



Arun Narayanan

# RENEWABLE-ENERGY-BASED SINGLE AND COMMUNITY MICROGRIDS INTEGRATED WITH ELECTRICITY MARKETS



Arun Narayanan

## **RENEWABLE-ENERGY-BASED SINGLE AND COMMUNITY MICROGRIDS INTEGRATED WITH ELECTRICITY MARKETS**

Dissertation for the degree of Doctor of Science (Technology) to be presented with due permission for public examination and criticism in the Auditorium of the Student Union House at Lappeenranta-Lahti University of Technology LUT, Lappeenranta, Finland on the 22<sup>nd</sup> of November, 2019, at noon.

Acta Universitatis  
Lappeenrantaensis 878

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ISBN 978-952-335-440-1  
ISBN 978-952-335-441-8 (PDF)  
ISSN-L 1456-4491  
ISSN 1456-4491

Lappeenranta-Lahti University of Technology LUT  
LUT University Press 2019

# Abstract

**Arun Narayanan**

**Renewable-energy-based Single and Community Microgrids Integrated with Electricity Markets**

Lappeenranta 2019

136 pages

Acta Universitatis Lappeenrantaensis 878

Diss. Lappeenranta-Lahti University of Technology LUT

ISBN 978-952-335-440-1, ISBN 978-952-335-441-8 (PDF), ISSN-L 1456-4491, ISSN 1456-4491

The deployment of renewable-energy-based microgrids in the electrical power system is a well-known pathway to realize sustainable energy goals. Further, *community microgrids* incentivize residential houses to exchange renewable electricity production with each other. Community microgrids can also be interconnected to form *microgrid clusters* to improve their operations and economics. Community microgrids and microgrid clusters reduce interactions with the external grid, promote grid independence, optimize renewable energy usage, and enhance grid resilience and reliability.

Today, many electricity markets across the world have, completely or partially, transitioned from regulated monopolies to open electricity markets. Hence, it is important to interconnect microgrids with the electricity markets, keeping in mind the roles of all the stakeholders of an electricity network—the DSO, retailers, customers, society, etc. The broad aim of this dissertation is to *develop concepts and solution methodologies for implementing community microgrids and microgrid clusters with the objective of economically and fairly allocating their economic resources to residential customers, retailers, and the distribution system operator (DSO), considering local electricity market designs and external electricity market connections.*

This dissertation first examines single microgrids. Novel linear optimization-based methodologies are presented to cost-effectively dimension the distributed energy resources (DERs) in a single microgrid for full loads, partial loads (i.e., load fractions), and flexible loads (i.e., shiftable loads). These methodologies are also used to investigate whether a microgrid's electrical loads can be cost-effectively met by using 100% renewable energy sources (RES) supported by battery energy storage systems (BESS). A small city in Belgium, Kortrijk, is used as a case study to illustrate the methodology. From a purely economic viewpoint, RES–BESS systems are not cost-effective even with flexible loads when reference RES and non-RES costs from 2014 are used. This is because in 2014, NRES were significantly cheaper than RES–BESS systems.

The dimensioning methodologies are then used to investigate the long-term economic benefits obtained by Finnish residential customers who install photovoltaic (PV)–BESS microgrid systems and participate in the Nordic electric power market. We found that even when a BESS of 6.4 kWh is included to support the PV production, the reference levelized cost of electricity (LCOE) for PV (in 2015) of 0.20 €/kWh is expensive. However, at half the LCOE of 0.10 €/kWh, electricity from PV panels is preferable over electricity from the grid. In addition, we

demonstrate that Finnish residential customers have significant long-term benefits from using PV and PV-BESS systems.

The economic potential for DSOs to utilize BESS for decreasing outages in low-voltage (LV) single microgrids is also examined. A mixed binary linear programming (MBLP) model is applied to a typical Finnish rural electricity network where a BESS is assumed to be installed at the substation to reduce outages. This MBLP model makes it possible to determine the minimum capacity and optimal schedule of the installed BESS. The tradeoff between improvements in reliability and the costs of BESS can also be determined, including the situation wherein the BESS is used for peak shaving when there are no outages. We found that Li-ion-based BESS can be cost-effectively used for interruption management only if their decrease to one-third of their costs in 2016.

We extend our analysis to community microgrids and microgrid clusters. We present a general mathematical formulation of the microgrid cluster problem, taking into consideration the requirements, costs, and profitabilities of different stakeholders. Subsequently, we present a novel methodology to enable fair allocation of the profits that are obtained by the co-operation between the customers of a community microgrid. In a test case with a Finnish LV microgrid, our methodology saved  $\approx 8\%$  when the customers collaborated as compared to no collaboration, whereas the methodology saved  $\approx 25\%$  in a microgrid test case in Austin, Texas. Prosumers benefited more from our methodology than a conventional auction-based trading mechanism, whereas consumers benefited less, especially in the Finnish environment. The methodology promotes fair allocation of the cost resources of a microgrid and encourages RES proliferation. Finally, the impacts of another recently proposed electricity tariff design—power-based tariffs (PBTs)—on p2p electricity exchange between residential customers in a community microgrids are also investigated.

This dissertation presents and discusses methodologies, results, and analyses that form building blocks for the broader research community to solve bigger problems. In essence, they represent small steps toward a larger goal—to *promote electrification using RES to transform not only the environment but also people's lives*.

**Keywords:** microgrid, community microgrid, microgrid cluster, electricity market, renewable energy, optimization, game theory

## Acknowledgements

*A university is just a group of buildings gathered around a library.*

*The library is the university.*

Shelby Foote

The primary research work of this doctoral dissertation was carried out at the Laboratory of Electricity Market and Power Systems in LUT University (LUT) from September 2015 to August 2019. Some parts of this research were also conducted at IBCN (now IDLab), Dept. of Information Technology, University of Ghent, Belgium from June 2014 to August 2015. The study was supported by a grant from the Academy of Finland toward a collaborative project—“Photovoltaic (PV) based grid-interactive and off-grid electricity system”—with Indian Institute of Technology (IIT), Delhi, India and IIT, Bhubaneswar, India.

*When I am forgotten, as I shall be,*

*And sleep in dull cold marble,*

\* \* \* \*

*Say, I taught thee.*

William Shakespeare

I wish to thank Prof. Jarmo Partanen for giving me a PhD position at LUT in 2015 and for making important inputs into the writing of the dissertation. I am grateful to Prof. Chris Develder, Ghent University, for introducing me to the world of mathematical optimization and especially for showing me how to think about problems. Tero Kaipia acted as my second supervisor for two years and gave me excellent guidance and suggestions. He was always approachable and ready to listen to my ideas and improve them. I am very grateful for his warm support and useful feedback. Prof. Lassi Roininen kindly spent an afternoon with me trying to understand the implications of the Shapley value and to prove important concepts relevant to the dissertation, and I am very thankful to him for his valuable efforts. I continue to take inspiration from Prof. Tuomo Kassi and his keen desire to learn, which was apparent during a course we did together. Thanks also to my pre-examiners Prof. Matti Lehtonen and Prof. Ari Pouttu for readily and kindly reviewing my dissertation.

*I'm not the smartest fellow in the world, but I can sure pick smart colleagues.*

Franklin D. Roosevelt

*Kiitos*, my colleague and friend Nadezda Belonogova, for patiently listening to problems, questions, and stories from not only my dissertation but also my life. I am very thankful to my room-mates Jouni Haapaniemi and Juha Haakana for their smiles, little jokes, and chatter that made the workplace very warm and welcoming. Thanks also to Janne Karppanen and Ville Tikka who were always happy to help me every time I was stuck with a problem, usually related to Linux or data. And *kiitos paljon* to other colleagues and friends—Prof. Jukka Lassila, Prof. Samuli Honkapuro, Gonzalo Mendes, Aleksei Mashlakov, Evgenia Vanadzina, and Salla Annala—who made the lab a cheerful and fruitful place to work. A huge thank you to Prof. Pedro Nardelli for trusting me and offering me a position as a researcher. Piipa Virkki, Päivi Nuutinen, Marika Hyrylä, Sari Damsten, and Saara Merritt really eased my working life in LUT, for which I am very grateful. I also thank the cordiality and friendliness of Matthias Strobbe and Kevin Mets in Ghent.

*A friend loves you for your intelligence, a mistress for your charm, but your family's love is unreasoning; you were born into it and are of its flesh and blood.*

André Maurois

My parents—Amma, Achan, Aai, and Baba—physically reside in a far away land but have had immeasurable impacts with their constant spiritual presence and encouragement. My pesky brothers—Anup and Sushrut—annoyed and encouraged me at the same time, as is their wont, and I am thankful to them for being around. Pinku-tai and Rajesh-dada always look out for me, for which I am ever grateful. Thanks also to Anitha, my sister-in-law. And special thanks to my god-daughter Swara whose laughter and games have sparked immense joy and happiness, and to my niece Anvita who has also been a wonderful de-stresser.

*By all means marry; if you get a good wife, you'll become happy; if you get a bad one, you'll become a philosopher.*

Socrates

Nothing that I can say about my wife Amrita Karnik's role in this dissertation would be sufficient. Life is not life and research is not research without her luminous presence. And indeed, this whole new adventure would not have begun but for her suggestion to do a masters in renewable energy technology; this dissertation is as much her vision as mine. She has been my willing sounding board at all junctures. But, more than anything else, special thanks for all the wondering and the wandering and all the pondering and the pandering.

*Friendship! mysterious cement of the soul,*

*Sweet'ner of life, and solder of society.*

Robert Blair

There was never a dull time with Rahul Kapoor around, whether it be sports, arguments, kayaking trips, or other adventures, and for this and much more, I am always grateful. *Iso kiitos* to Santeri Pöyhönen and Viktoriia Kapustina for some wonderful conversations, games, bike repairs, and happy times. And thank you, Mariana Carvalho, Pedro Giornio, Sergio Oroczo, and Javier Orozco for your lovely gestures of kindness that eased and brightened many of my days. Numerous other friends from LUT—Salman Khan, Miguel Juamperez, Tatiana Minav, Jani Heikkinen, Michael Starichenko, Arvind Solanki, Victor Mukherjee, Ivan Kalyakin, Naresh Kumar, Gulshan Kundra, Tomi Johansson, Mehul Bansal, Samira Ranaei, Arash Hajikhani, Behnam Ghalamchi, Zahra Rasti, Rajshree Patel, Mehar Ullah, Nikita Uzhegov and Maria Uzhegova—also contributed to making my student and PhD life less stress-ful and enjoyable. I am grateful for all the fun!

Thanks also to my friends from India—Umesh, Ananth, Subba Rao, Smitha, Shamanth, and Krupa (and Saachi, Impana, and Siddhanth)—who have stood by me in good and bad times; life would not be the same without them. Janet Quadras has always been an enriching presence in my life and my PhD. I had some great discussions with Pallavi Jonnalagadda especially on statistics and literature. I am also thankful to Krishnan CMC, Sreedha, Prashant, Selva, Frederick, Lakshmi, and Akshay for their kindness and friendship during my year at Ghent. Nishant and Sanaa's warm hospitality and affection will always be treasured. A particularly special shout out to the former, Nishant, with whom I have had innumerable conversations about life, universe, science, PhDs, chess, and just about everything. Thank you for being a willing listener to my wandering thoughts and idle philosophizing on all things under the sun and for pitching in with so many fantastic reflections of your own. Lets keep the ideas flowing!

*"Free software" is a matter of liberty, of freedom, not price. To understand the concept, you should think of "free" as in "free speech," not as in "free beer".*

The Free Software Foundation

I continue to be amazed at the free and open source software (FOSS) community who unselfishly do so much excellent work for everyone to use with complete freedom. My dissertation would not have been possible without the liberal use of fantastic software such as Lyx, LaTeX, LibreOffice, Firefox, Thunderbird, GNU Project, Ubuntu, Mate, Fedora, Clementine, GIMP, Zotero, Workrave, Calibre, and Variety; programming languages such as Python and Octave; and communities such as Wikipedia, StackOverflow, and StackExchange. Words are insufficient to express my gratitude to (and appreciation of) these torchbearers of all that is good about humankind.

*Linus Van Pelt: You know, Charlie Brown, they say we learn more from losing than from winning.*

*Charlie Brown: Then that must make me the smartest person in the world.*

Charles Schulz, Peanuts

Finally, I am deeply indebted to cartoonists Randall Munroe, Zach Weinersmith, Bill Watterson, Charles Schulz, Jorge Cham, Stephen Pastis, and Garry Trudeau whose comics enriched and relaxed my days with their incredible humor and amazing perspectives on science, logic, philosophy, and life.

