages will have distinct effects on loads. Energy storages could be used to decrease customers’ load peaks or load peaks in the distribution network. On the other hand, using energy storages with microgeneration could reduce the electricity transmitted from the distribution network. Figure 3.16 gives an example of peak cutting in a distribution network with battery storage. The battery is discharged during the highest peak load times. When the loads are decreasing, the battery can be charged again. Battery capacity optimization has to be carried out individually for each case.

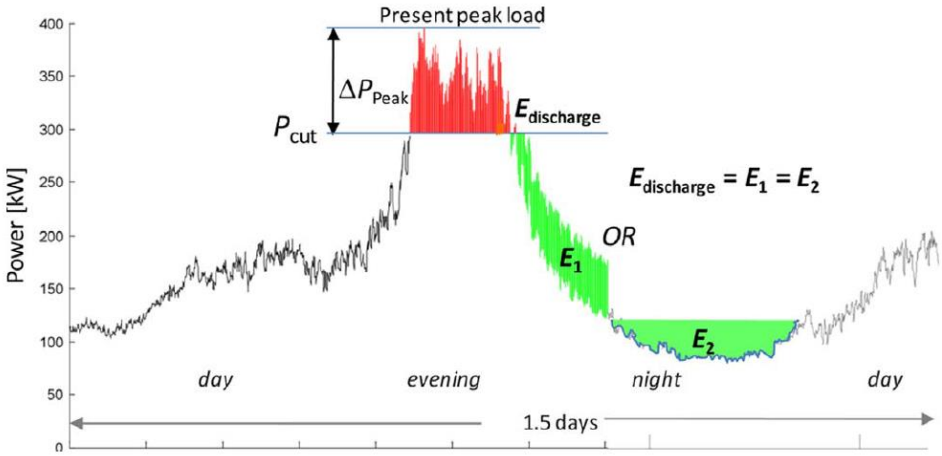

Figure 3.16. Energy storage usage in peak cutting (Lassila et al., 2012).

Basically, there are actually no battery storages in customer or distribution usage on a large scale in Finland at the moment (2015), but there are a lot of thermal storages such as electric storage heating. The first energy storages may probably be small-scale storages at low-voltage (e.g. residential) customers. This would require that the prices of storages be at a reasonable level. An economic incentive to purchase an energy storage has to come from savings in the electricity charges. The most usable applications will probably be associated with microgeneration, where customers utilize their own production, and peak load cutting at a customer level.

3.2.6 Demand response

There are various definitions of demand response (DR); for example, it is defined as changes in end-customers' electricity consumption from their traditional electricity usage patterns in response to changes in the price of electricity. Alternatively, demand response could be defined as designed incentives to encourage lower electricity use when the wholesale market prices are high or the power system is jeopardized (Albadi and El-Saadany, 2008). In Figure 3.17, demand reponse opportunities are classified into different programs. Overall, distribution is divided into incentive-based programs (IBP) and price-based programs (PBP).

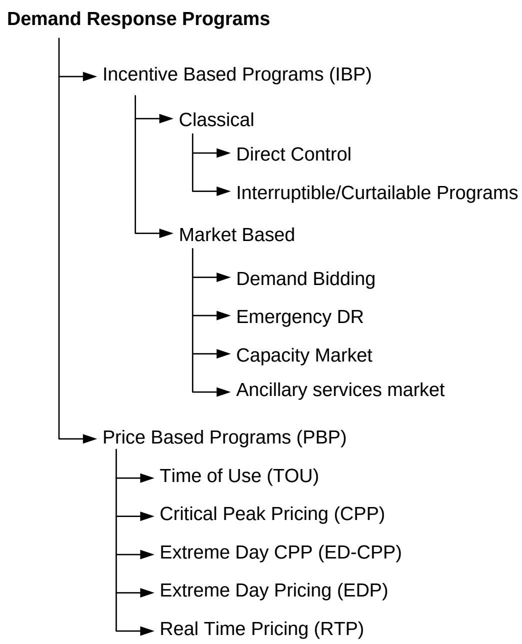

Figure 3.17. Demand response programs (Albadi and El-Saadany, 2008).

Electricity retailer should be the market facilitator in demand response markets. This would mean that the distribution network would be the marketplace and the retailer would control the customers' loads (Järventausta et al., 2015). Demand response may have different kinds of effects on the loads in distribution networks. Further, the network impacts depend on how the demand response is used. In demand response, the retailer can participate in different markets; the SPOT market, imbalance and balancing markets, and reserve markets. Table 3.6 lists national demand response capacities in different markets in Finland.

Table 3.6. Demand response capacity in Finland in 2015 (Fingrid, 2015).

Demand response in Finland	**2015**
Elspot market	200–600 MW
Balancing power market	100–300 MW
Frequency-controlled disturbance reserve	70 MW
Fast disturbance reserve	354 MW
Power reserve	40 MW

In the first phase, demand response customers are probably residential customers. In particular, customers with electric space heating have a significant load control potential. Actually, in Finland, this potential is already being exploited to some degree by the time of use (ToU) tariffs. Night-time electricity is cheaper compared with daytime, and therefore, customers typically use electric space heating at night. There is still a lot of potential for demand response, which is not utilized for demand response markets. The hourly based demand response market potential will increase in the future. The effects of demand response on electricity distribution have to be analysed locally, because the impacts are dependent on controllable loads at end-customers. Demand response has to be taken into account in the long-term load forecasting. For each load and customer type and different markets, a separate analysis has to be made. For instance, the network effects of the load control of electric heating customers have to be modelled separately in different markets.

3.3 Conclusions

The focus in this chapter was on the history and future of the electricity usage in Finland. The main interests were in questions why electricity consumption patterns are changing, what the main factors causing the changes are and how fast these changes will take place. There will be a need for different kinds of scenarios in the future. Scenarios can be made for technologies that are already widely in use. For instance, there are a lot of heat pumps installed in buildings, and the number of the future heat pumps can be based on previous trends. There are also technologies, which are not yet common in the markets such as energy storages and demand response. Scenarios for such technologies have to be based on different kinds of approaches. One approach can be an analysis of the price development of the technology; for example, what should the price of an energy storage be in order for the purchase to be affordable? If the price is known, it is possible to forecast when storages will reach this price level and how fast storages will enter the markets. Another approach could be to analyse what the penetration level of PV or other technologies should be in order for changes in consumption to be visible in load curves. For instance, scenarios can be made in which it is assumed that in a certain area 20 % of the residential customers will have PVs.

Some impacts of future changes on electricity consumption are presented in Figure 3.18. The figure is based on the results of a workshop held by a group of Finnish energy experts. The figure shows the potential effects on electrical energy and power. The figure demonstrates that energy efficiency actions, electric vehicles, customers' own electricity production, energy storages, and load controls are the factors having the greatest impacts on electricity consumption. There may also be other technologies that can have a major influence on electricity consumption; however, these are not addressed in this doctoral dissertation.

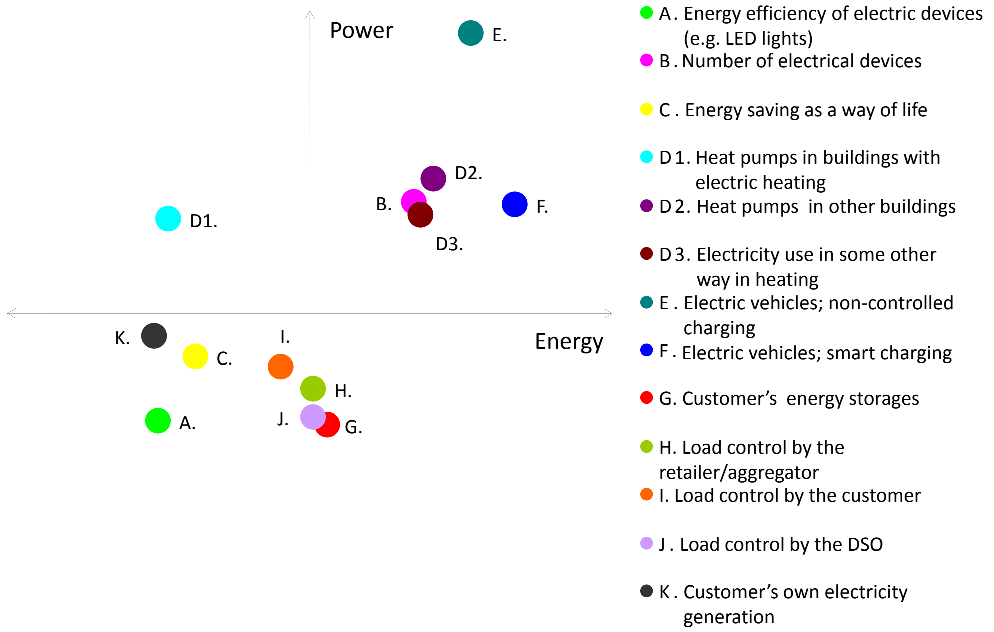

Figure 3.18. Changes in the future electricity usage.

The most significant changes may take place in residential customers' electricity usage. In practice, this means that customers will have many opportunities to manage their electricity consumption. Some customers may even be totally self-sufficient in electricity production. Ultimately, electricity distribution for residential customers may not be needed if customers are able to produce themselves the electricity they need. This would make long-term load forecasting more complex, and it could also require that the long-term factors of load changes should be identified early enough. It could also be necessary to regularly update the forecasts; from the perspective of network planning and network investments, unsuccessful forecasts would be worthless. There might also be a risk of inappropriate investments that are actually not needed. In addition, it may be possible that electricity connections are terminated or removed. Consequently, the impacts on the electricity distribution business would be undesirable. Altogether, different kinds of new technologies will increase challenges in electricity distribution, and irreversible changes will undoubtedly take place in the future.

Owing to the new technologies and changes in the electricity usage patterns, the traditional load forecasting process in electricity distribution has to be upgraded and supplemented with new tools. The effects of new technologies have to be modelled and analysed from the electricity distribution perspective. Energy and power in electricity distribution networks can be analysed more accurately compared with previous methods, because of AMR data and increasing amount of other data such as more detailed building and heating information, weather data, and customer specific data. These analyses will require a lot of data and different kinds of scenarios. The forecasting of the future electricity loads will definitely require a new forecasting process.

4 Load modelling and forecasting

A forecast of future electricity demand includes characteristics such as location (where), magnitude (how much), and time (when) that determine the requirements for the forecasting process. Electricity demand may spread into presently vacant areas, where there is no electricity demand at the moment. Thus, infrastructure must be established to meet the demand as it develops (Willis, 1996). Electricity distribution network strategies require long-term electricity load forecasting, which has to be taken into account in the network design. Thus, an in-depth study of the network load forecasts is necessary from the perspective of strategic planning. Load forecasting defines the requirements that have to be met by the future power system. Therefore, a distribution planner needs information of how much peak demand is needed for the capacity of future facilities. However, a poor or inappropriate load forecast will lead to different load estimates than the direction in which the loads will develop, which will jeopardize the entire planning process. Planning and construction of higher-voltage equipment for wide-ranging areas require more time compared with lower voltage levels. Consequently, a long-term plan that yields load forecasts for more than 15 years ahead are needed (Willis, 1996). Peak load forecasting gives information about the placement and amount of assets such as primary substation service areas and distribution feeders. Load planning can be carried out for the next five or ten years to determine the design criteria for a specific project. Nevertheless, the network equipment may meet supply requirements throughout their entire lifespan of 30 to 70 years (Spackman et al., 2007).

Load forecasting in distribution systems is performed in short-, medium- or long-term periods. Thus, the forecasting periods may vary significantly in length. For instance, short-term forecasting can be determined from one hour to a week (Lakervi and Holmes, 1995). Long-term forecasting, again, can be made for a period from several years to several decades ahead. Load forecasting can also be made for other timescales. According to (Srinivasan et al., 1995), short-term load forecasting (STLF) refers to up to one-day forecasting, medium-term load forecasting (MTLF) from one day to one year load forecasting, and finally, long-term forecasting (LTLF) applies to forecasts from one to ten years. Again, (Hong et al., 2014) shows that LTLF provides peak load and energy forecasts for one or more years, but it can be extended to a horizon of a few decades. This doctoral dissertation deals with long-term and very long-term (10–40 years ahead) changes in the electricity consumption. In the work, a forecasting process for electrical loads will be developed for electricity distribution networks.

Electrical energy and peak powers in the network are the most significant subjects of forecasting. Distribution planning is based on annual peak loads that the load forecasts estimate (Sallam and Malik, 2011). Geographical requirements for forecasts vary between different levels of the power system, although the forecasts are not dependent on the network topology. A typical and suitable area for the electricity distribution load forecasting is, for example, a district in an urban region or a specific area of a municipality in rural areas.

The structure of the chapter is the following. In the next section, load modelling is presented, because the present network loads constitute a basis for load forecasting. Section 4.2 introduces long-term load forecasting methodologies, the focus being on most typically applied ones. The final section concludes the chapter. A need for a new forecasting process has been identified that can take new loads and production into consideration in network planning. The requirements for the novel load forecasting process are described.

4.1 Load modelling in electricity distribution

Load modelling is widely used in different fields of electricity distribution. For instance, load information is applied to the planning of the distribution network, electricity production, load control, and customer tariffs, as a basis for customer services and estimated billing, and in connection with the consideration of the energy efficiency of electricity end-use (SLY, 1992).

Time resolution in load modelling has usually been an hour or 15 minutes (Lakervi and Partanen, 2008). Demand is often measured on an hourly basis. However, demand could also be measured on any other interval basis; seconds, one minute, 30 minutes, and daily (Willis, 1996). Even if hourly based models are used, it is not necessary to use an hour scale in the load modelling. Historically, hourly values have been the basic time unit in load modelling, and they have been found appropriate and accurate enough for load forecasting purposes. However, it will be possible to model loads in series of 10 minutes or even more accurately in the future. AMR systems may register data with shorter time resolutions in the future, and more accurate data on the end-use electricity consumption may be available.

Load modelling and statistical analyses of electricity consumption have traditionally been elements of research on electricity distribution. The objective of the load modelling is to produce customer profiles that describe the electricity consumers' varying consumption (SLY, 1992). Load modelling of electricity distribution networks is at the core of the electricity distribution network design. In theory, powers in different parts of distribution network nodes could be defined based on real-time measurements. In practice, however, distribution networks are so large that executing power and current measurements has not been possible so far. Load modelling is an important means to model the present consumption in the network. Annual energy consumptions and forecasts have been transformed into powers by applying various methods. These methods typically involve statistical analysis and wide-ranging measurements. Previously, load modelling has been made by using Velander's formula. The present load modelling method is based on load models as presented in (SLY, 1992). In the future, these methods can be replaced by new load models, which apply AMR data and clustering methods.

4.1.1 Velander's formula

Velander's formula (Lakervi and Holmes, 1995) has been used to define peak loads in the distribution networks by transforming electrical energy consumption into power. Velander's formula is written as

$$P_{\max} = k_1 \cdot W + k_2 \cdot \sqrt{W} \tag{4.1}$$

where $P_{\max}$ is the peak power in [kW], k_1 and k_2 are Velander's coefficients, and W is the annual energy consumption in [MWh]. The coefficients k_1 and k_2 are based on measurements and practical experiences. Table 4.1 gives examples of Velander's coefficients.

Table 4.1. Examples of Velander's coefficients (Lakervi and Holmes, 1995).

Customer group	**k_1**	**k_2**
Domestic	0.29	2.5
Electric space heating	0.22	0.9
Commercial (shops)	0.25	1.9

In practice, because of strong assumptions, loads do not follow Velander's formula. The formula is best suited for power modelling of large customer groups. On the contrary, it is not suitable for load estimation of an individual customer or a certain time. Moreover, estimation of the total peak power in the area requires that the highest powers of different customer groups are known. Therefore, different customer groups' power demand variation over different time periods has to be known. This variation can be managed by participation coefficients, which describe the electricity end-user's power in relation to the electricity end-user's peak power. However, a more accurate load modelling compared with Velander's formula can be achieved by profiling the electricity usage habits of different kinds of electricity consumers (Lakervi and Partanen, 2008).

4.1.2 Load models

SLY-based load models have been the most popular and efficient method to model electrical loads in Finland, because load models have represented the best knowledge of the electricity end-use. Load models include hourly load profiles, the standard deviation of hourly mean powers, and a temperature dependence analysis. Finally, large customer groups are used in the total electricity usage analysis. These groups constitute a hierarchical distribution (Lakervi and Partanen, 2008). Each calculated load model includes the following information (SLY, 1992):

- Model for an estimate of mean power for each hour in normalized temperature
- Model for the standard deviation of mean power for each hour in normalized temperature
- Estimate of the temperature coefficient for a defined time period
- Size of sampling unit for each hour, and
- Normal temperatures for each hour.

The hourly consumption of individual customers can be estimated by the load model. For practical implementation, characteristic load models have been generated. The load models include 46 different load profiles. The models are based on an electricity load survey made by SLY (Suomen Sähkölaitosyhdistys, the former Association of Finnish Electricity Utilities, now the Electricity Association Sener) for the year 1992. The load survey comprised almost 1200 customer metering points from 42 different DSOs. These measurements were performed in the 1980s and 1990s (SLY, 1992).

The electricity load survey is based on measured electricity end-use data, which are modelled by applying statistical methods. The results are reliable only with a certain probability (SLY, 1992). An individual customer's electricity consumption includes strong random variation; sometimes, the consumption is higher and sometimes lower than the mean power. As a result of the load model, a mean power can be obtained. However, the mean hourly power cannot be used as a peak power for an individual customer, because it is considerably higher than the mean power. Nevertheless, peak power is an interesting quantity, because it sets the guidelines for the network dimensioning (Lakervi and Partanen, 2008).

Customer grouping is an essential element of load modelling. The electricity end-users under study can be divided into groups, where the electricity end-use can be estimated accurately enough. In the load modelling, the customer classification is based on the customers' load types. In the SLY load survey, the initial target was to divide the customers further into smaller customer groups. However, it was found that the load variation was not essentially different in the new groups (SLY, 1992). Although it is possible to develop new customer groups, it is advisable to consider in advance for which purpose these new groups are actually needed. Table 4.2 presents the customer grouping of the residential customers in the SLY load models.

Table 4.2. Example of SLY customer grouping (SLY, 1992).

SLY customer group recommendation	**Customer groups based on the load survey**
01 One-family-houses	**100-602 Detached house**
010 One-family houses	Detached house, direct electric heating * 110 boiler < 300 l * 120 boiler 300 l * 130 underfloor heating > 2kW Detached house, partial electric storage heating * 210 short control time * 220 long control time Detached house * 300 electric storage heating Detached house * 400 heat pump heating Detached house, 2-time heating * 510 1-time tariff * 520 2-time tariff * 530 season tariff Detached house, non-electric space heating * 601 without electric sauna stove * 602 with electric sauna stove
020 Terraced house flats 022 Separately measured terraced house flats 030 Flat 032 Separately measured flats	Flats in terraced houses and blocks of flats, non-electric space heating * 611 without electric sauna stove * 612 with electric sauna stove
031 Co-measured flats	* 1020 Block of flats, including flats
040 Cottages (holiday homes)	* 1120 Cottage (holiday home) region, distribution substation service area

In addition to customer grouping, temperature dependence modelling is a crucial part of the load models. The dependence of electricity end-use on outdoor temperature has been taken into consideration in the load models by a linear calculation model (SLY, 1992):

$$q_{tod}(t) = q_0(t) + \beta \cdot \Delta T(t), \tag{4.2}$$

where $q_{tod}(t)$ is the measured electricity end-use at time t, $q_0(t)$ is the electricity end-use in the normal outdoor temperature at time t, β is the coefficient of the outdoor temperature dependence in the electricity end-use, and $\Delta T(t)$ is the deviation of the measured and normal outdoor temperature at time t. The normal outdoor temperature refers to the calculated reference temperature. Long-term average outdoor temperatures are applied in the load modelling (SLY, 1992).

Topographies constitute the basis for the load models of the whole year. They present an estimate of the mean hourly power and standard deviation in a certain outdoor temperature for each hour of a year. The sum of the mean hourly powers in a topography is equal to the annual energy consumption. Another widely used method is index series, where the year is divided into 26 two-week periods. For each customer group, mean powers are calculated separately for two-week periods. In addition, two-week and hour-specific indices are determined for different seasons. The weekday model is divided into three categories: workday, eve, and holiday. All workdays are assumed to be similar in the two-week periods, which decreases the amount of data under review. Index series is a relative method of presentation (SLY, 1992). For a certain time *i*, an absolute value of mean hourly power can be calculated from the index series as:

$$P_{ri} = \frac{W_r}{8736} \cdot \frac{Q_{ri}}{100} \cdot \frac{R_{ri}}{100}, \tag{4.3}$$

where P_{ri} is the mean hourly power of customer group r for time i, W_r is the annual electrical energy consumption of customer group r, Q_{ri} is the two-week index for customer group r for time i (an external index), and R_{ri} is the hourly index for customer group r for time i (an internal index) (SLY, 1992).

The peak load can be estimated by statistical methods, assuming that similar customers' load variation in a certain time is in accordance with the normal distribution. For a certain probability (excess probability) a, the peak power can be calculated if the standard deviation is known, and it is assumed to be normally distributed. The peak power $P_{\max}$ of a number (n) of several similar types of electricity end-users can be calculated by (Lakervi and Partanen, 2008):

$$P_{\max} = n \cdot \bar{P} + \mathrm{z_a} \cdot \sqrt{n} \cdot \sigma \ , \tag{4.4}$$

where $\bar{P}$ is the average power in [kW], z_a is the normal distribution coefficient, and σ is the standard deviation. Standard deviation has a significant impact on one customer's or a couple of customers' peak loads. Therefore, standard deviation has to be taken into account for instance when planning low-voltage lines. If the number of customers increases, the effects of random variation decrease. Typically, 1 % or 5 % excess probabilities are used for the peak load when dimensioning the load capacity of lines. There is a major difference in peak powers between 1 % and 5 % excess probabilities, if the standard deviation is high compared with the mean power. This is a common situation in customer groups in low-voltage networks. The application of 1 % excess probability leads to overdimensioning of the network. The highest load demands of different kinds of customers do not usually occur at the same time. The total loads of different customer types are typically lower than the sum of individual customers' peak loads. Peak load can be calculated as (Lakervi and Partanen, 2008)

$$P_{\max} = n_1 \cdot \bar{P}_1 + n_2 \cdot \bar{P}_2 + z_a\sqrt{n_1\sigma_1^2 + n_2\sigma_2^2}, \quad (4.5)$$

where n_1 and n_2 are the numbers of certain types of electricity customers. In practice, levelling-out of peak load intensities may take place because of the time variation in the electricity use between different customer groups. Another reason for levelling-out is that if the number of customers increases, the effect of random variation decreases. This can also be detected in increasing peak load times (Lakervi and Partanen, 2008).

As mentioned above, the peak power of the individual customers' sum load is usually lower than the peak load sum of the individual customers. This is typically taken into account by levelling coefficients. The levelling coefficient can be calculated by dividing the peak power of the individual customers' sum load by the peak load sum of the individual customers (SLY, 1992):

$$\mathrm{L}_r(n) = \frac{\max\sum_{k=1}^{n} P_k(t), t=1,\ldots,8760)}{\sum_{k=1}^{n}\max(P_k(t), t=1,\ldots 8760)}, \quad (4.6.)$$

where $\mathrm{L}_r(n)$ is the levelling coefficient for customer group r when the number of end-users is n and $P_k(t)$ is the power for customer k at time t. The value of the coefficient depends on the customer group and the number of end-users. This requires that for each customer group and different numbers of the end-users, a specific coefficient has to be determined (SLY, 1992).

Load models are over 20 years old, which means that they cannot take into account changes in the end-use behaviour or new technologies. For example, a residential customer's load curve may have negative values in summertime because of microgeneration, when electricity is supplied to the distribution network. As a conclusion, we may argue that traditional load models are no longer accurate enough or appropriate for load modelling or load forecasting in modern electricity distribution systems. Further, AMR data provide means for new load modelling methods. In addition, the load modelling method has partly become outdated. However, there are elements such as the determination of standard deviation that will be involved in the advanced load modelling methods. Moreover, AMR data enable regional load profiles when national load profiles are not used anymore. The dependence of outdoor temperature, considering a single customer, is also an example of the new methodology in load modelling.

4.1.3 AMR data and clustering method

Because of the changes in the electricity usage, the load models should be updated applying the new AMR data. Once the customer has been classified into a certain customer group, the customer's load profile and the customer group are hardly ever updated to respond to the load profile of the most suitable customer group. However, the customer type may change, for example, if the customer switches from one heating solution to another. There might also be other errors like misclassification. In addition, some customers may have such an uncommon load behaviour pattern that they do not fit into the customer profiles of the load models. It is a challenging task for the DSO to detect the changes and update the system (Mutanen et al., 2011).

AMR measurements have revolutionized the load modelling. AMR data can already be applied to load modelling in electricity distribution, but the application of data will be even more efficient in the future. AMR data provide hourly based information of the customer's electricity consumption for each hour of the year, which means that the customer's load data can be analysed on an hourly, daily, weekly, monthly, or yearly basis. Furthermore, loads can be modelled in any period of time. Previously, only annual energy consumption values were available. Figure 4.1 illustrates AMR data of three residential customers (detached house) and the total consumption curve of these customers. The data shows, for example, how the highest mean hourly power of one day is comprised. The figure demonstrates how the electricity end-use and network loads can be compiled from AMR data.

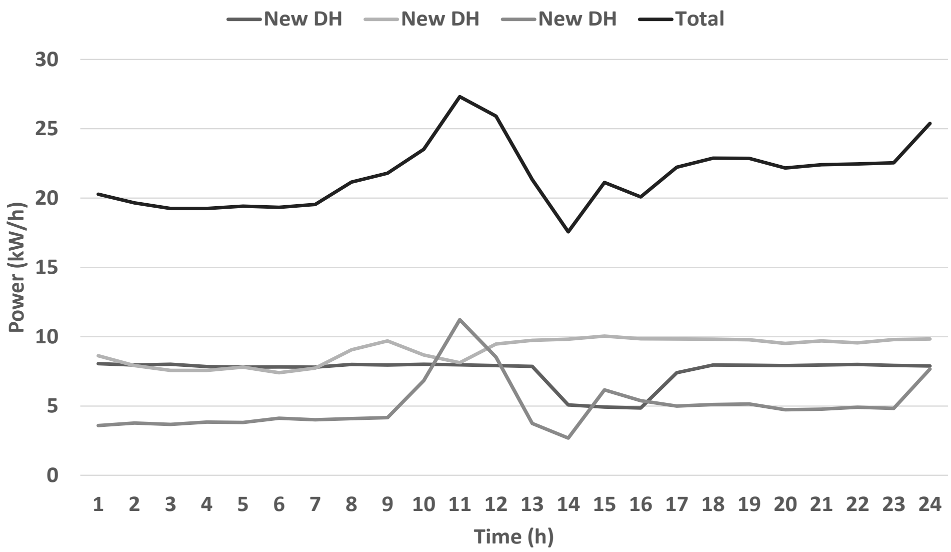

Figure 4.1. AMR data curves and the total curve of three customers on January 1, 2011.

By summing each customer's consumption curve in the distribution network area, the total load curve in a primary substation can be calculated. This is not an exact load curve, because network losses are not considered. However, it models electricity consumption of the customers with high enough accuracy. These kinds of load patterns can be generated for any part of a distribution network from a customer point to the primary substation, including feeders, secondary substations, and network nodes. Figure 4.2 depicts an AMR-based load curve in a primary substation in one year.

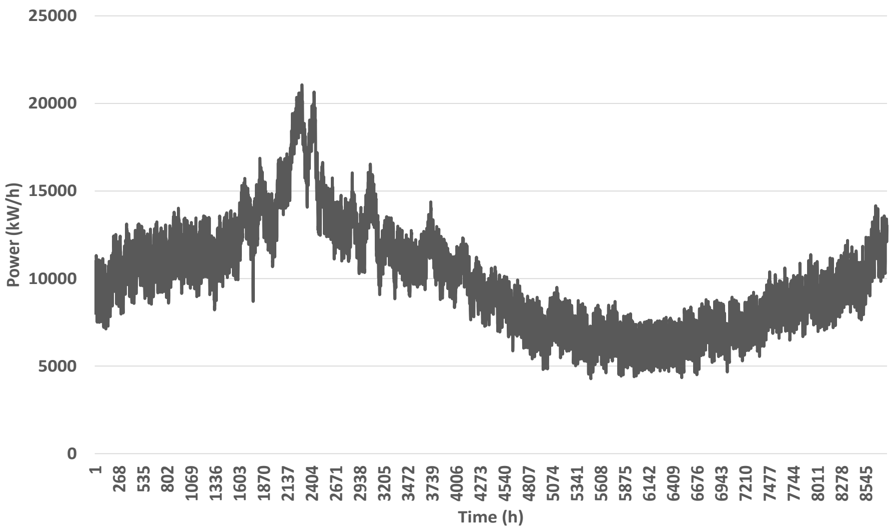

Figure 4.2. Network load curve in a primary substation based on AMR data.

According to (Rimali et al., 2011), AMR data can be analysed and represented by new and inventive methods; hourly series can be based on

- Separate areas
  - Various geographical areas, e.g. streets, blocks, districts, and villages
  - Various network points, e.g. the customer metering point, connection point, distribution cabinet, LV feeder, secondary transformer, MV feeder, and primary substation
- Various time periods or time stamps
  - Hourly series consisting of 24 values/day
  - Analysis can be based on certain time stamps, e.g. winter/summer, day/night, workday/weekend, minimum/maximum load, or one week/one month periods, and
- Certain customer types.

Customer classifications have traditionally been made based on daily load profiles, and the target has usually been, for instance, in tariff generation or planning of a marketing strategy (Mutanen et al., 2011). The purpose of use determines the customer classification approach. A basic rule is that AMR measurement data are required from at least one year to develop load profiling (Mutanen et al., 2013). Various types of clustering methods have been presented for customer classification and load profiling. For example, classical clustering and statistical techniques, data mining, self-organizing maps, neural networks, and fuzzy logic methods have been suggested for the analysis and modelling of the customer electricity consumption behaviour (Mutanen et al., 2011), (Räsänen et al., 2010), and (Chicco et al., 2006).

AMR measurements can be used to update load profiles of a customer class and to reclassify customers. A customer can be classified into a customer group, the load model of which is closest to the customer's AMR-based consumption. This guarantees that the load profiles are kept up-to-date despite the changing electricity end-use. At the same time, the number of errors such as sampling and geographical generalization will decrease. A considerable proportion of customers may shift to another customer group, when the customers are reclassified based on AMR data (Mutanen, 2013).

Predefined customer groups can be used to reclassify the customer groups. There are also other techniques that can be used for customer grouping. In (Rimali et al., 2011) and (Rimali, 2011), a key value method has been proposed for the classification of electricity end-use. The method is based on the application of AMR data. An individual customer's hourly measurements are analysed and classified into certain key value classes. For each key value, limit values are set, and then, based on this approach, a customer is clustered into that specific class.

AMR data may incorporate a lot of data that may be challenging to use in the clustering algorithms. Clustering calculation can be speeded up by applying dimension reduction. Therefore, it may be necessary to reduce the amount of data, for instance the amount of raw data. For example, this can mean reduction of AMR measurements that are used in the analysis (Räsänen et al., 2010). The amount of data can be reduced by principal component analysis (PCA) (Koivisto et al., 2013) and (Rimali, 2011). In addition, there are also Sammon maps and curvilinear component analysis (CCA) that have been suggested for the purpose (Chicco et al., 2006). Dimension reduction can be made by using pattern vectors, which describe the average consumption of each customer. The pattern vectors can consist of four seasonal temperature dependence values and 2016 values that comprise 12 months x 7 days x 24 hours. These values describe the average hourly consumption by representing type weeks for each month. The benefit of pattern vectors is their understandable nature and the fact that they can be used to produce individual customer-specific load profiles (Mutanen, 2013). Consequently, these methods can be applied to enhance the clustering approach.

Clustering is an analysis scheme that determines how the data are organized. Clustering algorithms divide the data into clusters, where the observations in the same cluster are of similar type (Mutanen, 2013). All customers should not be clustered simultaneously. For instance, small residential customers have to be clustered separately from large industrial customers, because clustering is based on expected load values. Moreover, different sizes of customers have a different standard deviation (Mutanen et al., 2011). Euclidean distance is generally used in clustering algorithms; it is used for the similarity measure in the clustering algorithm (Mutanen et al., 2011). The Euclidean distance between two n-dimensional vectors x and y is formulated as

$$d_E(x, y) = |x - y| = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (4.7)$$

Euclidean distance is used as a measure between the input variables. In addition to the formulation of the Euclidean distance, the clustering method is needed. For instance, the K-means method is a widely used clustering method. An algorithm assigns the nearest points to the cluster centre. The average of all the points in a cluster is called a centroid. The k-means algorithm is the following:

1. Choose the number of clusters k
2. Randomly assign k points as cluster centres
3. Assign each point to the nearest cluster centre
4. Recompute the new cluster centres
5. Repeat 3 and 4 until the assignment does not change (Mutanen, 2013).

The number of clusters has to be determined in advance according to the principles of k-means clustering (Koivisto et al., 2013). This requires knowledge of the potential number of customer groups. However, the customer classes and their number are not known accurately in advance. Therefore, an unsupervised clustering method has also been introduced. (Mutanen et al., 2011) has proposed an iterative self-organizing data-analysis technique algorithm (ISODATA) as a customer clustering method. The ISODATA algorithm is a variation of the k-means approach. It includes heuristic provisions for splitting and merging the existing clusters. However, a starting value *K* for the number of clusters and threshold values is needed. The final number of clusters is between *K/2* and *2K*. The user must have an estimate of the number of clusters. Threshold values depend on the stochastic characteristics and the number of customers. If the input parameters are suitable, the ISODATA algorithm may produce better results than the k-means (Mutanen, 2013). At present, the most popular methods are probably the k-means and ISODATA.

Updated and clustered profiles produce better load modelling results compared with the original and existing load profiles, namely the SLY load models (Mutanen et al., 2013) and (Mutanen, 2011). (Räsänen et al., 2010) have also found that the clustered load curves give better estimates of the customers' electricity loads compared with the existing load models. In addition, these models together contribute to a better and more complete understanding of the electricity demand of the customers. Further, (Chicco et al., 2006) have discovered that clustering techniques are extremely useful. It has been found that the k-means and ISODATA may be the most practical clustering methods for the classification of electricity distribution customers (Mutanen, 2011). Load model update seems to be a more efficient method to improve the load profiling accuracy than the reclassification of customers. Figure 4.3 shows the results of a comparison of a reclassification and a load profile update. Reclassification of customers has to be carried out before updating the load profiling so that the updated customer group load models are the nearest load profile for all customers (Mutanen, 2013).

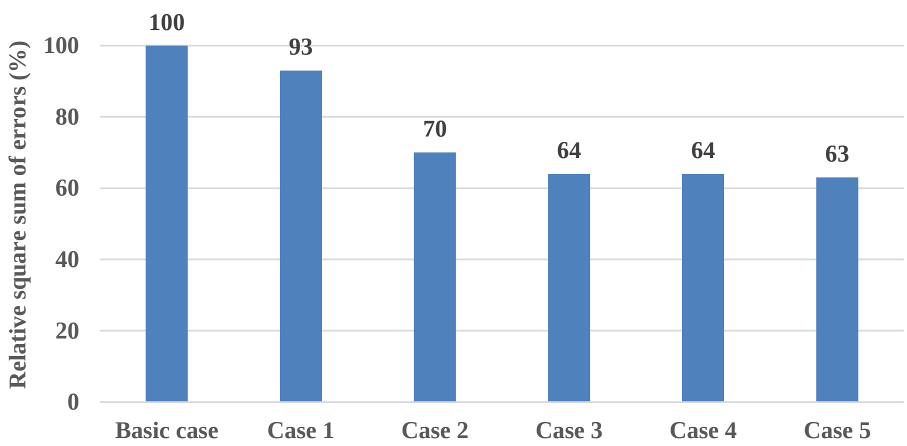

Figure 4.3. Relative square sum of errors between different load profiling methods. The modelled customers are residential customers. The basic case consists of the original classification and the SLY load models. Case 1 refers to the customer reclassification and the SLY load models. Case 2 covers the original classification and the updated load profiles, Case 3 represents the customer reclassification and the load profile update with K-means clustering. Case 4 is the customer reclassification and the load profile update with ISODATA clustering, and finally, Case 5 represents individual load profiles (Mutanen, 2013).

There can be customers with exceptional end-use behaviour, as a result of which these customers do not fit into any of the predefined customer classes or clusters. Individual load profiles can be defined, and they are the most suitable solution in this case (Mutanen, 2013). In addition, (Mutanen et al., 2011) states that individual load profiles determined with pattern vectors produce better results in the next-day load forecasting than the previous year's measurements that are applied as individual load profiles. Pattern vectors are used for dimension reduction of the AMR data by using data values that describe the average hourly consumption.

AMR data yield updated information of the loads compared with traditional load models and more accurate load modelling analysis options compared with the present analysis. They also provide new opportunities to model loads with new methods in distribution networks. Customer classification can also be performed more reliably. Consequently, load modelling can be carried out accurately and even for a specific geographical area. This serves as a good starting point for the load modelling.

4.1.4 Summary of load modelling

The DSOs use customer class load profiles mainly for load modelling. Each customer can be linked with the customer information system (CIS) to one customer class load profile, which typically has 20–50 customer classes in Finnish DSOs. Moreover, large customers can be modelled with load profiles of their own. Customers are also connected to a geographical network model. The network information system (NIS) enables network calculations that apply the load models (Mutanen et al., 2011). The data that the NIS applies should be updated, and they should reflect the present network state. This way, the data provide exact information of the current network state, which will be important for the long-term load forecasting.

Electricity end-users have typically been classified into predefined customer classes, and loads of individual customers have been estimated with customer-class-specific hourly load profiles. However, this system involves some error sources such as sampling error, geographical generalization, profile drift, customer classification, and outliers. Sampling errors may derive from misclassified measurements of the existing customer class load profiles or from an insufficient number of measurement points. Load profiles are defined based on a national load research, which involves geographical generalization. Further, the profiles drift because electricity end-use fluctuates constantly, but the profiles are not updated. Errors in the customer classification occur, for instance, if the customer type changes because of a change in the heating solution. Customers' exceptional load behaviour does not necessarily fit into any of the predefined class load profiles, in which case such customers are outliers (Mutanen, 2013). However, AMR measurements can remove these error sources. Customer classification and load profiling can be carried out based on actual consumption data. Classification and load profiling can be also updated once a year, for instance, because of constant AMR data collection. Load profiles can be determined for each region, and thus, the effect of geographical generalization can be removed. Finally, outliers can be detected and individual load profiles can be defined for exceptional load profiles (Mutanen, 2013).

Almost every customer has a smart meter in Finland, and the penetration of smart metering is rapidly increasing also elsewhere around Europe. This enables the use of smart metering data in load modelling in a wide scale. However, AMR data have been collected for only a few years in Finland, which limits the analysis at the moment. After a few years there will be a lot of AMR measurements available, which will be a significant benefit for the load analysis. On the other hand, this means that the amount of data will grow radically, and DSOs have to have appropriate information and communications technology (ICT) systems.

Another benefit of the novel type of load modelling is that it can be applied to recognize the electricity end-use, for instance heating systems in customer points based on data measurements and disaggregation of heating loads from the recorded AMR data. There are some preliminary results of applying mathematical methods to identify these loads (Niska, 2013). However, more analyses are still needed. Load identification is also an important element of load modelling. For instance, identification of such loads as heat pumps and production such as PV systems is of significance from the perspectives of load modelling and forecasting.

In (Mutanen, 2013) it has also been shown that clustering methods can be applied for load profile updates and customer classification. Several methods have been studied, and there are many algorithms applicable to these purposes. Further, the differences in results between the clustering methods seem to be small. Therefore, it has been concluded that the comprehensibility and computation speed are more relevant factors than the accuracy of the results (Mutanen, 2013). Although many methods to model loads and classify customers have been presented, they are not yet in universal use. It is even probable that not all the methods or the best ones are known yet. Consequently, there are many options available for load profiling, modelling, and application of AMR data. However, the DSOs require knowledge on how the data can be used comprehensively, and the load modelling requires a universal method for this purpose. Eventually, AMR data will yield better load profiles in the future.

Regardless of the AMR data and clustering methods, the expectation and standard deviation values and calculations apply the same methodology as before. However, reclassification, load profile updates, clustering, individual load profiling, and temperature dependence parameters can be developed and enhanced with AMR measurements (Mutanen, 2013).

One conclusion related to the load modelling is that the demand for load modelling is dependent on the purpose of use. AMR data increase opportunities to use customers' load profiles for load forecasting purposes. Thus, it is possible to forecast loads with more accurate initial data compared with the present annual energy forecasting approach. From the long-term load forecasting perspective, load modelling should cover all customers of the case area, because an individual customer may have a significant impact on the loads in the distribution network. From this point of view, it is highly important that the same type of customers are classified into same customer groups. Therefore, it does not matter if a consumption behaviour of an individual customer does not completely correspond to a certain customer group. Instead, it is more important that there is sufficient and correct information of the customers. The most essential customer information is customer type (e.g. residential, service), heating method (direct electric heating), heating demand, and information of additional equipment such as solar panels.

From the long-term load forecasting perspective, load modelling does not have to be extremely accurate. In the STLF, the accuracy is highly important, but in the LTLF, the significance of accuracy is lower. Some methods in the load modelling process reduce the AMR data. Data reduction can be used for load modelling and customer classification, but for the long-term load forecasting, annual AMR data are needed. At the end, an expert or planner can decide which clustering method is used.

At present, it seems that a clustering method is needed for load modelling, but the situation can be totally different in the future. It may be possible that the customers' electricity end-use will change significantly, and there may be differences in the end-use between the customers of the same type. For instance, a customer living in a detached house with direct electric heating may consume less electrical energy because of the improved energy efficiency achieved by insulation and an air source heat pump. In addition, the same customer may have solar panels and a plug-in hybrid electric vehicle. This kind of development may pose new requirements for load modelling in the future.

4.2 Long-term load forecasting methodologies

Annual energy consumption instead of power has been used as the starting point for load forecasts. Load forecasting has usually been made based on energy consumption, as it has been known for all customers. However, energy consumption does not provide enough information for the follow-up and planning calculations, or operation of loads in network areas. Thus, energy consumption has to be transformed either into peak power or power of a certain time period (Lakervi and Partanen, 2008).

Load estimates play a vital role in the network design. The main methods to produce forecasts of future power demands have traditionally been econometric modelling, extrapolation, and simulation methods. All these methods have special application targets of their own, but combinations of these methods have also been used. Significant errors may occur if the forecasting method does not take into account the area under review. Forecasts cannot be based on average values of load growth, and each area has to be analysed separately (Lakervi and Holmes, 1995).

Most short-term forecasting methods apply statistical techniques and artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems in load forecasting. In medium- and long-term forecasting, end-use modelling and econometric approaches are the most commonly used ones. The customer information, that is, the size of the houses, technology changes, customer behaviour, and population dynamics are typically included in the end-use approach by statistical and simulation models (Sallam and Malik, 2011). There is no single forecasting method that would be efficient in all situations. The load forecasting method depends on the nature of data available and the nature and details of the forecasts. Occasionally, it can be appropriate to apply more than one method. Long-term forecasts usually take into consideration several issues such as the historical load data, the number of customers in different categories, and the electrical equipment in the area (Sallam and Malik, 2011).

The purpose of this section is to present different load forecasting (LF) methods, especially from the perspective of long-term load forecasting. The following paragraphs introduce the most typical long-term electricity load forecasting methods in brief. Not all forecasting methods are presented because they are not necessarily suitable for long-term forecasting purposes or they are very seldom used. There are also similarities and differences between the short- and long-term methods. Short-term methods are used for distribution network operation purposes while long-term forecasting is typically used for planning. However, some elements of the short-term load forecasting can also be applied to long-term load forecasting. Many of the following methods can apply different methods to support the main method. However, in the following sections the main forecasting methods are classified, and the links to other methods are described in brief. At the end of this chapter, it is shown which of these methods can be applied to the new long-term load forecasting.

4.2.1 Econometric modelling

Econometric modelling of electricity consumption is typically based on correlation between electricity consumption and economic parameters. Gross domestic product (GDP) and effects of electricity prices are examples of these parameters. However, the model is not appropriate for small areas and individual distribution system studies (Lakervi and Holmes, 1995).

The econometric approach uses the relationship between the load and the driving parameters. The relationship can be nonlinear or linear, and it is based on historical data available. The method can be used with various customer groups and for the system as a whole. A benefit of the method is that it is simple to apply while a drawback is the assumption of holding the relationship established for the past to be applicable to the future. This means that new parameters cannot be taken into consideration (Hossein and Sepasian, 2011).

Econometric factors are typically based on per capita incomes, employment level, and electricity prices. The models are usually applied in combination with the end-use approach. Forecasts related to population changes, economic development, industrial construction, and technology development are typical elements of long-term forecasts. The method combines economic theory and statistical analysis in the electricity demand forecasting. Econometric modelling estimates the relation between the energy consumption and factors affecting the consumption. The least square or time series methods are used to determine these relationships (Sallam and Malik, 2011).

Econometric modelling, end-use modelling, and combinations of these are the most frequently used methodologies for medium- and long-term load forecasting. Appliances, the sizes of houses, the age of equipment, technological changes, customer behaviour, and population dynamics are typically included in the statistical and simulation models, which are based on the end-use approach. Furthermore, long-term forecasts include forecasts on the population changes, economic development, industrial structure, and technology development (Chow et al., 2005).

4.2.2 Extrapolation/trending methods

Extrapolation methods are purely statistical methods. In these methods, future demand is estimated from historical data. Predictions of electricity usage can be generated from consumption data for the next few years. In the long term, the consumption trend often follows an S curve (Figure 3.1). In the first phase, there may be a high rate of demand growth, but after the customers' dwellings have become saturated with electrical equipment, the rate will decrease (Lakervi and Holmes, 1995).

The trending method can be applied with historical load data, which can be obtained by extrapolating the past load patterns into the future. The most popular trending method is polynomial curve fitting, which uses multiple regression to fit a polynomial function into historical peak load data. By extrapolating that function into the future, a forecast can be made. Trending is most suited for large area forecasting. However, it is relatively inaccurate when applied to small areas (Willis, 1996).

The trend extrapolation method applies historical data to forecast the loads in the future. A curve fitting approach can be used to determine the load for the target year. The method is simple to understand and implement. The trend analysis assumes that the trends in various load parameters remain unchanged over the study period. If there is a major change in the economic growth, the approach is not able to forecast the future load. The method can be modified and improved to a certain extent. For instance, more weight can be added to the loads into the end of the past period (Hossein and Sepasian, 2011).

4.2.3 Spatial forecasting

In broad terms, spatial analysis can be defined as the quantitative study of phenomena that are located in space. In a spatial analysis, observational data are available on some system operating in space, and methods are explored to explain the system. The main aim of the analysis is to enhance understanding of the system (Bailey and Gatrell, 1995).

The peak demand has to be known on a local basis. Therefore, spatial forecasting has to be applied to estimate the peak demand in each small area in the system. Spatial load forecasting is the first phase in determining the future distribution system design. The objective is to produce information for the distribution planning in a way that serves the load forecasting process. Basically, this means defining the amount, timing, and locations of the future loads as accurately as possible in a manner that fits the long-range planning needs (Willis, 1996).

Generally, the network planning areas can be quite roughly defined, and they can be based on municipal or district areas. Spatial forecasting, instead, requires more accurate regional borders, customer groups, and characteristic consumption estimates. Electric loads are location dependent. The existing information and forecasts of population, housing, and industrial development are vital information for the local area planning. These data combined with the existing and past consumptions can serve as a starting point for actual load forecasts. More information can be available from the customer loads, network system data, and known developments (Willis, 1996).

Spatial load forecasting supports the planning process, because it reveals where the future load will develop and when the expected load changes will take place. Information of the location of the future load growth is one of the main requirements for spatial load forecasts. Because of the nature of spatial load forecasting, scenarios are needed. The time when the load growth takes place is also of importance. The amount, location, and timing of the future load changes have to be modelled as accurately as possible (Sallam and Malik, 2011).

In a spatial load forecast, the geographic location of electricity demand is obtained by dividing the case region into many small areas. These areas may vary in size and be irregular in shape. For instance, the areas may be the service areas of a primary substation or feeders, or square areas of the network. The small-area load forecasting method is an extrapolating load forecast technique that analyses the electricity consumption trends in a feeder area. It is a feasible method for irregularly shaped and sized areas (Willis, 1996). Spatial load forecasting has been shown to be one of the most applied methods for the electricity distribution load forecasting. The long-term spatial load forecasting is a viable tool for land usage planning or to consider future loads under different scenarios for planning purposes (Fan et al., 2011).

Spatial electric load forecasting can be divided into nonanalytic, trending, and simulation methods. Nonanalytic methods do not perform an analysis of historical or base year data in the production of the forecast. This kind of forecasting depends entirely on the decisions made by the forecaster. Trending methods forecast future loads by extrapolating while simulations analyse and model the changes in the electric loads. Trending methods use historical load data to extrapolate past load patterns into the future. The advantage of the trend methods are simplicity and ease of use. A disadvantage is that they ignore possible factors for instance related to population growth, urbanization, and prices (Sallam and Malik, 2011).

4.2.4 End-use modelling

Electric demand modelling and load identification of a customer group as a function of time is important in load forecasting. End-use load modelling of a customer class is a viable method in the spatial load analysis. In load modelling, the end-use models represent a bottom-up approach. Electricity usage is divided into three categories: customer classes, end-use classes within each customer class, and appliance categories within each end-use. Basically, end-use models work similarly as load models to analyse and forecast the end-use curve shape (Willis, 1996).

The end-use method models the electricity usage patterns of different devices and systems. End-use models are based on individual characteristics of the electricity use of the residential, commercial, and industrial customers. For example, electricity is consumed for water heating, air conditioning, refrigeration, and lighting in the residential sector, whereas in the industrial sector, the majority of electricity is consumed by electric motors involved in industrial processes. The method is based on the principle that a certain amount of energy is needed for the services (Sallam and Malik, 2011).

Electricity end-use consists of different elements; for instance, lighting is one part of electricity end-use. In addition, lighting can be divided into electricity end-use of a certain lamp type such as an incandescent lamp, a fluorescent lamp, and a sodium vapour lamp. Each lamp type has a load behaviour of its own (Sallam and Malik, 2011). Figure 4.4 demonstrates an example model for an end-use system. As shown in the figure, end-use models are a bottom-up approach to model loads. Electric load demand modelling requires customer classes. The total system load can comprise customer classes, end-use classes within each customer class, and appliances within each end-use class.

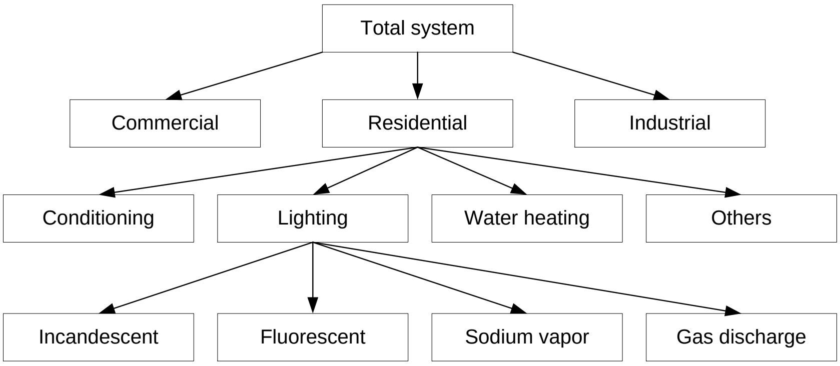

Figure 4.4. Hierarchy of end-use models (Sallam and Malik, 2011).

The forecasting results of applying the end-use model are: 1) the shape of the future load curve, 2) determination of the peak load, and 3) information of the energy end-use development (Sallam and Malik, 2011). End-use models are applied to define the shape of the future load pattern, peak load, and energy usage. Typically, these vary as a result of the appliance mix, appliance technology and efficiency, customer mix or demographics, and the total number of customers. For example, a change in the appliance mix can refer to a change from electric space heating to a heat pump, and a change in the appliance technology can mean replacement of a refrigerator by a more energy efficient one. Finally, for instance in rural areas, a change in the number of customers can mean a decrease from 10 000 residential customers of today to 7 500 residential customers after ten years (Willis, 1996). End-use models are an alternative to the traditional demand forecasting. The accuracy in the modelling is dependent on the consumption details available. In (Paatero and Lund, 2005), it has been shown how this approach has been applied to the demand side management (DSM).

4.2.5 Scenario analyses

Scenario planning is a method for cases where uncontrollable and irreducible uncertainty is involved. A scenario is a description of a plausible future. In scenario planning, a few contrasting scenarios are used to study the surrounding uncertainty. The method can incorporate various quantitative and qualitative information. The scenario provides a systemic methodology to think creatively about an uncertain and complex future. An essential target of scenario planning is to review several possible futures that involve various uncertainties in the system. However, the purpose is not to focus on the accurate forecast of a single outcome (Peterson et al., 2003).

Various possible decisions, events, and consequences can be addressed in more detail with the scenario analysis. Scenarios are alternatives for possible future events and their results. Scenario modeling weighs up uncertainties that are not controllable. Therefore, it is possible to take into account unknown factors that pure statistics-based models cannot anticipate. Long-term forecasts are usually made by taking different scenarios into consideration. Moreover, it should be possible to produce “what if” type experiments quickly and conveniently (Niska et al., 2011). Multi-scenario planning includes several plans to cover the various probable consequences of the future development. Circumventing multi-scenario planning by using average or probabilistic forecasts is a mistake often made in distribution planning. This approach may lead to a poor performance combination with high costs (Willis, 1996).

Forecasting is a stochastic problem in nature. Long-term load forecasting can provide multiple forecasts based on various scenarios (Hong et al., 2014). If the horizon of the forecast is long, the forecast becomes more scenario dependent. Typical scenarios can include new major transport links, energy efficiency policies, re-zoning of land, or demand side management. There are various types of scenarios that can be considered in long-term forecasts; for instance end-use change, re-zoning, and micro-scale scenarios (Spackman et al., 2007).

4.2.6 Simulation method

Simulation methods are based on specific annual consumption curves of individual customer groups, and the number of customers in each customer group. Each customer group has to be analysed separately in the simulations. Typically, simulations are based on a large amount of data. The future development can be forecasted from national information and modified for local use. The simulation method is very useful in areas where significant developments are expected to take place such as a notable increase in the number of population or buildings (Lakervi and Holmes, 1995). Simulation methods typically apply analyses of the local geography, location economy, land use, population demographics, and electric load consumption (Sallam and Malik, 2011). Figure 4.5 gives an example of how to apply a simulation method to combine information systems and model loads in the spatial approach.

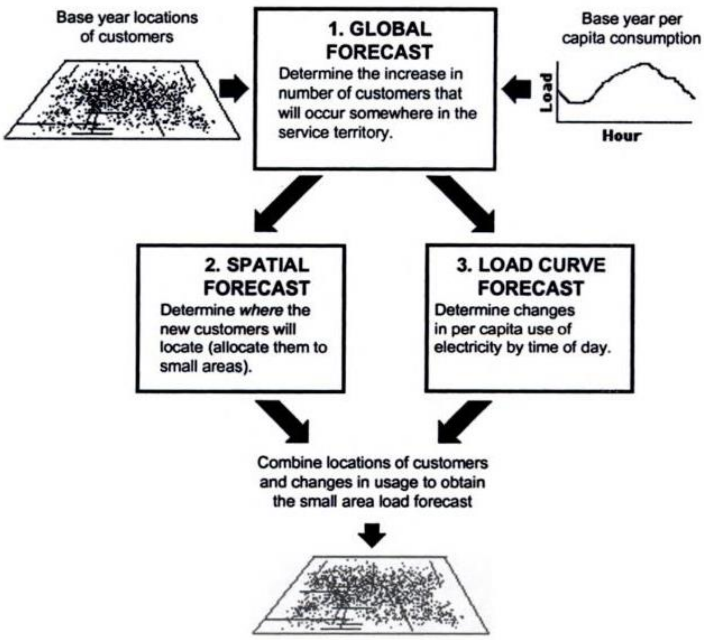

Figure 4.5. Simulation approach deals with the customer locations and consumption separately. Finally, it combines the information with a small-area forecast (Willis, 1996).

The distribution load forecasting method based on simulation aims at reproducing or modelling the load process. The objective of simulation is to forecast where, when, and how the load(s) will develop. Simulation is applicable to long-range forecasting with high spatial resolution, and together with the multi-scenario planning, it is a viable tool for forecasting. Furthermore, if the simulation method is applied correctly, it is more accurate than the trending methods. An important characteristic of simulation is that it is well applicable to very small areas with high spatial resolution. However, the simulation method requires more data and more knowledge from the planner (Willis, 1996).

4.2.7 Other long-term load forecasting methods

In addition to the previous models, different kinds of other forecasting models have been introduced in the literature. Various regression models, time series analyses, artificial neural networks, and fuzzy logics have been proposed for load forecasting (Wang et al., 2012), (Daneshi et al., 2008), (Bianco et al., 2009), (Ghods et al., 2011), and (Alfares and Nazeeruddin, 2002). Modern computational intelligence (CI) methods such as support vector machines and self-organizing maps have also been mentioned in the context of forecasting electricity consumption loads (Ghods et al., 2011) and (Räsänen et al., 2010). (Sallam and Malik, 2011) have listed advantages and disadvantages of these methods (Table 4.3).

Table 4.3. Advantages and disadvantages of short-term load forecasting methods (Sallam and Malik, 2011).

STLF Technique	Advantage	Disadvantage
Stochastic time series	Ease of understanding and implementation and accuracy of its results	Longer computational time for the parameter identification
Multiple regression	Model the relationship of load consumption and other factors, e.g. weather, day type, and customer class	Finding functional relationship between weather variables and current load demand is difficult
Expert system	Incorporates rules and procedures used by human experts into software that is then able to automatically make forecasts without human assistance	Works best only when a human expert is available. Also, an expert's knowledge must be appropriate for codification into software rules.
Fuzzy logic (FL)	Model uncertain data often encountered in real life. It is able to simultaneously handle numerical data and linguistic knowledge	Requires a thorough understanding of the fuzzy variables as well as good judgment to select the fuzzy rules and membership functions
Artificial neural networks (ANN)	It combines both time series and regression approach. It is able to perform nonlinear modeling and adaptation and does not require assumption of any functional relationship between load and weather variables	The inability of an ANN to provide an insight into the nature of the problem being solved and to establish rules for the selection of optimum network topology
Fuzzy neural networks	Some of the uncertainties in the input/output pattern relationships are removed by the FL thereby increasing the effectiveness of the ANN	—

However, the majority of these approaches in load forecasting have mainly been applied to short-time load forecasting. (Hong et al., 2014) points out that most of the literature on load forecasting concentrates on the short-term load forecasting. In those cases, the forecasting horizon is typically two weeks or less. Only a few of the publications present practical approaches that have been verified in field implementations at utilities (Hong et al., 2014). A quite common characteristic of long-term forecasting methods is variation in the forecasting time range. The term long-term forecasting may refer to a period shorter than a year in one context while in the other case it may mean a forecasting period up to ten years. Thus, it is of essential importance to define the forecasting period, and the forecasting range has to be decided in advance. Some of the short-term load forecasting methodologies can possibly be applied to the load modelling in the future. Furthermore, the effects of new technologies on electrical loads in the short-term forecasting bring important background information for the long-term load forecasting.

4.3 Conclusions

Electricity distribution networks have to withstand changing net load profiles and the potential of additional loads with specific characteristics. The time and rate at which new technologies will emerge and to what extent they will penetrate into distribution systems will vary significantly between areas. The net load profiles of individual customers will differ more from each other and be less predictable than today. In addition, the development towards a more sustainable power system requires electricity distribution networks that support distributed energy resources. A more sustainable energy system will lead to fundamental changes in the supply and demand of electrical energy (Veldman et al., 2013). The introduction of microgeneration and new types of demands will alter the present profiles of electricity demand and generation. New technologies will have various characteristics in terms of size and time when they generate or consume electricity. Strongly changing profiles of energy end-use imply a change in the use and development of the networks (Shaw et al., 2010). Forecasting of the future peak loads caused by the new technologies on the networks will be a significant source of uncertainty (Blokhuis et al., 2011). Thus, the effects of new technologies have to be investigated by studying various scenarios with different penetration degrees (Veldman et al., 2013).

Energy and power forecasts require information of the number of customers and the electricity consumption of the customer groups. A suitable amount of data and a realistic area for the forecasting can be, for instance, the present supply areas of a primary substation. Thus, the total energy consumption forecasts at the DSO level should be based on the sum of the separate forecasting areas. New technologies like microgeneration and energy storages have to be taken into consideration in the forecasting methodologies. In addition, AMR data have to be applied and processed for long-term forecasting purposes. Consequently, a new long-term electrical load forecasting process has to be developed.

The current approaches are not very accurate and straightforward methods to forecast loads in the long term. Basically, most of the above-presented methods are applicable to traditional electricity load forecasting. The methodologies based on load history alone are not accurate enough methods any longer. Historical consumption data cannot be used as initial data alone, because more detailed and new type of data are needed for the forecasting process. As mentioned above, it may be possible to improve the traditional forecasting system with AMR and other data. This alone will transform the whole forecasting procedure. In addition, novel forecasting processes are required for the new types of electricity end-use. As a result of the increasing amount of data and the changing operating environment, a lot of parametrization will be needed in the forecasting process. For instance, the development of population can be estimated to increase in the next ten years, but decrease after that for the following 30 years. Further, in (Spackman et al., 2007) it is shown that extrapolation and econometric forecasting methods are not recommendable for the long-term distribution network forecasting. The extrapolation approach cannot estimate the eventual saturation of small land areas. An econometric forecast for small areas relies on estimations of socioeconomic variables in those small areas, and these forecasts are not always available.

DSOs have typically used spatial load forecasting and simulation methods in the long-term load forecasting. Forecasts have to be spatial so that it is possible to estimate where the loads will be located. Spatial analyses have been made for a long time, but the method seems to be evolving. More accurate data and location information together with AMR data provide new opportunities for spatial analysis (Niska and Saarenpää, 2013). Spatial analysis is a fundamental forecasting method in electricity distribution; spatial load modelling is required to consider long-term development of loads in different geographical areas and long-term scenarios. Further, power is location dependent, which calls for a spatial analysis. Again, network planning requires that the case region and the forecasting period have to be determined. AMR data make it possible to model electricity end-use and classify the customers with clustering algorithms more accurately.

A picture of the future can be painted by making scenarios. Traditional long-term load forecasting has used scenario analysis when forecasting the future characteristic consumption and the number of customers. Further, a scenario analysis is needed in the forecasting system. Volume and consumption forecasts are based on scenarios in the same way as before. In addition, a scenario approach is needed to make approximations of the number and capacity of the future technologies, because there is no statistics available on future technologies. Here, scenario-based modelling plays a crucial role, when the impacts of the future energy technologies are forecasted. A scenario-based approach in the long-term forecasting is considered a useful method; however, in scenario-based forecasts there is an abundance of parameters to be taken into account. Examples of the required parameters are population forecast values and the amount of microgeneration capacity. The role of parameters is essential from the perspective of the final results. However, the parameters include a lot of uncertainties.

End-use models can be an excellent instrument in spatial load forecasting. If a spatial simulation model based on land use is applied, end-use modelling together with the spatial forecast model may produce good results (Willis, 1996). Electricity end-use will change radically, and therefore, end-use modelling is needed for the long-term load forecasting. Further, there is an increasing amount of data available of the customers, customer devices, and end-use. This provides more accurate data and opportunities to apply end-use modelling.

In the long-term load forecasting, it is also necessary to classify the same type of customers into the same customer groups. This calls for customer information of all customers in the area under study. In practice, customer information is required on what kinds of customers there are, and what kind of consumption behaviour these customers have. Based on this information, it is possible to make estimates on how the end-use of a certain type of customers will develop in the future. This kind of modelling requires end-use modelling and a parametric approach. Considering the future technological changes, information is needed about new devices and their load behaviour. End-use modelling supports also this perspective. End-use modelling will be a viable tool in the long-term load forecasting; it can be used to forecast the impacts of the future energy technologies. It is the most efficient method to approximate the future impacts on loads. Finally, a simulation method is needed to model the final results. A simulation method is used to gather the data and calculate the final results. Consequently, a combination of these methods can be the best approach for the long-term load forecasting.

Long-term load forecasting requires different objectives compared with shorter forecasts, and STLF methods do not work for LTLF purposes. Short-term methods typically aim at minimizing errors, which is not needed and cannot necessarily be achieved in the long-term forecasting. For example, there is no need for a forecasting accuracy of 2 % for ten years ahead. Firstly, it is impossible to make forecasts with such accuracy; secondly, the primary substation dimensioning can be, for instance, 16 MW and in that case, 2 % is not a relevant accuracy.

A single forecasting methodology cannot take into consideration the variable operating environment and changes in the electricity end-use. Therefore, a combination of various forecasting methodologies is needed. This kind of a hybrid approach is required, because the forecasting process has to combine data and forecasting parameters from different sources and separate methods. Moreover, energy and power forecasts are separate from each other. The solution to forecast and model future electricity end-use will provide a combination of different electrical load forecasting methods. This doctoral dissertation proposes a novel long-term load forecasting process for electricity distribution that applies spatial analysis, clustering, end-use modelling, scenario analysis, and a simulation method. This approach and the forecasting process apply separate methods and different data systems. It also makes it possible to use AMR data and takes into account possible changes in the electricity end-use.

New and different approaches for long-term load forecasting in electricity distribution are needed. Electricity end-use may change radically, and therefore, a new kind of process is required to forecast energy and power in electricity distribution. The new process will also make forecasting more accurate and reliable in the long term. Each distribution network area and electricity distribution company have specific characteristics of their own. Consequently, making objective load forecasts requires knowledge of the case area, and expertise of the area will be emphasized in the long-term load forecasting. According to (Nagasaka and Al Mamun, 2004), long-term load forecasts are always inaccurate, the peak demand is dependent on temperature, and some of the necessary data are not available. The forecast accuracy can be verified and established only afterwards, when the actual consumption figures are known. If the network planner can make the correct decisions based on the load forecasts, there is no error in the forecast from a practical viewpoint. However, it is emphasized that a long-term load forecast is not an attempt to forecast future load exactly. The objective of the forecasts is to support network planning, not to forecast future loads with a minimum error. Most importantly, the forecast should accurately represent the load under conditions that are specified as part of the distribution planning scenario and criteria (Willis, 1996). It is pointed out that scenarios are only a good help in making forecasts. Finally, the planner of the network decides the parameters and makes the forecasts and analyses.

The most radical change in the long-term forecasting compared with the present and previous forecasting methodologies is that the forecasts are based on hourly powers, which makes it possible to estimate powers in different areas and in any time period of the year. In practice, this means that the impacts on energy can be calculated from powers, if forecasts are made for the whole year. As described above, both power and energy are key elements in electricity distribution. Moreover, business planning is also dependent on the energy and power. Energy has an impact on revenue while power has an influence on network investments and thereby on network costs.

The increasing amount of data will provide new opportunities to make load forecasts in the long run. In particular, AMR data bring totally new options to forecast loads in electricity distribution networks. More accurate analyses can be made at different network levels. In addition, the initial stage in the consumption analysis is exact because of the AMR data. In spite of the AMR data, standard deviation and excess probability have to be taken into account in the same way as before. This aspect has not changed, and probability calculations have to be involved in the network planning.

Hence, the main difference between the traditional and new long-term forecasting is that the forecasts are based on hourly powers, not annual energy. AMR data and forecasts related to the future energy technologies are radical changes in the forecasting system. Similar analyses and forecasting tools are found for long-term purposes. (Kaartio, 2010) has developed spatial long-term load forecasting; in his study, the effects of MG, EVs, and HP on the network loads are discussed. The study does not apply AMR data. (Shaw et al., 2010) and (Veldman et al., 2013) have studied the effects of EVs, PVs, and HPs, and analysed their possible impacts on the network. (Niska et al., 2011) has presented a model on how to apply AMR data for a scenario-based electricity load prediction tool for electricity distribution. The study does not describe how to model loads in the long term and how the effects of the new energy technologies could be taken into account.