Arun Narayanan  
October 25, 2019  
Lappeenranta, Finland

*To my wife Amrita Karnik,*

*“my north, my south, my east and west,  
my working week and my Sunday rest,  
my noon, my midnight, my talk, my song”*



*No problem can withstand the assault of sustained thinking.*

*Voltaire*

*It's a magical world, [...], ol' buddy...*

*Let's go exploring!*

*Bill Watterson*



# Contents

Abstract

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## List of appended publications

This thesis is based on the following (JUFO-level) refereed publications. The publishers have granted the rights to include them in this dissertation.

### Publication I

Narayanan, A., Mets, K., Strobbe, M., and Develder, C. (2019). Feasibility of 100% renewable energy-based electricity production for cities with storage and flexibility. *Renewable Energy*, 134(4), pp. 698–709.

### Publication II

Narayanan, A., Kaipia, T., and Partanen, J. (2016). Economic benefits of photovoltaic-based systems for residential customers participating in open electricity markets. In: *PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2016 IEEE*, pp. 1–6. Ljubljana, Slovenia: IEEE.

### Publication III

Narayanan, A., Kaipia, T., and Partanen, J. (2017). Interruption reduction using battery energy storage systems in secondary substations. In: *PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2017 IEEE*, pp. 1–6. Torino, Italy: IEEE.

### Publication IV

Narayanan, A., Haapaniemi, J., Kaipia, T., and Partanen, J. (2018). Economic impacts of power-based tariffs on peer-to-peer electricity exchange in community microgrids. In: *European Energy Market (EEM), 2018 15th International Conference on the*, pp. 1–5. Lodz, Poland: IEEE.

The author is the principal author and investigator in all the papers. In this dissertation, the publications are referred to as **Publication I**, **Publication II**, **Publication III**, and **Publication IV**, respectively. Reprints of each publication are included at the end of this dissertation.

Additionally, the original work presented in Chapter 4 of the dissertation has been submitted to IEEE Transactions on Smart Grids (Narayanan, A. and Partanen, J. (2019). Profit allocation methodology for co-operative energy exchange in community microgrids, *IEEE Transactions on Smart Grids*, Submitted).

Other publications by the author are not listed in the dissertation.



## Nomenclature

### Symbols

$\alpha$	shifted load fractions	-
$b_i$	binary decision variables to decide whether load will be met ( $b_i = 1$ ) or not ( $b_i = 0$ )	-
$B_t$	battery energy storage system (BESS) capacity at time $t$	kWh
$B_{t-1}$	BESS capacity at time $t - 1$	kWh
$B_\Delta$	$B_t - B_{t-1}$	kWh
$c$	Number of consumers in a community microgrid	-
$C_b$	cost of BESS energy	monetary unit/kWh
$C_{capecx}$	capital expenditure	monetary unit/kW
$C_{custij}$	costs to the $j^{\text{th}}$ customer in the $i^{\text{th}}$ microgrid	monetary unit
$C_{D,m}$	monthly fee to DSO	€
$C_{D,e}$	electricity usage fee payable to the distribution system operator (DSO)	€/kWh
$C_{DSOp}$	costs to the $p^{\text{th}}$ DSO	monetary unit
$C_{efficiency}$	costs required to be paid to the regulator by DSO for not meeting efficiency targets	monetary unit
$C_{equip}$	costs paid for purchasing equipment	monetary unit
$C_g$	cost to purchase $P_g$	monetary unit/kW
$C_{grid}$	costs paid by the customer to the electricity authorities	monetary unit

$C_{inst}$	costs paid for installing equipment	monetary unit
$C_{main}$	costs paid for maintaining equipment	monetary unit
$C_{pv}$	cost of solar (PV) energy	monetary unit/kWh
$C_{planning}$	expenditure by DSO on planning the network	monetary unit
$C_{purchase}$	electricity purchase costs of retailer	monetary unit/kWh
$C_{quality}$	costs required to be paid to the regulator by DSO for not meeting quality targets	monetary unit
$C_{reliability}$	costs required to be paid to the regulator by DSO for not meeting reliability targets	monetary unit
$C_{ret_{kl}}$	costs to the $l^{\text{th}}$ retailer in the $k^{\text{th}}$ microgrid	monetary unit
$C_{risk}$	cost of the risks to retailer	monetary unit
$C_{S,a}$	agreement fee payable to the supplier	€/kWh
$C_{S,e}$	monthly fee payable to the supplier	€/kWh
$C_{spot}$	spot price payable to the supplier;	€/kWh
$C_T$	electricity tax	€/kWh
$C_w$	cost of wind energy	monetary unit/kWh
$\delta$	maximal fraction of the load that was shifted to later time steps	-
$E_g$	energy from grid	kWh
$E_{pv}$	energy from photovoltaic (PV) installation	kWh

---

$E_w$	energy produced from wind turbines	kWh
$E_{fl}$	flexible load energy	kWh
$E_{infl}$	inflexible load energy	kWh
$E_{g_{i,j}}$	electrical energy taken from the grid by the $j^{\text{th}}$ customer in the $i^{\text{th}}$ microgrid	kWh
$E_{l_{ij}}$	load energy of the $j^{\text{th}}$ customer in the $i^{\text{th}}$ microgrid	kWh
$E_{e,i}$	Excess (or deficit) electrical energy of a customer $i$	kWh
$E_l$	Total electricity consumption of a community microgrid	kWh
$E_{l,i}$	Electrical load of a customer $i$	kWh
$E_{l \setminus \{i\}}$	Total electricity consumed if a community microgrid without a customer $i$	kWh
$E_p$	Total electricity produced in a community microgrid	kWh
$E_{p,i}$	Electrical production of a customer $i$	kWh
$E_{p \setminus \{i\}}$	Total electricity produced by a coalition without a customer $i$	kWh
$E_{res_{ij}}$	RES energy produced by the $j^{\text{th}}$ customer in the $i^{\text{th}}$ microgrid	kWh
$\gamma_{frc}, \gamma_{reac}, \gamma_b, \gamma_{oth}$	binary variables for the corresponding microgrid service to be “switched on” or “switched off”	-
$I(t)$	irradiance	W/m <sup>2</sup>

$k_{ch}$	charge parameter of the BESS	-
$k_{dch}$	discharge parameters of the BESS	-
$k_i$	binary decision variables to model interruption ( $k_i = 1$ ) or no interruption ( $k_i = 0$ )	-
$m$	number of microgrids	-
$n$	Number of residential customers in a community microgrid	—
$n_i$	number of customers in $i^{\text{th}}$ microgrid	-
$N$	Total number of (finite) players in a game; also the grand coalition	-
$N_j$	total number of customers at a location $j$	-
$p$	Number of prosumers in a community microgrid	-
$P_g$	power from grid	kW
$P_{g^{i,j}}$	power taken from the grid by the $j^{\text{th}}$ customer in the $i^{\text{th}}$ microgrid	kW
$P_l$	load power	kW
$P_{l_{ij}}$	power demand of the $j^{\text{th}}$ customer in the $i^{\text{th}}$ microgrid	kW
$P_{res_{ij}}$	RES power produced by the $j^{\text{th}}$ customer in the $i^{\text{th}}$ microgrid	kW
$\phi_i$	Shapley value of a player $i$	-
$r$	annual outage time for a location $j$	-
$R$	revenue obtained by a microgrid through various microgrid services	monetary unit
$R_{der}$	renewable energy resource of distributed energy resource	kWh

---

$R_{DR}$	revenue obtained from any incentives offered for DR/DSM programs	monetary unit
$R_{DSO}$	revenue of DSO	monetary unit
$R_{cust}$	revenue of customer	monetary unit
$R_{exch}$	revenue obtained by selling (or sharing) electricity to (with) other customers	monetary unit
$R_{fre}$	microgrid revenues obtained from supplying frequency regulation services	monetary unit
$R_{misc}$	the revenue obtained from any miscellaneous activities	monetary unit
$R_{others}$	microgrid revenues from any other services	monetary unit
$R_{pb}$	microgrid revenues obtained from supplying power balancing services	monetary unit
$R_q$	revenue obtained by the $q^{\text{th}}$ microgrid	monetary unit
$R_{react}$	microgrid revenues obtained from supplying reactive power compensation services	monetary unit
$R_{revenue}$	revenue generated by the customer	monetary unit
$R_{sales}$	retailer revenue from electricity sales	monetary unit
$\rho_i$	Marginal contribution of a player $i$	-
$S$	Any coalition among the members of a game; $S \subset N$	-
$T_k$	total number of time steps without interruption	-
$t$	time step	-
$T$	total time considered	-

$v(N)$	Payoff of the grand coalition $N$	-
$v(S)$	Payoff of a coalition $S$	-
$W_s$	wind speed	-

## Abbreviations

AA	Adaptive-aggressive
AMR	Automatic meter reading
CAPEX	Capital expenditure
DER	Distributed energy resources
CDA	Continuous double auction
DG	Distributed generator
DR	Demand response
DSM	Demand-side management
DSO	Distribution system operator
EBT	Energy-based tariffs
EMS	Energy management system
EV	Electric vehicles
FIT	Feed-in-tariffs
LCOE	Levelized cost of electricity
LV	Low voltage
LVDC	Low voltage direct current
MBLP	Mixed binary linear programming
MILP	Mixed integer linear programming

MC	Marginal contribution
MV	Medium voltage
NRES	Non-renewable energy sources
OPEX	Operational expenditure
p2p	peer-to-peer
PBT	Power-based tariffs
PMU	Phasor measurement unit
PV	Photovoltaics
RES	Renewable energy sources
T & D	Transmission and distribution
TSO	Transmission system operator
VPP	Virtual power plant
ZI	Zero intelligence



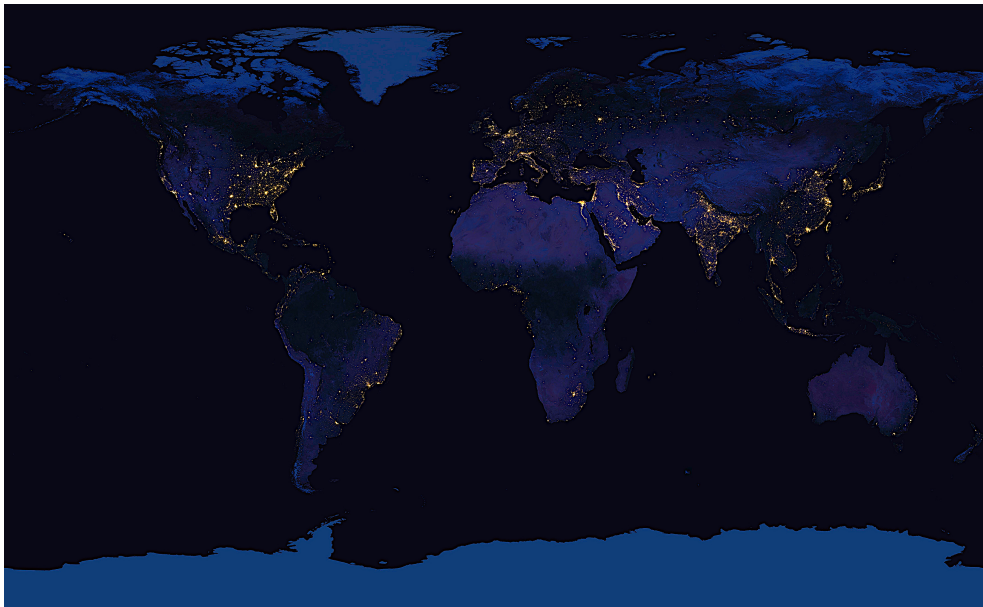
## **Part I**



# 1 Introduction

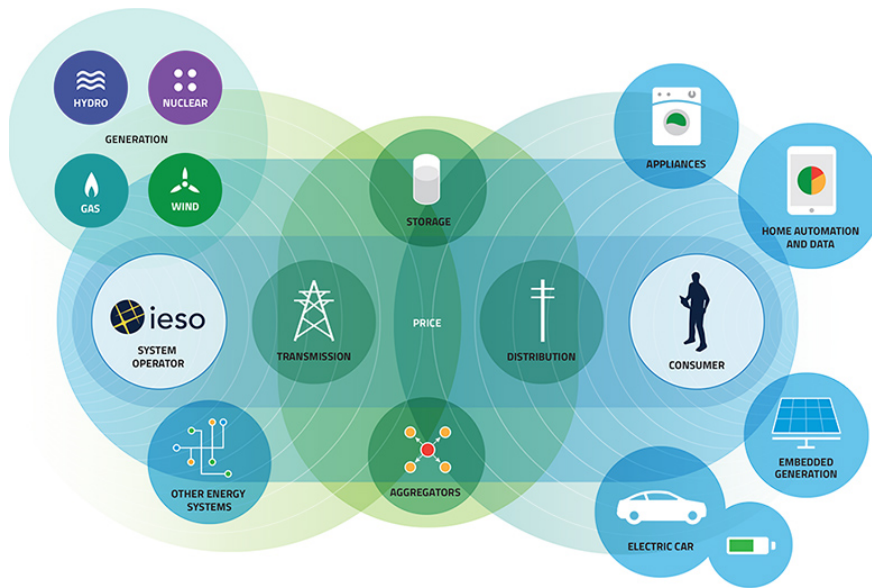
## 1.1 Background

**Electrification** is widely recognized as one of the greatest achievements of the 20<sup>th</sup> century, if not *the* greatest achievement (Constable and Somerville, 2003). By enabling technological progress and driving innovation, electrification has made strong and wide-ranging economic, social, and cultural impacts across the world. Electrification promotes industrial output and economic growth and is a necessary condition for reducing global poverty (Figure 1.1). Moreover, the availability of electricity influences numerous socio-economic factors, ranging from health to education (World Bank, 2017).