In (Rimali et al., 2011), (Filik et al., 2011), and (Filik et al., 2009), AMR data have been applied to the long-term load forecasting in electricity distribution. These studies present how the AMR data can be modelled in the LTLF, but do not discuss how different future energy technologies could be forecasted universally. (Rimali et al., 2011) also proposes how to connect different data systems to each other. In (Huikari, 2015), it has been described how AMR data can be used in the LTLF, and a scenario analysis has been made on the future loads. The work also suggests that a scenario tool is needed for the LTLF.

The studies described above have connection points to this doctoral dissertation. However, these studies have not developed a comprehensive long-term load forecasting process for electricity distribution. Thus, the contribution of this dissertation is a new approach for the LTLF in electricity distribution. Here, AMR data is a starting point for the forecasting process. The changes in society and the operating environment are included in the process. The use of data from various databases, both the external and internal ones of the DSO, is introduced. Finally, it is described how to forecast impacts of the future energy technologies on the electrical energy and power in distribution networks.

5 Novel long-term load forecasting process

Traditionally, it has been possible to forecast electricity end-use based on annual electrical energy consumption, because electricity end-use has not included loads such as microgeneration that would totally alter load patterns. However, new loads and production, evolving technologies, and changes in society will have various impacts on future loads. In particular, considerable changes in powers and energy of the electricity end-use will take place. Because of these changes in the operating environment, advanced forecasts are needed. In addition, new data sources can yield more accurate information of the present loads and customers. Especially, AMR data will revolutionize modelling of the present load analysis. Thus, owing to these factors, previous forecasting approaches are not valid anymore. Therefore, a new long-term load forecasting process (LTLF) is needed.

The future electricity load forecasting process has to produce estimates of future energy and power demand in the long term for areas of all kinds: urban and rural areas and population centres. The forecasting of future loads in the distribution network is quite a challenging task: various changes take place in different areas and different times, and these changes can have diverse effects on loads. A typical example of such changes is heat pumps, which can either increase or decrease power demand. Forecasts of future electrical energy and the highest powers in different geographical locations are required for distribution planning.

5.1 Structure of the forecasting process

A novel long-term electricity load forecasting is a multi-phase process, which requires a lot of data from different sources. Long-term electrical loads can be forecasted by applying volume (number) and consumption (load) approaches, but the effects of the future energy technologies have to be calculated separately. This is explained by the fact that the future technological changes may have radical impacts on electricity consumption, which requires a new approach. In the context of this doctoral dissertation, future energy technologies are related to energy efficiency, energy storages, electric vehicles, microgeneration, and demand response.

The future electricity load forecasting consists of a present load analysis for long-term load forecast, volume and consumption forecasts, and forecasts of the future energy technologies. The present load analysis can be considered a load modelling phase that includes spatial combination of data, AMR data, seasonal dependence, and a customer group analysis. This produces information of the present load analysis in the case area and works as a basis for the region-specific forecasting. Volume and consumption forecasts in the forecasting process cover information about changes in the operating environment such as how the number of population, means of livelihood, and building stock have developed and are anticipated to develop in the area in the future. The impacts of the future energy technologies are forecasted at the same time. Figure 5.1 illustrates a basic structure of the process, including the present load analysis, the volume and consumption forecasts, and the future energy technologies forecast. The new element in the process consists of clustering and end-use modelling of the present loads, in particular, end-use modelling, scenarios, and simulation methods to forecast the volume, consumption, and future energy technologies.

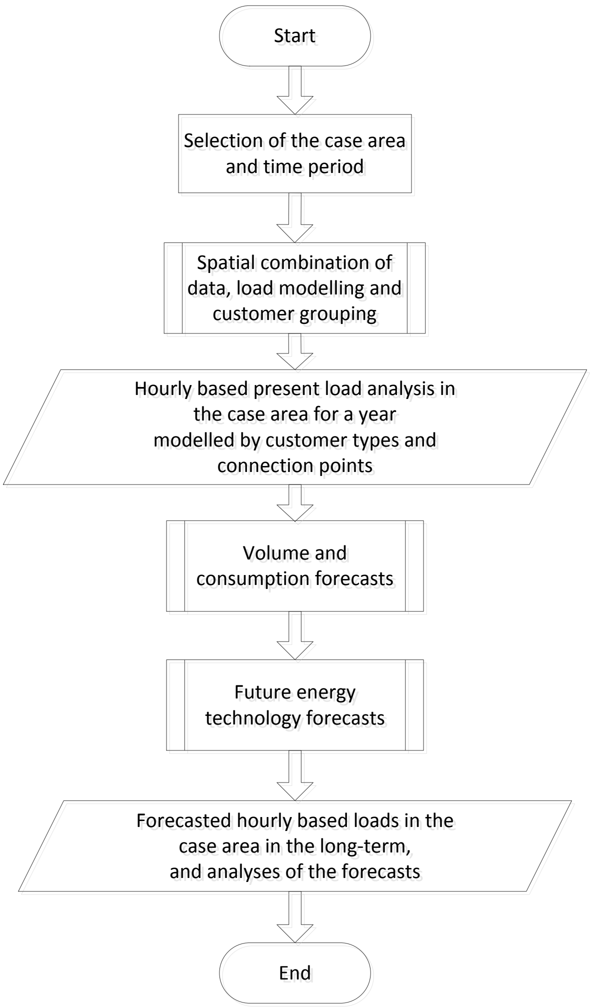

Figure 5.1. Outline of the long-term load forecasting process in electricity distribution.

The novelty of the new LTLF process lies especially in the combination of forecasting techniques and new data sources, which include application of AMR data. Future energy technologies have to be forecasted by end-use modelling. The effects of the future technologies on loads are so exceptional that end-use modelling is the only suitable method. A scenario approach is also needed, because there are no data on how the future energy technologies may evolve.

The forecasting process has to be divided into different elements. By dividing the process into separate elements, it is possible to analyse individual proportions of the process. Before actual load forecasting, various preliminary tasks such as load modelling have to be accomplished. Finally, the present loads for long-term forecast in the area can be formed. The volume, consumption, and future energy technology forecasts represent the main forecasting process. The volume, consumption, and future energy technology forecasts have to be focused on the case area. For example, the forecast according to which 50 % of the residential customers in the area will purchase a PV system by 2030 can be focused on different kinds of detached house customers. Then, it is possible to forecast the impacts on the loads in the case area. New customers in the area have to be taken into consideration in the volume forecasting. Basically, the volume and consumption forecasts are traditional forecasts with AMR data. This phase produces initial forecasting results of the case environment.

Mean hourly powers constitute a basis for load forecasts. The highest powers can be analysed on an hourly basis, whereas energy forecasts are typically based on annual energy calculations. Forecasts based on a whole year (8760 h) also enable an energy analysis at an annual level, and it is reasonable to make load forecasts for the whole year. The major difference between energy and power forecasts is that energy forecasts should be annual-level forecasts in order to get a comprehensive picture of energy consumption. Another option is to make energy and power forecasts for a certain time period of the year. It is reasonable to limit the long-term forecasting to a certain area and time period as too large amount of data may be quite difficult to handle and analyse. Moreover, a selected forecasting time period makes it easier to set different parameters for the forecasting period. Another benefit is that a shorter time period requires less information for forecasting. The time period can be, for instance, a week or a month during the highest load period in the case area. It is highly important to select the time period appropriately, because loads vary considerably within and between different time periods. Typically, the highest loads occur during cold winter days, when electric space heating is needed. On the other hand, when considering microgeneration, it is reasonable to make load forecasts for the summer period, when the potential of photovoltaic (PV) production is at highest.

As a result, the novel load forecasting process yields hourly based power forecasts. Based on the forecasts, it is possible to calculate the effects on energy consumption. The key methodologies of the forecasting process consist of spatial analyses, clustering, scenarios, end-use modelling, and simulation methods. A forecasting task is a generic problem, which comprises several tasks. The first tasks in the forecasting process are to define and delineate the research area and to decide upon the time scale and period for the forecast. The basis for the research area is that it covers only a DSO's network area. It is practical to limit the forecasting to primary substation areas, which are quite close to district areas in urban areas and traditional municipal areas in rural areas. This way, the size of the forecasting area is adequate for forecasting and the data are manageable. Making a spatial load forecast for instance for districts in urban areas can be challenging, because these areas do not necessary follow any other spatial borders in the urban area (Rimali, 2011). This can be managed by dividing the case area into smaller areas.

The main starting point for the spatial analysis is the determination of the case area. Here, a map application may be needed that can support the forecasting process. It allows to select the case area and generate forecasts spatially. As mentioned above, the areas to be examined (target areas) and the forecasting periods can be similar types of areas and time periods as before. In the literature there are studies that have used actual distribution network areas in the long-term load forecasts. For instance, (Spackman et al., 2007) has used distribution network and feeder service area boundaries as a basis for a spatial study. It is not reasonable to include a distribution network in the forecasts of the area to be studied. It is essential to forecast loads spatially, which corresponds to a situation in which the load forecasts are made for an area without a distribution network. After forecasting regional loads, the present loads can be compared with the forecasted loads. By taking this approach, it is possible to estimate the need for network investments, for example, a location for a new primary substation. Further, it is possible to make a spatial load analysis, which helps to plan new network investments. Moreover, this kind of an approach provides an opportunity to make a load analysis for the present network, because it is possible to compare the present loads with the forecasted loads, for instance in distribution network nodes. The target area should remain almost the same between years so that it is easier to analyse how the loads have developed and may develop in the future. Thus, it is advisable to keep the feeder areas unchanged.

5.2 Present load analysis

The present load analysis is made based on the selected case area and time period. In addition, a spatial analysis and a combination of data are needed before forecasting. Spatial analysis can yield general information such as additional information of customers and real estates in the case area. A spatial approach requires that consumption data are modified suitable for spatial forecasting, which means an analysis of customers and connection points. (Hyvärinen et al., 2012) has also pointed out that before forecasting, the case area has to be selected, information on customers or connection points and other relevant background information have to be gathered, and the level of review has to be decided upon, that is, whether the focus is for instance on the customer type, connection points, or something else.

The present load analysis can be divided into spatial combination of data, AMR data processing, seasonal dependence determination, customer grouping, and clustering elements. In practice, this is the load modelling phase presented in Section 4.1.3. However, a new load modelling approach for the LTLF purpose is presented in more detail here. All customers from the case area are incorporated in the present load analysis. The simplified structure of the present load analysis is illustrated in Figure 5.2. The figure presents the method to produce load profiles for customer groups.

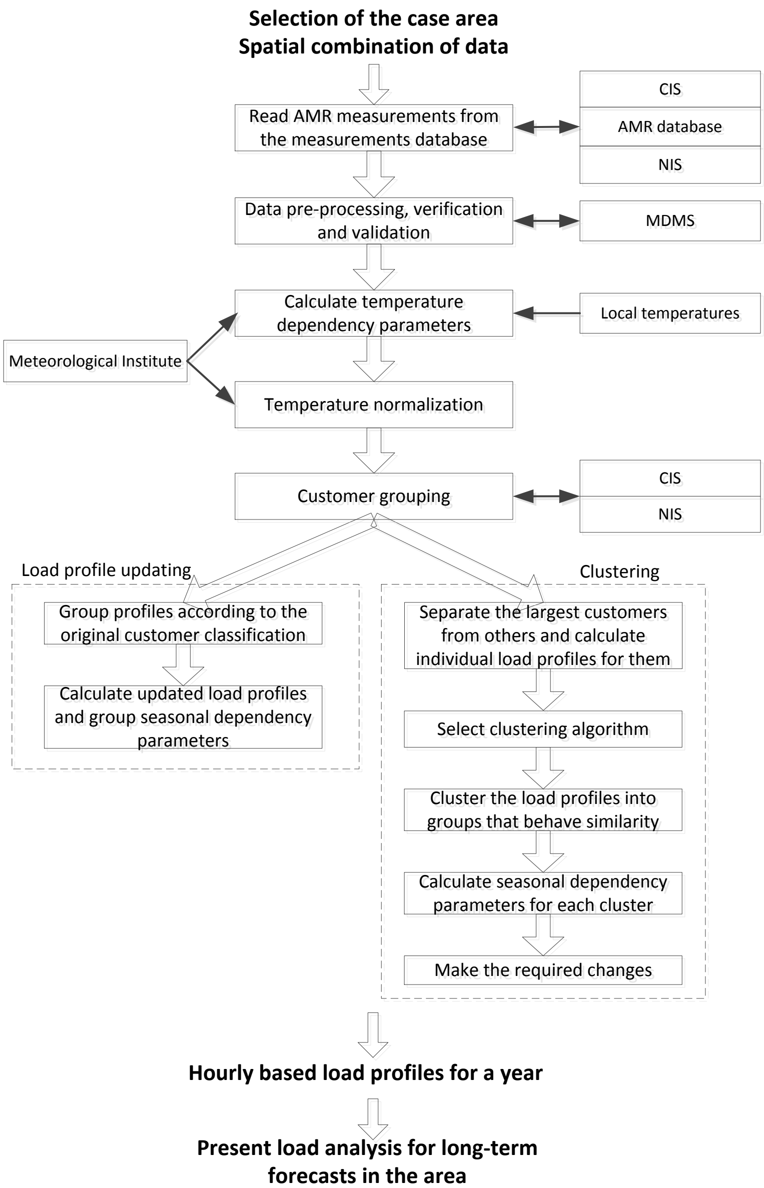

Figure 5.2. Customer classification processes and the present load analysis process for long-term load forecasting. Adapted from (Mutanen et al., 2013).

Basically, the present load analysis consists of a spatial analysis, clustering methods, and end-use modelling. Spatial combination of data produces additional information of the customers in the case area. AMR data have to be processed before customer grouping. After AMR data processing, the temperature dependence is calculated and normalization is made. Customer grouping and clustering are needed because of diverse customer types.

For the LTLF purpose, load profiles have to be updated or customer profiles have to be clustered. A clustering method can be used as a tool to cluster the customers and load profiles. End-use modelling, again, can be used to define season-dependent loads or to model the proportion of other electricity end-use of the loads. Finally, load hourly profiles give the present load information for long-term forecasts of the case area. The present load analysis is the starting point for forecasting.

5.2.1 Spatial combination of data

A spatial analysis is needed to produce information of the case area. The long-term electricity load forecasting process in electricity distribution may employ data from various data sources. Data sources are needed before forecasting for the spatial combination of data and for the forecasting purpose itself. The increasing amount of data and advanced technological systems make data processing more efficient and accurate. Defining and delineating the most essential data and using the data efficiently are important in the forecasting process. Data sources can be divided into the DSO's internal and external ones. The DSO's internal data sources to be applied to a forecasting process can include for instance a customer information system, a network information system, and a metering database. The DSO's external data sources such as municipal registers and Statistics of Finland provide data about the case area and information for forecasting purposes. Public authorities have opened their databases to public in Finland; for instance, the Population Register Centre gives access to location and building data systems (Population Register Centre, 2013). The National Land Survey of Finland has opened a data system where information of building surface areas, heating systems, and map systems can be reached (National Land Survey of Finland, 2014).

A DSO's internal data consists of several data systems. The AMR database is one of the main elements for the forecasting system. AMR data constitute the basis for the construction and confirmation of load models. In addition, AMR data expand the information and options for the long-term load forecasting. A challenge related to the AMR data is that they represent the total load of the end-use point instead of separate appliances or sub-load component loads such as space heating and lighting (Niska and Saarenpää, 2013).

A DSO's customer information system (CIS) includes all information available of each customer. Each customer has an electricity meter, in other words, a metering point. DSOs have typically the following information of their electricity customers: customer location, supply voltage, fuse size, number of phases, customer class (residential, agriculture, public, service, industry), consumption (annual electricity consumption, 2-time tariff consumption), and additional information (heating system, type of domestic hot water heating system, electric sauna stove) (Mutanen et al., 2011).

Electricity is mainly consumed in different kinds of buildings, but other possible systems consuming electricity are found for example in community maintenance, and street lighting. In larger buildings such as blocks of flats, there is one connection point for the whole building, which feeds several and separately measured customers. Consequently, one connection point can consist of one or several customers (Koivisto et al., 2013). (Koivisto et al., 2013) points out that it is useful to analyse connection points for load modelling purposes, because the DSO's long-term scenarios have to spatially simulate the effects of the future city construction activities on the electrical load demand. Again, (Rimali, 2011) has concluded that a property could be a starting point for the load forecasting in scenario-based forecasting.

The specific electrical load demand of the present buildings (kWh/m^2) is important input data for simulations. Furthermore, in the real estate data, it is essential to have information of kWh/m^2 for separate customer types. Further, electricity consumption data and real estate data should be linked to each other (Koivisto et al., 2013). The majority of the real estates (properties) include only one connection point. An alternative is that a property has several connection points. For instance, one property may include several buildings. These cases can be combined and analysed as an individual connection point. Challenges arise when one connection point supplies several properties. In that case, it has to be defined which customer points of the connection points are located in a certain property (Rimali, 2011). So far, it has not been possible to link the AMR data of an individual customer and a part of the property (Koivisto et al., 2013). In practice, this means that the electrical end-use of customers can be modelled individually, but for a spatial forecast it is reasonable to model the loads of connection points.

All information from different databases can be connected to a certain real estate. This makes the connection as simple as possible and load forecasts can be made more versatile. Some information has to be filtered before the connection points and properties are automatically connected to each other in order to obtain satisfactory results (Rimali, 2011). After filtering the data, the connection with properties and connection points can be made. Now, new information of the customers can be obtained. Comprehensive data sources serve as the basis for the spatial combination of data; there are various data that can be applied to complete customer information. (Niska et al., 2013) has gathered geographic data from public sector information sources such as socioeconomic grid data, building information, and meteorological data for load modelling. External data sources may include systems maintained by municipal, provincial, or national bodies like Statistics Finland as suggested in (Kaartio, 2010) and (Rimali et al., 2011).

Information of the buildings and heating systems in the case area are needed for forecasting purposes. Data about heating systems of buildings are available in the DSO's external data sources. The DSO's data systems are seldom linked and updated to the DSO's external databases. (Niska et al., 2011) has used information of the Finnish Population Information System in a simulation tool, which includes data of the total floor area and volume of buildings, the age of buildings, construction materials, façade materials, the primary fuel and heating system, and the number and age of inhabitants. These are relevant information and should be included in the information of customer. The Population Register Centre has a Population Information System (PIS), and the National Land Survey of Finland has a Land Information System (LIS) that provide data of real estates. In addition to the PIS and the LIS, municipal registers can give data of real estates. Municipal registers may include many registers like real estate, town planning, building, address, population, and planning registers. These registers can linked with each other based on addresses or map coordinates. A real estate in a municipal register can be linked to connection points in the NIS and AMR data with coordinates in most cases (Rimali, 2011). The real estate is typically the most accurate level at which the municipal register can be appropriately linked to the electricity consumption data. Some information in the municipal register is available only at the building level. This information can be applied to the real estate level by summing (e.g. floor area and number of customers), taking into consideration the most common option (heating system, purpose of use), or calculating average values (construction year of the building) (Rimali, 2011). Figure 5.3 demonstrates a DSO’s external and internal data for an individual real estate. One real estate (property) may include several buildings, and one building may have several DSO’s customer points. The DSO’s external and internal data contain various information. In the figure, examples of data sources are given.

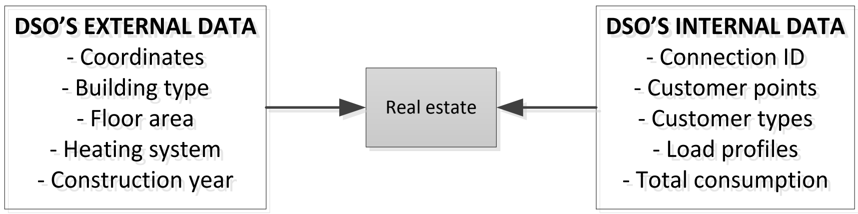

Figure 5.3. Example of the types of information that a DSO’s external and internal data may incorporate.

(Kaartio, 2010) has found that integration of different data systems for a spatial analysis facilitates forecasting and planning. Although the connection of databases is somewhat challenging, for instance a connection between addresses and coordinates is a potential solution. (Kaartio, 2010) has suggested that the customer connections in the network information system and the building information could be linked by address data. It was concluded that it is not possible to link the connection point and building information reliably enough; the main reason for this was the discrepancies and divergences in documentation (Kaartio, 2010). The address-based approach may produce errors in targets located in street intersections. Such locations may include various addresses, some of which may be erroneous. This, again, produces errors when connecting the data systems. It seems that a coordinate-based approach could be more reliable (Rimali, 2011). When connecting different databases, the major challenges lie in ensuring a rigorous connection process and the reliability of the integrated system. Large data volumes cannot be processed and modified manually. The increasing amount of information in separate data systems makes it easier to gather data. For instance, if the data system included information of the customer point, connection point, and property number, the connection of data systems could have less errors and be simpler (Rimali, 2011). Figure 5.4 shows an example of how databases could be linked to each other.

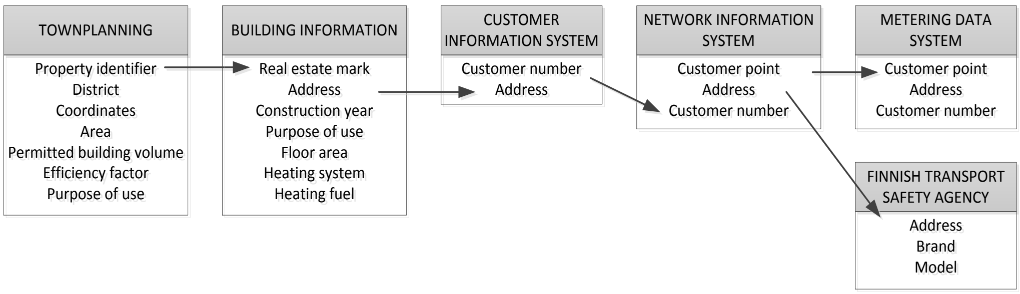

Figure 5.4. Example of linking of the data systems (Kaartio, 2010).

The NIS and CIS can be connected to each other by using connection point or customer point information. The metering database can be connected to the NIS and the CIS with customer point information. Figure 5.5 presents an example of the connection between different data sources. The majority of the data are available from the DSO's internal data systems; AMR and customer information databases. These customer data can be supplemented from the DSO's external data sources, for instance, by building and heating type information from municipal registers.

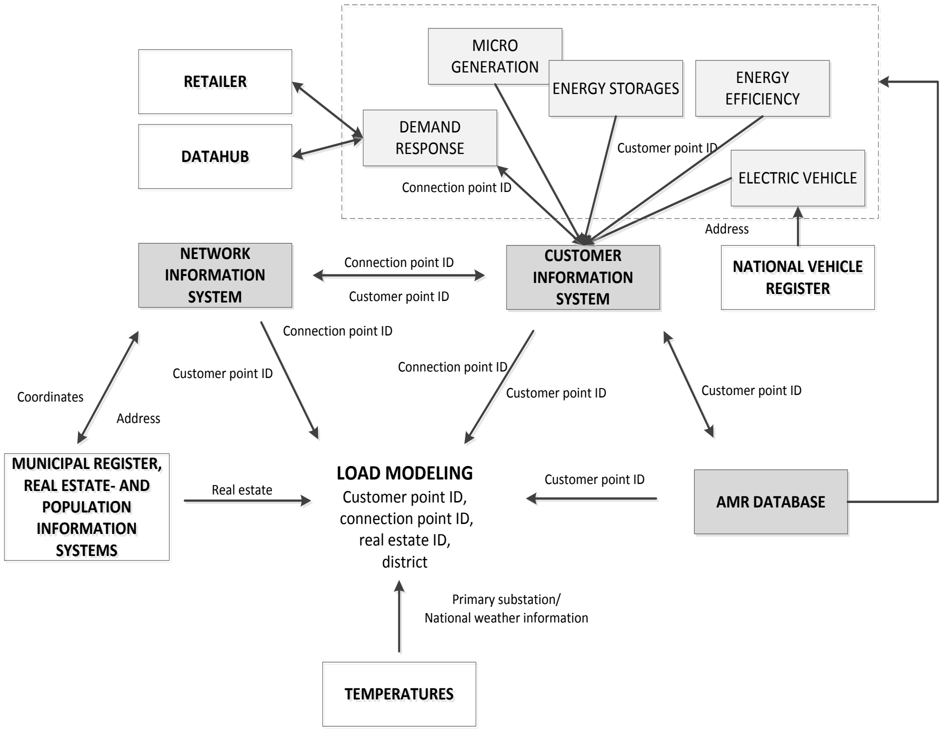

Figure 5.5. Example of links between different data systems. In addition to the municipal register, the Population Information System (PIS) and the Land Information System (LIS) can produce real estate data (adapted from Rimali et al., 2011).

New technologies are not necessarily included in the customer information system at the moment. However, this would be important in the future to obtain more accurate information of customers. Table 5.1 shows the customer information of new technologies required for forecasting.

Table 5.1. Example of information demands of future energy technologies.

ID	Building type	Building year	Heating system (HS)	Supplement HS	PV	EV	DR	ES
1	Detached house	1950	Oil heating	AAHP	5 kW			
2	Detached house	2010	Direct electric heating	AAHP			2 kW	5 kWh
3	Row house	1987	District heating					
4	Flat	1967	District heating			1 EV		

Spatial combination of the information from different sources with the DSO's data constitutes the main step after the case area selection. Spatial combination of data enables a more efficient load analysis of the present loads. Therefore, it is advisable to pay special attention to the collection and combination of data.

5.2.2 AMR data processing

By applying AMR data it is possible to analyse certain individual hours instead of the previous annual electricity use. These analyses can serve as a good approach for load forecasting, because they constitute a basis for spatial analysis together with for instance the building forecast (Rimali, 2011). Electricity consumption varies as a function of time, which means that the AMR data have to be analysed strictly based on time stamps. The AMR data collection from the databases and the connection to the selected area have to be carried out in a reliable way. This requires that customer information are stored in the process. The amount of AMR data depends on the number of customers in the area and the time period under study.

Typically, there may be fluctuation in the consumption curves between different years. Hence, it is useful to collect AMR data for the whole calendar year and separately from each year. Thus, the time ranges are the same and different years can be compared with each other. The main requirements for the AMR data are validity and correctness. Therefore, AMR data require validation and verification. AMR data may contain errors because of faults in metering or communication, or data format changes can generate errors. These errors can be seen as missing or exceptional values, or outliers (Mutanen et al., 2011). Outliers are failed measurements or customers whose electricity end-use is very different from average customers. There are two main types of outliers; customers whose electricity end-use varies considerably in some months can be detected by comparing an individual customer's monthly energy with all customers' average monthly energy. Customers whose intraday end-use variation is very high compared with other customers can be filtered out (Mutanen et al., 2011).

There are various ways to track outliers from the AMR data. For example, (Koivisto et al., 2013) has adopted an approach that customers the maximum hourly peak consumption of which is higher than 100 times the average hourly consumption are eliminated. Missing values can be estimated from the data set by linear interpolation. The exceptional values can be estimated by comparing the previous hourly values (Mutanen et al., 2011). If the measurements include errors and erroneous values, such values have to be removed from the measurements, or an approximate of new and more suitable values is required.

The meter data management system (MDMS) processes AMR data in the metering database at various levels of data validation and verification. The number of errors has decreased along with the evolving metering and data management systems. Consequently, the quality of data is at a quite high level in Finland at present.

5.2.3 Seasonal dependence

There are many weather elements such as wind and solar radiation that affect electric loads, but the outdoor temperature dependence is one of the most significant factors. Outdoor temperature is widely taken into consideration in distribution network calculations (Mutanen, 2013). The data of outdoor temperatures can typically be achieved by measurements at the primary substation. Data can be also obtained from the Finnish Meteorological Institute (FMI), which collects measurements from several locations around Finland (Finnish Meteorological Institute, 2014).

Outdoor temperature may have a significant impact on electrical loads. In Taiwan, it was found that the power demand increases by 4 % when the outdoor temperature rises by 1°C in summertime. This can be mainly explained by the high percentage of air conditioners (Lin et al., 2006). When considering electric heating loads, it is often assumed that a 1°C change in the outdoor temperature causes a 4 % change in electricity consumption. However, almost all customer groups are dependent on the outdoor temperature in one way or another. The temperature dependences (variations in temperatures and electric powers) may have different kinds of time delays, which are mainly due to heat stored in buildings. Further, different customer types may involve various time delays (Mutanen, 2010). Thus, modelling the temperature dependence can be a challenging task. Therefore, distribution network calculations typically apply a load model where temperature is linearly dependent in a certain temperature range (Mutanen et al., 2011).

In practice, the electric load dependence on the outdoor temperature is nonlinear. This is due to the use of additional heaters during the coldest weather, when extra heating power is needed. The situation is similar during warm weather, when air conditioning is needed. Therefore, a linear temperature dependence model requires seasonal or monthly parameters. The seasonal parameters can be divided into four and monthly ones with 12 parameters (Mutanen, 2010).

Outdoor temperature varies between different years, and therefore, the AMR measurements have to be normalized to the same temperatures. For this purpose, the customer-specific temperature dependence parameters have to be calculated by applying linear regression. However, so far, there has been only limited knowledge of the correct temperature dependence parameters. The temperature dependence parameters can be calculated from AMR data. This ensures that regional differences are taken into account in the temperature dependence (Mutanen, 2010). AMR measurements can be normalized to the long-term average outdoor temperatures if the temperature dependences have been calculated (Mutanen, 2013).

Previously, national long-term monthly average temperatures have been applied. At present, it is possible to use regional long-term daily average outdoor temperatures, which are more accurate than previous data. This type of data are available from the Meteorological Institute. Thus, it is advisable to apply regional long-term (30 a) average temperatures instead of national data. In addition, the variation in outdoor temperatures is better represented by daily average outdoor temperatures than by monthly averages. This method can be applied to take into account the energy consumption normalization in network loads. However, long-term daily average outdoor temperatures do not take into consideration the load variation caused by the coldest temperatures, and thus, too low peak powers may occur in the network loads. Therefore, the shape of the network load has to be determined more accurately. This can be achieved by using the hourly outdoor temperatures from the same year as the AMR data applied. The dispersion of long-term outdoor temperatures at the daily level can be calculated from the relation of hour-level temperatures and average day-level temperatures. When this relation is multiplied by an average long-term temperature, the reasonable dispersion for the outdoor temperature can be achieved. Thus, the normalized load represents the regional long-term outdoor-temperature-corrected energy in the distribution network, but the shape of the network load is based on the measured AMR data. Both the temperature dependence calculation and normalization are carried out before the customer grouping phase.

After clustering, temperature dependence parameters can be calculated applying the same method as in the customer-specific method. The final load profiles represent electricity end-use based on daily average temperatures in the long term. Calculation of the difference in electricity consumption between the expected long-term average and the target temperature can be modelled as follows (Mutanen, 2013):

$$\Delta P(t) = \propto \cdot (T_{\mathrm{ave}} - E[T(t)]) \cdot E[P(t)] \qquad (5.1)$$

where

$\Delta P(t)$	outdoor-temperature-dependent part of load P at time t
α	temperature dependence parameter [%/$^{\circ}$C]
T_{ave}	outdoor temperature (daily average)
$E[T(t)]$	expectation value of the outdoor temperature at time t (long-term daily average temperature)
$E[P(t)]$	expectation value of the load at time t

All seasonal variation is not due to weather conditions and outdoor temperature. Lighting varies also by seasonal periods. Outdoor and interior lighting patterns vary from winter to summer (Willis, 1996). Seasonal indoor lighting dependence can be take into consideration in the end-use modelling, when the day length can be modelled by a mathematical approach.

5.2.4 Customer grouping and load profiling

In the long-term forecasting, the customer groups have to be valid and the AMR data correct. However, the customer grouping phase can be problematic; a significant challenge is to define a suitable number of customer groups. In addition, customers have to be classified reliably, because the existing customer groups in the DSO's data systems are not necessarily valid. More information of customers can be obtained from spatial combination of the DSO's external and internal data. Typically, the same types of customers have similar load curves, but there may be large variations in loads. Furthermore, there may be significant differences between customer groups. There are many possible ways to classify customers. Previously, the customer classification has been made based on national-level models in Finland. These SLY load profiles include numerous customer groups and precise classifications (SLY, 1992). Figure 5.6 shows a typical example of the customer classification in Finland.

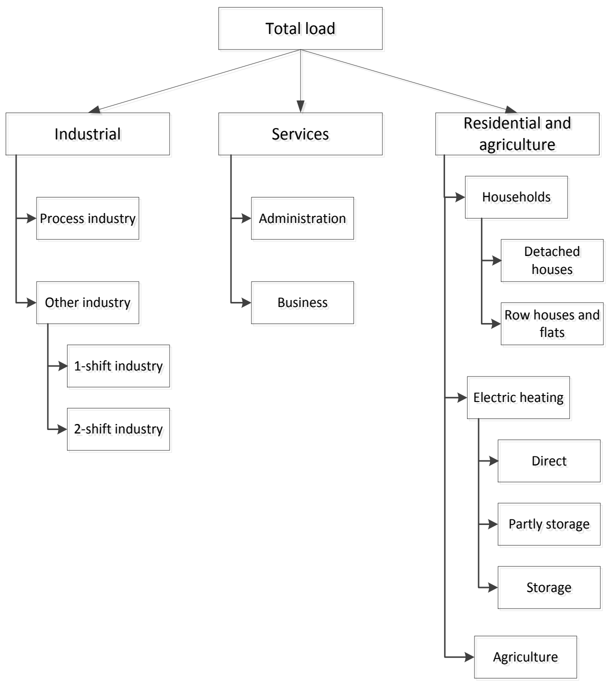

Figure 5.6. Example of customer grouping. Reproduced from (SLY, 1992).

However, the DSOs may also have classified their customers by themselves. In the customer grouping, the type, characteristics, and number of customers in the research area should be determined. Further, the amount of initial data has an impact on the number of customer groups. At least, the customers should be grouped into the following main categories: residential, agriculture, service sector, and industrial customers. Further, the residential customers should be divided into detached and terraced houses, apartments, and holiday homes. In addition, detached houses with direct electric and non-electric heating should be analysed separately. Consumption in agricultural, industrial, and service groups may vary markedly. Again, different building types and buildings with electric heating systems should be analysed separately. It is reasonable to study specific customers with significantly diverging electricity consumption patterns separately.

Customer grouping plays a crucial role in the forecasting process. The main benefit of the customer classification is that a similar analysis can be made for the same type of customers. For instance, customers living in detached houses with electric space heating can be modelled in a similar way in the whole case area. The categories have to be analysed separately, because the consumption patterns differ significantly from each other. Furthermore, the loads within the customer groups may vary considerably.

Basically, the number of customer groups should not be too large, because the number of analyses will increase accordingly. In (Lakervi and Holmes, 2003) it is stated that the number of customer groups should be less than 15 in order to keep the analysis work within reasonable limits. Nowadays, however, the computational capacity is higher, and thus, also the number of customer classes can be larger. An essential decision in the case area is to determine the suitable number of customer groups.

In general, customer grouping can be managed by applying load modelling methods. There are several options to group the customers, for instance the DSO's present customer grouping supplemented with AMR data or a clustering method. These methods are presented in Section 4.1. Basically, there are two alternatives to carry out customer grouping: a load profile updating method or a clustering method. In the load profile updating, predefined customer groups are used. In the clustering approach, the new load profiles are produced with the new customer groups, where predefined customer groups can be used as a starting point for clustering. By combining clustering and AMR data it is possible to produce load profiles for each customer group. The normalized AMR data have to adequately represent the customer's loads. Futher, exceptions or events that do not fit into the load profiles have to be removed. Exceptional values can be eliminated for instance by using representative type weeks as discussed in section 4.1.3. The customers' AMR data should be scaled to 1 so that customers of the same type are classified into the same category. Customer information like annual energy consumption, location, and other additional information can be maintained despite the clustering process. This provides an opportunity to scale the customer profiles based on annual energy consumption, when the load profile uses the characteristic hourly based load profile for a year, and the annual electricity end-use is the same as in the initial stage. After clustering the customer data, it may be difficult to specify different customer types. Here, cross-checking with the original customer type classification can be applied to compare the customer types. The clustering results and the predefined load models may contradict each other. However, the customer groups and customer data can be updated by clustering, and better information of the loads in the case area can be obtained. If exceptions or other unusual phenomena occur in this phase, the required changes are made, and possibly, the clustering phase has to be repeated. Finally, the load profiles and customer groups for load forecasting are achieved.

Clustering benefits are illustrated in Figure 5.7. The figure shows the clustering results of the predefined detached house customers with direct electric heating. The clustering results show that predefined customer groups may include totally different types of customers. The customers that do not belong to the predefined customer group have to be removed from that customer group, and transferred into a customer group that fits best. After the clustering results, customers have been classified into selected groups, and a load curve has been obtained for each customer group on an hourly basis for a year.

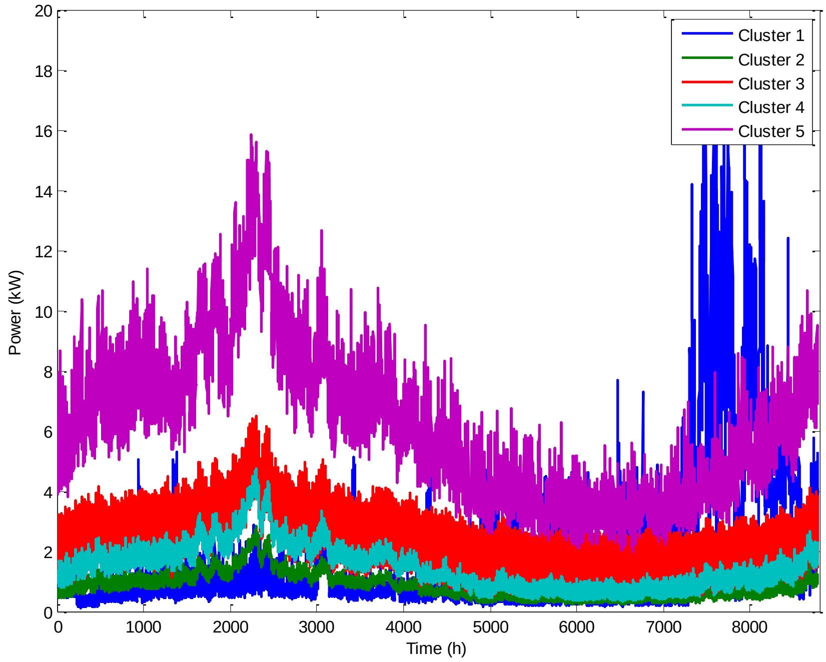

Figure 5.7. Clustering results of the predefined electric heating customers in the case area.

Eventually, the customer grouping produces results that can be applied easily and diversely to the forecasting and modelling of the present loads for long-term load forecasting purposes. In the forecasting process, clustered and normalized load profiles of customers can be applied. Clustered profiles are reasonable a choice for small-scale customers such as residential customers. For large-scale customers, normalized individual load profiles can be applied, as described in section 4.1.3.

In spite of the fact that clustered curves may produce excellent results, they may involve issues that do not always represent all customers very well. In the clustering, the customer's original load profile (normalized profile) is changed over to a clustered profile. Thus, the customer's new profile pattern and peak power can be different from the normalized profile. However, in network loads, energy and peak power are almost the same at the primary substation and secondary substation level. On the whole, this means that there have to be enough clustered profiles if the profiles better represent the original load profile, and the clustered profiles are accurate enough.

5.2.5 Summary of the present load analysis

The forecasting area has to be selected carefully in order for the forecasts to remain almost the same between different years. In addition, all loads should be included in the present load analysis and forecasts. The present load analysis is the basis for the load forecasting process. Hourly based electricity end-use data, seasonal dependences, and new flexible methods for customer grouping offer a new and efficient starting point for long-term forecasting. Moreover, it brings a new approach to customers' electricity end-use modelling. Seasonal dependences are taken into account, because from the heating and cooling perspectives, outdoor temperature dependence is an important factor in the load modelling.

A lot of customer information is obtained from the DSO's external data sources. Combining data from external information sources and the DSO's internal data sources may be a complicated task. Data have to be made compatible for the selected case area, which requires interfaces, expertise, and local knowledge of the area. The combination of information from different data sources has to be performed automatically and reliably. Especially, connection of data with real estate and building information has to be carried out with care. Combination of data is more complicated in urban areas compared with rural areas; in urban areas there are more real estates (properties) that may include several buildings and different customer points. Further, the AMR data produce an extensive amount of data annually. For instance, if the DSO has 200 000 customers, this means about 1.75 billion units of data annually. Such a large amount of data has to be processed and modelled carefully and efficiently. However, there are great differences in the amount of data between different DSOs.

Additional information of the customers, for instance information of customer classification, building types, and future energy technologies should be gathered into a data system (e.g. the CIS) in order for all the required data to be available. The information of new technologies like microgeneration, energy storages, and load control customers should be added to this data system. In addition, interfaces to the other data systems should work efficiently. Altogether, data sources involve a lot of data that have to be included in the present load analysis process.

In addition to customer grouping, other characteristic load information may be needed. Characteristic loads per capita, per floor area, or per volume may be applied in forecasting (Hyvärinen et al., 2012). At least real-estate-based analyses are used for the LTLF when analysing the present loads in the case area. In the real-estate-based approach, the results can be given by connection points. For instance, information of properties such as average electricity end-use per floor area for a certain customer class (kWh/floor area-m^2) can be used (Rimali, 2011). Characteristic load curves per floor area can be calculated by using linear fitting with a constant term, linear fitting without a constant term, and dividing consumption. The simplest method is to divide consumption by floor area, and it is an accurate enough method. The information can be used as a load profile for modelling the consumption of new buildings (Rimali, 2011).

Load changes between different years should also be analysed. This has to be done after the customer grouping phase, when a customer's end-use can be compared with previous years. The customers' historical AMR data can be used to evaluate the changes in electricity consumption. It is preferable to use only the recent consumption data for load forecasting, because it guarantees a higher accuracy. If there is considerable variation in loads between different years, this variation should be taken into account in the present load analysis. For example, the information of a change in the heating system or improvements in insulation could be taken into account in characteristic loads per floor area or a change in the load profile compared with the previous year. However, there has to be an option to make customer-point- and connection-point-based forecasts. Customer-point-based forecasts are preferable, but connection-point-based forecasts may also be needed, for instance, if a PV system installation is forecasted on the roof of a block of flats.

5.3 Volume and consumption forecasts in the forecasting process

(Willis, 2002) has found that electrical energy and power changes in a certain spatial area are consequences of two factors:

1. Customer volumes change in the area. This can be modelled, for instance, as the number of customers or the floor area

2. Customers' electricity end-use change, which can be modelled, for instance, as characteristic loads per customer of the floor area.

Volume and consumption forecasts can be made after the present load analysis. Basically, these are traditional forecasts with new type of data. Volume and consumption forecasts consist of the present loads that include load profiles for different customer types, volume forecasts that cover existing customers and new customers, and electricity consumption forecasts. Spatial volume, consumption, and future energy technology forecasts can be combined with a simulation method, which produces results of the spatial LTLF.

Forecasts are made on an hourly basis, enabled by AMR data. The total power of the network can be obtained by summing the loads of all customers, or all customer groups at the same hour. Annual electrical energy forecasts can be calculated from hourly based results. Previously, annual electricity consumption was used as a basis for load forecasting, but now load forecasts are based on load profiles and hourly powers. This forecasting approach assumes that weekday variation does not produce a significant error into the forecasting results.

Volume and consumption forecasts have to be focused on a certain spatial area. This spatial volume and consumption forecasting may apply several data sources as the basic information of forecasting. Figure 5.8 illustrates the volume and consumption forecasting and different data sources. Both the DSO's internal and external data sources give good information for forecasting volumes and consumptions in the case area.

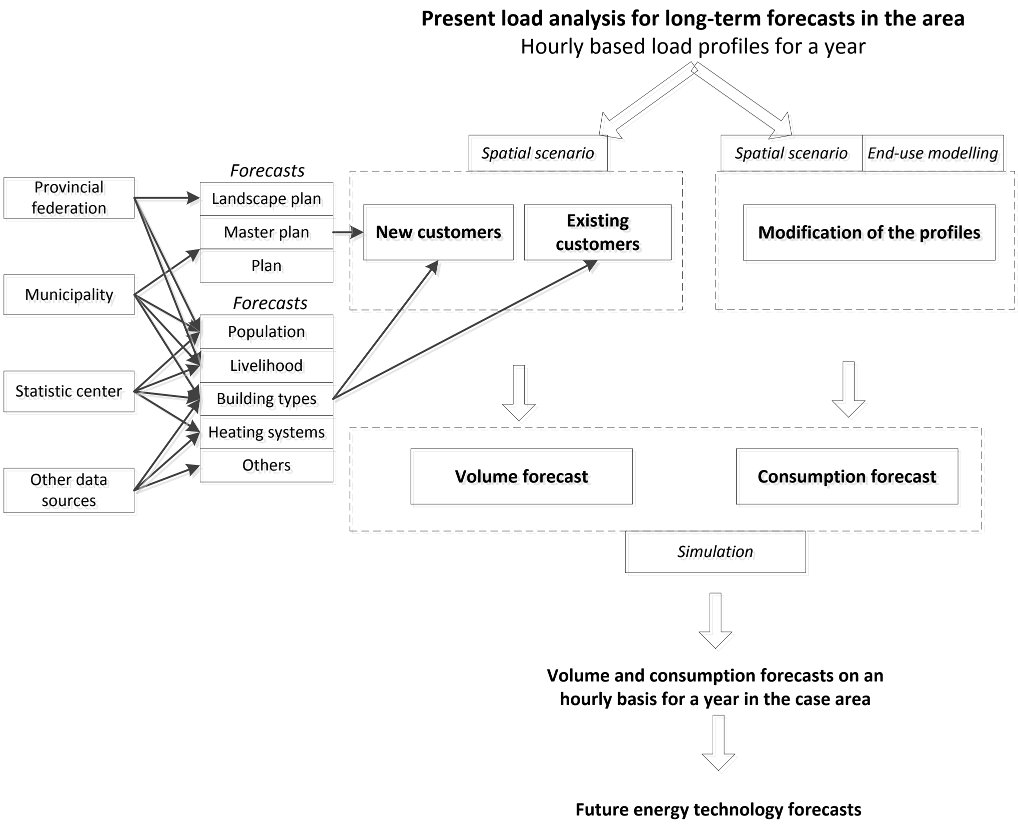

Figure 5.8. Forecasting of the volumes and consumptions.

The DSO's internal data provide historical information of the numbers of customers and consumptions. These can be analysed and used for making forecasts. The DSO's external data sources often produce parameters and forecasts such as population forecasts that can be applied to forecasting. In volume and consumption forecasts, end-use modelling and scenario approaches are used. Volume forecasts are scenario forecasts, where the number of customers is forecasted. Consumption forecasts are based on end-use models and scenario forecasts. It is possible to model how customers' electricity end-use will develop. For example, a load profile can be modified over a certain period to correspond to the development that has been forecasted. In the scenario approach it is forecasted how the consumption of a certain customer group will develop in the future. For instance, the development of the national economy may have impacts on the electricity consumption of industrial customers. Therefore, scenarios of the economic structure and means of livelihood can produce information for scenarios of electricity consumption.

The amount of data from different fields of society is increasing. Municipalities and other organizations are collecting increasing volumes of data. However, there may be major differences between the municipal data registers; some municipalities provide exact information of buildings while others do not give such detailed information. Municipalities may hold extensive data sources such as information of the number of customers, means of livelihood, and the number of workplaces and population characteristics.

National data, again, yield information of the national consumption and the general development of the average customers. Statistics Finland has gathered socioeconomic grid data that include annually updated variables for areas of 1 x 1 km and 250 m x 250 m. These data comprise information of the population structure, education, type of activity, and income (Statistics Finland, 2014). (Niska et al., 2013) has proposed a computational approach for spatiotemporal modelling that consists of fixed spatial grids, for example 250 m x 250 m. This approach could apply regularly updated public and geographic information. Other data sources may be for instance universities, the Energy Industry, Motiva (affiliated Government agency specialized in energy and material efficiency), and other interest groups. They can provide various statistics (e.g. on dwelling and electricity end-use), distribution network recommendations, and characteristic consumptions (Kaartio, 2010). These data can be used as such as forecasts, or they can be analysed and processed further in order to make scenarios based on them.

5.3.1 Volume forecasts

Basically, volume forecasts estimate the number of different kinds of customers in the case area. The number of future electricity end-users in the case area consists of two elements: the existing and new customer points. The number of different kinds of customers always depends on the DSO’s location. For instance, service sector customers typically use the largest proportion of electricity in urban areas, whereas the number of population may have a significant effect on the energy consumption in the countryside.

The forecasts of population, means of livelihood, building stock, dwellings, recreational homes, and heating systems can be applied in volume forecasts. There might be also other forecasts that can be used in forecasting. The main DSO’s external data sources are provincial and municipal registers, Statistics Finland, and other data sources. It is pointed out, however, that forecasts obtained from these sources may also have errors that have to be taken into account in load forecasts.

(Rimali, 2011) has also pointed out that the general development at the national level also has to be taken into consideration in the spatial forecasts. Electricity consumption is affected by regional socioeconomic factors like the number of population and workplaces, land-use planning, energy prices, and economic and political incentives. Social and structural changes have to be taken into account when making volume and consumption forecasts. Structural changes are mainly related to the development of population and means of livelihood, manifested for example by urbanization, ageing of population, and the economic structure.

Basically, different kinds of statistics and forecasts are municipality specific. Data have to be made comparable with the selected case area, because the statistics and forecasts may be made for areas that are different from the DSOs' network areas and the selected case area. Then, the forecasts have to be focused on the case area. For instance, if the DSO operates in a region of three municipalities, material from all three municipalities may be needed.

The DSO's customer information system yields information of the present customers in the case area. It is reasonable to forecast the number of customers by customer type. It is possible to draw up scenarios of the loss of customer points in the case area by using historical data. The number of customer points will remain unchanged unless demographic changes, that is, the decreasing population, reduce the number of buildings. The loss of buildings is typically low in urban areas, and new buildings are built in the same locations. Instead, structural changes in population take place in the countryside, and the loss of buildings can be considerably higher. However, there are typically no forecasts for the loss of buildings. If this loss is to be taken into account, it can be estimated by the construction year of the buildings. The DSO's external data registers have typically information of the construction year, and it thus is possible to use this information in the forecasts.

New customers

Load forecasting is especially important when planning new customer connection points to the case area. New customer points are forecasted separately from the existing buildings in the case area, because loads in new buildings can be significantly different in the future compared with the present consumption. For example, the total electricity demand in traditional houses is completely different from new zero or plus energy houses. Electricity consumption in different kinds of buildings should be considerably smaller in the future compared with present buildings. On the other hand, new houses have recently been built, which are significantly larger than older buildings. In new buildings, the building and heating types have to be considered, and the potential of future energy technologies have to be estimated.

Land-use planning levels in Finland are divided into provincial plans, master plans, and district plans. Provincial plans are the highest level in the planning, and they are produced by provincial and municipal federations (Salmi et al., 2006). A master plan, again, covers a municipality or a part of it, and identifies the main purpose of use of the area. Planning is typically made at a very general level, for example, a reservation for a dwelling may also include courtyards in a residential area. A town plan may include the whole residential area or only a single site. It defines strictly what is allowed to be built and where. A town plan includes information of the permitted building volume, the efficiency factor, the floor number, and the purpose of the area. Town planning is typically uncertain by nature, and an area can be planned right before construction, or the construction may not follow the plans (Kaartio, 2010). Further, road and street planning may have impacts on district planning, which may determine the location of the buildings. Figure 5.9 demonstrates different levels of land-use planning. Detailed information is obtained from master plans. This information can be used especially in forecasting the future loads of new customers.

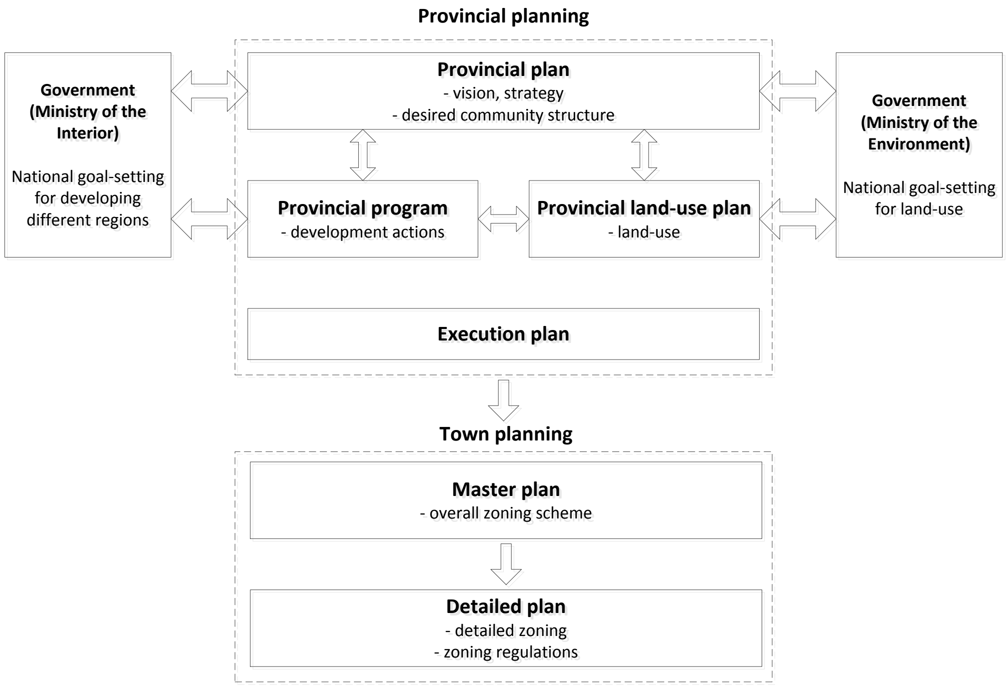

Figure 5.9. Planning levels based on the Finnish Land-Use Act (Rimali et al., 2011).

However, there are also land-use areas that have not been planned beforehand. Typically, these areas are in the countryside. A municipal authority grants the permission to build new buildings, and hence, information of these buildings can be obtained from municipal registers. The number of these buildings can be compared with the building forecasts, when more information of potential new buildings is gathered. Thus, the DSO should also have information of the construction year of the buildings.

Land-use planning is a two-way process, where the DSOs tell in which places electricity distribution networks are planned to be built, and the land-use planners tell in which areas new buildings and loads can be estimated to be found (Rimali, 2011). A practical example of the use of different land-use planning levels for load forecasting can be found in (Moilanen, 2011). The study has used land-use plans to forecast future electrical loads in northern Finland.

From the perspective of the LTLF, planning and construction of new buildings in different time periods provide useful information. Information of potential new buildings is obtained from different levels of planning. The plans also reveal what kinds of buildings are planned and when the buildings are expected to be completed. The building type and purpose of use (e.g. residential or service) also determine the customer and load types. If this information is known, load models can be constructed for the new customers by using the DSO's databases. This way, it is possible to define the loads for the new customers. Figure 5.10 presents an example master plan, which is based on real estates. The plan is a part of volume forecasts.

Figure 5.10. Example of real estate and town planning. Data can be transferred into the NIS, where they can be used for load forecasting (Hyvärinen et al., 2012).

However, new customer points are not necessarily located in buildings. There are also loads such as street lighting and pumping stations that do not necessarily include a building. New loads of this kind may be more challenging to be taken into account in load forecasting, if there are no long-term plans of such loads. The amount of such loads may increase in the future. For instance, there might be EV charging stations or PV generation that may have radical impacts on network loads because of high loads or significant production volumes in a small area.

5.3.2 Consumption forecasts

Consumption forecasts can be based on consumption scenarios and end-use models of loads. Long-term consumption of different customer groups can be analysed by studying consumption data several years backwards. For this purpose, it is useful to analyse only the customer points that have existed for the whole research period, the connection type of which has not changed, and the consumption data of which are available for the whole research period (Rimali, 2011). Historical consumption can be used to analyse why changes in consumption have taken place. These analyses and prevailing assumptions of the basic load development are the basis for consumption forecasts. Information of customers' electricity end-use will grow in the future. This opens up new opportunities to analyse and forecast loads.

Previously, consumption forecasts were based on annual energy consumption. Annual energy can be divided per floor area, per capita, or per room volume. In addition, specific demand have been expressed in kWh/m^2 or annual peak demand (in kW) or kW/m^2. These variables yield more information for consumption forecasts. AMR data provides an opportunity to use hourly based consumption forecasts, and load forecasts can be generated for each customer group. Thus, values per floor area or per capita can also focus on an hourly level. An analysis based on AMR data facilitates the monitoring of changes in consumption. Significant changes may occur in consumption during a month, for instance, because of the trade cycle. Load analyses suitable for monitoring purposes are spatial and typically based on customer types, connection points, or customer points (Hyvärinen et al., 2012).

It is possible to make consumption forecasts in which a customer's hourly load profiles are modified for LTLF purposes. AMR data make it possible to use end-use modelling in consumption forecasts. For instance, the present load analysis of the loads can produce information of the seasonal dependence of the loads in the case area. For instance, an industrial customer's 2 % load growth over the next five years can be taken into account by allocating the growth evenly to each hour of the year. In addition to end-use modelling, there have to be scenarios on how these loads will develop in the future.

Load forecasts of the new customers can be based on known load profiles of the same type of customers. It is advisable to use the construction year and customer type of the present buildings as a basis for the load modelling. The loads of the new buildings could be applied to the load profiles for buildings to be constructed. For this purpose, information of land-use plans, including floor area and the number of flats, and heating systems should be retrieved from the plans. There are different techniques to estimate the loads. For example, if land-use plans define the lot area and the floor area ratio, the floor area (m^2) can be calculated by multiplying these values. In addition, if the consumption demand per floor area (peak kW/m^2 or kWh/m^2, a) is known, the required energy and power can be calculated and forecasted for a new customer.

Future energy technologies have to be taken into account when planning a new customer point to the network. If new buildings or customers apply some future energy technologies, these should be taken into account in the load estimation of the building. There are two options to model these kinds of loads. Similar kinds of loads could be found from the DSO's database, and the load profile can be scaled for the new customer. Another option is to model the future technologies as a part of the total end-use.

Typically, outdoor-temperature-normalized electricity consumption may vary between years, if there are no significant changes in the electricity end-use. In a larger spatial analysis, this fluctuation typically disappears. On the other hand, the economic trends in society may have impacts on service and industrial customers' consumption. For service and industrial customers, such dependences can be taken into account by different kinds of regression models (Hämäläinen, 2014).

5.3.3 Summary of the volume and consumption forecasts

To sum up, the forecasting process comprises present load analysis, volume, and consumption forecasts, and forecasts of future energy technologies. Basically, the present load analysis as well as volume and consumption forecasts vary because of the increasing amount of accurate data from the DSO's internal and external data sources. The major change in the forecasting process is taking place because of the AMR data, which enables comprehensive analyses for forecasting purposes. Further, advancements in computer technology enable large-scale and precise present load analyses and forecasting.

For the forecasting process it is necessary that the DSO's internal databases, viz. CIS, NIS, and the metering database are updated and operate efficiently. Furthermore, the connection to external data sources such as municipal and real estate registers should work reliably. However, data collection and combination require more effort from the DSOs, which have to modify and link the authority databases with each other. Volume and consumption forecasts use other forecasts as background information that has to be taken into consideration.

The master and town planning play an important role when predicting new customers in the network area. Especially, the role of land-use planning is essential in urban areas. Data provided by these planning processes make forecasting of the new customers more reliable. However, there may be differences in the availability of information about municipal areas. This has to be taken into account in different areas.

5.4 Future energy technologies in the forecasting process

Basically, forecasting of the future energy technologies and their effects on load behaviour and network loads is an essential part of the LTLF. For instance, energy storages can decrease peak powers while electric vehicles can increase peak powers. Consequently, the totally new types of loads call for new types of modelling and forecasting.

(Willis, 1996) has presented an integrated resource planning (IRP) process that includes the assessment of alternative resources that could substitute, reduce, or shift the need for power system additions. Alternative resources are often referred to as distributed energy resources (DER), and in distribution systems, the related planning process is sometimes called distributed resource planning. The objective of the technique is to combine or integrate these resources with the distribution system.

Future energy technologies such as energy efficiency technologies, electric vehicles, energy storages, demand response, and microgeneration can take place on various time scales. Each technology has to be forecasted for a customer group individually. The purpose of use, timescale, locations, and the number of technologies are needed for the forecasts. There have to be scenarios of the numbers and capacities of the energy technologies in different time periods. These characteristics require a scenario-based approach. (Willis, 2002) has suggested that with scenario modelling it is useful to make a "what if" analysis and study the impacts of different features separately. In practice, this means that a scenario of its own is made for each possible alternative, which is modelled separately. This helps to analyse what kinds of effects certain scenario alternatives may have.

Basically, there are two different methods to apply end-use modelling: either completely new load profiles are used or the existing profiles are modified. New technologies like EVs have new types of load profiles that require new load profiles. On the other hand, some future technologies such as demand response may change the existing load patterns, and this requires reformulation of the existing load patterns. (Rimali et al., 2011) has also stated that new loads and production have to be modelled with new load patterns. Therefore, end-use modelling is the most suitable method to forecast effects of this kind. (Kaartio, 2010) and (Rimali, 2011) have suggested that changes in customers' heating systems or improvement in energy efficiency can be modelled by adjusting the customer's electricity end-use profile according to the change. Furthermore, (Rimali, 2011) has suggested that yet another method can be to add hourly load series to the present consumption as a response to the change. These hourly series can also include negative values because of energy efficiency, which may decrease electrical loads (Rimali, 2011). End-use profiles require a lot of measurements so that exact load curves for the new technologies can be modelled. In forecasting it is necessary to apply a method capable of using different sizes of end-use models, and the user has to be able to modify the curves if required.

End-use modelling and spatial scenarios are the most advisable methods to model and forecast the effects of the future energy technologies in a certain area. As a whole, the LTLF of the future energy technologies is based on spatial analysis, end-use modelling, and scenario and simulation techniques. Figure 5.11 shows the most relevant energy technologies and the most important factors for forecasting the effects of these technologies. Consumption forecasts and future energy technology forecasts have to be made simultaneously, because both forecasts are based on load profiles, and they have effects on each other.

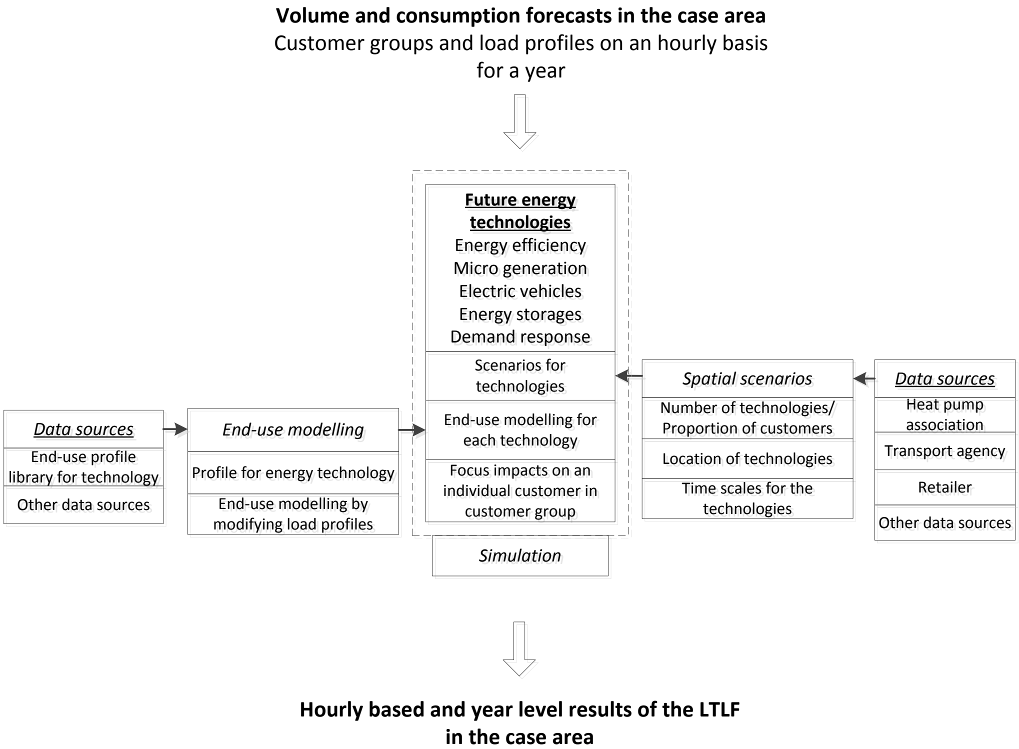

Figure 5.11. Future energy technologies in the forecasting process.

Future energy technologies have to be modelled for an individual customer. This requires that the customer's load profile and customer information are known. End-use modelling can be made by using profiles for technologies or modifying the customer end-use profiles. Profiles for technologies can be based on average measured load profiles or modelled profiles, or theoretical load profiles. This approach needs many parameters related to the end-use and technologies. The capacity of the technology has a great impact on the end-use loads. Distribution of the technology capacities has to be taken into account in forecasting. This means that technologies have to be scaled to correspond to the suitable size of the forecasted capacity. For instance, if a PV system profile is for 2.5 kW, this profile has to be scaled when using other capacities. In addition, profiles that are outdoor temperature dependent such as heat pumps have to be normalized to the same long-term outdoor temperatures as the base loads. Spatial scenarios define the effects on the network loads. Scenarios have to define the number of technologies in the case area on different time scales. Scenarios of the owners or locations and timescales of the technologies in the network area are also needed.

Forecasting of the future technologies also require a lot of data from the DSO's internal and external data sources. The amount of data is increasing, and all possible sources are not necessarily even known yet. Considering the DSO's internal data sources, the customer information system may provide the most essential data. External data can be obtained from the heat pump association, electricity retailers, transport safety agency, and other data sources. These data sources can produce scenarios on how technologies may evolve in the future. Next, it is considered how future technologies can be modelled in general at the customer level. By applying customer-level end-use models, it is possible to forecast the effects on distribution network loads by applying scenarios.

5.4.1 Energy efficiency

Energy efficiency may consist of several actions and technical solutions, but improved insulation of buildings, heating systems, and lighting may have the greatest potential in energy saving. Therefore, these are modelled for the long-term load forecasting purpose. If there were data available of the electricity end-use of the other device groups, it would be possible to forecast these loads. The insulation improvement of buildings with electric space heating can be forecasted when the proportion of electric heating is known. In the customer classification phase it was shown how the outdoor temperature dependence can be calculated. Figure 5.12 illustrates the proportion of direct electric heating of the total end-use for an individual customer for one day in wintertime. The calculation is based on mathematical modelling, not on measured heating loads. Other approach is to use metered data or estimate the heating demand of a building by applying information of the building area and the characteristic heating demand per floor area.

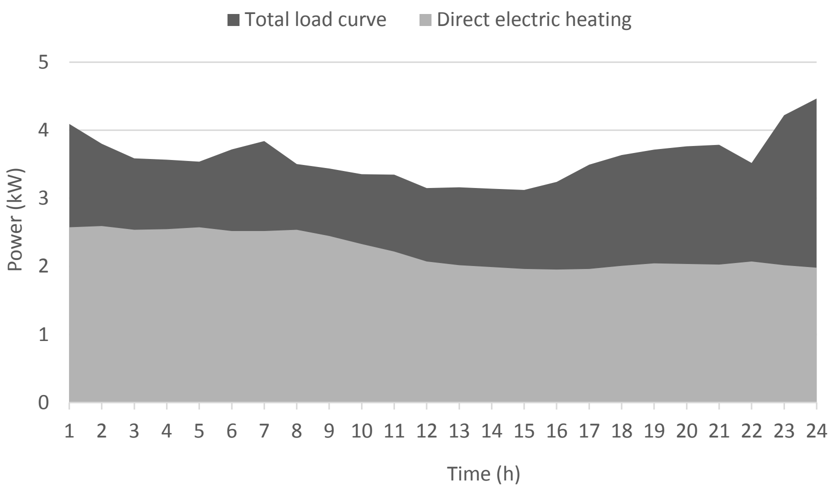

Figure 5.12. Calculated proportion of the direct electric heating load of the total customer load.