**Figure 1.1:** The impact of electrification: electrification has literally and figuratively *brightened* the world (Picture Credit: NASA Earth Observatory (2016)).

Historically, electrical power systems have focused on centralized production, transmission, and distribution of electricity. The traditional electricity grid is designed and constructed with a “top-down” architecture where large centralized power plants supply electricity via transmission and distribution networks to passive consumers (Mullally and Byrne, 2015). This approach has been remarkably successful in ensuring reliable, efficient, and low-cost electric power supply across large distances and diverse landscapes (Allan et al., 2015). However, in the last decade, this classical unidirectional electrification model has been re-examined after facing challenges from new drivers for change, primarily the necessity to counter threats from climate change and industrial pollution and to create a clean environment in a healthy and habitable planet, and secondarily, the huge increase in electricity demand and the formation of electricity markets (Farid et al., 2016).

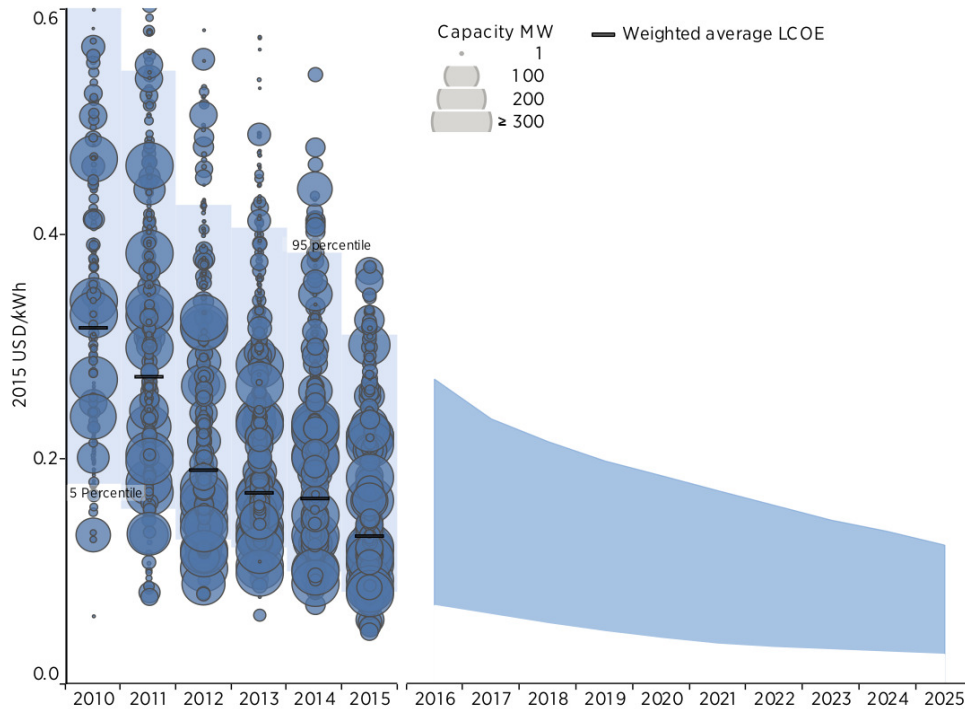


**Figure 1.2:** Small-scale renewable-energy-based distributed energy resources (DERs), such as distributed generators, storage devices, and appliances, interacting with centralized energy resources such as large electricity production plants (Source: Independent Electricity System Operator (IESO) (2018)).

Climate change and environmental pollution are major global challenges of the 21<sup>st</sup> century, threatening to destroy the natural world and human existence in the long term, while endangering human health, well-being, and mortality in the short term (Pearce, 1996; Remoundou and Koundouri, 2009). Hence, drastic and immediate remedial actions are required to mitigate their repercussions (United Nations, 2016). Governments, industries, and researchers are making enormous research and development efforts to promote the development and utilization of clean, sustainable, and renewable energy sources (RES) and technologies, such as solar, wind, biomass, or hydropower, that offer a more environment-friendly solution than traditional non-RES (NRES) such as fossil fuels like coal or oil. The European Union (EU), for example, has set ambitious targets for 2030—to reduce greenhouse gas emissions by 40% compared to 1990, to ensure a share of at least 27% of RES, and to achieve at least 27% energy savings compared to business-as-usual scenarios (European Council, 2014).

In particular, there have been significant technological and economic advancements in the development and utilization of small-scale renewable-energy-based distributed energy resources (DERs) such as distributed generators (DGs, e.g., small hydro, biomass, biogas, solar power, wind power, and geothermal power); battery energy storage systems (BESS); and eco-friendly controllable appliances (Figure 1.2<sup>1</sup>). Small-scale DERs can be installed locally; for example, photovoltaic (PV) panels can be installed on the rooftops of buildings (and potentially walls and windows as well), and their electricity production can be supported by locally installed BESS (Cuce, 2016). DER systems have the benefits of being decentralized, independent, flexible,

<sup>1</sup>Copyright © 2017 Independent Electricity System Operator, all rights reserved. This information is subject to the general terms of use set out in the IESO's website ([www.ieso.ca](http://www.ieso.ca)).



**Figure 1.3:** Global utility-scale weight average levelized cost of energy for solar energy from 2010–2025 (Source: Copyright © International Renewable Energy Agency (IRENA) (2016)).

modular, and close to the load. Further, sustainable local electricity production with renewable-energy-based DERs is beneficial to smaller communities (Pueyo et al., 2013); for example, electrification can be achieved in areas with limited or no access to the grid, thereby potentially revolutionizing small economies and electricity-deficit areas (World Bank, 2017).

These benefits have been further boosted in recent years by the tremendous decrease in the cost of renewable-energy-based DERs, especially PV systems. Figure 1.3 shows the capacity weighted average levelized cost of energy (LCOE<sup>2</sup>) range for utility-scale PV projects. The past trends from 2010–2015 and the projection toward 2025 indicate a continuously decreasing tendency. The LCOE decreased by  $\approx 58\%$  from 2010–2015 and is expected to decrease by another  $\approx 59\%$  (from 0.13–0.055 US\$/kWh) until 2025 (International Renewable Energy Agency (IRENA), 2016). Similarly, the cost of wind production and BESS have also been decreasing steadily (International Renewable Energy Agency (IRENA), 2016). Moreover, the field of power electronics devices, which deals with the conversion and control of electrical power and are integral to power systems, is undergoing a “second revolution” with improved efficiencies, faster speeds, and lower costs (Iacopi et al., 2015).

<sup>2</sup>The LCOE is essentially based on a simple equation—the cost to build and operate a production asset over its lifetime divided by its total energy output over that lifetime (monetary unit/kWh)—and considers the initial capital, discount rate, and the costs of continuous operation, fuel, and maintenance. The LCOE thus represents the full life-cycle costs of a generating plant per unit of electricity (Ueckerdt et al., 2013).

The increasing proliferation of renewable-energy-based DERs; the benefits of sustainable local electricity production; the introduction of open electricity markets and competitive electricity trading; and the urgent need to upgrade and transform the electric grid to meet modern demands and challenges have strongly encouraged recent research efforts into **renewable-energy-based microgrids**.

## 1.2 Renewable-energy-based microgrids

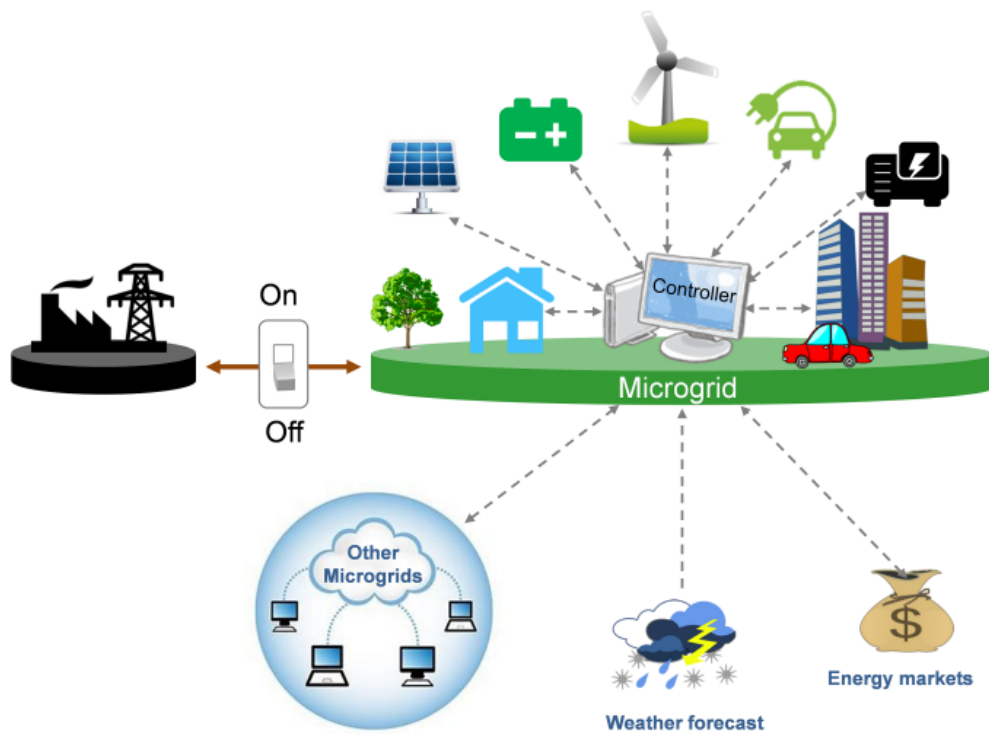
Around 2001, Lasseter proposed the microgrid concept as a new paradigm for defining the operation of DGs (Lasseter, 2001, 2002; Lasseter and Paigi, 2004). Microgrids were envisaged as a solution to integrate small-scale DGs and DERs ( $< 50$  kW) whose low voltages at the interface and other characteristics were leading to a new class of problems. Lasseter gave a fundamental definition of a microgrid as follows: “*a microgrid is a cluster of micro-sources, storage systems and loads which presents itself to the grid as a single entity that can respond to central control signals*” (Lasseter, 2001). The essence of this microgrid concept (Figure 1.4) was the idea of a flexible, controllable interface between the microgrid and the external power system, which essentially isolates the two sides electrically and yet connects them economically (Lasseter, 2001).

Today, this basic definition has expanded to include both smaller and larger grid sizes so that essentially, *any electrical network that comprises a producer and a consumer can be considered a microgrid*. A solar-powered calculator is, for example, a microgrid, whereas a BESS is not a microgrid because it acts as either a producer or a consumer. Moreover, depending on the applications and operational areas, the definition and applicability of the term microgrid are continuously evolving. Microgrids of the size and scale of small devices, e.g., a solar-powered calculator or a laptop, are often referred to as *picogrids* or *nanogrids* (Chandan et al., 2017; Nordman et al., 2012). A residential house with a rooftop PV installation is also often called a microgrid (a *small* microgrid), although some literatures refer to such houses as *nanogrids*. In general, the term microgrid (Figure 1.4) is most commonly used for a group of residential houses connected to the external grid through a transformer—with the possibility to disconnect from the grid—and this is the meaning used in this dissertation<sup>3</sup>. Irrespective of the sizes, all microgrids typically consist of one or more of the following components—energy resources (centralized or decentralized, e.g., see Figure 1.5<sup>4</sup>), loads, smart power electronic devices, a master controller, and protective devices as well as communication, control, and automation systems (Parhizi et al., 2015).

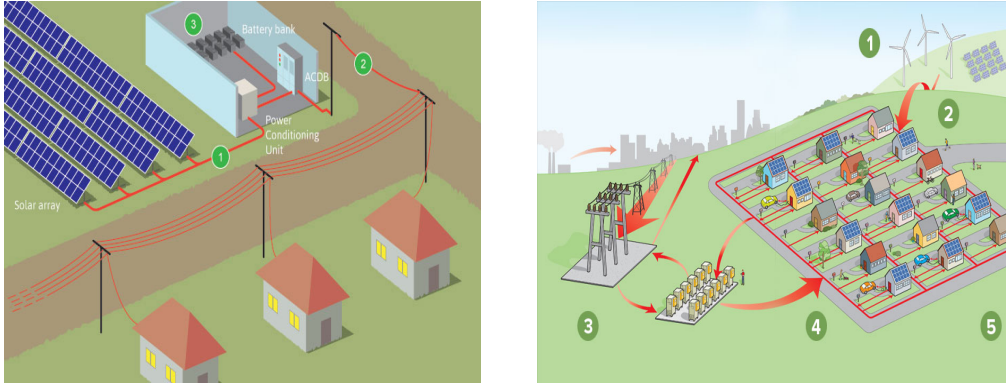
The possibility for microgrids to operate in both grid-interactive and islanded modes makes the electrical network more flexible and intelligent and offers higher resilience and reliability against storms and outages (Planas et al., 2015). In the grid-interactive (or grid-connected) mode, the microgrid maintains supply and demand power balance by interacting with the main grid, for example, by purchasing power. The microgrid can also trade excess power generated

<sup>3</sup>Note that “large” microgrids ( $> 10$  kW) are referred to as *minigrids* in several countries especially in South East Asia and Africa (Moner-Girona et al., 2016).

<sup>4</sup>(a) Copyright © 2015 Krishi Technologies Ltd. All Rights Reserved. (b) Copyright © 2019 Sierra Club. All Rights Reserved.



**Figure 1.4:** A renewable-energy-based microgrid; a central controller manages a group of interconnected loads, energy storage systems, and production systems within a clearly defined boundary. The controller also supervises interactions with the main grid as well as other microgrids, based on decisions that are made using information about current scenarios, forecasts, and electricity markets (Source: Berkeley Lab (2018)).



(a) A microgrid with centralized energy resources (Source: Krishi Technologies India Pvt. Ltd. (2018)).

(b) A microgrid with decentralized energy resources (Source: Ferris (2014)).

**Figure 1.5:** Microgrids with centralized energy resources and distributed energy resources such as solar panels, battery banks, and power electronics devices.

in the microgrid and provide ancillary services. In the islanded (or offgrid or stand-alone) mode, the primary aim is to act independently and ensure that disturbances in the main grid do not affect the power supply (Tsikalakis and Hatziaargyriou, 2008). The real and reactive power generated within the microgrid must now be balanced with the local load demands. A microgrid may transition between these two modes due to faults and outages, power quality issues, or for economical reasons (Olivares et al., 2014). Microgrids thus have high potential to enable smooth transitions from the existing centralized architecture to a flexible, hybrid architecture that exploits scalable dispersed solutions.

Microgrids are especially suitable and beneficial for the massive integration of DGs and DERs because they enable technical problems to be solved in a decentralized manner, reducing the need for complex central co-ordination. (Olivares et al., 2014). Microgrids offer significant benefits to the customers and utility grid as follows (Basu et al., 2011; Madureira and Peças Lopes, 2012; Planas et al., 2015; Parhizi et al., 2015):

1. Improved reliability and resilience due to the ability to disconnect from the main grid (islanded or offgrid mode);
2. Higher power quality by managing local loads;
3. Reductions in carbon emissions by enabling the utilization of diverse RES;
4. Economic operations and system loss reductions by reductions in transmission and distribution (T&D) costs;
5. Deferral of investment in distribution network upgradation by reducing power flows in feeders;
6. Energy efficiency by enabling quick responses to real-time market prices; and

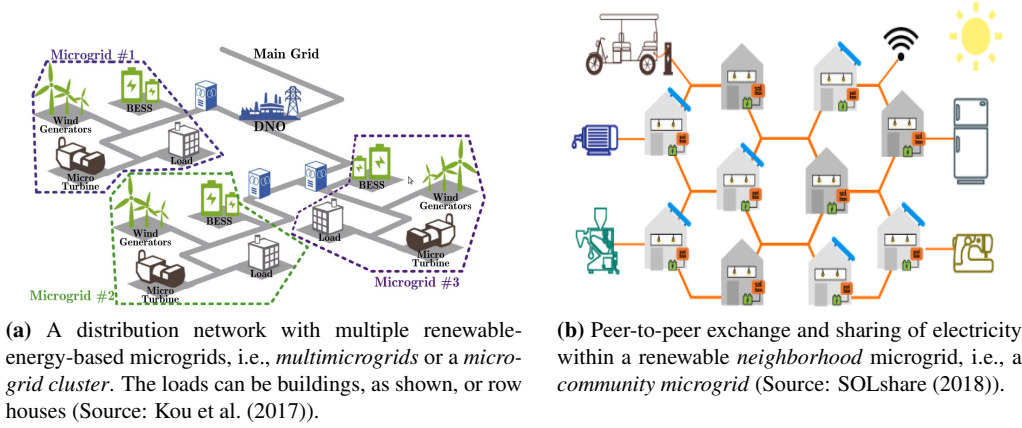
7. Increased revenues due to possibilities to exploit excess energy for new ancillary markets.

At the same time, the seamless deployment of microgrids faces several technical and economic challenges as follows (Rocabert et al., 2012; Olivares et al., 2014; Palizban et al., 2014a,b; Gamarra and Guerrero, 2015; Palizban and Kauhaniemi, 2015; Bouzid et al., 2015; Parhizi et al., 2015; Venkatraman and Khaitan, 2015):

1. Planning issues such as selection of power production mix, sizing, siting, and economic load dispatch;
2. Optimization of co-ordinated control of microgrids to manage instantaneous active and reactive power balances, energy balances, power flow etc.;
3. Upgradation of protection concepts, technologies, and implementations, especially by leveraging modern communication capabilities;
4. Development of communication and security paradigms, technologies, and methodologies specifically applicable to microgrids;
5. Economic optimization of microgrid resources;
6. Island-mode detection, transition to island mode, and stable islanded operation of microgrids; and
7. Management of microgrids in the market environment.

The reliability, resilience, operation, and economics of microgrids can be enhanced further by interconnecting them to form a cluster. Such a microgrid interconnection is often referred to as *multimicrogrids* or *microgrid clusters* (Figure 1.6a) (Saleh et al., 2015; Che et al., 2015, 2017). The main objective to form such microgrid clusters is to reduce interactions with the utility and promote grid independence. In some cases, residential customers within a neighborhood microgrid exchange electricity with each other. Such a microgrid with internal peer-to-peer (p2p) electricity exchanges is typically called a *community microgrid* (Figure 1.6b). Since the extra electricity resources of any customer are shared and not wasted, community microgrids also increase grid independence. Microgrid clusters and community microgrids have been proposed as a way to reduce losses, improve efficiency, decrease costs, and move toward a “net-zero-energy” society (Chakraborty et al., 2015). Since community microgrids may themselves comprise many residential microgrids exchanging electricity, they are also a type of microgrid cluster. In this dissertation, the term “community microgrid” refers to a neighborhood of residential houses, which may or may not themselves be microgrids, that perform p2p electricity exchange. Microgrid clusters refer to a group of neighborhood microgrids interconnected to form a cluster. Both these concepts are further elaborated in Chapter 3.

Small autonomous microgrids with NRES-based production have existed since the beginning of electrification. Today, the demonstrated technical and economical feasibility of renewable-energy-based DERs have made it possible to integrate them into microgrids (Olivares et al., 2014). The efficient integration of such *renewable-energy-based microgrids* into the centralized electricity grid is a highly researched pathway to realizing sustainable energy goals (Lasseter and Paigi, 2004; Hatziaargyriou et al., 2007; Olivares et al., 2014; Planas et al., 2015). Further,



**Figure 1.6:** Simplified illustrations of a microgrid cluster and a community microgrid.

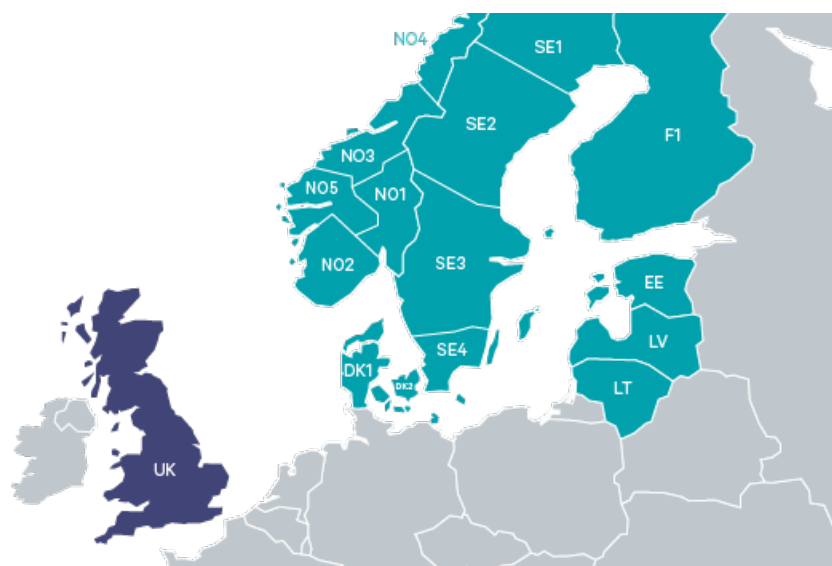
microgrids and their associated problems, such as energy management, control, stability, protection, reliability, and communication, have been extensively discussed in recent years (Ghareeb et al., 2013; Unamuno and Barrena, 2015b,a; Bouzid et al., 2015; Parhizi et al., 2015; Gamarra and Guerrero, 2015; Hare et al., 2016; Khan et al., 2016).

At the same time, another recent development has attracted the attention of electricity distribution researchers—the formation of **open competitive electricity markets** whose success is best exemplified by the **Nordic electricity market** model.

### 1.3 Overview of the Nordic electricity market

Before 1990, the electricity supply industry consisted of vertically integrated monopolies, comprising *privately owned utilities with public regulation* (e.g., in the US); *publicly owned utilities*, either as centralized state ownership (e.g., in France or India) or decentralized local ownership (e.g., in Scandinavia); or some mixture of both (e.g., in Germany or Spain) (Serrallés, 2006). The transition from regulated monopolies to transparent competitive fair electricity markets began in the late 1980s. In 1989, the United Kingdom became the first European country to begin the process of liberalization (Electricity Act of 1989) (Serrallés, 2006). Subsequently, in the 1990s, other countries in Europe and elsewhere began to deregulate their electricity sectors, unbundle electricity production from transmission and distribution, and open the sector to free enterprise and open competition (Newbery, 2013).