The effects of energy efficiency upgrade by enhanced insulation on electrical loads can be calculated if the proportion of the electric heating load is known. The decrease in electric heating demand is estimated by parametrization. An improvement in building insulation decreases electric heating demand, and it is assumed that it has a direct impact on a customer’s electricity end-use. The end-use profile for a certain hour after the energy efficiency action can be modelled as

$$P_{riI} = P_{ri} - P_{rieh} \cdot (1 - \eta_{rI}) \tag{5.2}$$

where

P_{riI}	hourly power for a customer group *r* at time *i* after insulation improvement *I*
P_{ri}	original hourly power for a customer group *r* at time *i*
P_{rieh}	hourly power for outdoor-temperature-dependent proportion of electric heating for a customer group *r* at time *i*
η_{rI}	efficiency factor between the new and old insulation systems for a customer group *r* at time *i*.

The annual electrical energy end-use W_{rI} for a certain customer group, after improvements in insulation, can be calculated by using hourly power information:

$$W_{rI} = \sum_{i=1}^{n} P_{riI} \tag{5.3}$$

where *n* is the number of hours in a year. The above equations can be applied to forecast the effects of energy efficiency improvements obtained by building insulation on electricity end-use. For the efficiency factor, parametric values that are less than one can be used, and η_I can be approximated to be 50–90 %. Examples of these values are presented in Table 3.3. Insulation of buildings has been assumed to have an influence on electric space heating buildings only. However, it is assumed that insulation improvements do not have an impact on cooling in these analyses.

The electricity end-use may also decrease because of the energy efficiency improvements in heating systems. From the perspective of electrical loads, the major change in heating systems will take place if heat pumps are installed. There are already a lot of heat pumps in buildings, but there is no information on what kinds of heat pumps have been installed and in which kinds of buildings. Scenarios of the number of heat pumps in different types of buildings can be based on the number of heat pumps found in national statistics that are focused on the case area.

The most popular heat pump types are air and ground source heat pumps. A trend seems to be that ground source heat pumps are installed as the main heating system into buildings with oil and electric space heating (Hellman, 2013). Air source heat pumps are typically installed as supplementary heating systems. These heat pump types can also be used for cooling in summertime. Heat pumps typically increase the electricity end-use in non-electric-heated buildings and decrease the end-use in electric-heated buildings. The LTLF of heat pumps can be made by using end-use models for heat pumps. Figure 5.13 shows a measured heat pump load curve for one day in April. In (Laitinen et al., 2011), a load profile has been developed for a ground source heat pump. One method to generate a load profile is to use AMR measurements and separate heat pump customers by applying mathematical methods as in (Hellman, 2013). The application of measured heat pump profiles may be considered the most efficient method for the LTLF.

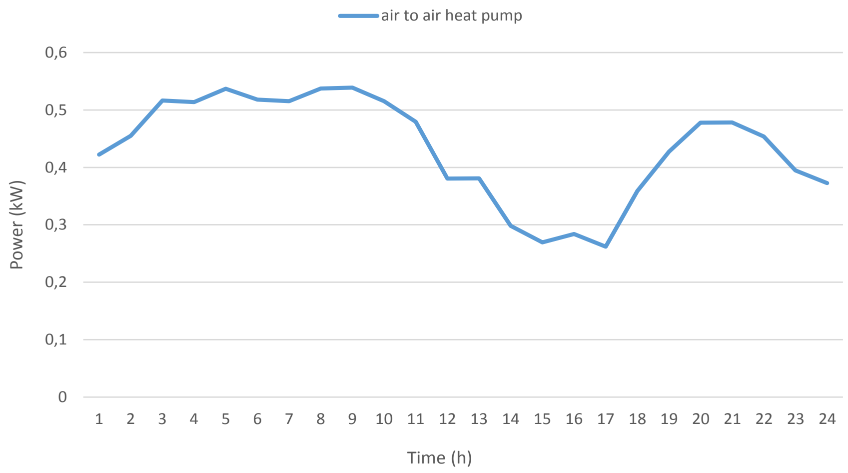

Figure 5.13. Air source heat pump, maximum heat production 6 kW, load profile.

The operating efficiency of an air source heat pump depends on the outdoor temperature. The operating efficiency of a ground source heat pump instead is not dependent on the outdoor temperature. However, the heating demand of heat pumps depends on the outdoor temperature. Heating demand can be based on measurements. If measurements are not available, and the heating demand of a customer is not known, the heating demand can be calculated based on the construction year of the building, floor area of the building, and the characteristic heating demand per floor area (Motiva, 2015) and (Statistics Finland, 2014c). Other options could be to use average heating demands or measured heating demands for different kinds of buildings. In any case, the amount of heating demand is needed for forecasting. Because of the variation in outdoor temperatures, the heat pump load profiles have to be normalized to the target outdoor temperatures. Thus, the base load of the customer, heating demand, and heat pump load are normalized to the same outdoor temperature.

End-use profiles are dependent on the heat pump type. A typical characteristic of ground source heat pumps is that they are not dimensioned to fully cover the heating demand. The reason for this is that the acquisition costs increase if the heat pump is dimensioned to completely cover the heating demand. Then, heating can be carried out, for instance, with electric resistances during the coldest weather. Further, a ground source heat pump can also heat service water. On the contrary, an air source heat pump is typically an additional heating system, and it can cover only a part of the total heating demand. In any case, the modelling requires that the heat pumps have to be scaled according to the heating demand.

The efficiency of a heat pump system is measured by the coefficient of performance (COP) or the seasonal performance factor (SPF). The COP determines a relation of heating provided to the electricity consumed by the heat pump. The COP varies in different circumstances. The SPF, again, is an average COP over a year. The interaction of insulation and heat pumps is taken into consideration by calculating the effects of insulation on the heating demand before forecasting the impacts of heat pumps.

The modelling also depends on which kind of a heating system the heat pump will replace and in which kind of a building. The effects of heat pumps on loads can be modelled by adjusting the proportion of heating demand by the COP or by using heat pump end-use profiles. This can be made as follows. It can be assumed that the electric heating demand decreases when a heat pump is installed into a house with direct electric heating. An electrical power load curve after the heat pump has been installed into a building with direct electrical heating can be modelled as

$$P_{riHP} = P_{ri} - P_{rieh} \cdot (1 - \frac{1}{COP}) \tag{5.4}$$

where

P_{riHP}	hourly power for a customer group *r* at time *i* after heat pump installation *HP*
P_{ri}	original hourly power for a customer group *r* at time *i*
P_{rieh}	hourly power for the outdoor-temperature-dependent proportion of electric heating for a customer group *r* at time *i*
COP	coefficient of performance (efficiency factor) of the heat pump for a customer group *r* at time *i*.

With a measured heat pump profile, the impacts of a ground source heat pump on the total load of the direct electric heating customer can be modelled by

$$P_{riHP} = P_{ri} - (P_{rieh} - HP_i) \tag{5.5}$$

where HP_i is the heat pump profile at time *i*. If a heat pump is installed into a building with non-electric heating, it increases the electricity end-use. If an air source heat pump is installed as a supplementary heating system, the rest of the heating demand will be produced with the main heating system. Thus, the load profile of the target outdoor-temperature-normalized air source heat pump load profile can be added to the present load. If a ground source heat pump is installed into a building with non-electric heating, the heating demand has to be defined, and the heat pump load profile has to be scaled to the heating demand; then, it can be added to the basic electrical load. Thus, the heat pump effects on electrical power in buildings with non-electrical heating can be modelled as

$$P_{riHP} = P_{ri} + HP_i \tag{5.6}$$

where HP_i is the temperature-corrected heat pump profile. If electric storage heating is replaced with a ground source heat pump, Equation 5.5 can be applied for the electric heating time at night and Equation 5.6 for the time when the electric storage heating is not used. In addition, heat pumps can be used for cooling. The cooling demand of a building has to be determined, and it defines the cooling capacity. This also requires that the cooling characteristic are included in the heat pump profile. Cooling with a heat pump can also be modelled by Equation 5.6.

The annual electrical energy end-use W_{rHP} for a certain customer in a customer group after heat pump installation can be written as

$$W_{rHP} = \sum_{i=1}^{n} P_{riHP} \tag{5.7}$$

where n is the number of hours in a year. The third energy efficiency action to be modelled is energy efficient lighting. The proportion of indoor lighting load should be separated from the other loads. A customer load after energy efficient lighting has been installed can be modelled as

$$P_{riL} = P_{ri} - P_{ril} \cdot (1 - \eta_L) \tag{5.8}$$

where

P_{riL}	hourly power for a customer group r at time i after energy efficiency in lighting L
P_{ri}	original hourly power for a customer group r at time i
P_{ril}	hourly power for an indoor-lighting-dependent proportion for a customer group r at time i
η_L	efficiency factor between the new and old lighting systems.

The effect of energy efficient lighting on the annual electrical energy for a certain customer group W_{rL} can be calculated by using hourly power information

$$W_{rL} = \sum_{i=1}^{n} P_{riL} \tag{5.9}$$

where n is the number of hours in a year. The efficiency of lighting can be estimated by parametrization of the lighting efficiency.

End-use modelling of energy efficiency may be difficult to comprehend in practice. Next, an example of the effects of end-use modelling is presented. The end-use is modelled for the whole year on an hourly basis. The modelling is carried out for an individual customer. Figure 5.14 demonstrates the effects of the energy efficiency improvement by insulation. The simulation assumes that if the outdoor temperature is below +10°C, electric space heating is needed. By applying this method it is possible to calculate the electric heating demand. The figure demonstrates a load profile of a detached house with direct electric heating. Electric heating demand is modelled to decrease by 30 %. In practice, the impacts of insulation improvements can be seen over the heating period from autumn to spring. The electricity demand decreases in the heating period, which makes the load profile more even. The electric heating load was separated from the customer's total load on a day level in figure 5.12, from which can be estimated the simulation effect on a day level.

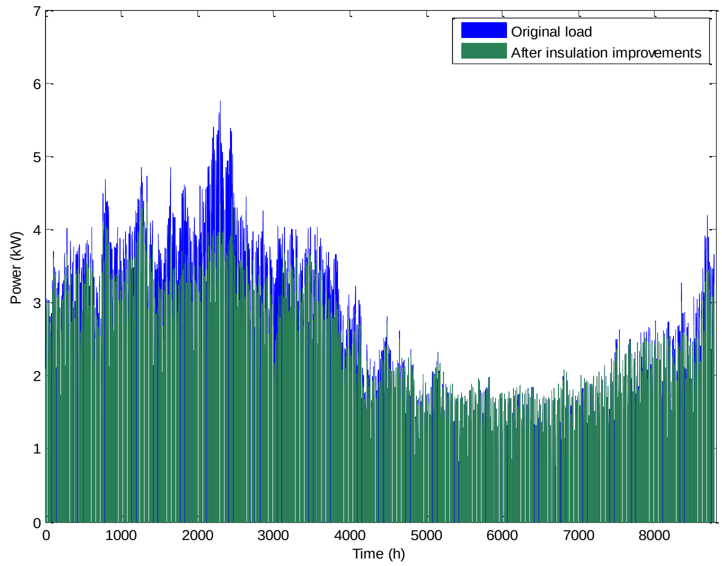

Figure 5.14. Modelling of the effects of energy efficient heating in a detached house with direct electric heating.

The effects of the energy efficiency actions on the electricity end-use were that the highest mean hourly power decreased by about 1 kW, and the annual electrical energy usage decreased by about 2 MWh.

5.4.2 Microgeneration

Photovoltaics will probably be the most popular method of microgeneration. Therefore, end-use profiles for PVs are presented. There may be other microgeneration technologies such as wind power and μCHP, which could be forecasted by the same method as PVs; only other end-use profiles instead a PV profile would be required. Forecasting the capacity of the PV systems is important. The capacity has to be estimated for each case individually. The capacity of the system has a major impact on the end-use profile. The area of the roof can determine the capacity of the PV system. For example, in a block of flats, the PV system capacity can be estimated based on the floor area. Thus, especially in the LTLF, the effects of the PV system have to be focused on the real estate. Figure 5.15 presents the end-use profile for the PV generation of 5 kWp.

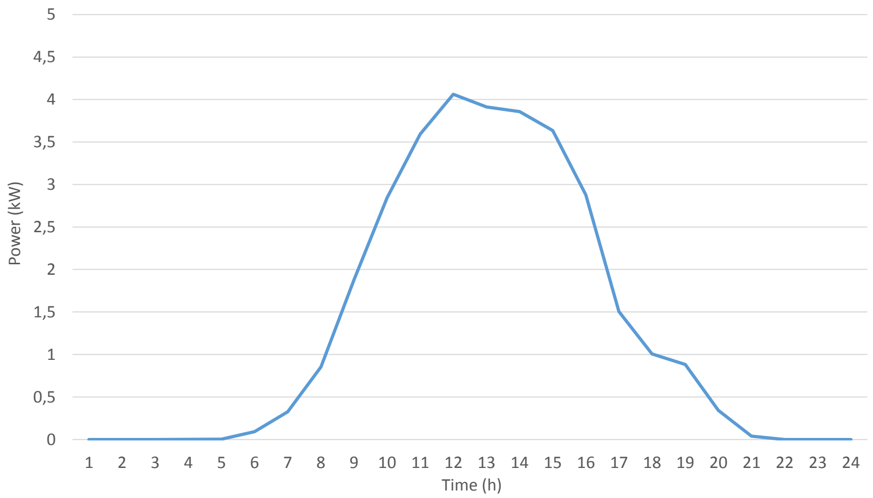

Figure 5.15. Measured profile for a 5 kW PV system, the time label starts at 00.00 a.m.

The installation angle of the systems will also have an impact on the distribution of the optimal PV production. The end-use profile for a certain hour, after a microgeneration system has been installed, can be modelled as

$$P_{riMG} = P_{ri} - P_{rimg} \tag{5.10}$$

where

P_{riMG}	hourly power for a customer group/property r at time i, after microgeneration installation MG
P_{ri}	original hourly power for a customer group/property r at time i
P_{rimg}	hourly power production profile of microgeneration for a customer group/property r at time i.

The annual electrical energy after application of microgeneration for a certain customer group W_{rMG} can be calculated by using the hourly power information

$$W_{rMG} = \sum_{i=1}^{n} P_{riMG} \tag{5.11}$$

where n is the number of hours in a year. The impacts on electrical energy may vary between different years because of varying solar radiation. This can be taken into account by using long-term average solar radiation values for PV production in the case area. Microgeneration may have significant impacts on energy consumption and powers. If the consumption is low and the solar production is high in summertime, the power can be supplied to the network, and thus, the direction of power flow can change.

5.4.3 Electric vehicles

Electric vehicles will increase the electricity end-use. The impacts on network loads depend on the charging type and how charging is carried out. The end-use model can be an average model that can be modified suitable for forecasting. In Figure 5.16, an average EV charging load profile is modelled for 1-phase non-optimized charging.

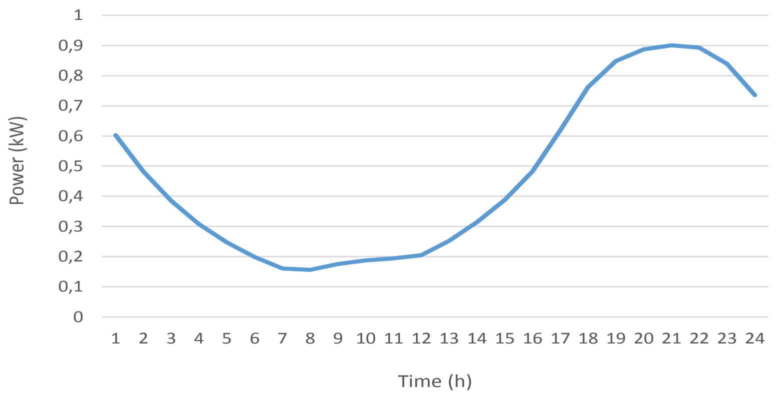

Figure 5.16. Example of an end-use profile for basic EV charging (Tikka et al., 2011).

The electricity usage of EVs depends on the consumption per vehicle, the usage behaviour of EVs, and the driving distances. Power modelling of electric vehicles depends on many issues such as the location of charging, the time when the cars will be charged, the mode of charging (fast, basic, slow), and the method of charging. This information should be used to forecast electrical load changes in the case area. If there is a load profile for the end-use of EV charging, the power load of an EV is written as

$$P_{riEV} = P_{ri} + P_{riev} \qquad (5.12)$$

where

P_{riEV}	hourly power for a customer group *r* at time *i* when the electric vehicle *EV* is charging
P_{ri}	original hourly power for a customer group *r* at time *i*
P_{riev}	hourly power load profile for an electric vehicle *EV* for a customer group *r* at time *i*.

The effect of EVs on the annual electrical energy for the customer group W_{rEV} can be calculated by using the hourly power information

$$W_{rEV} = \sum_{i=1}^{n} P_{riEV} \qquad (5.13)$$

where *n* is the number of hours in a year. Electric vehicles will have significant impacts on electrical loads. The total energy consumption and peak powers are affected by the number of EVs in one customer point, charging characteristics, the capacity of batteries, and location. The power demand of charging in the case area depends on the charging characteristics, the number of EVs, and the charging locations. The end-use profile has to be scaled and modified to correspond to the demands of the EV charging in the case area.

The charging of EVs can be optimized from several perspectives. Charging can be carried out by dump or smart charging. Dump charging refers to charging without any external charging signals. Basically, a customer charges the EV whenever it is possible. Smart charging can be based on optimized charging according to the network loads or the price of electricity markets such as SPOT prices. Optimization based on network loads does not necessarily increase the network peak loads. The SPOT-price-based charging is based on optimizing the electricity prices of the customer. This may increase the peak loads. Moreover, if a customer has microgeneration, it can be used for the EV charging. Thus, the impacts on the end-use profile will decrease.

Figure 5.17 shows the effects of EV charging on network loads. Charging of the EVs is started by basic charging when the EVs are at home. In optimized charging, the EVs are charged at night-time. Loads will grow in the basic charging, and in the optimized charging the loads will remain at the same level as original loads, although the amount of charged energy is the same in both charging cases. Together with AMR data it is possible to model, for example, the impacts of EVs on the customers' load profile and the total load profile of these customers. The total hourly based consumption can be obtained at the customer level, but end-use modelling would also require information at the appliance level. At the moment, this should be estimated from the consumption curves.

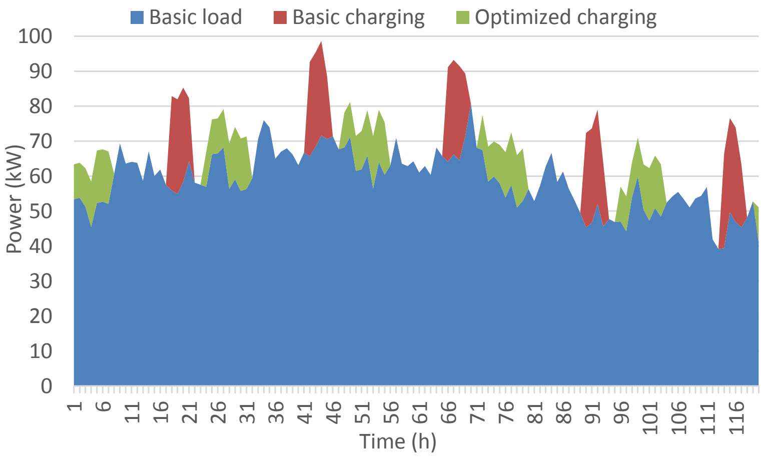

Figure 5.17. Electricity consumption of residential customers and the effects of EVs with basic charging and optimized charging.

In addition to charging of the EVs, batteries can be used as electricity storages. In this case, the battery will decrease a customer's end-use profile. Consequently, the loads in the distribution network will also decrease, as shown in (Lassila et al., 2012).

5.4.4 Energy storages

There are many ways to use batteries. The main purpose of energy storages is probably peak load shaving and storing energy produced by microgeneration. Figure 5.18 illustrates the effect of peak cutting on loads at a customer level. The loads are cut with the energy storage between 20:00 and 22:00 hours, and the energy storage is charged between 22:00 and 24:00 hours.

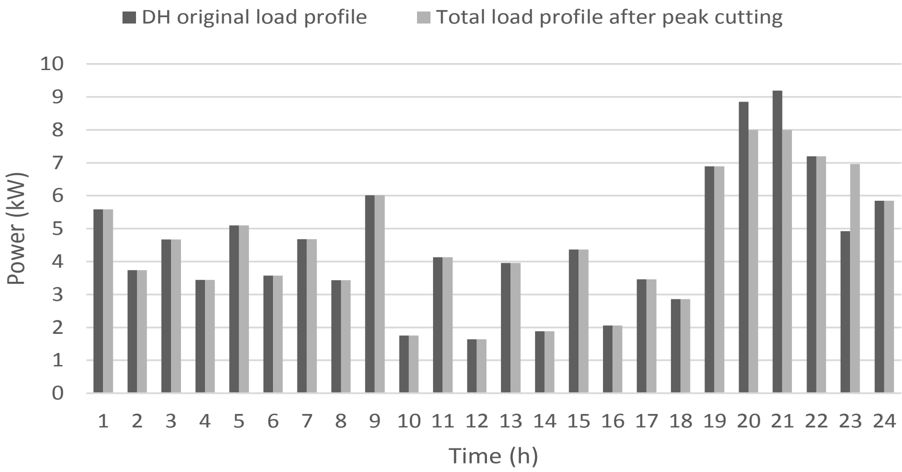

Figure 5.18. Peak cutting of customer loads with an energy storage.

The most challenging task in the energy storage modelling is to optimize a suitable energy storage for each customer. Dimensioning of the energy storage can be based on different factors such as the price of the energy storage or an option to store energy produced by microgeneration.

A method for peak cutting is required; one option is to define a limit on the allowed load. The effects of the energy storages on peak power cutting, when $P_{ri} > P_{risv}$, can be modelled as

$$P_{riESpc} = P_{risv} \tag{5.14}$$

where

P_{riESpc}	hourly power for a customer group *r* at time *i* after the energy storage is used for peak cutting *ESpc*
P_{risv}	set value for peak hourly power cutting for a customer group *r* at time *i*.

Then, the hourly power discharged from the storage has to be taken into account. It is assumed that the energy storage has enough capacity to discharge. The hourly power is now written as

$$P_{riES} = P_{ri} - P_{risv}, \tag{5.15}$$

where P_{riES} is the hourly power taken from the energy storage, and P_{ri} is the original hourly power for a customer group r at time i. Charging of the energy storage can be started when $P_{ri} < P_{risv}$, which can be modelled as an end-use load

$$P_{riESpc} = P_{ri} + \frac{P_{riES}}{\eta} \tag{5.16}$$

P_{riES} is the hourly power taken from the energy storage, and η is the efficiency of the energy storage system. In addition, a condition $P_{ri} \leq P_{risv}$ has to be valid during charging. The efficiency of a battery storage system can vary significantly. The effect of peak cutting with an energy storage on the annual electrical energy for a certain customer group W_{rESpc} can be calculated by using the hourly power information

$$W_{rESpc} = \sum_{i=1}^{n} P_{riESpc} \tag{5.17}$$

where n is the number of hours in a year. However, changes in electrical energy are minor. The application of an energy storage in relation to energy production by microgeneration is a different task compared with peak cutting. Surplus energy produced by microgeneration could be stored in an energy storage. Figure 5.19 illustrates the load profile of a detached house profile and the energy produced by a PV system of 5 kW. The orange curve indicates how much storage capacity would be needed to store the surplus electrical energy produced by microgeneration. The capacity of the energy storage should be a couple of dozens of kWh in order to be able to store all the renewable energy produced during a day.

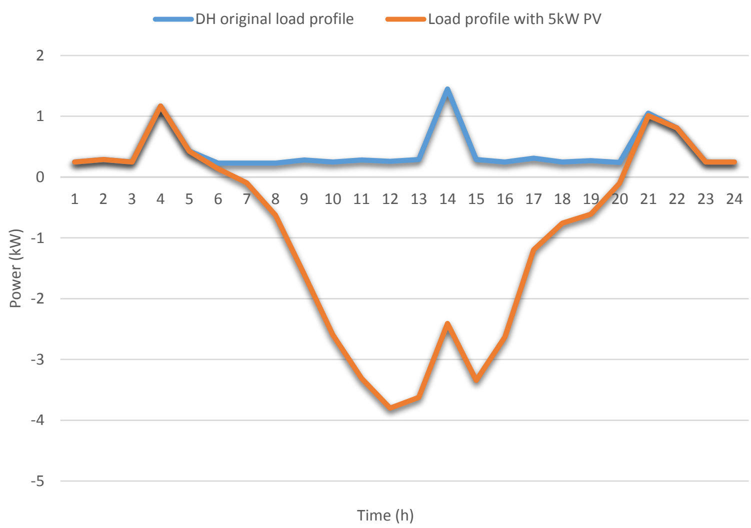

Figure 5.19. Total load profile of a detached house customer with microgeneration. The amount of energy supplied to the network is indicated by orange.

There are several methods to store surplus energy produced by microgeneration. The most favourable method from the distribution network perspective would be that production would not produce negative peak loads to the network. Thus, a similar peak shaving approach is adopted as in peak cutting. Basically, when surplus electricity supplied to the network exceeds the set value, the energy storage is charged. The total load after microgeneration installation P_{riMG} is represented in Equation 5.10. This equation is valid when microgeneration is available. The effects of the energy storage with microgeneration on the electricity end-use, when $P_{riMG} < P_{risv}$, can be modelled as

$$P_{riMGES} = P_{risv} \tag{5.18}$$

where

P_{riMGES}	hourly power for a customer group r at time i after the microgeneration installation MG with the energy storage.
P_{risv}	set value for negative peak hourly power of a surplus electricity for a customer group r at time i.

Then, the exceeding hourly power of the set value is charged into the energy storage. It is assumed that the energy storage has enough capacity to charge. The hourly power is now written as

$$P_{riES} = P_{riMG} - P_{risv} \tag{5.19}$$

where P_{riES} is the hourly power charged into the energy storage. Discharging of the energy storage can be started when $P_{riMGES} > 0$, which can be modelled as an end-use load

$$P_{riMGES} = P_{riMG} - P_{riES} \cdot \eta \tag{5.20}$$

where P_{riES} is the hourly power discharged from the energy storage, and η is the efficiency of the energy storage system. In addition, a condition $P_{riMGES} \geq 0$ has to be valid during discharging.

The effect of microgeneration and energy storage combined on the annual electrical energy for a certain customer group W_{rMGES} can be calculated by using hourly power information

$$W_{rMGES} = \sum_{i=1}^{n} P_{riMGES} \tag{5.21}$$

where n is the number of hours in a year. Energy storages may have significant impacts on electrical loads. On the other hand, the effects on electrical energy consumption are minor. If microgeneration is stored for own use, the amount of annual energy from the network will change significantly. All in all, the application of energy storages is quite complicated, because the energy storages should be optimized for each customer with a suitable method. In addition, there are not many practical applications available at the moment to use energy storages as a part of a customer's electricity system. However, energy storages may be introduced in a larger scale in the future. The number, size, and purpose of use of energy storages have the greatest impacts on the electricity end-use.

5.4.5 Demand response

Load modelling of demand response can be performed in different ways. It seems that in general, demand response is managed by some other party than the DSO. Thus, the distribution network should offer a marketplace for demand response. From the retailer's perspective, demand response may have different kinds of impacts on loads. The DSO should have information of customers, location, and time when loads will be controlled, and what kinds of loads are controlled (Järventausta et al., 2015). Typically, these loads may participate in hourly electricity markets, and they are controlled at an hourly level. These markets are normally SPOT, ELBAS, balancing, imbalancing, and reserve markets.

There are two kinds of loads; some loads like lighting do not produce a payback effect, while other loads such as direct electric heating have a payback effect. Therefore, two different methods have to be used to forecast the effects of demand response in load forecasting. For the payback effect, the load type has to be known. The most common load that has a payback effect is probably direct electric heating.

Modelling of the payback effect assumes that the off-controlled energy will take place in the next hour/hours. There can be different variations of which part of the loads can be controlled. The greatest effects come from controlling the total load potential. Basically, the assumption is that all heating loads are controlled off. It is also possible to partly control the loads and different time periods. The effect of demand response on the end-use load, when controlling loads off, can be modelled as

$$P_{riDRoff} = P_{ri} - P_{riDRpro}, \tag{5.22}$$

and when the payback effect appears in the following hour/hours, it can be modelled as

$$P_{riDRon} = P_{ri} + P_{riDRpro} \tag{5.23}$$

where

$P_{riDRoff}$	hourly power for a customer group *r* at time *i* after controlling loads off *DRoff*
P_{ri}	original hourly power for a customer group *r* at time *i*
$P_{riDRpro}$	proportion of the controlling hourly power load *DRpro,* for a customer group *r* at time *i*
P_{riDRon}	hourly power for a customer group *r* at time *i* after controlling loads on *DRon.*

The number of load control times and the duration of the load controls play a major role in the effects on the load changes. However, changes in the electrical energy are minor in this approach. Therefore, the effects on the electrical energy are not modelled.

5.4.6 Summary of forecasting the future energy technologies

The LTLF of the future energy technologies is based on electricity end-use modelling and spatial scenarios, which are combined with simulations. The consideration of different future energy technologies, heat pumps, electric vehicles, and microgeneration require end-use profiles. Different scenarios such as a fast case scenario and basic scenario are needed to analyse the effects of various combinations of loads in distribution networks. Forecasts are typically based on national trends, which are concentrated on scenarios for the case area. The timescales and the predictability of the technologies pose challenges: energy efficiency seems to be a continuing trend, and changes are constantly taking place, whereas microgeneration, energy storages, and EVs will take place in different time periods. Therefore, there will be a need for different kinds of scenarios to approximate the number of devices in different time periods. For example, there are the following methods for this task:

- All customers of a certain customer group will apply a certain energy technology progressively over the next decades
- Various proportions of the customer groups will have a certain energy technology and capacity in a certain timescale
- Limit values are defined for the effects of the technologies, and the impacts on different customers are focused on

Other scenarios can also be generated that are combinations of previous scenarios. The most suitable scenarios have to be chosen case specifically, and scenarios have to be focused on the case area. Some national scenarios have been presented in Section 3.3. A lot of parameters have to be chosen to forecast the future energy technologies. The numerical values of various parameters can be defined in different ways. Therefore, different kinds of approximations and approaches are needed. The parameters play a highly important role in the forecasting system.

The increasing amount of data and diverse electrical end-uses make forecasting more tedious compared with previous approaches. There is a need for a common register of different data sources that the long-term load forecasting could utilize; the register would make data acquisition easier. (Hyvärinen et al., 2012) has also suggested to draw up a master material for forecasting purposes, which would provide a basis for making forecasts. This master material could update real estate information and possible changes in master plans automatically to the forecasting material database (Hyvärinen et al., 2012).

5.5 Conclusions

Electricity distribution is changing from the traditional environment to the future environment, as presented above. This will lead to a situation where the previous load forecasting methods do not work anymore and a new LTLF process have to be developed. On the other hand, a need for different kinds of forecasts has also increased. A new forecasting process can give information about how electrical loads will develop spatially. As a result of the new forecasting process, spatial power forecasts can be obtained for the case area, and energy forecasts can be obtained by summing the power results in the area. Annual energy forecasts are the most relevant ones for the case area. This requires that the load forecasts are based on an hourly, year-level (8760 h) analysis. Figure 5.20 presents the new forecasting process, which is based on measured hourly powers. AMR data are used to model the present and new customers, to model the loads of separate customer groups, and to forecast the effects of future energy technologies.

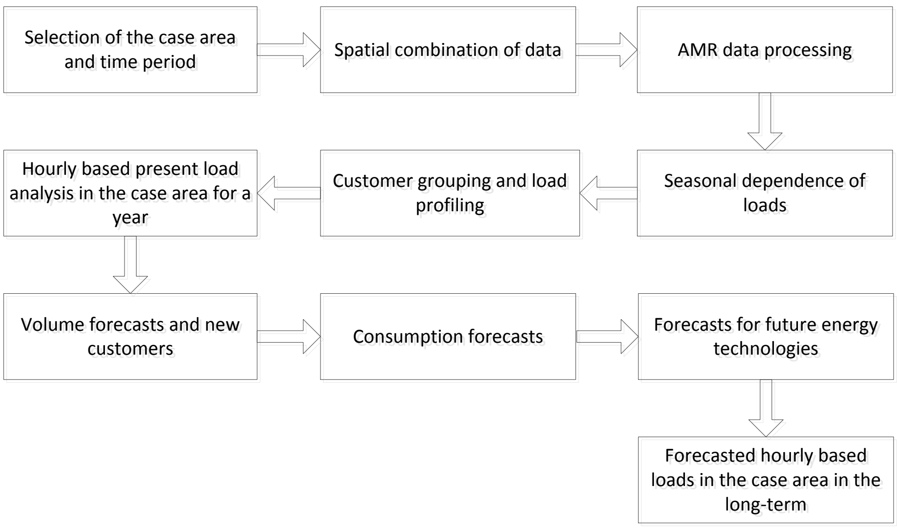

Figure 5.20. LTLF process for electricity distribution.

The research area may be located in the area of several municipalities, and thus, the data have to be modified and focused on the right area, or the data have to be connected with different records. The forecasting system and combination with different databases must work efficiently, reliably, and automatically when updating and modifying the data. In addition, application of data sources constitutes a significant part of the forecasting process. Almost all the data used in the forecasts can be found from different kinds of data sources. Hence, the use of data plays an important role in the LTLF process. Integration of the DSO's internal data sources as well as integration of external data sources may pose challenges. Therefore, development of the databases is highly important. The information of the electricity end-use will increase significantly also in the future. In practice, this means that more device group specific data can be obtained.

Completely new data will probably be available in the future, making it easier to generate forecasts. This will help to analyse parameters for the scenarios. Updating the customer information is necessary from the perspective of long-term load forecasting. The amount of data grows constantly, and the opportunities to utilize data will increase in the future.

It would be important to record information of the new technologies to the DSO's databases. Another option is to find new technologies based on consumption changes and behaviour. It would be useful to provide updates annually, because it gives a better starting point for the present consumption. Eventually, new possible future technologies such as fuel cells and µCHP can be integrated into forecasting by end-use modelling. In the forecasting system there has to be an option to modify the end-use models. In practice, there should be a library for different kinds of end-use profiles and a model for modification of the existing load profiles. Moreover, it may be advisable to use local end-use models than a universal model for a certain area. Further, it could be advisable to generate a new and separate database for load forecasting purposes. This database could register information and facilitate various load studies. This means that more accurate initial data can be applied and more accurate forecasts can be obtained.

Flexible forecasting requires suitable timescales. Timing of the consumptions, volumes, and new technologies plays a crucial role. Therefore, it is important to keep systems updated so that the most accurate analysis of the present loads can be obtained. Changes in consumption take place in different time periods, and they can have a great impact on general planning of the network. Forecasting of the new technologies is challenging, but the different types of scenarios help to make a suitable sensitivity analysis. The longer the forecasting period, the higher the uncertainty of the forecasting results may be. The variation and number of errors of the scenarios increase in the long term.

To sum up, the role of local experience on the network area under study is emphasized. The person who makes the forecast has to estimate the aspects to be taken into account in the forecasts in each case individually. Further, an ability to make different kinds of scenarios for individual areas is required, and the effects have to be forecasted by a scenario approach. A remarkable benefit in the new process is that forecasts can be adjusted and updated every year when new and updated information for forecasting is available. Finally, the person producing the forecasts makes the final decisions of the parameters and scenarios.

The new long-term load forecasting process for electricity distribution consists of different phases that apply various different methods. The developed process is generic by nature, and it is universal for all kinds of areas. In total, the process is logical and easy to apply in practice. However, it requires a lot of information of the customers and data for forecasting. Altogether, this chapter has produced a methodology for the LTLF. This emphasizes the relevance and novelty of the doctoral dissertation.

In addition, the developed forecasting process has been modelled in practice. An analysis method has been generated to model the changes. This forecasting prototype method works in a Matlab simulation model environment. The prototype has instruments to make a present-state analysis of the forecasting area, volume- and consumption forecasts, and future energy technologies. The main focus is in the modelling of the future energy technologies and the AMR data processing in the forecasting tool. Basically, the forecasting tool can be considered to be a part of the distribution network planning tool, which enables various simulations in the case area. Next, it is studied how the forecasts work in practice, and what kinds of impacts the new future energy technologies will have on loads in electricity distribution.

6 Analysis of the LTLF process impacts on the business environment

A new long-term load forecasting process provides spatial hourly power results. From the technical perspective, the highest mean hourly powers are an important parameter, because network planning is based on them. As network planning and network investments have an impact on the DSO's business, new investments have to be taken into account in the business planning. Annual electrical energy consumption can be forecasted based on hourly powers. Annual energy forecasts especially at the DSO level are needed, because together with tariffs, energy consumption has effects on the DSO's revenue, and thereby on the DSO's business and strategic planning. Moreover, network tariffs are based on business planning. Figure 6.1 presents the impacts of the load forecasting process on the electricity distribution business.

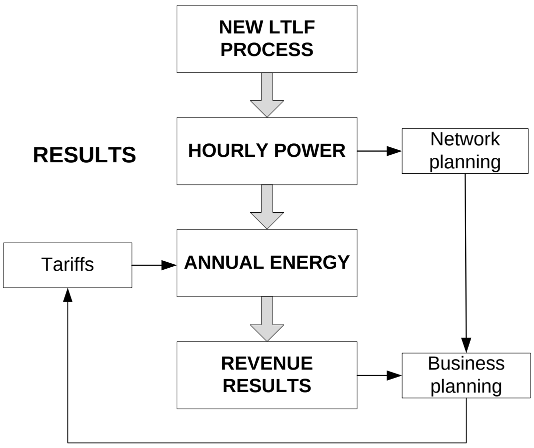

Figure 6.1. New long-term load forecasting process for electricity distribution yields forecasting results in hourly powers. The impacts on annual energy and revenue can be defined based on hourly powers.

Changes in the electricity end-use depend on several issues such as the network location and area and the emergence of future energy technologies. Network areas can be very dissimilar, which means that the LTLF has to be made individually for each area. Indicative information of the effects of changing electricity end-use on the electricity distribution business is needed. In addition, the proposed forecasting process has to be tested. For this purpose, a case study is required.

6.1 Case study of future energy technologies

The new long-term load forecasting process will be tested in this case analysis. The process follows the methodology presented in Chapter 5. The objective of the case study is to test the methodology and to model the possible effects that future energy technologies may have on the electricity distribution business. The process also describes the present load analysis quite extensively. Volume- and consumption forecasts, instead, are not presented. The impacts of future energy technologies on electricity distribution are studied, because they are assumed to have the most significant effects on loads. Volume and consumption forecasts are not incorporated in the case study, because such data of the spatial development of the case area such as census data, building forecasts, and real estate information are not available for analysis. Thus, the constraints of the research data usage and the lack of data set limits on the presentation of the case analysis. Simulations of the volume and consumption forecasts could have been provided; nevertheless, simulations without actual data would only have tested the forecasting process, which could also be made without this phase. However, the new long-term load forecasting process can be tested without volume and consumption forecasts. Despite the fact that volume and consumption forecasts are not made, all elements of the forecasting process, namely the spatial analysis, clustering, scenarios, end-use modelling, and simulation, are applied to forecast loads in the case area. The main assumption of this doctoral dissertation is that new technologies will significantly change electrical energy and power in distribution networks. Scenarios of future energy technologies and their effects on electrical energy and power are presented; however, it is emphasized that the results are only indicative. The target is to attest that future energy technologies may have radical effects on electrical loads in electricity distribution.

The case study is made for a single primary substation area with nine feeders. The primary substation includes a population centre and rural areas in Central Finland. The distribution network comprises 457 km medium-voltage network, 793 km low-voltage network, 469 secondary distribution transformers, and 5624 connection points. AMR data are available from all customers for the target period of 10 June 2010–31 October 2012. The AMR and network data have been modified for the Matlab simulation model. Customer density (network length/a customer) is 164 m/customer in the case area while the median value in Finland is 157 m/customer. The number of customers in the connection points is 1.35, and the ratio of the low-voltage network length to the medium-voltage network is 1.74 (the national values in Finland are 1.41 and 1.97, respectively). The number of secondary distribution transformers per medium voltage line kilometre is 1.03 (the medium value in Finland is 1.01). To sum up, it can be stated that the case network area is a typical representative of an average electricity distribution network area in Finland.

The forecasting in the case area is based on AMR data available for each customer for the period of November 2011–October 2012. Over that time, the total energy consumption was 88.4 GWh and the highest mean hourly power 21.1 MW. As presented in Section 5.2, outdoor temperature correction has to be performed before load forecasting. Customer-specific temperature dependence parameters for four seasons are calculated from AMR data. Outdoor temperature correction is based on regional long-term daily average outdoor temperatures. This means that after normalization, the applied AMR data represent long-term outdoor-temperature-corrected energy consumption, and the network load pattern represents the shape of the measurements for the year 2012.

The case network area includes approximately 7600 customers, and the customers are classified into 38 predefined SLY customer groups. The number of customers varies from 250 to over 2000 customers on different feeders. A majority of the customers, are classified into the category of detached house customers. Around 30 % of the customers are residential customers, who live in terraced houses and blocks of flats. Almost 1 % of the customers are found in the group of industrial customers, 2 % of the customers in agriculture, 2 % in public services, and about 4 % in private services. The rest of the customers are categorized by the DSO's own classification. This information is gathered in Table 6.1.

Table 6.1. Predefined classification of customers in the case area.

Total number of customers	**100 %**
Detached houses	60 %
Terraced house and apartment customers	30 %
Agriculture	2 %
Industry	1 %
Administration	2 %
Business	4 %
Others	1 %

Basically, in load forecasting, all the 38 predefined customer groups can be used. Predefined customer groups serve as a good starting point for customer grouping. If customer types emerge that have to be classified separately, the customer group and load profile for such customers can be formed in the clustering phase. From the perspective of forecasting the future energy technologies, the most interesting customers are residential customers. Residential customers cover over 90 % of the total number of customers in the case area. Therefore, residential customers are in the focus of attention here. In addition, residential customers may probably be interested in new technologies, as for example heat pumps have been installed into households (Adato Energy, 2013). However, agriculture, industrial, administration, and business customers will also employ different kinds of technologies.

As presented in Chapter 5, customer grouping can be based on load profile updating or clustering methods. Here, a clustering method is applied. The largest customers are separated from others, and individual load profiles are used for those customers. The rest of the customers are clustered by a k-means method, and for those customers, clustered load profiles are used. The clustered load profiles are scaled according to the customer's annual energy consumption. The total space electric heating load has been calculated after clustering. In this model, an approximation has been used that electric heating is needed if the outdoor temperature is below +10°C. Thus, after the customer grouping process, 33 different customer groups are found for the forecasting from the case area.

After the outdoor temperature normalization and customer grouping phase, the present load analysis for long-term forecasts in the area can be generated. In this phase, the load profiles are hourly based for a year. Volume and consumption forecasts could be made based on these load profiles. The effects of outdoor temperature normalization and clustering results on the network loads are illustrated in Figure 6.2. The green line describes the processed network load, which is used in the forecasting process. The starting time in the figure is the 1st of November. The same approach is also applied to the figures in the following sections. The outdoor-temperature-normalized peak load is 19.3 MW, and the electrical energy is 88.4 GWh. The peak operating time is 4600 h.

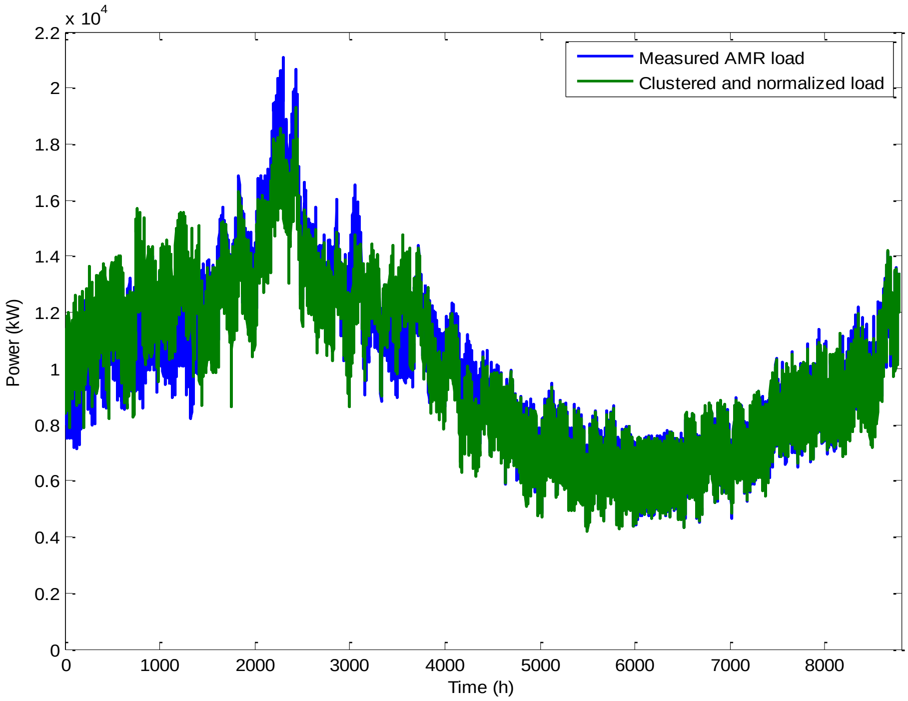

Figure 6.2. Difference between the measured AMR load (blue) and outdoor-temperature-normalized and clustered network loads (green).

The case study reviews the future energy technologies related to energy efficiency, microgeneration, electric vehicles, demand response, and energy storages. Modelling of these technologies is addressed in more detail in Section 5.4. The target is to test the methodology in practice. Therefore, forecasts are made for residential customers only. In addition, the target of the case study is not to make a load forecast for the case area, but to model the impacts that these future energy technologies may have on the electricity distribution. The results are presented from the perspective of electrical energy, power, and distribution revenue.

6.2 Effects of future technologies on power and energy

The effects of future technologies on the annual electrical energy and the highest mean hourly powers are evaluated by using the same forecasts in the case area. Certain future energy technologies are forecasted, and the results are presented for each technology. The effects on distribution loads are studied by comparing the results with original network loads (normalized and clustered long-term network loads). The effects on the loads are obtained in hourly powers at a year level when the future highest mean hourly powers can be determined, and the impacts on the annual electrical energy can be calculated from the powers. The following sections address the effects of future energy technologies on powers and energy in the distribution network area.

6.2.1 Energy efficiency

There are several energy efficiency actions and technologies, which may have an impact on the electricity end-use. Section 5.4 demonstrated how to model the effects of insulation, heating systems, and lighting on the network loads. Here, it is assumed that the most significant effects on the loads will be associated with heating systems, if heat pumps are installed. The main focus is on ground and air source heat pumps (GSHP and ASHP) installed into detached houses. In the heat pump forecasts it is assumed that a part of the customers in detached houses with non-electric heating will replace their oil heating systems by ground source heat pumps, and customers in detached houses with direct electric heating will install an air source heat pump. Customers with non-electric heating may also have other heating systems than oil heating such as district heating and wood heating. It is assumed that 70 % of the customers in detached houses with non-electric heating will have a ground source heat pump in the case area. These customers are selected randomly based on their annual energy consumption. There are no accurate spatial data available of different heating types and demands of the case area for the forecasts. Therefore, it is assumed that general spatial data from Statistics Finland can be applied for the case area. Direct electric heating customers are clustered from the AMR data. It is assumed that all detached houses with direct electric heating will have an air source heat pump in the case area.

The GSHP and ASHP data are modelled by hourly based data (Laitinen et al., 2011). The heat pump data are outdoor temperature normalized to the same target temperatures as the original network load. The heating demand for detached houses with non-electric heating in the case area is based on average annual heating demands, the data of which are available. The heating demand is determined by information of the construction years of the detached houses, floor areas and heating demands per m^2 in the case area (Motiva, 2015) and (Statistics Finland, 2014c). In the GSHP analysis, heating of water is included in the heating demand and forecast. However, a suitable hourly power model for heating of water is not available for forecasting. The normalized ground-source heat pump hourly data are scaled based on the customers' annual heating demands. The heating demand for customers with direct electric heating is calculated from the AMR data. The coefficient of performance (COP) for the GSHP is estimated to be three, and the COP for the ASHP is obtained from the heat pump hourly data. First, the effects of ground source heat pumps in detached houses with non-electric heating are presented. In Figure 6.3, the effects of GSHPs are illustrated in the case area when heat pumps have been installed into some detached houses with non-electric heating.

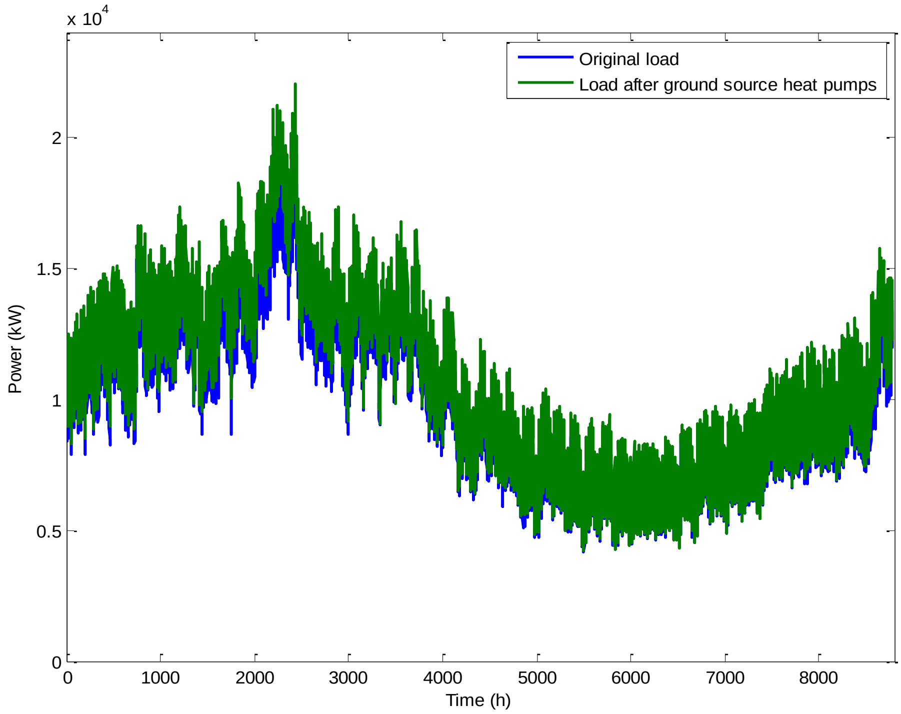

Figure 6.3. Effects of ground source heat pumps on the loads in the case area.

The result is that the highest mean hourly powers would increase by about 14 % compared with the original loads in the case area, if all detached house customers with non-electric heating had ground source heat pumps. The annual electrical energy consumption would increase by about 7 % in the area. Figure 6.4 illustrates the effects of GSHPs in a two-week period over the highest network load period.

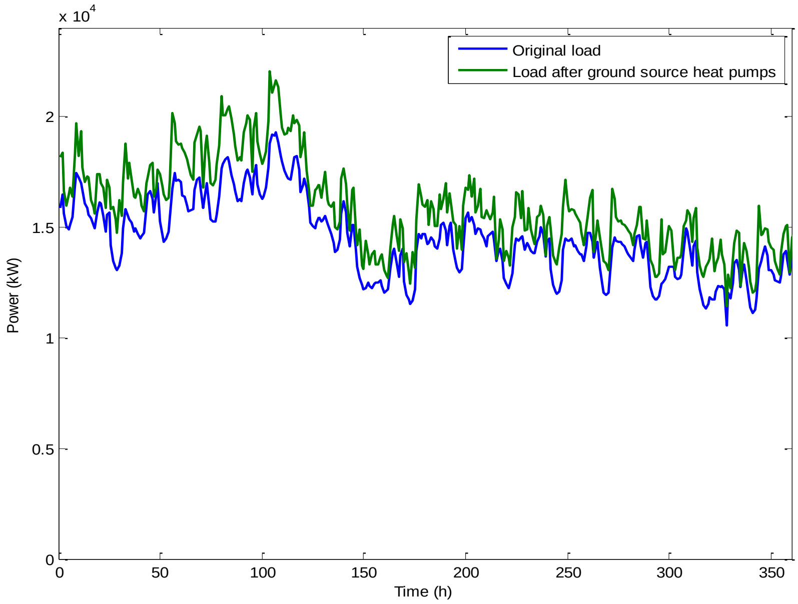

Figure 6.4. Effects of ground source heat pumps on the loads in the case area in a two-week period.

The results are also studied at the district transformer level. The impacts of heat pumps on the highest mean hourly powers at the secondary transformer level in the case area are shown in Figure 6.5. The highest mean hourly powers of the original load and the impacts of GSHPs are compared with the nominal powers of the secondary transformers. It seems that the loads of the distribution transformers will increase considerably, and some of the secondary transformers may be overloaded. Thus, in this scenario, GSHPs will increase the annual energy and the maximum power in distribution networks.

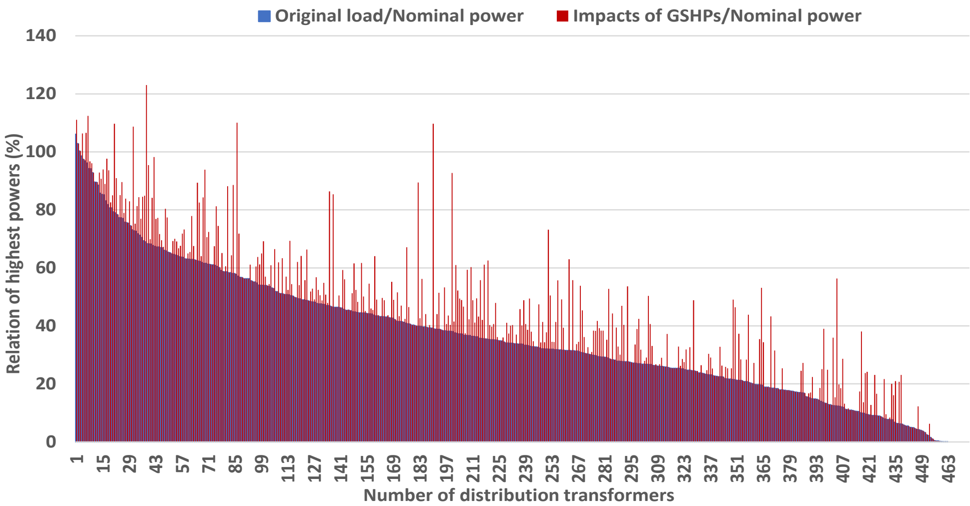

Figure 6.5. Effects of ground source heat pumps on loads at the secondary transformer level.

The impacts of air source heat pumps on direct electric heating customers can be seen in Figure 6.6. The heat pumps may increase direct electric heating customers' loads during the coldest weather even by 9 %. The highest mean hourly power may increase 2 % in the case area. The reason is that the COP of the ASHPs decreases below 1 during the coldest weather, and it is assumed that the ASHPs are operating during the coldest weather. In this scenario, the total annual electrical energy consumption may decrease by 5 % in the case area.

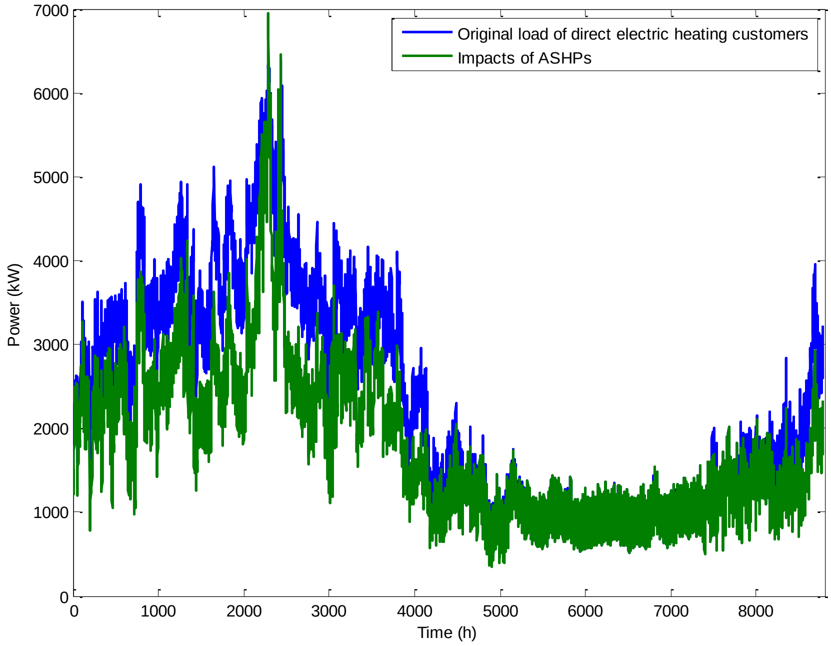

Figure 6.6. Effects of air source heat pumps on direct electric heating customers' loads.

The effects of air source heat pumps on the secondary transformers can be seen in Figure 6.7. It can be noticed that ASHPs in buildings with direct electric heating decrease the annual electrical energy consumption, but increase or decrease the highest hourly powers at the secondary substation level. The reason why hourly powers increase at the secondary substations is that the highest hourly powers of the original loads occur during the coldest weather, when the consumption is already at the highest level. Thus, the ASHPs increase the consumption if the COP decreases below 1. On the other hand, the ASHPs decrease electricity consumption. This, again, may decrease the highest hourly powers in some secondary transformers in the case area when the original consumption is not at the highest level at the secondary substation.

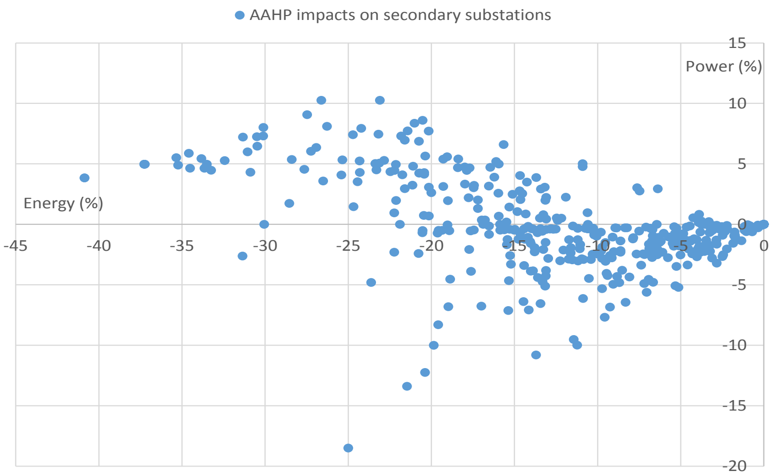

Figure 6.7. Effects of air source heat pumps on loads at the secondary substation level in per cent.

The total effects of heat pumps on the highest mean hourly loads and the annual electrical energy at the feeder level are depicted in Figure 6.8. The highest mean hourly powers will increase significantly on all feeders, but the annual energy flow may increase or decrease.

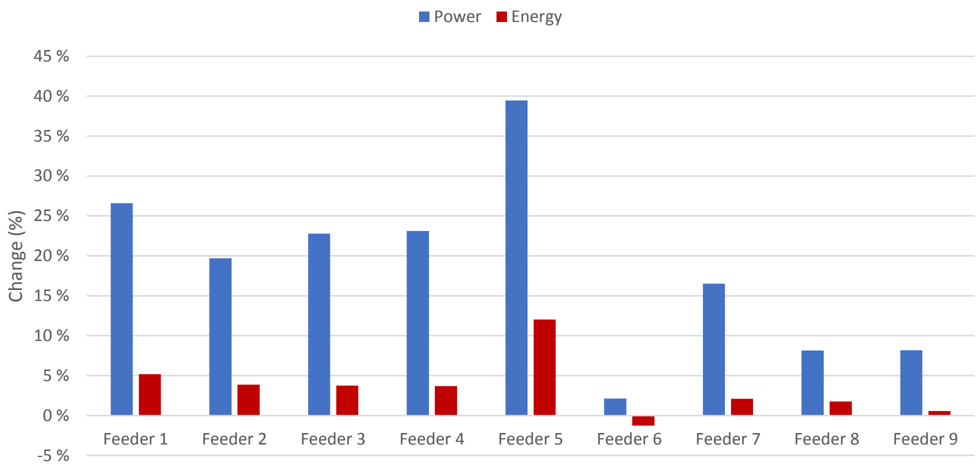

Figure 6.8. Effects of heat pumps on power and energy on different feeders.

In these scenarios, the total impacts of heat pumps on power are forecasted to increase the network loads. On the other hand, the heat pumps may decrease or increase the annual electrical energy flow at different network levels. Ground source heat pumps may increase the annual energy and power at different network levels. Air source heat pumps, instead, may decrease the annual energy flow at different network levels, but they may increase or decrease powers at different network levels.

6.2.2 Microgeneration

Solar power will probably be the most popular microgeneration technology in the future. It is forecasted that the most popular capacity of a PV plant is 5 kW. In this scenario, it is assumed that all detached house customers with direct electric heating in the case area will have a 5 kW PV system. Customers of this kind have typically higher electricity consumption than other residential customers. Therefore, it is forecasted that these customers will install solar panels. This number of customers accounts for about 25 % of the total number of end-customers in the case area.

A production curve is required to forecast the effects of microgeneration on loads. A theoretical hourly based production curve for the case area has been applied from (National Renewable Energy Laboratory, 2015). The PV is estimated to have an array tilt of 45°, the system losses are estimated to be 14 %, and the array azimuth angle is 180°. Figure 6.9 shows the results of PV on the network loads.

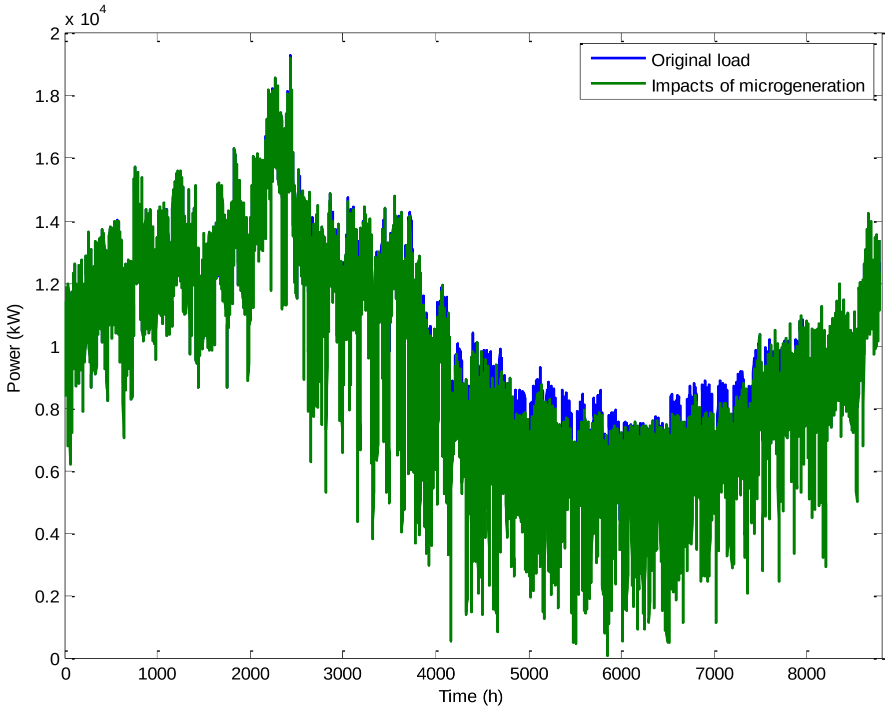

Figure 6.9. Effects of microgeneration (green) on the original loads (blue) at the primary substation area.

The use of PV generation in the peak load time in winter in Finland is considered almost negligible. Therefore, it is very likely that PV systems do not have an impact on peak electric loads in the distribution network. In the summertime instead, the situation may be totally different. The result shows that in summer, the network load can be even negative at the primary substation level, and it will be possible to supply electricity to the transmission network. Thus, the annual electrical energy flow at the primary substation area would decrease by about 9 %. Figure 6.10 shows the results of PV on the network loads in July.

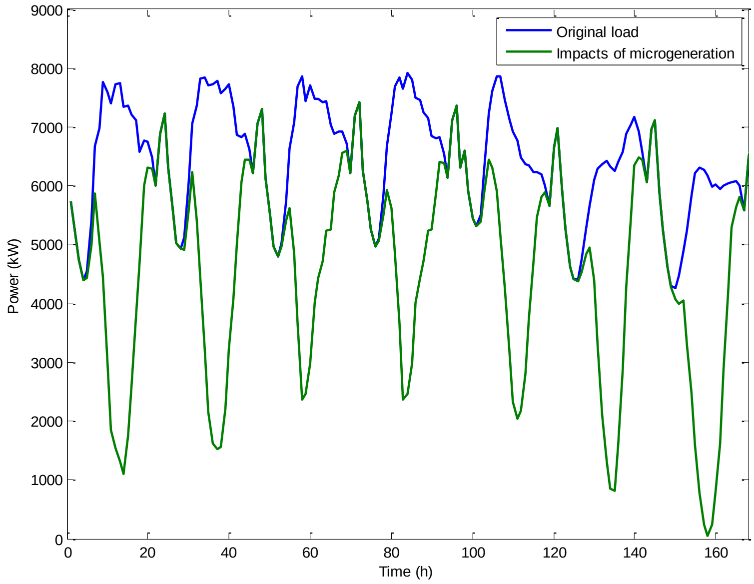

Figure 6.10. Effects of microgeneration (green) on original loads (blue) at the primary substation area over a one-week period in July.

Photovoltaic (PV) systems can produce a negative energy flow to the network, if the consumption is lower than the solar power production. This can also cause difficulties at the lower distribution network levels. The effects of PV on the secondary transformers with the same scenario are illustrated in Figure 6.11. The highest mean hourly powers of the original load and the lowest hourly powers of the impacts of PV systems are compared with the nominal powers of the secondary transformers.

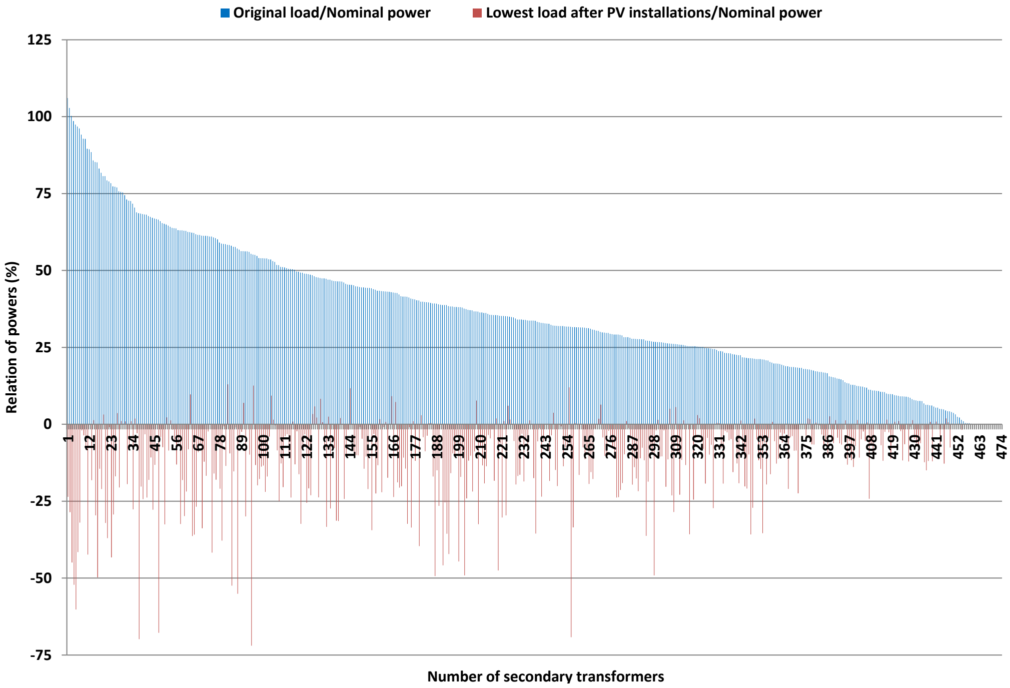

Figure 6.11. Effects of microgeneration on loads at the district transformer level.