Different countries have pursued different paths toward the liberalization of the electricity sector, and among them, New Zealand, parts of Australia, the Nordic countries, Ontario, and Brazil have had reasonably successful experiences with the adoption of many key components of the “textbook model” (Joskow, 2008). The first common, integrated, multinational electric power market in the world is the Nordic electricity market that began with the electricity reform in Norway in 1991, and it was soon followed by Sweden (1996), Finland (1997), and Denmark (2002) (Sioshansi and Pfaffenberger, 2006). Today, the Nordic electricity market—called the

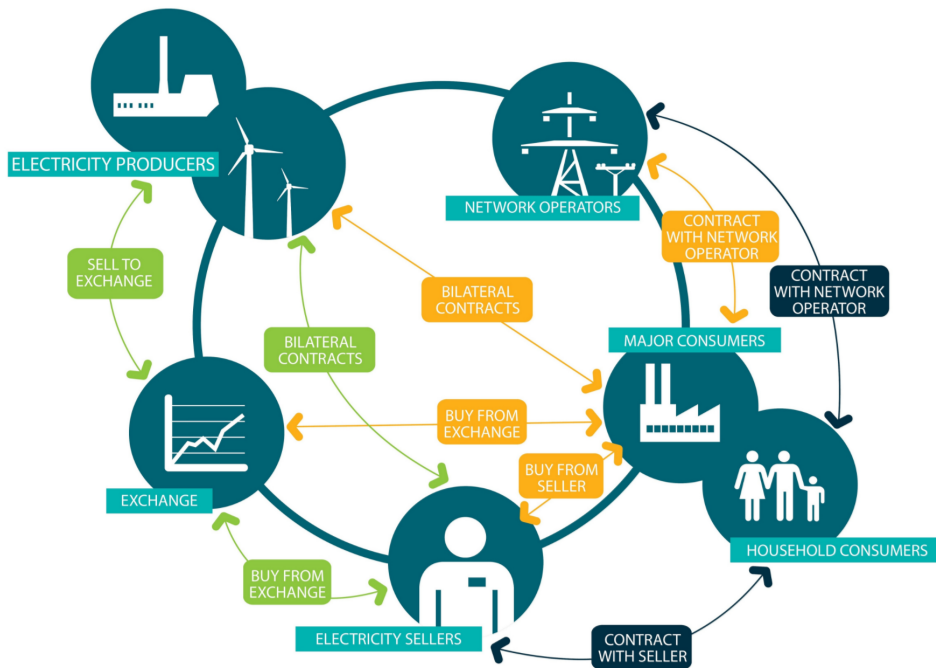


**Figure 1.7:** Countries participating in Nord Pool and the Nord Pool market's bidding areas, as of 2018. NO1–NO5: Norway; SE1–SE4: Sweden; F1: Finland; DK1–DK2: Denmark; EE: Estonia; LV: Latvia; LT: Lithuania; UK: United Kingdom (Source: Nord Pool (2018a)).

Nord Pool—is the largest electrical power market in Europe, and its operations have expanded to encompass the Baltic countries—Estonia, Lithuania, and Latvia—as well as other countries (Figure 1.7 (Nord Pool, 2018a)).

In Nord Pool, the major commercial stakeholders and actors are large-scale producers, distributors (transmission system operators (TSOs) and distribution system operators (DSOs)), suppliers or retailers, and traders and brokers. Today, more than 370 companies are responsible for power production in the Nordic and Baltic countries. Around 500 DSOs ensure that the power reaches the end user. Different countries have different regulations for the distributor. However, in general, every distributor has a monopoly over a certain geographical area; hence, they are highly regulated. For example, their maximum profit levels are usually fixed to maintain stable and reasonable prices. An end user has only one choice with regard to the TSO or DSO. Further, around 380 suppliers, also called retailers, buy power either through Nord Pool or directly from a producer and then resell it to small and medium-sized companies and households using different types of contracts such as fixed price contract, market price contract, etc. An end user can choose from a range of suppliers but cannot choose a supplier from another country as of today. In addition, traders may own the power while the trading process is ongoing so that a trader may make producer–retailer or retailer–retailer power transactions. Finally, brokers may act as intermediaries, playing the same role as estate agents in a property market; they do not own power but connect actors who are willing to trade with each other (Nord Pool, 2018c). Trading in a typical electricity market like Nord Pool is shown in Figure 1.8.

Nord Pool is enacted in each country by national laws, and governmental authorities act in supervisory and regulatory roles to ensure that the industry operates in compliance (Ministry of

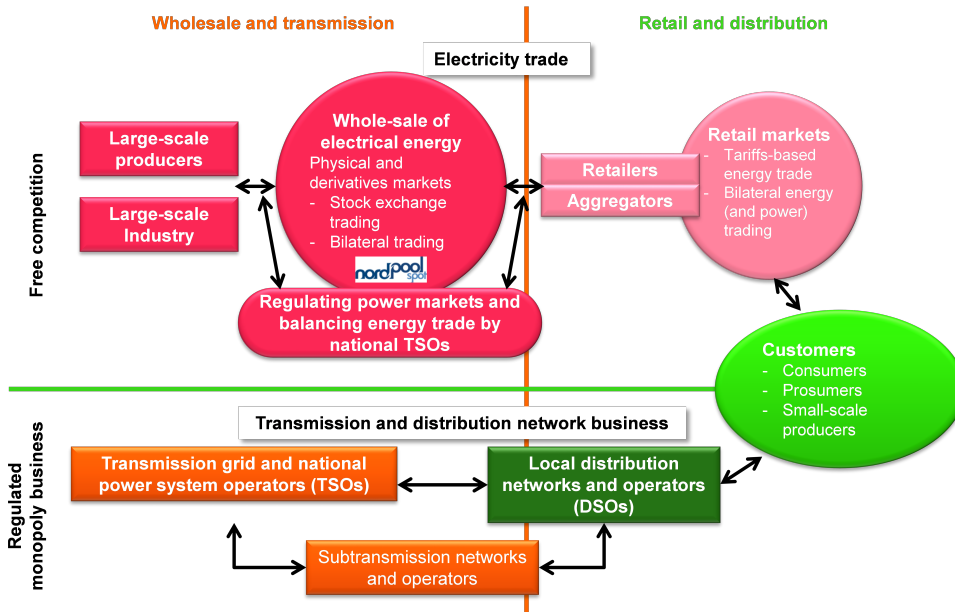


**Figure 1.8:** Trading in a typical electricity market (Source: Elering AS (2018)).

Trade and Industry, 2013). For example, Finland enacted new electricity market legislation in 1995 to deregulate the electricity industry and enable free enterprise and external competition, and Finland also became a part of Nord Pool (Ministry of Trade and Industry, Finland, 1995). In Finland today, network business is a regulated monopoly, whereas DSOs are owned by private parties or local communities, and not the state. The TSO Fingrid—as well as some of the largest producers—are owned jointly by the state, energy companies, and private investors. Customers can freely choose their supplier from mostly private companies. Figure 1.9 illustrates the Finnish electricity market model.

The Nord Pool market is divided into two products—physical and financial. The physical products of the power exchange are traded to ensure the physical delivery of electricity. Financial products such as derivatives are used to adjust the risks, for example, by hedging, to meet the selected organization strategy.

The main arena for trading power physically is a day-ahead market called Elspot. Sellers and buyers make contracts for delivering electric power the following day. The deadline for submitting power bids for delivery the following day is 12:00 CET of the current day. The trading system calculates the *hourly prices*—the intersection of the sell and buy curves (Figure 1.10a)—and it is announced to the market at 12:42 CET or later. Subsequently, the trades are settled. From 00:00 CET the next day, power contracts are physically delivered (i.e., the agreed power is provided to the buyer by the seller) every hour in accordance with the contracts (Nord Pool, 2018b). Note that the *time resolution* in the Elspot market is *hourly*. In order to handle con-



**Figure 1.9:** Principled illustration of the electricity market model in Finland (Source: adapted by Kaipia (2018) from original illustration by Reima Päivinen, Fingrid, 2012).

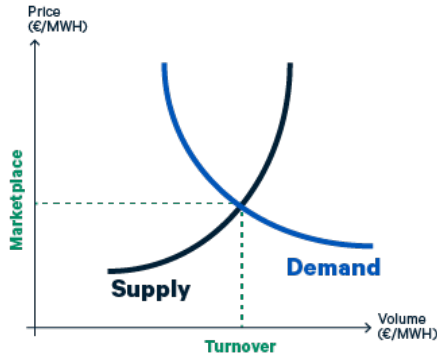
gestions in the electricity grid, different prices—called *area prices*—are allocated for different bidding areas. Simultaneously, an unconstrained market clearing reference price—called the *system price*—is calculated without any congestion restrictions by setting capacities to infinity (Figure 1.10b).

In addition, Nord Pool offers an intraday continuous market—Elbas—to supplement the day-ahead market and secure the necessary balance between supply and demand. The majority of the volume is handled on the Elspot day-ahead market. The intraday market is used to enable volumes to be traded close to real time to ensure real-time power balance. The capacities available for Elbas are published at 14:00 CET every day. Trading takes place continuously until one hour before delivery. The best prices—highest buy price and lowest sell price—are set as the Elbas price based on a first-come, first-served principle.

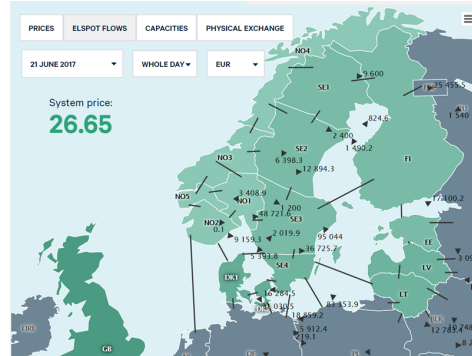
The Nordic electricity market has additional trading mechanisms, technicalities, and schemes, which will be elaborated, as and when relevant, in the remaining chapters.

## 1.4 Motivation

The deployment of renewable-energy-based microgrids in the electrical power system has been a highly active research area since around 2002. The concept and promise of microgrids have been extensively discussed in the literature (Hirsch et al., 2018). However, at the time when this dissertation work began in 2015, most of the work on microgrids had focused on fairly small details of highly specific solutions, whereas wider perspectives of systems engineering questions



(a) Intersection of the sell and buy curves to determine hourly Elspot prices.



(b) System price and flow of power between bidding areas for a day in 2017; when calculating the system price, flows are considered either as import/sales or as export/purchase orders.

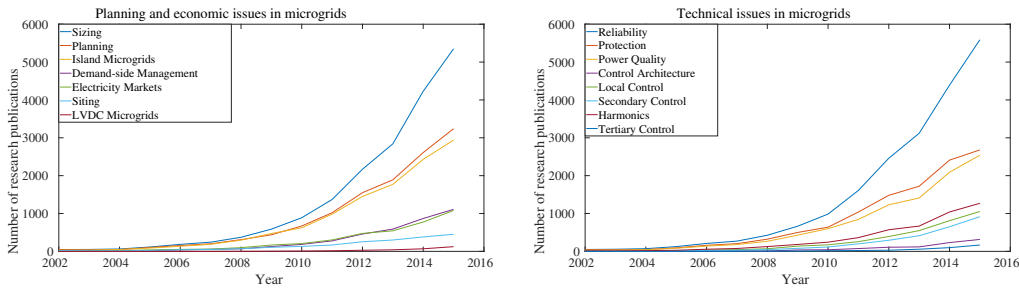
**Figure 1.10:** Elspot price formation and example system price with power flows between bidding areas (Source: Nord Pool (2018b)).

addressing global needs were only narrowly considered. Microgrids were a widely researched solution for various issues, ranging from energy efficiency improvement to the electrification of remote areas, but there were substantial differences in the extent to which these topics had been studied.

To compare research progress on important topics in the development of microgrid technologies until 2016, we first determined the number of research publications on microgrids from 2002 using relevant keywords on Google Scholar (Figure 1.11). Figure 1.11a shows that most of the researches till 2016 focused either on conceptual studies such as sizing and planning or on achieving reliability by islanding or otherwise. Siting and low voltage direct current (LVDC) networks were considerably less researched. In particular, researches into the integration of microgrids into electricity markets were comparatively recent and fewer in number (as of 2016). In Figure 1.11b, the technical aspects of microgrids, such as control paradigms, protection, and reliability, are compared. Local control and energy management systems (EMSs) were highly researched topics until 2016, along with historically well-understood fields such as protection and reliability. In contrast, studies into the tertiary control of microgrids were comparatively limited; for example, we could not find many survey literatures on microgrid clusters connected to the medium-voltage network. Further, community microgrids in which small microgrids, such as residential houses, interact and support each other were just beginning to receive serious research attention.

Thus, most published researches dealt with specialized microgrid applications under certain idealized conditions and assumptions. There were two especially prominent lacunae in the literature until 2016. First, many studies had examined the collaboration between small microgrids at the distribution level (Saad et al., 2012). However, researches into the co-operation between large interconnected microgrids at the transmission level and the aggregation of resources were relatively few. Moreover, collaborating microgrids were typically considered community-

owned and community-operated independent off-grid microgrids that excluded other potential stakeholders such as the DSO and the retailer. As a result, few studies had studied how multiple stakeholders—DSO, retailer, the society, and producers—could participate and involve themselves in the collaboration, for example, by aggregating internal microgrid resources.