The figure shows that from the perspective of network dimensioning, PV will not pose a challenge, if the installed PV capacities are 5 kW or less, and the penetration level of microgeneration plants remains moderate as presented in this analysis.

6.2.3 Electric vehicles

The impacts of EVs on the loads depend on the number of EVs, their charging type and time, and location. It is forecasted that 25 % of the customers will have electric vehicles in the case area. In the scenario, the EV fleet is considered to be owned by residential customers living in detached houses. Further, in addition to basic charging without optimization, it is assumed that the charging power is constant 3.6 kW per car, the energy consumption of the vehicle is 0.2 kWh/km, and the battery capacity of the vehicle is sufficient for most of the daily trips (Tikka et al., 2011). Figure 6.12 shows how the loads will increase in the case area. The highest mean hourly power will increase by about 5 % in the case area. The annual electrical energy consumption will increase by about 8 %. The effects on loads are divided equally for the whole year.

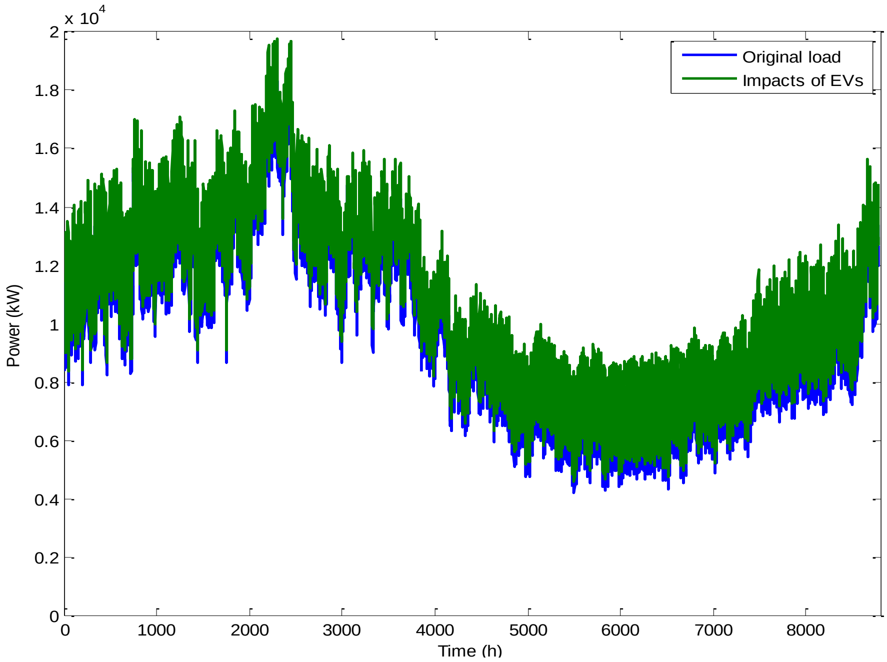

Figure 6.12. Effects of electric vehicles (green) on original electrical loads (blue) in the case area.

Figure 6.13 shows how the loads will increase in the case area over a two-week period.

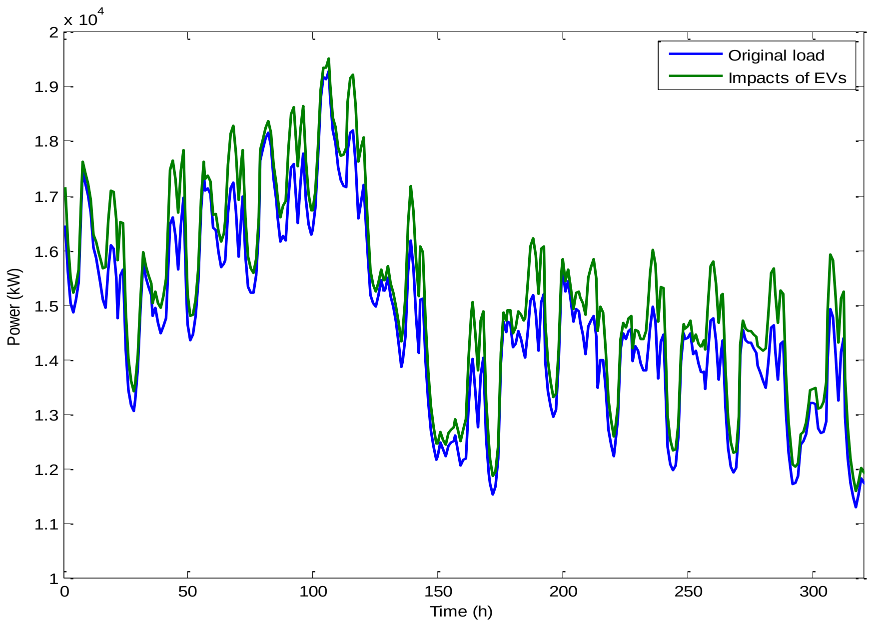

Figure 6.13. Effects of electric vehicles (green) on the original electrical loads (blue) in the case area over a two-week period.

The same forecast is modelled at the secondary transformer level in Figure 6.14. The highest mean hourly powers of the original loads and the impacts of EVs are compared with the nominal powers of the secondary transformers. We may conclude that the highest mean hourly powers will increase at the secondary transformer level, but the growth does not affect the dimensioning.

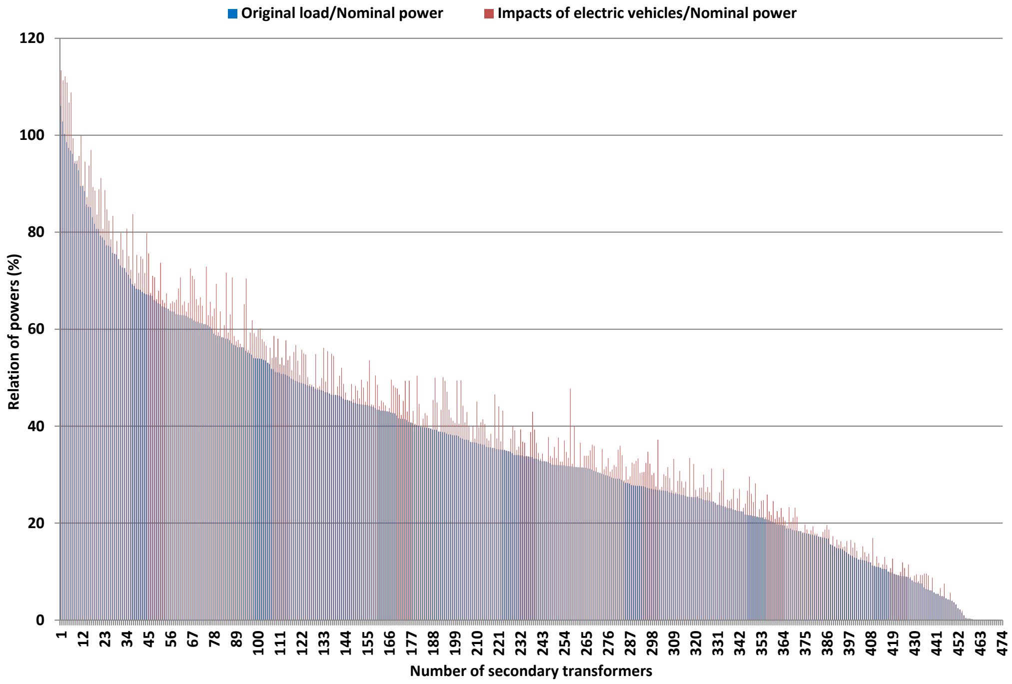

Figure 6.14. Effects of electric vehicles on loads at the secondary transformer level.

If charging is optimized from the network point of view, the network loads increase less or loads do not necessarily increase at all. The optimization can also be made based on electricity price, but the impacts on network loads are not modelled here.

6.2.4 Energy storages

The electricity distribution end-customers can apply energy storages, for example, to peak load cutting or in connection with microgeneration. For both cases, the capacity of the energy storages is determined for each customer, because it defines how much energy can be stored and discharged. If energy storages are used in connection with microgeneration, the capacity demand of the energy storages and the results on loads will be different compared with peak load cutting. Figure 6.15 presents the required capacity for energy storages related to the microgeneration in the case area when the generation capacity is 5 kW. The customers are the same as in the microgeneration case above. It is assumed that the customer tries to decrease the power supplied to the network by one kilowatt. This is the limit set on the lowest mean hourly powers in a year.

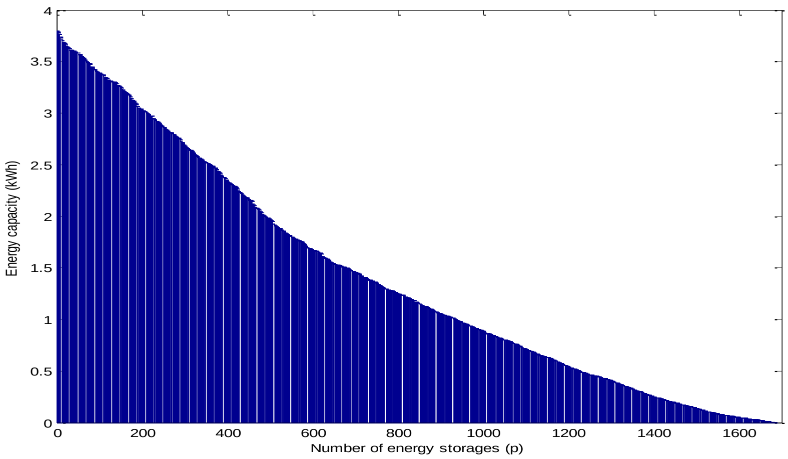

Figure 6.15. Minimum required energy storage capacity for customers with microgeneration.

Basically, this is also considered peak cutting. The methodology is the same as in Section 5.4, and the forecast is equivalent to the peak cutting approach. The impact on loads in the case area is slight with these energy storage capacities. The lowest power increases from about 0.05 MW to 0.4 MW. Figure 6.16 presents the results in July.

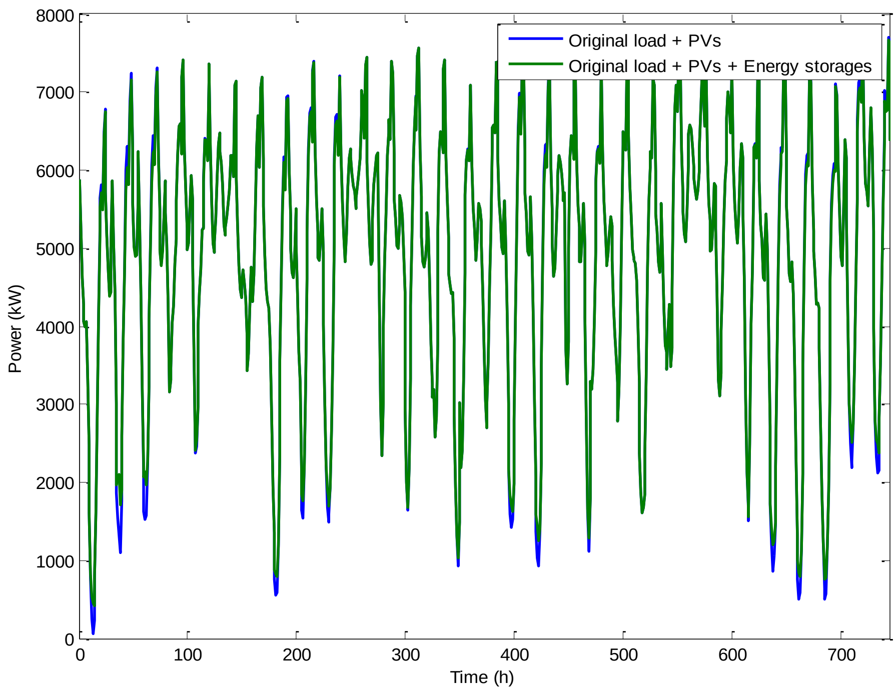

Figure 6.16. Impacts of energy storages associated with microgeneration in July.

The annual electrical energy consumption increases by about 0.1 % compared with the original load together with PV production. Figure 6.17 presents the corresponding results for one day in July. It can be seen from the figure that the energy storages cut the lowest network peaks, which are due to microgeneration. On the other hand, electricity is used from the charged storage when there is no PV production available. Some customers' electricity consumption is so low in summertime that they can take their electricity from the energy storage for several hours.

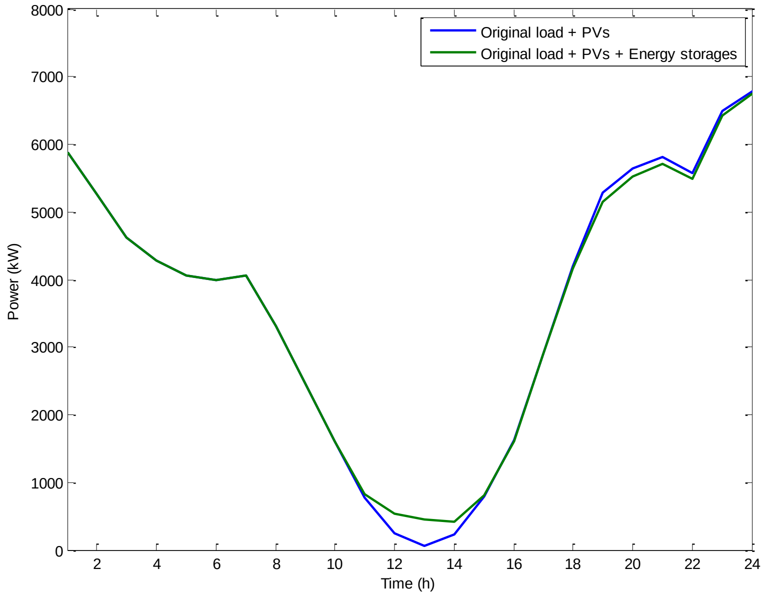

Figure 6.17. Impacts of energy storages associated with microgeneration in a one day in July.

It is assumed that a detached house customer with direct electric heating has a 5 kW PV system and an energy storage, the customer would probably like to exploit his/her own production as efficiently as possible. On average, a customer could manage with the PV production even for four months, if there were a storage that could store all the energy in this case. The customers whose electricity end-use over a year is lower would manage even a longer time without energy from the network.

In peak power cutting, it is assumed that a customer has an energy storage, which is used to cut the customer's peak loads to a certain predetermined limit. For example, if a customer's highest mean hourly power is 14.3 kW, the limit for peak cutting can be 13 kW or 14 kW. In this approach, we have to define the minimum energy storage capacity that is required to cut all the highest mean hourly powers during a year to the set limit. Figure 6.18 illustrates the required capacity of the energy storage from the customers in detached houses with electric heating. The customers' highest mean hourly powers are rounded down to the nearest integers and cut by 1 kW. This is the limit for the highest mean hourly powers in a year.

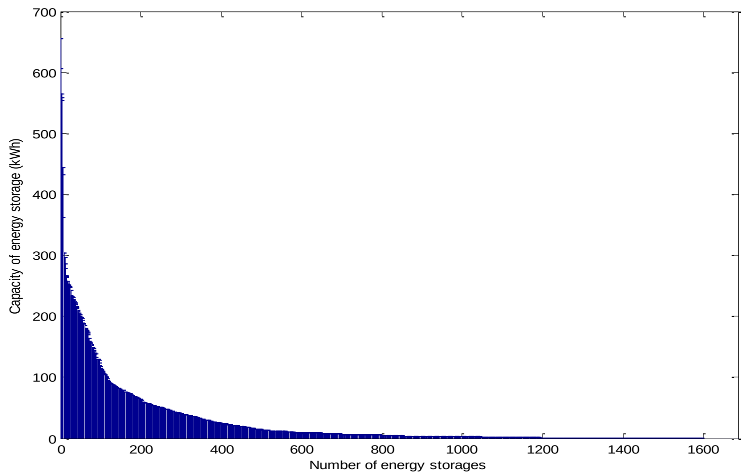

Figure 6.18. Minimum required energy storage capacity of residential customers.

There are customers who would need a considerably high energy storage capacity in this analysis. This is due to the clustered load profiles. Individual hourly power spikes in the clustered load profiles are clearly smaller compared with unadjusted AMR data. Thus, decreasing the power limits requires higher energy storage capacities in this approach. The effects of peak cutting on the loads in the case area are modelled in Figure 6.19. It can be seen that there are no significant effects on original loads (blue) in the case area. The highest mean hourly power decreases by 3 % in the case area.

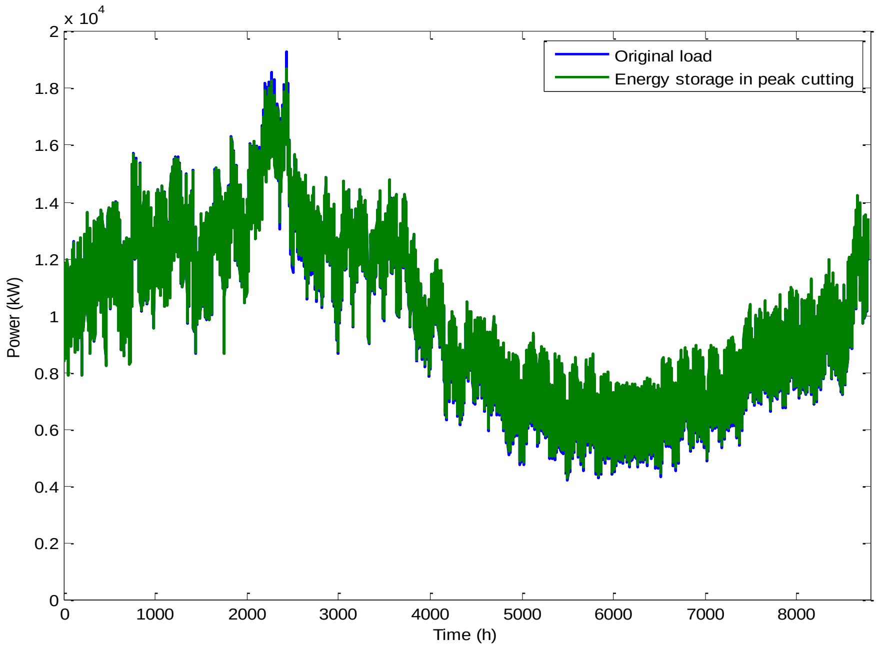

Figure 6.19. Effects of energy storages on loads in peak cutting in the case area.

There are no major effects on electrical energy either; the annual energy consumption will increase less than 0.5 % because of the 90 % efficiency of the energy storage. The number of energy storages and the amount of peak cutting should be greater in order to have significant effects on network loads.

6.2.5 Demand response

The effects of demand response on the distribution loads depend on the amount of loads and load types, and the load control sequence. In this case study, electric heating loads were controlled over a three-month period by the retailer. All direct electric heating loads in the case area were controlled in the hourly electricity market. The highest mean hourly power may grow by almost 25 % in the case area because of the load control. Figure 6.20 shows how loads will increase in the SPOT-price-based control in the case area. The SPOT-, balancing-, imbalancing-, and reserve-based demand response will increase the loads in the case area.

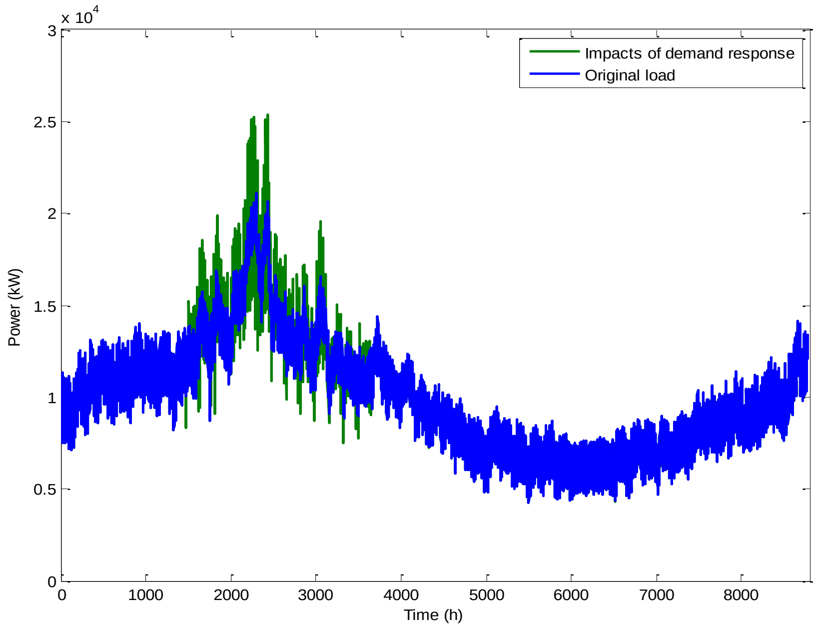

Figure 6.20. Effects of SPOT-price-based load controls at the primary substation level.

If the retailer is a market operator who controls the loads, it may be possible that loads are controlled at a time that is not suitable from the distribution network's perspective. Figure 6.21 demonstrates the effects of load control taking place in different markets on network loads in different feeders in the case area.

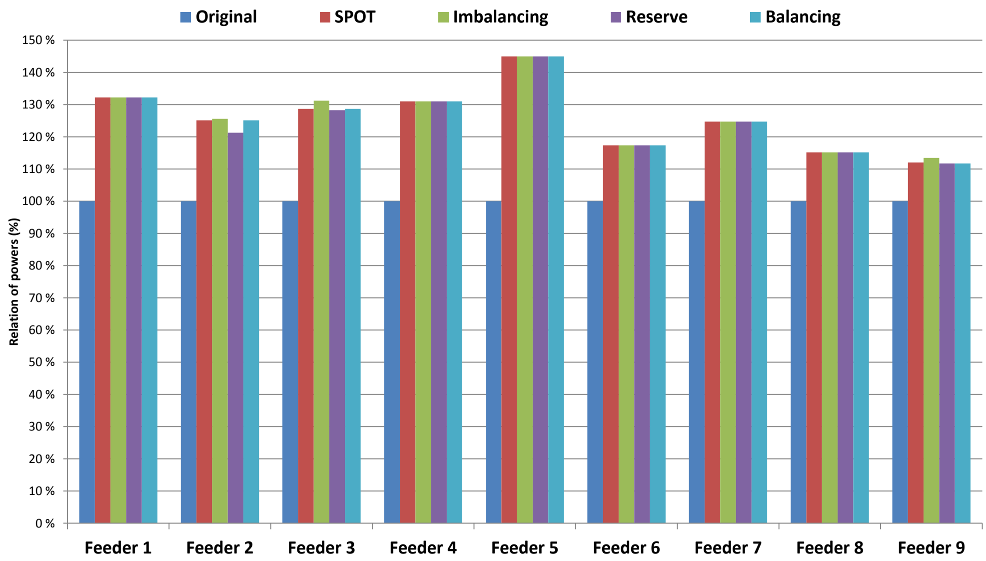

Figure 6.21. Effects of load control in different markets on the highest loads at the feeder level.

This demand response approach does not have an influence on electrical energy consumption, because it is assumed that the same amount of energy will appear on the next hours when the loads are on again. The impacts on electrical energy will occur if the retailer controls the loads that do not have a payback effect. Then, controlled load would remain unused, and electrical energy would be saved.

6.2.6 Summary of the impacts

In Chapter 3 a power/energy map was given, and the effects of different technologies on the electricity end-use were estimated. In this chapter, most of those technologies have been analysed and the results are presented with a similar map in Figure 6.22. Estimated and forecasted effects on energy and power have significant differences. The main reason for this can be the different scenarios and initial assumptions. In this scenario, the demand response has the greatest impact on power, because the load control capacity was considerable. On the other hand, the load control potential could be even higher because only the direct electric heating loads were included in this study.

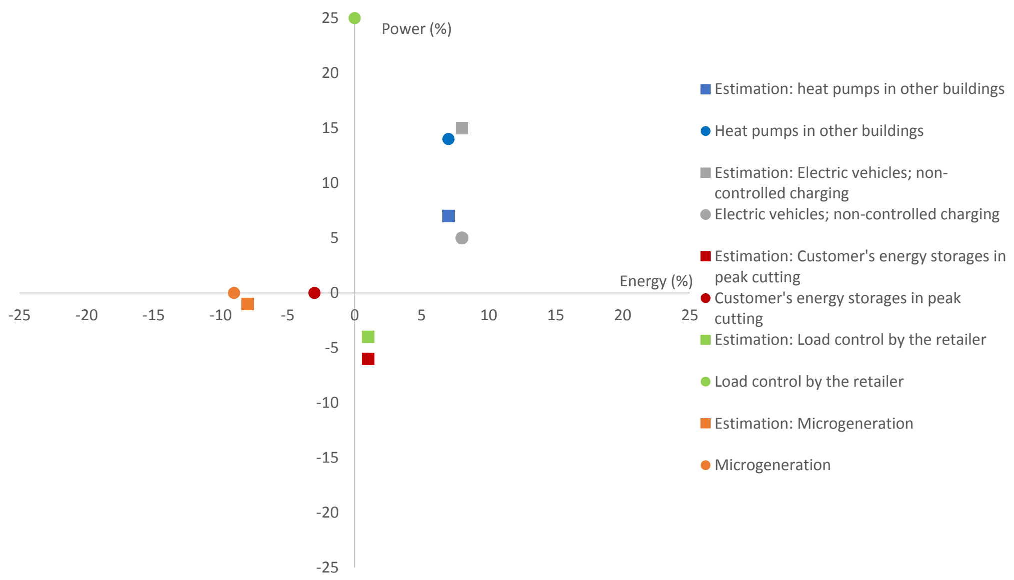

Figure 6.22. Estimated and forecasted effects of different technologies on power and energy in the case area.

From the DSO's perspective, the worst scenarios are if the power loads increase and the energy consumption decreases. Consequently, microgeneration and demand response are the most challenging issues on the network. On the other hand, heat pumps in non-electric heating buildings and controlled charging of the EVs may have positive effects on the electricity distribution business. The penetration level of the technologies in the case study is relatively low. For example, the number or EVs could be notably higher, and thus, the effects on the network loads will be considerable. The greatest effects on the network loads will probably become from microgeneration, electric vehicles, and demand response. The penetration levels of microgeneration and electric vehicles can be high, and they will have large effects on energy and power. In addition, demand response may have a radical impact on the network loads but the effects on the energy are minor. Demand response can cause significant spikes to the loads. However, the results depend on the logic of the load controls, capacity of the loads, and the sequence of the controls.

6.2.7 Total effects of future technologies

Future energy technologies will have different kinds of effects on loads. Energy efficiency technologies may decrease or increase the highest loads in the long term. In general, microgeneration does not typically have an impact on the highest loads in Finland, because the highest loads take place in cold wintertime, and microgeneration does not decrease loads at that time. Electric vehicles will increase network loads and energy consumption. On the other hand, customers' energy storages will slightly decrease peak loads. Demand response can increase loads, if the retailer operates as a market facilitator.

The total effects of the future technologies are forecasted in the case area. Table 6.2 presents the assumptions and scenarios of the future technologies in the basic scenario.

Table 6.2. Assumptions and scenarios adopted when forecasting the total effects of the future technologies in the case area.

Technology	Scenario	Proportion of the customers of detached house customers/ all customers
Energy efficiency	Detached houses with non-electric heating will have a ground source heat pump	25 % / 10 %
Microgeneration	Detached house customers will have 5 kW PV system	35 % / 15 %
Electric vehicles	1-phase charging, basic charging, non-optimized , on average charging profile	35 % / 15 %
Energy storages	Utilizing of storages for customers' peak cutting	50 % / 20 %
Demand response	Direct electric heating customers' heating loads are controlled	50 % / 20 %

The contradictory effects on loads have to be taken into account in the total effects. For example, the ASHP decreases the direct electric heating load, and thus, the load control potential of direct electric heating is smaller than in the original case. The overlapping possibilities has been eliminated from the scenarios. Thus, the impacts of customers' energy storages in peak cutting have been considered in the demand response potential. There are no other overlapping cases with these technologies and scenarios. It is concluded that modelling of the total impacts has to be dynamic. This requires that forecasts of the new technologies have to be based on time scales. This way, it is possible to prevent overlapping of the forecasts.

In Figure 6.23, the total impacts of these future technologies on loads are modelled in the case area with the scenarios presented above. In demand response forecasting, forecasts related to SPOT-based markets have been used.

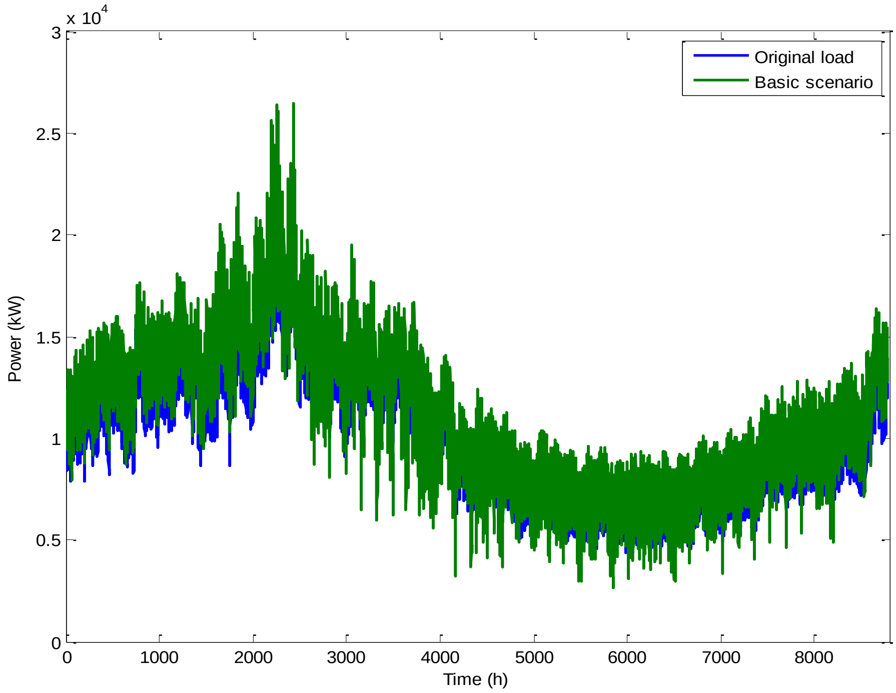

Figure 6.23. Total effects of future technologies on loads in the case area.

The highest mean hourly powers may increase by about 35 % in the case area. The lowest mean hourly power decreases. The total impacts on electrical energy are interesting; with these scenarios, the annual electrical energy may increase about 5 %. It seems that the highest mean hourly powers will increase considerably, and the electrical energy may change only slightly with these scenarios. A more precise analysis of the results can be obtained from Figure 6.24, which presents the results over a one-week period during peak period time in the case area.

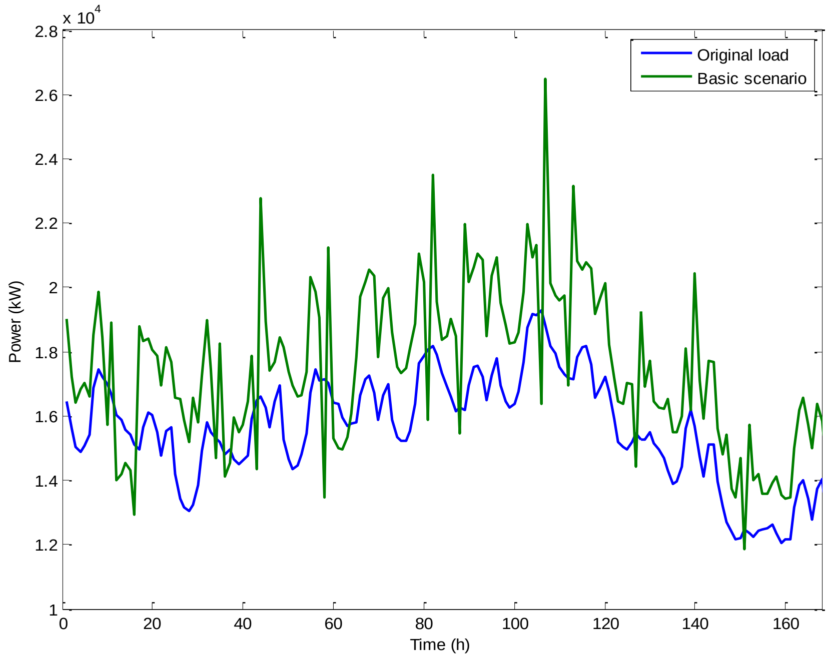

Figure 6.24. Total effects of future technologies on loads in the case area over a one-week period.

The loads will become spikier in the future, and the shape of the load curve will also change. Figure 6.25 presents the total results at the feeder level. It seems that the powers will increase on each feeder, but the total effects on energy are lower.

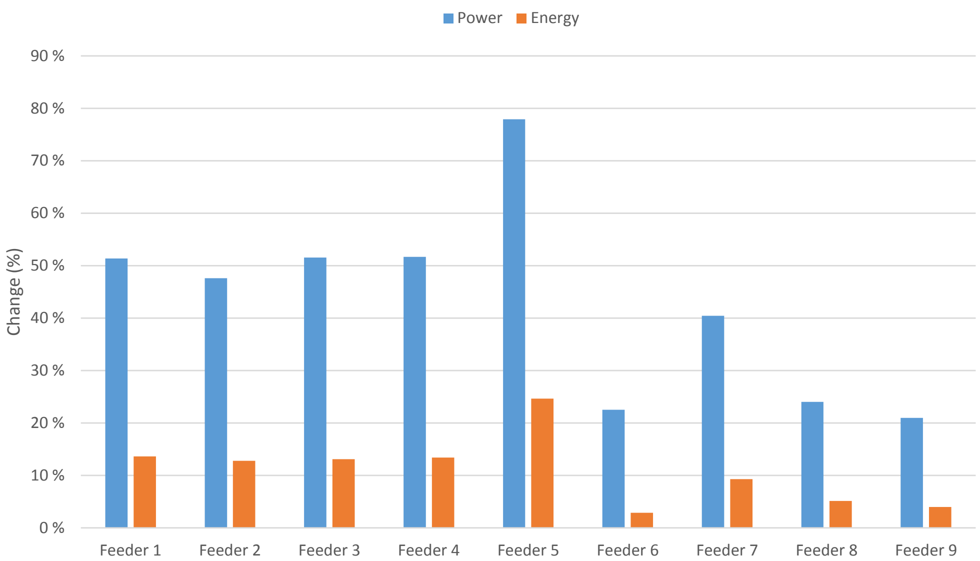

Figure 6.25. Total effects of future technologies on power and energy at the feeder level.