(a) Quantitative evolution of research publications on planning and economic issues. (b) Quantitative evolution of research publications investigating technical issues.

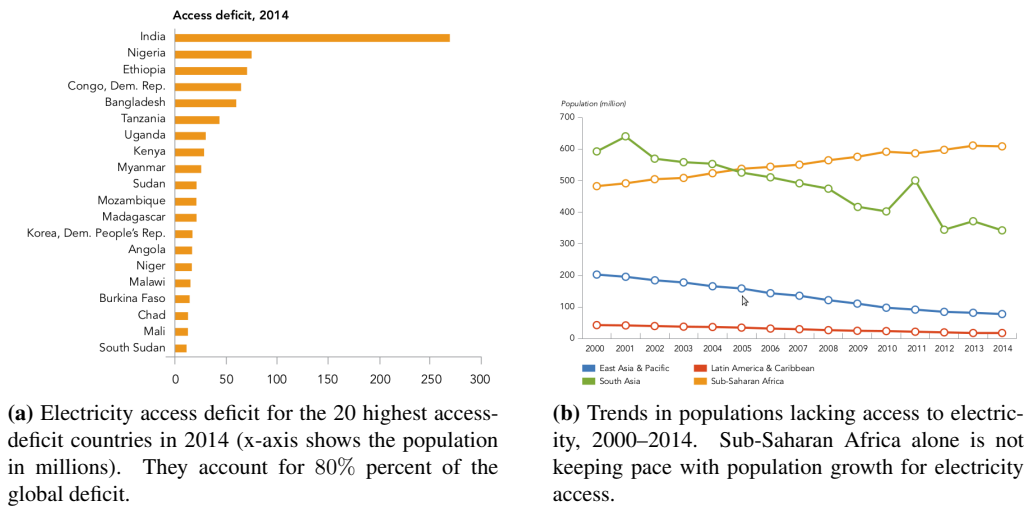
**Figure 1.11:** Trends in research publications on microgrid topics from 2002–March 31, 2016, obtained using searches on Google Scholar.

Second, there were relatively few studies on the integration of microgrids with electricity markets. Some studies had proposed conceptual frameworks and designs, but few had proposed workable solutions to the related technical and practical issues. The aggregation of microgrid resources for transacting with the external market, for example, selling ancillary services, was insufficiently explored. The researches so far had also neglected the impacts of such integration on all the relevant stakeholders in electricity distribution—the retailer who sells electricity, the DSO who delivers electricity, and the residential customers who use electricity. At the same time, the electricity market models also did not encourage the effective development of modern grids, especially renewable-energy-based microgrids, and innovative and interesting market models to boost the adoption of RES still had to be researched.

Besides shortcomings in theoretical advances, there were (and continue to be) significant barriers to successfully deploying microgrids in practice. In fact, specific practical implementations are very few even today (2018); for example, in the U.S. and in Asia, the share of operational, under development, and proposed (RES and NRES-based) microgrids is 42% of the market, but Europe trails with 11%, Latin America with just 4%, and the Middle East and Africa with a mere 1% share of the market. Further, most of the microgrids are installed either in remote areas, college campuses, military installations, or industrial buildings (Hirsch et al., 2018). Practical implementations are few and mostly specialized. Microgrids have barely penetrated into utility distribution grids, residential neighborhoods, or cities, because their adoption has been hindered by several barriers such as legal and regulatory uncertainties, utility opposition, costs, etc.<sup>5</sup> (Fowlie et al., 2018).

Sustainable local electricity production by adopting and deploying renewable-energy-based microgrids is important not only for promoting sustainability but also for reducing energy poverty

<sup>5</sup>Nevertheless, microgrid adoption is expected to gather pace in the next decade.



**Figure 1.12:** Global status of access to electricity. (Source: International Energy Agency (IEA) and © World Bank (2017)).

(Yadoo and Cruickshank, 2012; Williams et al., 2015; Mandelli et al., 2016; Hubble and Ustun, 2018). As of 2014, more than 1 billion people were living without access to electricity, and most of them were living in small—often scattered—communities in sub-Saharan Africa and developing Asian countries (Figure 1.12) (World Bank, 2017). With renewable-energy-based microgrids, electrification can be achieved in such areas with limited or no access to the grid, thereby potentially revolutionizing small economies (World Bank, 2017). In particular, PV-BESS microgrid systems are relatively easy to install locally, making them a potential solution for supplying electricity to rural communities (Podmore et al., 2016). Governments can install PV-BESS microgrid systems in a centralized manner in rural communities, thereby reducing the impacts of investment costs on the community, while promoting economic development.

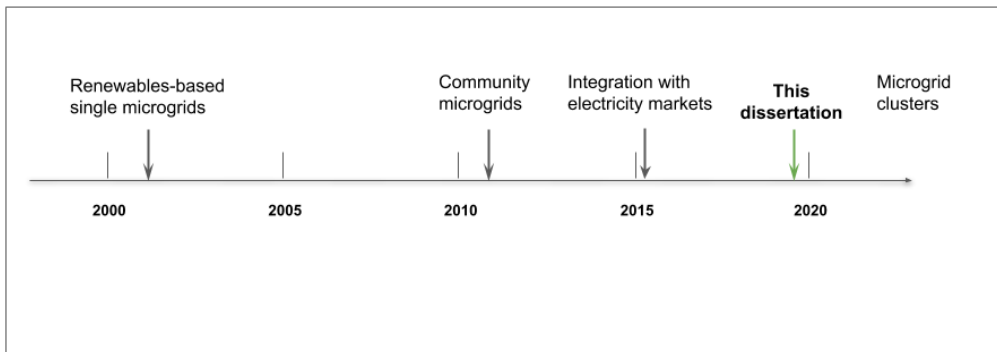
In summary, the interconnection of microgrids with each other and with electricity markets as well as the roles of all the stakeholders of an electricity network—the DSO, retailers, customers, society, etc.—needed further research. Moreover, many countries have unique environments and historically different electricity infrastructure development, which offer novel challenges and opportunities for innovations to enable smooth transitions to practically applicable renewable-energy-based electrification. PV-based microgrids have been established as a highly feasible technological concept as well as an increasingly economical choice for meeting the energy system development needs globally. Therefore, it was important to develop strong insights into the implementation of PV-based single and community microgrids.

This dissertation was also strongly motivated by social factors, especially the importance of increasing global electricity access and improving a community's energy independence, reliability, and security. PV-based microgrids have been proposed and discussed as an effective method to achieve these objectives. The methodologies, analyses, results, and discussions presented in this dissertation are small steps toward this larger goal of *promoting electrification*.

using RES to transform not only the environment but also people's lives.

## 1.5 Objectives of the dissertation

The main hypothesis for the research carried out in this dissertation is that *researches and developments in the control and utilization of renewable-energy-based microgrids, comprising small-scale distributed energy resources, can establish strong foundations for making radical shifts to sustainable electrification and improving electricity access to communities*. Figure 1.13 shows the progress in researches carried out over the last 20 years to test this hypothesis as well as the position of this dissertation in the microgrid research trends. As shown, the dissertation aims to try to fill the gap in the pathway from renewable-energy-based single microgrids to community microgrids to microgrid clusters, while enabling effective integration with the electricity market.



**Figure 1.13:** Microgrid research timeline over the last 20 years; this dissertation's position in the microgrid research trends is also marked.

First, broad dissertation objectives were set after taking into consideration the abovementioned hypothesis and the motivations discussed in Section 1.4, and the following main general problem was formulated:

*To develop methods for implementing single microgrids, community microgrids, and microgrid clusters in electricity distribution networks with the objective of allocating the resources of the microgrids to their stakeholders (e.g., customers, DSOs, and/or retailers), while considering*

1. *reasonable optimization criteria such as economic feasibility, fairness, efficiency, justice, social welfare, or their combination;*
2. *the perspectives (i.e., sub-objectives) of the different stakeholders;*
3. *different microgrid types, e.g., minigrids or multimicrogrids (large-scale), microgrids (neighborhood-scale or residential-household-scale), and nanogrids (equipment-scale); and*
4. *various systemic issues such as electrical grid interaction and independence, local electricity market designs, and external electricity market connections.*

This problem is extremely broad and solving it fully is beyond the scope of this dissertation<sup>6</sup>. Hence, the research problem was simplified to have the following objective—to *develop concepts and solution methodologies for implementing community microgrids and microgrid clusters with the objective of fairly allocating their combined resources to residential customers, retailers, and the DSO, considering local electricity market designs and external electricity market connections.*

Keeping in mind this objective, the following related sub-objectives were set and explored:

- *Developing methodologies to solve the sizing problem in single microgrid planning, which can be used to determine*
  1. *if it is feasible to supply single microgrids with 100% RES; and*
  2. *whether residential customers can economically benefit from installing PV-BESS microgrid systems;*
- *Developing methodologies to analyze whether DSOs can economically utilize BESS, or other DERs, in PV-BESS single microgrids;*
- *Mathematically formulating the problem of interconnecting and aggregating small microgrids with the objective of economically allocating its resources to residential customers, retailers, and the DSO;*
- *Developing methodologies to economically and fairly distribute the resources of a community microgrid to its customers, and*
- *Analyzing the benefits of community microgrids to customers with different electricity tariff designs.*

## 1.6 Scientific contributions

This dissertation makes the following scientific contributions:

1. Novel methodologies to cost-effectively size (or dimension) the DERs in a single microgrid are introduced for full loads, partial loads (i.e., load fractions), and flexible loads (i.e., shiftable loads). Further, these methodologies are used to investigate the feasibility of cost-effectively employing 100% RES and RES-BESS systems in single microgrids.
  - (a) The presented optimization models can be generally applied (or extended) to different types of microgrids.
  - (b) The partial-loads methodology can be especially valuable for planning partial access to electricity in electricity-deficit areas.
  - (c) The proposed two-dimensional generalized flexibility model can be used to analyze and exploit flexible resources in different microgrid systems to enable cost-optimum utilization of RES production.

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<sup>6</sup>Other allied technical aspects of microgrid implementation, such as challenges with communication, protection, electric lines, power electronics devices, etc., are also beyond the scope of the dissertation. They are being comprehensively investigated by other researchers across the world.

2. The sizing methodology is extended to investigate the long-term economic benefits obtained by residential customers installing PV-BESS microgrid systems and participating in the Nordic electricity market.
3. The economic potential for a DSO to utilize BESS for decreasing outages in LV microgrids is analyzed using an innovative mixed-integer linear programming-based model. This research demonstrates that DSOs have additional opportunities and motivations to use BESS to increase their profits and actively participate in the integration of renewable energy in microgrids.
4. A mathematical formulation is developed to model p2p electricity exchange in microgrid clusters considering the requirements, costs, and profitabilities of different stakeholders. Further, a potential solution design along with descriptions of the solution components that need to be constructed to fully solve this microgrid cluster problem is also presented.
5. A novel methodology to enable the fair allocation of profits obtained after co-operative p2p electricity exchange between the customers of a community microgrid is developed.
6. The impacts of another recently proposed electricity tariff design—power-based tariffs (PBTs)—on the electricity exchange between residential customers in a community microgrids are investigated.

## 1.7 Outline of the doctoral dissertation

This doctoral dissertation is organized into two parts. Part I introduces the research subject; discusses the questions, methodologies, and results described in four selected relevant publications; presents new concepts and methodologies; and discusses the significance and shortcomings of the presented methodologies and results. Part II is a compilation of the full text of the four most relevant research publications.

Part I is further divided into the following chapters.

**Chapter 2** discusses *the planning of microgrids* first from the perspective of residential customers and subsequently from that of DSOs. Methodologies to cost-optimally solve the selection and sizing problem of DERs in a microgrid are presented for full, partial, and flexible loads. These methodologies are applied to determine the cost-effectiveness of meeting the loads of a city-scale microgrid using 100% centralized RES. The chapter then focuses on smaller low-voltage residential microgrids, particularly addressing the question of whether a residential customer who installs PV-BESS systems (to form a microgrid) can benefit in the Nordic electricity market. Finally, the author's investigations into the manner in which DSOs can benefit from using BESS in a microgrid, specifically by applying them for decreasing outages, are presented.

**Chapter 3** first introduces the concepts, benefits, and challenges of implementing *community microgrids* in which residential households in a neighborhood exchange electricity. Subsequently, *multimicrogrids* or *microgrid clusters*, in which several community (typically low-voltage distribution) microgrids interact with each other and with the transmission system, are described. This chapter then states a general microgrid cluster problem; proposes a general

mathematical formulation to analytically state the problem; and presents a solution methodology design to devise techniques to approach the problem.