The first figure of the total effects describes a basic situation in the case area. The scenario forecasts that there will be different kinds of technologies that will have impacts on the network loads. It is also possible to make various scenarios for DSOs. Figure 6.26 presents the effects of the low-energy scenario. In the low-energy scenario, energy consumption decreases and loads increase. In practice, this would mean that there would be a lot of AAHP, microgeneration, and demand response potential.

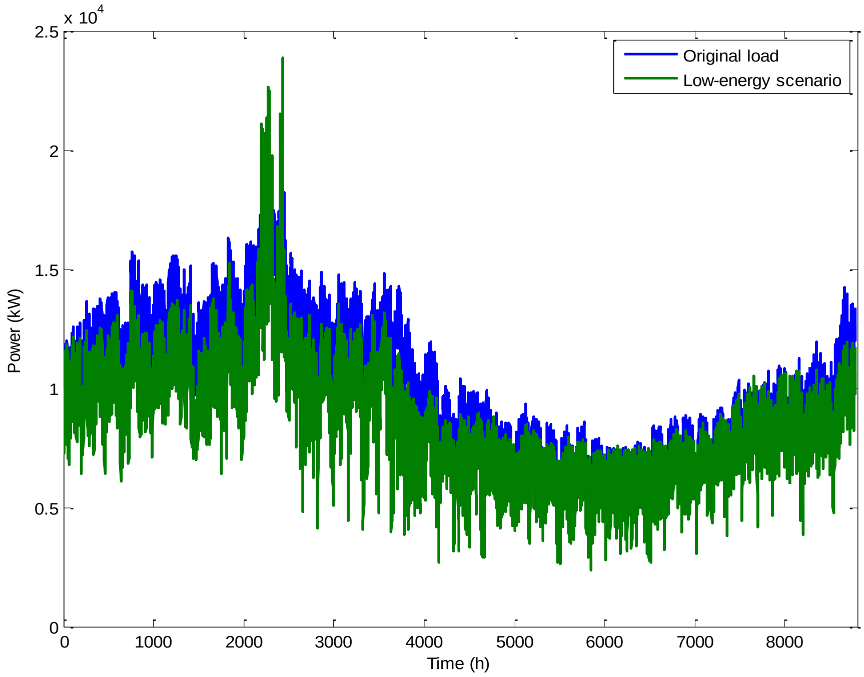

Figure 6.26. Total effects of future technologies on loads in the case area with the low-energy scenario.

The parameters in technology forecasts are the same as in the basic case. The results show that the power loads increase by about 25 % and the energy consumption decreases by 15 % in the case area. In the high-energy scenario, the optimal case would be that the energy consumption would increase and the power loads would decrease. This high-energy scenario is modelled in Figure 6.27. This scenario includes GSHPs, EVs, and energy storages. The parameters are the same as in the basic case, but demand response, ASHPs, and microgeneration are not included in this scenario. The results indicate that the power increases by about 15 % but the energy consumption increases by 13 % in the case area.

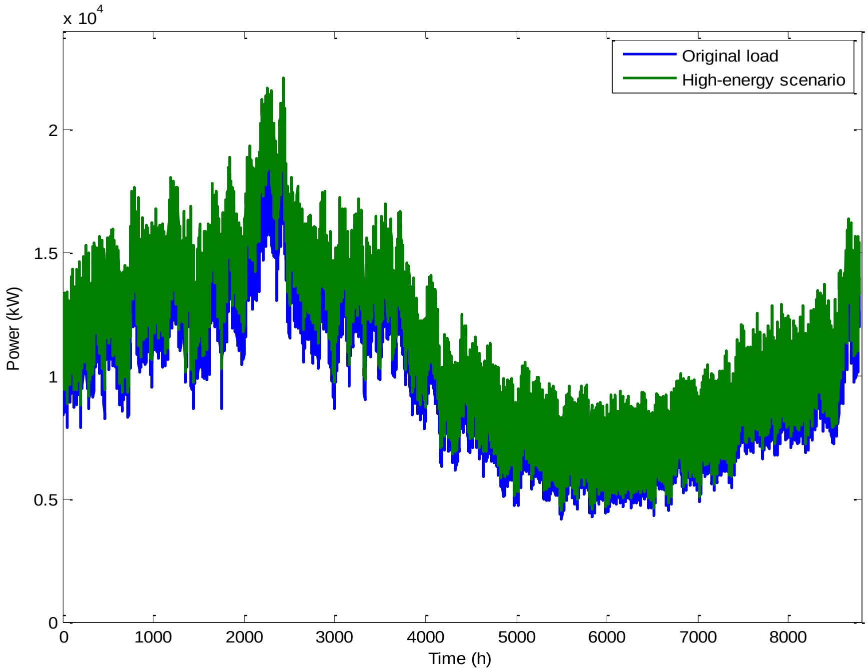

Figure 6.27. Total effects of future technologies on loads in the case area with the high-energy scenario.

The load profiles in all three scenarios are totally different, and the maximum variation in energy from the lowest to the highest energy consumption is about 30 %. The corresponding value in power loads is found in the basic case, when the increase in loads is about 20 %. The results of the different scenarios are illustrated in Figure 6.28.

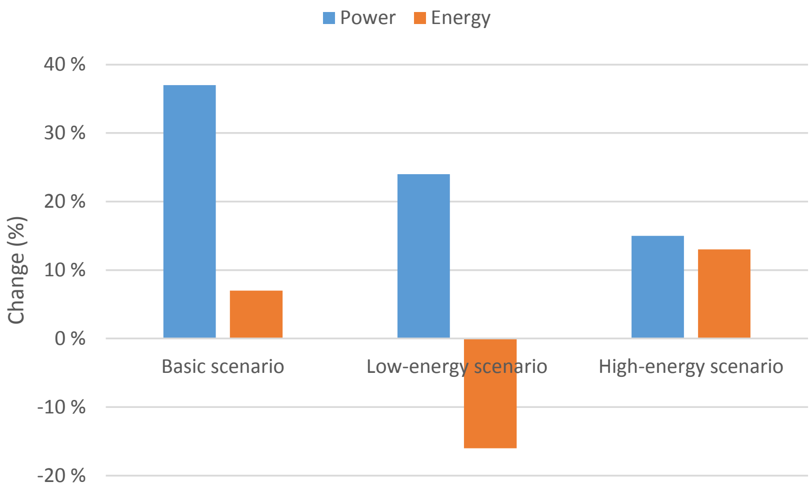

Figure 6.28. Total effects of different scenarios in the case area.

The above scenarios have only included the impacts of the new technologies, assuming quite a low penetration level. In addition, these scenarios have been made for residential customers. If these scenarios had taken into consideration the number of customers, all kinds of customer types, and the penetration of the technologies had been higher, the effects on the network loads would have been considerably higher.

6.3 Impacts of future technologies on the DSO's revenue

Changes in electricity end-use will have impacts on loads in electricity distribution. These will influence electrical energy consumption, loads, and the distribution business. The situation will be challenging in the electricity distribution business, if the costs increase but incomes decrease or remain at the same level in the future. The revenue may decrease, if the number of customers or energy consumption decreases. Some future energy technologies like microgeneration and energy efficiency may play the major role in decreasing the energy consumption. If network powers increase, it means that also costs will rise. This is a consequence of the fact that the network dimensioning mainly depends on the power.

Distributed energy resources and demand response will have impacts on electric loads and energy transmitted through the distribution network. This, again, has short- and long-term effects on the DSO's costs, revenue, and profit. The DSOs' tariff structures are mostly based on electrical energy in Finland, and as a consequence, an energy-based distribution tariff will have direct impacts on electricity distribution companies' revenue (Tuunanen et al., 2012). This will increase pressure to raise network tariff prices. Thus, changes in electricity end-use will have effects on the DSOs' revenue and business. New business planning methods such as tariff planning and new business models are needed to respond to future changes in the electricity distribution business environment in the long term. Figure 6.29 illustrates the distribution of the tariff structure in the case area.

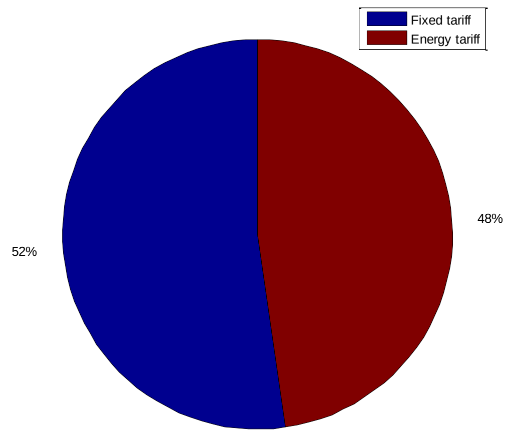

Figure 6.29. Distribution of the fixed (blue) and energy (red) distribution tariff.

Both the fixed and energy distribution tariff cover almost 50 % of the total revenue in the residential customers case. Hence, we can analyse three main scenarios and the effects on the revenue and distribution tariffs. In the basic scenario, electrical energy remains at the same level but the power loads increase. Basically, in this case, the distribution revenue remains at the same level with the present tariff structure. In the worst case scenario, the energy consumption decreases by 14 % and the power increases by 13 %. This scenario is the most challenging one from the distribution revenue perspective, because the revenue would decrease with the present tariff structure and prices. The energy consumption will increase by 15 %, and the power is forecasted to increase by 5 % in the high energy scenario. The high energy scenario is a good option for DSOs, because the energy consumption grows and changes in the power loads do not necessarily pose challenges. Generally, the level of costs is increasing, and this would mean that the prices of energy and the fixed tariff should be raised in any case.

In practice, the worst case scenario may be challenging if the energy consumption decreases. It will decrease the DSO's revenue with the present tariff structure. Thus, it is necessary to raise the distribution prices to earn at least the same revenue as today. The pressure to price increases may be even higher because of the increasing power demand and level of costs. If the energy consumption decreases by 14 %, it can be calculated how much the distribution prices have to be increased in order to earn the same amount of revenue:

- If the price increase is focused on all types of energy tariffs, the price increase is 16 %. In practice, this would mean that the energy prices have to be raised by 0.0028–0.0045 €/kWh to earn the same revenue as today.
- In the case where the price increase is focused on all types of fixed tariffs, the price increase is 13 %. This would mean that fixed charges have to rise by 1.7–3.0 €/month per customer.
- If the price increase is made equally for all tariffs, it would mean that the price increase would be about 7 %.

It can be concluded that if the revenue is affected by energy consumption, it is reasonable to focus the pressures of price increase on fixed tariffs. This solution decreases the dependence of revenue on energy consumption, and thus, it makes the revenue more constant. The negative side is that the customers' opportunities to influence the distribution charges will decrease with the present tariff principle, because fixed tariffs are based on the main fuse size.

6.4 Implications of the case impacts

Network location will have effects on changes in the electricity end-use in the future. The changes may vary between DSOs and network areas, especially between rural and urban areas. All changes will take place over a long-time period. In addition, the results are temperature normalized, which means that variation in outdoor temperature between different years may cause extra fluctuation to the results. The case network environment is a typical Finnish electricity distribution environment. The case area includes rural and population centre areas. The forecasts and parameters related to the forecasting process such as outdoor temperature are based on average values, because the values have to represent long-term values, and the modelling of the network loads has to be reasonable from the perspective of energy and power. This guarantees that the results are at a medium level. The results can be different in urban areas, because for instance the customer structure is different. However, the results show where the electricity distribution business is heading.

The LTLF involves various uncertainties, which cannot be completely eliminated. However, the scenario approach can take different future alternatives into account, and the scenarios can be updated on an annual basis, which produces more information of the network area and possible load changes in the area. This case study has shown that future energy technologies will have a significant impact on distribution network loads, energy, and power, and the DSO’s revenue in the long term. The effects of the technologies depend on many issues, as was mentioned above. The most important question is how technologies will take place in the operating environment. However, it has to be borne in mind that volume- and consumption-related factors like the number of people will have significant effects on loads.

The methodology has been tested with residential customers, and the results in the case area are only based on forecasts of residential customers. However, the greatest impacts on network loads may be found in the groups of residential customers, because they are typically the largest customer group and may be willing to acquire new technologies (Leenheer et al., 2011) and (Annala et al., 2012). In rural areas, the loads will develop differently than in urban areas. In this work, the main focus is on rural areas, which have a lot of residential customers. Further, new technologies may have more radical impacts on the loads in the countryside.

Traditionally, the network load forecasts have been based on energy forecasts, which are converted into power forecasts by load models. Energy forecasts are typically based on the estimation of the annual growth in energy consumption. For instance, the present network planning tools apply the approach of regularly increasing annual load consumption. Load forecasts are based on energy forecasts and load models. If energy is forecasted to increase constantly, there is a similar trend also with power. Consequently, different annual load growth percentage estimates for the highest mean hourly power in the case area have been applied. This is illustrated in Figure 6.30. In the figure, the annual electrical energy and the highest mean hourly power are estimated to increase with three different growth percentages in the case area. In addition, the annual energy forecasts with the new long-term load forecasting process are indicated in the figure. It can be seen that the forecast produce totally different forecasting results. The results of the new long-term load forecasting on the highest mean hourly powers are also indicated in the figure. The loads will increase in every scenario, but there are a great differences in the forecasts.

However, the power results may be totally dissimilar at the lower network levels with the new load forecasting process because of the future energy technologies. Thus, we may conclude that the effects of the future energy technologies cannot be forecasted by the previous method; further, errors in electrical energy forecasts will have significant impacts on the distribution business.

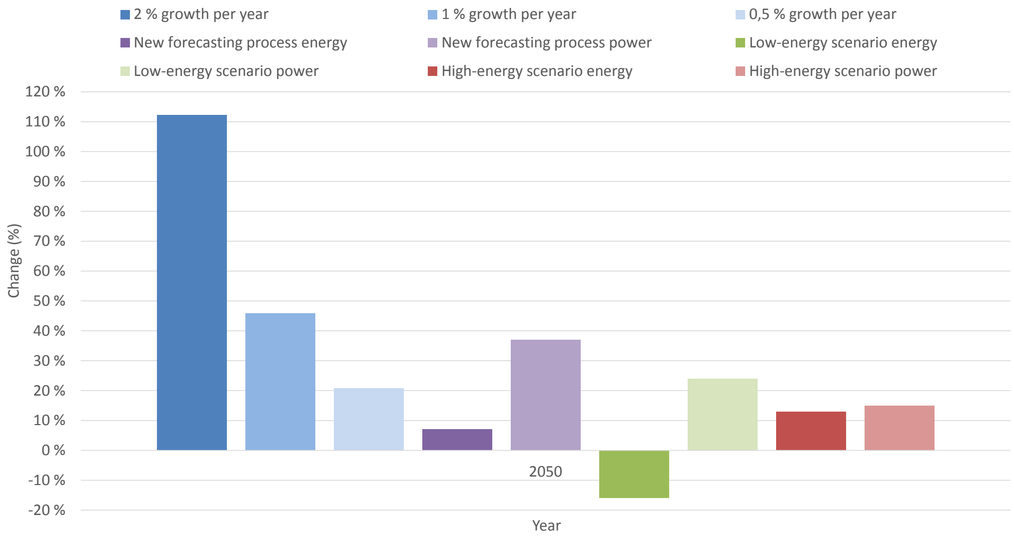

Figure 6.30. Forecasting of the future electrical energy and the highest mean hourly power with the annual energy consumption growth percentage and with the new load forecasting process in the case area.

This proves that electricity end-use will change significantly and that previous load forecasting and modelling methods are no longer valid. We may conclude that it is impossible to reliably forecast loads in different areas with the previous methodologies. The previous methodologies cannot take into account the impacts of microgeneration and other future energy technologies. Further, they may lead to different conclusions of the future network loads and can be problematic from the network planning perspective.

This section has shown that changes in the electricity end-use may pose challenges for network and business planning. Several variables have to be taken into account when considering the future business environment. The main challenges in the electricity distribution operating environment are that electricity end-use deviates from the previous consumption trends. In addition, more challenges may arise as a result of major changes in the number of customers and the structure of livelihood. Electricity end-use, energy, and power may vary considerably in the future. This may reduce incomes and require large investments by the DSOs. Therefore, the increasing costs and peak loads may lead to challenging and problematic situations. This is an extremely undesirable situation from the perspective of the distribution business. Therefore, new methods to manage the impacts are needed.

6.5 Management of the impacts of future challenges

As mentioned above, the electricity distribution business will face various challenges in the future. These challenges can have adverse effects on the DSOs' business, and therefore, different ways to respond to these challenges have to be found. There are different methods to develop the distribution system; for instance, energy storages, load control, and new distribution pricing methods are proposed to react to the upcoming challenges (Järventausta et al., 2015), (Rahimi and Ipakchi, 2010) and (Palensky and Dietrich, 2011). The DSOs' operating environment is regulated, which means that opportunities to answer to the changes are limited. However, distribution pricing and demand-side management (DSM) could be solutions to respond to the challenges. More efficient utilization of the distribution network capacity is a key element against the increasing loads. Distribution pricing may also have impacts on the utilization of the distribution network capacity. At the same time, a new type of distribution pricing may tackle challenges in business planning (Geode report, 2013) and (Eurelectric, 2013).

6.5.1 Electricity distribution pricing

Changes in the electricity end-use lead to a situation where the electricity distribution business calls for new solutions. New business models may be needed in the smart grid environment to develop business opportunities. New methods for the electricity distribution business, especially for pricing, will also be needed. Customers do not necessarily comprehend the present pricing scheme. Moreover, the pricing methods do not provide appropriate incentives, and the customers' means to influence their electricity bill are limited. From the DSOs perspective, a pricing scheme should be cost-reflective and ensure adequate and predictable revenue in the future operating environment. The present pricing scheme does not meet these demands (Partanen, Honkapuro, and Tuunanen, 2012).

The major part of the distribution revenue comes from distribution charges. An inappropriate business model may raise the distribution prices considerably. A smart grid environment can be the basis for a new type of energy pricing and create a totally new operating environment for electricity distribution. Residential customers, in particular, may put effort to reduce their electricity consumption. However, if the customers' electricity distribution bills are based on energy and the DSOs' costs are stable or increasing, the DSOs have to be prepared to adjust their business models (Tuunanen et al., 2012).

The EU and Finnish legislation set limits on the distribution tariff structures. Regulation of the electricity distribution sector limits the revenue of the DSOs, but the DSOs can determine their pricing methodology mainly by themselves. Introduction of different tariff structures and an analysis of their suitability for the electricity distribution companies, as well as their impacts on the energy efficiency incentives and demand side management (DSM) are discussed in more detail in (Tuunanen et al., 2012) and (Partanen, Honkapuro, and Tuunanen, 2012).

In the low-voltage network, power-based distribution pricing would help to prevent too high power peaks (Mandatova et al., 2014) and (Sæle et al., 2015). The effects of power-based distribution pricing on the loads at different network levels are diverse. Some results of power-band-based tariffs are presented in (Järventausta et al., 2015) and (Partanen, Honkapuro, and Tuunanen, 2012). The effects of the power-based tariff structure can be modelled in a case area. It is assumed that the customers have an incentive to cut their peak powers. Figure 6.31 demonstrates how the loads would change in the case area if every residential customer decreased their highest mean hourly powers by 1 kW in a year.

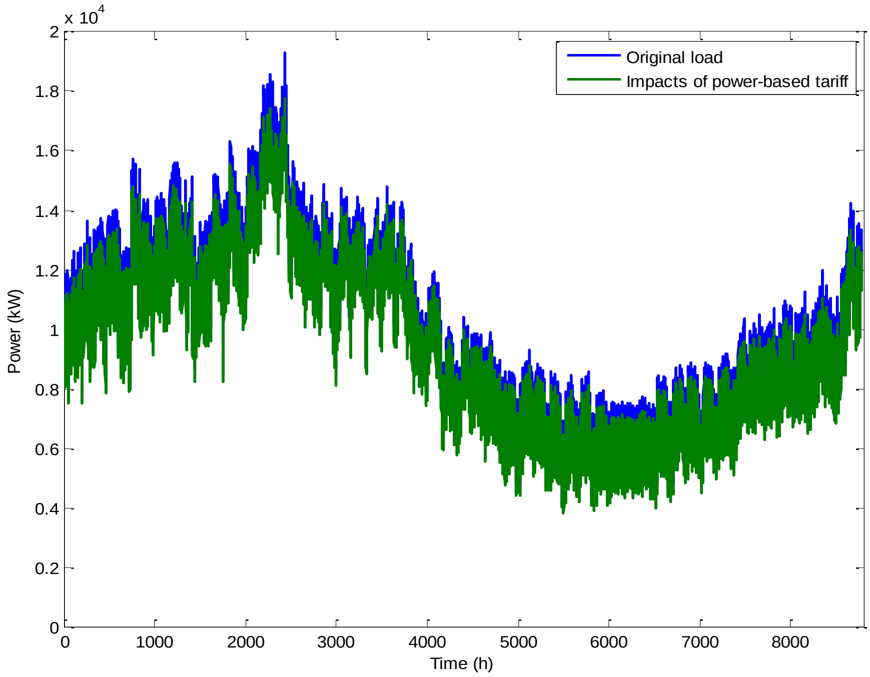

Figure 6.31. Possible impacts of the power-based tariff on distribution loads.

It can be seen that cutting the customers' highest mean hourly powers will decrease loads in the case area. Similar results have been obtained in (Järventausta et al., 2015), (Sæle et al., 2015), and (Partanen, Honkapuro, and Tuunanen, 2012). Power-based distribution tariffs could decrease network loads and improve the utilization of the distribution network capacity. The main benefit would be that it would prevent an increase in the highest mean hourly power in the optimal situation.

6.5.2 Demand-side management

There have been various attempts to reduce the customers' peak electricity consumption and to even out the load curves. In addition, electrical network loads and production may need balancing in the future. Different kinds of solutions have been proposed; for instance market-based demand response, demand-side management (DSM), energy efficiency, and load control (Palensky and Dietrich, 2011), (Rahimi and Ipakchi, 2010) and (Geode report, 2014). Demand-side management (DSM) can be defined as an array of measures to improve the energy system on the consumption side. It may involve enhancement of energy efficiency, incentive-based energy tariffs, and real-time control of distributed energy resources (Palensky and Dietrich, 2011). The DSOs would need means to manage loads in the distribution network. Controllability and predictability of loads can be a useful and essential resource to avoid distribution network challenges; the DSO would manage customers' loads to avoid peak loads.

The total network loads consist of various load types in electricity distribution networks. Thus, load management requires an appropriate control system. Basically, from the DSO's perspective, load management may be needed only occasionally, for instance during the highest peak load times or in exceptional distribution service situations. Thus, the DSO's load control would be based on optimization of the network loads. The main load control period would be in wintertime, because loads are then typically at highest in the network. If the customers' consumption behaviour is known, it could be possible to control the customers' electricity in the most efficient way. AMR data can be applied to determine controllable electrical loads. This adds resources to balance electricity consumption (Järventausta et al., 2015). However, this would require a smart grid environment.

6.6 Conclusions

The most important contribution of the chapter was to show that the developed methodology works in practice. The methodology applies average end-use profiles when modelling the new technologies. Thus, the final power load results are mean values. Standard deviation is not presented in the final forecasting results, because it does not bring any additional value to the forecasting results. Instead, standard deviation is needed for the planning of the actual distribution network. However, when making end-use profiles of the new technologies, it is possible and advisable to apply standard deviation to model new technologies. Despite the forecasting results at certain long-term outdoor temperatures, the network has to be dimensioned based on the critical temperatures. The network has to endure cold and hot outdoor temperatures, which means that critical dimensioning of the distribution network is required. This has to be taken into account in the long-term network planning.

Revenue is one of the key elements in the electricity distribution business. The main part of the revenue comes from electricity distribution charges. If energy consumption decreases, distribution prices have to be increased in order to get the same revenue. In addition, revenue will fluctuate in the future, if the total energy consumption varies considerably. However, more efficient utilization of the network capacity could decrease distribution costs in the long term. From this perspective, a new electricity distribution pricing model or demand-side management could be viable solutions.

The effects of changes and challenges on the DSOs' business environment can be significant. There are many alternative scenarios concerning the adoption of new technologies and their possible volumes in the future. At present, it seems that energy efficiency and heat pumps are the prevailing and continuing trends. These trends will probably increase in the future also. Micro generation is already in a wide-scale use in Europe, and it will very likely to gain ground also in Finland. Other technologies such as energy storages and EVs will gain a foothold in the future, but their volumes are difficult to forecast.

The DSOs' options to manage the impacts of future challenges are limited. Inevitably, there are challenges coming outside of the DSOs, and the DSOs cannot prevent the development. However, the DSOs can develop their networks to adapt to the changing conditions. In addition, electricity distribution pricing and demand-side management have been suggested as methods against the adverse effects of changing electricity end-use. These methods provide tools for the DSOs to react to changes and make their businesses more cost-reflective. However, a question may arise: Should a power-based distribution tariff be taken into account in the forecasting process? Considering the power-based tariff structure, there is a feedback element involved in the loads. Consequently, the tariff structure may have impacts on loads in the future, and thus, it could be an element of the forecasting process.

7 Conclusions

Many changes have taken place in electricity end-use over the last few decades. The amount of modern conveniences such as entertainment electronics, electric saunas, and air conditioning, has increased electricity consumption and changed electricity end-use profiles. These changes have led to a situation where the old load profiles that have been applied to load forecasting are not applicable as such any longer. Further, there are many issues that may bring changes to the use of electricity in the future. The most significant effects may arise from new technologies such as electric vehicles and from structural changes such as the number of population and the structure of livelihood. New technologies may revolutionize electricity end-use. For example, micro generation may supply electricity to the network, which is a totally new situation in electricity distribution. Moreover, new technologies may have different kinds of impacts on energy and power in distribution networks, which will make forecasting more complicated. For instance, air to air heat pumps may decrease electrical energy consumption in direct electric heating buildings, but increase peak power during the coldest weather. In general, these changes will significantly alter customers' electricity end-use patterns, which can finally been seen in the distribution networks. The result is that the effects on energy and power in the network may be considerable and versatile.

The amount of data that can be used for forecasting has also increased noticeably and will continue to grow in the future. Especially, AMR data provide hourly based electricity consumption data, which has opened up new opportunities to develop the long-term load forecasting process for electricity distribution. Previously, load forecasts have mainly been based on energy consumption and various forecasting analyses of energy consumption. Energy forecasts have been converted into load forecasts by load profiles that are over 20 years old. However, AMR data make it possible to apply hourly power based forecasts, and energy forecasts can be calculated from hourly powers. On the whole, there is a need for a new long-term load forecasting process, and the topic is current at the moment.

A novel long-term forecasting process has been developed in this doctoral dissertation. The forecasting process is a generic model, and it can be applied to forecast energy and power in electricity distribution networks. The process consists of the present load analysis, volume- and consumption forecasts, and forecasts related to new technologies. The future electrical loads in the distribution networks can be forecasted in the long term by applying a forecasting process that consists of different methodologies: a spatial analysis, a clustering method, end-use modelling, scenarios, and a simulation method. In addition, the forecasting process applies AMR data and several data sources. The forecasting process is needed for the long-term load forecasting, because one methodology alone cannot take into account the changing operating environment. Electricity load forecasting in distribution networks is always based on the case area. Therefore, a spatial analysis is needed. A clustering method is required to process the extensive AMR data. The impacts of the future energy technologies have to be estimated by end-use modelling. Eventually, the forecasts have to be based on scenarios, because scenario modelling is the most suitable method for long-term processes. All these forecasts and analyses can be modelled at the network level by simulation.

An implication of this doctoral dissertation is that considering the new technologies, energy efficiency, micro generation, electric vehicles, demand response, and energy storages may have the most significant impacts on network loads. These technologies may take place in different time periods, for instance, energy efficiency is now the prevailing trend. In addition, micro generation, for instance, is taking place in Europe.

The methodology has been tested in a case network environment. The case network is a typical rural and population centre area, which corresponds to an average network area in Finland. The case results can be considered indicative also for other network areas, but the forecasts and analyses have to be made case specifically for each network areas. In the case study, it has been analysed how the future network load patterns will look like in the future. The results show that power loads may increase by several dozens of per cents in the long-time period in the basic scenario. In addition to changes in power levels, also the shape of the network loads will change. At the same time, energy consumption does not necessarily increase. In addition, low- and high-energy scenarios have been made for the case area, and it seems that there will be an increase in powers in both cases while the energy consumption may vary.

The roles of energy and power are of importance, because power loads have an effect on the technical planning of the electricity distribution network, and energy forecasts have impacts on electricity distribution business planning. It can be concluded that powers and energy consumption will develop in different ways in the future. Therefore, the previous long-term forecasting methods are no longer applicable. In addition, if the energy consumption grows slightly or even decreases, it means that also the distribution revenue decreases with the present tariff structure. However, it is concluded that DSOs can adapt to the changing operating environment by applying new business approaches. An electricity distribution pricing scheme and demand-side management could be solutions to adapt to the new business environment. For instance, a power-based distribution tariff could prevent the increase in network loads.

The main scientific contribution of this doctoral dissertation is the forecasting process to estimate the network loads in the electricity distribution environment in the long term. The work delineates the major impacts on electricity consumption in the networks and on the electricity distribution business. In this work, it is illustrated how the network load patterns change in the long term. Further, the work models the kinds of network load changes that the DSOs should be prepared for. In addition, the work suggests how DSOs can manage the challenges and develop their business.

In this doctoral dissertation, a forecasting process has been tested in practice, and it is concluded that the methodology is feasible. Verification and validation of the study has been performed by applying the forecasting process, and the results show that significant changes will take place in energy and power. The developed process is better capable of considering changes in energy and power than the present methodologies. The strength of the methodology is that it takes several approaches to new opportunities and information. In addition, the doctoral dissertation identifies the most technologies relevant in the future, which play an important role from the forecasting perspective. The methodology is also flexible for different kinds of scenarios and possible changes. The weakness of the methodology is that the forecasting process is long; it takes a lot of time, and errors in different parts of the process are possible. A lot of data and data sources are also needed. Therefore, the data systems should be efficient and reliable. Finally, preparing reasonable scenarios requires a lot of knowledge from a forecaster. This also limits the options to model and forecast results. Therefore, it would have been interesting to model volume and consumption forecasts in the case area. The forecasting process does not necessarily take all potential changes into consideration. Further, more detailed and accurate methods can be generated when information and knowledge accumulate. Nevertheless, the developed load forecasting process may provide more efficient tools to estimate future loads.

The DSOs could be considered to be the audience that would be most interested in the results of this doctoral dissertation as they need information of future loads for the distribution network and business planning. New planning methods for distribution networks will be needed in the future. All in all, distribution systems require new methods for restoration of energy, balancing of loads, and cost-reflective pricing schemes in the future. Here, demand-side management and distribution pricing will be essential tools to impact on distribution network loads.

Further, software companies that develop network planning tools will get knowledge of how to develop the forecasting and modelling of future loads. In the context of this doctoral dissertation, a long-term load forecasting tool has been generated, which could be further developed into actual software. Incorporation of the forecasting process into some network planning tools would be an extremely relevant and current topic.

Moreover, forecasted future loads can give new information for retailers, TSOs, and market aggregators. Changes in future loads will also have impacts on their operation environment or business. For example, retailers can enhance the accuracy of their future electricity procurement. This may promote the retailers’ business and provide new business models and opportunities. In addition, the end-customers can also benefit from the results. For instance, end-customers can make their use of electricity more effective and minimize their electricity costs. The results of this doctoral dissertation can also be applied for the development of the energy policy. For example, the results can be used to improve the electricity distribution pricing scheme, the principles of which are incorporated in law.

This doctoral dissertation has shown that the electricity distribution business environment is undergoing changes. Thus, it can be concluded that the regulation model will also need new approaches. Consequently, energy authorities may get new information to develop the regulation model. Changes in the electricity distribution business, especially in the

DSOs' revenue, will have impacts on regulation. If energy consumption decreases, the distribution prices also have to be raised. It is also possible that the role of fixed tariff will grow in the future. Consequently, these changes will have an influence on the regulation model.

The results can also be taken advantage of in the electricity end-use modelling. The results of the dissertation demonstrate how the load profiles may change the electricity end-use. These models may produce a lot of information of the electricity end-use for different operators. Further, in the energy storage system approach, the suitable energy storage capacity for customers has been estimated. This methodology can provide information for the dimensioning of energy storages.

Finally, methods and tools to respond to the changing business environment have been presented. Electricity distribution pricing and demand-side management could answer many challenges and increase the potential to develop the electricity distribution system. Altogether, business models in the electricity distribution sector call for development. The new models have to be compatible with the retail pricing, taxation, and the related models.

Future research can be related to the enhancement and further development of the forecasting process. In addition, the effects of other possible end-use changes should be studied. Various technologies have been modelled, but there are many other technologies that would be relevant to model and forecast; these include new types of technologies and their impacts on the electricity end-use. It would also be useful to incorporate μCHP and other microgeneration technologies into the forecasting process. Hourly power-based electricity end-use models and their development are of high importance. In addition, the increasing amount of device-specific data will play a key role in the future studies on electricity end-use modelling. Obviously, it would be advisable to test the developed methodology in different network environments. Models and forecasts for different kinds of customers are also needed. For example, studies on the impacts of energy efficiency at the service sector customers would be needed. Again, solutions should be developed for the DSOs to respond to the arising technical and economic challenges. Modelling and pilot studies of the DSM and power-based distribution pricing deserve further studies as well. Finally, long-term electricity load forecasting for more extensive areas, up to the national level, would be a current topic of research. There has been a lot of discussion about different generation types, but less attention has been paid to national load forecasts. Thus, there would be a need for national electricity demand, energy, and power forecasts.

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