**Chapter 4** considers the question of implementing electricity exchanges within a community microgrid such that the electricity exchange is fair to all participating customers. A novel Shapley value-based solution to this problem is presented, and its possibilities, benefits, and limitations are discussed. This chapter also discusses the implications and impacts of two market pricing mechanisms—one based on the current *energy-based tariffs (EBTs)* and another based on *PBTs*—on residential customers exchanging electricity with each other.

Finally, **Chapter 5** concludes the dissertation by broadly discussing the importance, relevance, and limitations of the studies. In this chapter, we also propose some future pathways that may be useful for researchers to improve the current approaches and understanding in this field and lead the world to a sustainable and cleaner energy future.

## 1.8 Summary of publications

This doctoral dissertation consists of four publications, one of which is a refereed and published journal article, and the other three are refereed and published conference publications. Additionally, an article based on Chapter 4 of the dissertation has been submitted to a journal.

**Publication I:** *Feasibility of 100% renewable energy-based electricity production for cities with storage and flexibility*

**Publication I** investigates whether it is feasible to cost-effectively employ 100% RES—including BESS—for producing electricity to meet cities' loads. The potential to use only RES to meet partial loads (e.g., by meeting load demands only for certain fractions of the time) is also investigated. The publication also evaluates the impacts of exploiting *flexibility* to make a 100% RES scenario cost-effective by using a flexible-load methodology that shifts fractions of load across time. In the context of the dissertation, the presented methodologies focus on the following question—*is it feasible to supply single microgrids with 100% RES, including BESS, in the case of full, partial, and flexible loads?* The results suggest that more innovative methods are needed to improve the penetration of RES, such as collaborations between the participants or integration between electricity, heat, transport and other sectors.

**Publication II:** *Economic benefits of photovoltaic-based systems for residential customers participating in open electricity markets*

**Publication II** focuses on the following question—*can residential customers economically benefit from installing PV-BESS microgrid systems?* The paper presents a method to determine the economic benefits obtained by residential customers when PV panels are installed on their rooftops, and their production is supplemented with BESS. The results suggest that installing PV panels is not beneficial for Finnish residential customers today considering current prices, but customers can obtain long-term benefits from using PV panels, especially with BESS.

**Publication III:** *Interruption reduction using battery energy storage systems in secondary substations*

**Publication III** attempts to answer the following question—*Can DSOs economically utilize*

*BESS, or other DERs, in PV-BESS single microgrids?* An MBLP model is presented to determine the economic feasibility of installing BESSs at a secondary substation in a medium voltage network. Using the methodology, the minimum capacity and optimal schedule of the installed BESS can be determined. The methodology was applied to a real substation network in Finland. All the interruptions were reduced, and peak shaving increased the cost savings. However, the costs of lithium-ion-based BESSs must decrease further before BESSs can be cost-effectively used for interruption management and peak shaving.

**Publication IV:** *Economic impacts of power-based tariffs on peer-to-peer electricity exchange in community microgrids*

**Publication IV** deals with p2p electricity exchange in community microgrids and the economic impacts of PBTs on customer costs. This publication answers the question—*what are the benefits of establishing community microgrids to customers whose electricity tariff structure is revised from EBTs to PBTs?* This is an important question because of the increasing pressure to fairly remunerate distribution system operators in a network. EBTs do not reflect the true cost of a DSO's network investment, which is highly dependent on the peak power in the network. On the other hand, a power-based distribution tariff scheme where customers pay for their peak load (€/kW) instead of consumed energy (€/kWh) has been proposed as a fairer and cost-deflective tariff design. We demonstrated that the tariff change from EBT to PBT did not significantly affect the customers' benefits from electricity exchange.

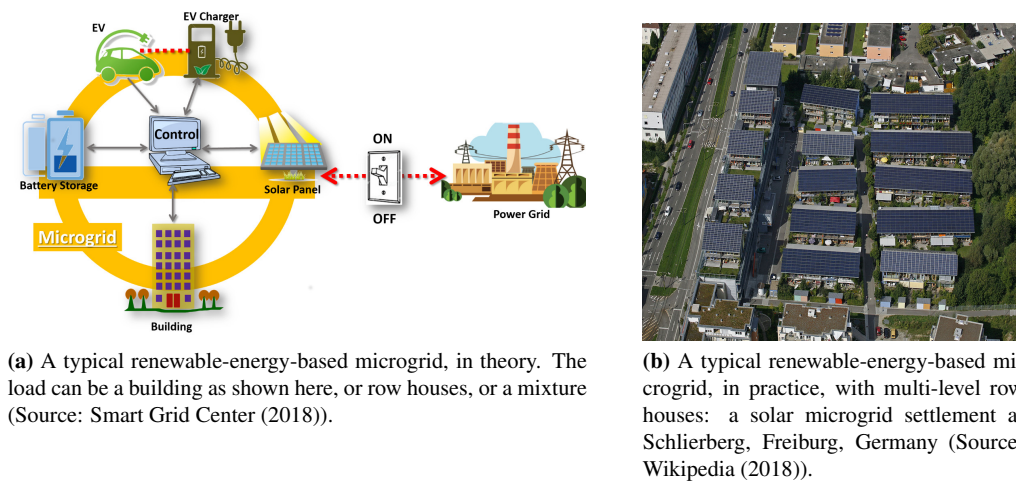
**Submitted Publication:** *Profit allocation methodology for co-operative energy exchange in community microgrids*

This submitted journal publication attempts to answer the question—*How can the profits of a community microgrid be economically and fairly distributed to its customers?* Using co-operative game-theoretic concepts, we present a novel methodology to derive a *simple* and *fair* formula to allocate the profits of a microgrid to its customers. We theoretically show that the proposed profit allocation methodology leads to higher profits for all customers than the profits in the non-electricity exchange case. In addition, we compare the results from applying the proposed methodology to two locations under different environmental conditions—an LV network in Finland and a neighborhood in Austin, Texas, USA.



## 2 Single microgrids

*Microgrids are localized small-scale grids that either operate independently (island mode) or connected to the grid (grid-interactive mode)* (Cintuglu et al., 2015). In a renewable-energy-based microgrid (Figure 2.1), a group of interconnected loads, energy storage systems, and renewable energy sources (RES) within clearly defined boundaries acts as a single controllable entity with respect to the grid. This chapter discusses three problems with the practical implementations of single microgrids. The first problem is to cost-optimally size the distributed energy resources (DERs) in a microgrid and to plan the usage of 100% RES with battery energy storage systems (BESS) (**Publication I**: Narayanan et al. (2019)). The novel methodologies used to solve this problem are extended to answer a second question—what economic benefits do residential customers obtain from installing PV-BESS microgrid systems in their houses (**Publication II**: Narayanan et al. (2016))<sup>7</sup>? Finally, the role of distribution system operators<sup>7</sup> (DSOs) in a microgrid is considered and an innovative method is proposed to show how they can benefit by using BESS (**Publication III**: Narayanan et al. (2017)).



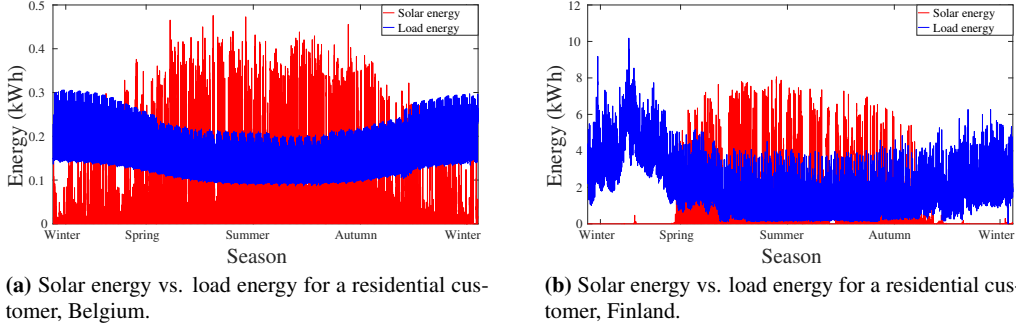
**Figure 2.1:** Typical renewable-energy-based microgrids.

### 2.1 Sizing and selecting distributed energy resources in microgrids

#### 2.1.1 General problem

Planning a cost-effective renewable-energy-based microgrid is a complex process due to uncertainties in long-term load and production forecasts, unforeseeable regulatory changes, and technical, environmental, geographical, and social constraints (Gamarra and Guerrero, 2015). In general, every microgrid should satisfy at least the goals of cost efficiency, reliability, and power quality, which may often be opposed to each other. As a result, the microgrid planning process is frequently based on tradeoff solutions. Typical microgrid planning problems are the

<sup>7</sup>Or utility companies.



**Figure 2.2:** Comparison of annual load energy and solar energy production profiles of a residential customer in Belgium and Finland.

selection, sizing, siting, and scheduling of DERs, and the planning process essentially comprises a sequence of optimization steps to solve them. This chapter examines the problem of the optimal selection and sizing of DERs.

The sizing problem stems from the fact that the load and RES-based production profiles do not coincide, i.e., the RES does not produce the exact electrical power (or energy) required by the load at a given time. These non-coincidences could occur not only in shorter time intervals such as hourly or daily load profiles but also in longer time intervals such as seasonal or annual profiles. Moreover, the differences are highly dependent on the geographical location and corresponding climatic conditions.

The seasonal sizing problem with solar energy is illustrated in Figure 2.2 for a randomly located residential customer in two different geographical regions, Belgium and Finland. In both cases, solar energy peaks in summer whereas the load peaks in winter. Finland has extreme seasonal variations, and there is no solar energy in winter at all. However, Finland has longer days in summer and therefore higher summer solar energy than Belgium. At the same time, the winter load in Finland is higher than the Belgian load.

When the production is greater than the load, the production can be controlled but other approaches are required when the load is greater than the production. There are two well-known and highly researched solutions to mitigate the inherent variability of RES (Beaudin et al., 2010). The first approach is to use a BESS to store excess electricity and to supply deficit electricity. Secondly, it may be possible to shift some loads without compromising end-user requirements using demand-side management (DSM) methodologies (Siano, 2014). Thus, as a result of the variability of RES, the problem of accurately sizing the DERs in the planning phase is additionally complicated by the necessity to employ BESS or DSM algorithms.

The most typical and important objective in sizing DERs is to meet the loads at minimum costs and as reliably as possible. The general planning problem for selecting and sizing  $n$  DERs in a grid-connected microgrid can be mathematically stated as follows:

$$\begin{aligned}
& \min \left[ C_{\text{capex}_1} \cdot P_{\text{der}_1} + C_{\text{capex}_2} \cdot P_{\text{der}_2} + \dots + C_{\text{capex}_n} \cdot P_{\text{der}_n} \right] + \\
& \min \left[ \int_{t=1}^{t=T} \left( C_{\text{opex}_1}(t) \cdot f(R_{\text{der}_1}(t), P_{\text{der}_1}) + \dots + C_{\text{opex}_n}(t) \cdot f(R_{\text{der}_n}(t), P_{\text{der}_n}) + \right. \right. \\
& \quad \left. \left. C_g(t) \cdot P_g(t) \right) \right] \quad (2.1)
\end{aligned}$$

such that

$$\begin{aligned}
& f(R_{\text{der}_1}(t), P_{\text{der}_1}) + \dots + f(R_{\text{der}_n}(t), P_{\text{der}_n}) + P_g(t) \geq P_l(t) \\
& \quad \forall t = 1, \dots, T \quad (2.2)
\end{aligned}$$

$$P_{\text{der}_i}, P_g(t) \geq 0; \quad \forall t = 1, \dots, T; \quad \forall i = 1, \dots, n$$

For all  $n$  DERs and  $i = 1, \dots, n$ ,  $C_{\text{capex}_i}$  refers to the capital expenditure (CAPEX) cost of  $\text{DER}_i$  (monetary unit/W);  $P_{\text{der}_i}$ , the nominal power of  $\text{DER}_i$  (W);  $C_{\text{opex}_i}$ , the operational expenditure (OPEX) cost of  $\text{DER}_i$  (monetary unit/W);  $f(R_{\text{der}_i}(t), P_{\text{der}_i})$ , a function that models the conversion of the renewable resources (e.g., irradiance  $I(t)$ , wind speeds  $W_s(t)$ , etc.) at the location to electrical power by a DER with nominal power  $P_{\text{der}_1}$  (W);  $P_g$ , the power produced from the grid (if and when needed) to balance the load (W);  $C_g$ , the cost of purchasing  $P_g$  from the main grid (monetary unit/W);  $P_l$ , the load power (W);  $T$ , the total time period considered; and  $t$ , each time step.

Equation 2.1 represents the planning objective to minimize the costs (CAPEX and OPEX) of using DERs as well as grid power, and the decision variables are  $P_{\text{der}_i}$  and  $P_g$ . Equation 2.2 ensures that the load is always met; if equality is strictly enforced, there is no wastage. Other constraints can also be included as applicable. In this formulation, optimal selection and sizing is achieved by the value selected for  $P_{\text{der}_i}$ . Here,  $P_{\text{der}_i} = 0$  means that  $\text{DER}_i$  is not selected and  $P_{\text{der}_i} > 0$  implies that  $\text{DER}_i$  is selected with nominal power equal to  $P_{\text{der}_i}$ .

### 2.1.2 Linear programming-based solution methodology

Numerous researches have attempted to solve the problem of the selection and sizing of distributed RES systems in the last few decades, and several analysis methods have been developed (Upadhyay and Sharma, 2014; Bhandari et al., 2015). **Publication I** presents a newly proposed linear programming (LP)-based methodology to solve the problem of the optimal sizing of PV–wind–BESS systems. The methodology is essentially used to answer the following question—what is the cost-optimal mix for a microgrid with PV–wind–BESS systems?

The problem presented in Section 2.1.1 is extremely complex due to the complicated technical characteristics of the DERs, system uncertainties, and large time horizon. For example, the function  $f(R_{\text{der}_i}(t), P_{\text{der}_i})$  can be nonlinear, and nonlinear optimization is generally harder to solve. Therefore, to make the problem tractable, the proposed methodology modifies Equa-

tions. 2.1 and 2.2 in three ways. First, *discrete* time steps are used, and as a result, secondly, electrical *energy* is considered instead of *power*. The effect of these changes is to reduce the computational overhead and make it possible to use simpler optimization methods such as LP. Finally, the levelized cost of energy (LCOE) is used for the cost. The motivation to use the LCOE is that it combines CAPEX and OPEX costs and therefore represents the full life-cycle costs of a generating plant per unit of electricity<sup>8</sup> (Ueckerdt et al., 2013).

By making these modifications, an LP-based methodology could be employed to calculate the electricity produced by DERs and thereby to size the system optimally. In the investigated problem, three DERs are assumed—wind and PV (collectively the RES) and BESS<sup>9</sup>. The RES–BESS system is supported by centralized non-renewable sources of energy (NRES). Thus, Equation 2.1 reduces to the following objective:

$$\min \left[ \sum_{t=1}^{t=T} C_w \cdot f_w(W_s(t)) \cdot E_w + \sum_{t=1}^{t=T} C_{pv} \cdot f_{pv}(I(t)) \cdot E_{pv} + \sum_{t=1}^{t=T} C_b \cdot |B_{\Delta}(t)| + \sum_{t=1}^{t=T} C_g \cdot E_g(t) \right] \quad (2.3)$$

where  $C_w$ ,  $C_{pv}$ , and  $C_b$  represent the monetary cost/unit for wind, solar, and BESS energy, and  $f_{pv}(I(t))$  and  $f_w(W_s(t))$  represent dimensionless “black box” functions for converting irradiance  $I(t)$  and wind speeds  $W_s(t)$ , respectively, to a fraction of the maximum possible solar and wind energy of a unit installation (1-m<sup>2</sup> and 1-kW installations, respectively). The decision variables  $E_w$ ,  $E_{pv}$ ,  $B_{\Delta}(t)$ , and  $E_g(t)$  represent the energies produced by wind turbines, PV plants, BESS, and NRES producers, respectively (Wh); here,  $B_{\Delta}(t) = B_t - B_{t-1}$ , where  $B_t$  is the BESS capacity (Wh) at time  $t$ .

The idea behind this problem formulation is to *determine the cost-optimal electrical energy required to meet the loads*. The RES–BESS–NRES system can then be sized based on the produced energy; that is, the produced energy can be used to determine the required nominal power to convert the renewable resource to electrical energy. Note that **Publication I** did not aim to determine the nominal power, but focused on determining and comparing the energy production with the objective to answer the question of whether it is possible to supply a microgrid with 100% RES.

Three types of constraints are required to solve the problem with the objective given in Equation 2.3—constraints to ensure that the load is met; constraints to model the RES–BESS–NRES operations; and constraints for the lower and upper bounds of the decision variables. The constraints for lower and upper bounds are straightforward ( $0 \leq \text{decision variable} \leq \infty$ ) and not explicitly discussed here. The constraints to model the RES–BESS–NRES operations are simplified because the technical characteristics and operations of RES and NRES are implicitly modeled in  $f_{pv}(I(t))$  and  $f_w(W_s(t))$ . For BESS, the following charge–discharge constraint is

<sup>8</sup>The LCOE is essentially based on a simple equation—the cost to build and operate a production asset over its lifetime divided by its total energy output over that lifetime (monetary unit/kWh)—and considers the initial capital, discount rate, and the costs of continuous operation, fuel, and maintenance.

<sup>9</sup>Technically, the RES–BESS system could be either centralized or distributed, depending on the logistics, and the model only assumed that a PV–wind RES system existed to supply electricity, supported by BESS.

employed:

$$-B_{max}/k_{dch} \leq B_{\Delta}(t_i) \leq B_{max}/k_{ch}, \quad \forall i = 1, \dots, T \quad (2.4)$$

where  $B_{max}$  is the maximum BESS capacity (kWh), and  $k_{ch}$  and  $k_{dch}$ , the BESS charge and discharge rates, respectively.

The LP method can be used to meet three types of loads—full loads, partial loads, and flexible loads—using three different models for the constraints for meeting the load.

**Full loads** In the first case, the LP sizing model is used to determine the cost-effective electrical energy required from the RES–BESS–NRES system to supply *full loads*. Hence, the constraint in the problem is written as follows:

$$f_w(W_s(t)) \cdot E_w + f_{pv}(I(t)) \cdot E_{pv} - B_{\Delta}(t) + E_g(t) \geq E_l(t), \quad \forall t = 1, \dots, T \quad (2.5)$$

**Partial loads** In the second case, the production resources must meet *partial loads*. What does *partial loads* mean and what is the motivation to meet partial loads? Since electricity from wind and solar electricity is intermittent, it is usually not possible to meet the entire load 100% of the time using RES alone. Further, planners may often have fixed resources to meet the loads, and options such as BESS to supplement RES production may not be viable. In such a case, planners can take advantage of the fact that RES is able to meet the load for at least  $x\%$  ( $x < 100\%$ ) of the time. Such loads that are met only partially, i.e., for only *fractions* of the (discrete) time steps, are called *partial loads*. In practice, planners can determine their RES installation and utilization based on the maximum number of hours that can be supplied by RES; they can also analyze the cost benefits when decreasing the supply security.

Partial loads basically imply that the electrical reliability of the system is reduced. Therefore, to model partial loads, we considered a well-known reliability index<sup>10</sup>—the *average service availability index* (ASAI)—defined as follows (Chowdhury et al., 2003):

$$ASAI = \frac{(\sum N_j) \cdot T - \sum(r_j \cdot N_j)}{(\sum N_j) \cdot T}$$

where  $N_j$  is the number of customers at a location  $j$ ;  $r_j$ , the annual outage time for  $j$ ; and  $T$ , the total time period considered (Billinton and Li, 1994). For a single location, this is equivalent to

$$ASAI = \frac{N \cdot T - r \cdot N}{N \cdot T} = \frac{T_k}{T}$$

where  $T_k$  is the total number of time steps without interruptions.  $ASAI \in [0, 1]$ ; for full loads,  $ASAI = 1$ , and for no loads,  $ASAI = 0$ .

Our problem now is that the production must meet the load demand only during *some* discrete time steps whose total is predefined by the ASAI. To solve this problem, the LP model is reformulated as a mixed binary LP (MBLP) model where binary decision variables  $b_i = \{b_1, \dots, b_T\}$ ,  $\forall b_i \in \mathbb{Z}_2$ , are used to decide whether the load will be met ( $b_i = 1$ ) or not ( $b_i = 0$ ).

<sup>10</sup>Any other suitable reliability criteria index can also be used.

As a result, the following constraint is added to the problem to define the total number of interruptions:

$$\sum_{t=1}^{t=T} b_t = T_k = \text{ASAI} \cdot T$$

The full load constraint in Equation 2.5 then becomes<sup>11</sup>

$$f_w(W_s(t)) \cdot E_w + f_{pv}(I(t)) \cdot E_{pv} \geq b_t \cdot E_l(t), \quad \forall i = 1, \dots, T \quad (2.6)$$

**Flexible loads** In the third case, the production resources must meet *flexible loads*. Microgrids typically comprise several *flexible resources*, i.e., resources whose electricity production or consumption can be shifted in time within the boundaries of end-user comfort requirements, while maintaining the total electricity production or consumption (MacDougall et al., 2013). A *flexible load* thus constitutes a *shiftable portion* of the total load. Examples of flexible loads include electric vehicles and household devices such as washing machines, heaters, etc. (Sadeghianpourhamami et al., 2016). The objective is to size the microgrid based on the amount of flexibility in the microgrid system.

**Publication I** considered the problem of sizing a microgrid system with RES–BESS–NRES production resources such that the produced energy meets flexible loads. A novel generalized two-dimensional flexible-load model was proposed to solve the problem of *exploiting flexibility*. The cost-effectiveness of using RES–BESS systems<sup>12</sup> to meet flexible loads was explored. Flexibility was characterized by two parameters: (i) a maximal fraction  $\delta$  of the load that is shifted to later time steps, and (ii) a maximal amount of time  $r$  over which the loads can be deferred. Flexible load energy  $E_{fl}(t_i)$  at time  $t_i$  ( $\forall i = 1, \dots, T$ ) is then defined as  $E_{fl}(t_i) = \delta E_l(t_i)$ , where  $\delta \in [0, 1] \subset \mathbb{R}$  and  $E_l(t_i)$  is the total load. The unshiftable or inflexible load  $E_{infl}(t_i) = (1 - \delta)E_l(t_i)$ .

$\alpha_{i,0}$  is defined as the inflexible load fraction (unshifted load), and  $\alpha_{i,1}, \alpha_{i,2}, \dots, \alpha_{i,r}$  are the flexible load fractions that are shifted from  $t_i$  across the subsequent  $r$  time steps  $t_{i+1}, t_{i+2}, \dots, t_{i+r}$ , respectively;  $\alpha_{i,j} \in [0, 1]$ . Thus, at the  $i^{th}$  time step  $t_i$ ,  $E_l(t_i)$  is distributed across  $r$  time steps:

$$E_l(t_i) = \sum_{j=0}^r \alpha_{i,j} E_l(t_i)$$

where

$$\sum_{j=0}^r \alpha_{i,j} = 1, \quad \forall i = 1, \dots, T \quad (2.7)$$

The load that is shifted *away* from  $t_i$ ,  $E_{fl}(t_i)$ , is given by

$$E_{fl}(t_i) = \sum_{j=1}^r \alpha_{i,j} E_{fl}(t_i) \quad (2.8)$$

<sup>11</sup>Note that only RES is considered in this formulation since we are examining the ability of RES to meet partial loads.

<sup>12</sup>It is trivial to include NRES as well.

and the unshifted load energy component  $E_{infl}(t_i) = \alpha_{i,0}E_l(t_i)$ . Note that  $r + t_i \leq T$  since a load cannot be shifted beyond the final time step. The total flexible load that has been shifted to a time step  $t_i$  from previous time steps,  $E_{fl}^*(t_i)$ , is given by

$$E_{fl}^*(t_i) = \sum_{k=1}^r \alpha_{i-k,k} E_l(t_{i-k}) \quad (2.9)$$

Therefore, Equation 2.5 can now be replaced by the following *flexible load constraint*:

$$f_w(W_s(t_i)) \cdot E_w + f_{pv}(I(t_i)) \cdot E_{pv} + B_{\Delta}(t_i) \geq \sum_{k=0}^r \alpha_{i-k,k} E_l(t_{i-k}), \quad \forall i = 1, \dots, T \quad (2.10)$$

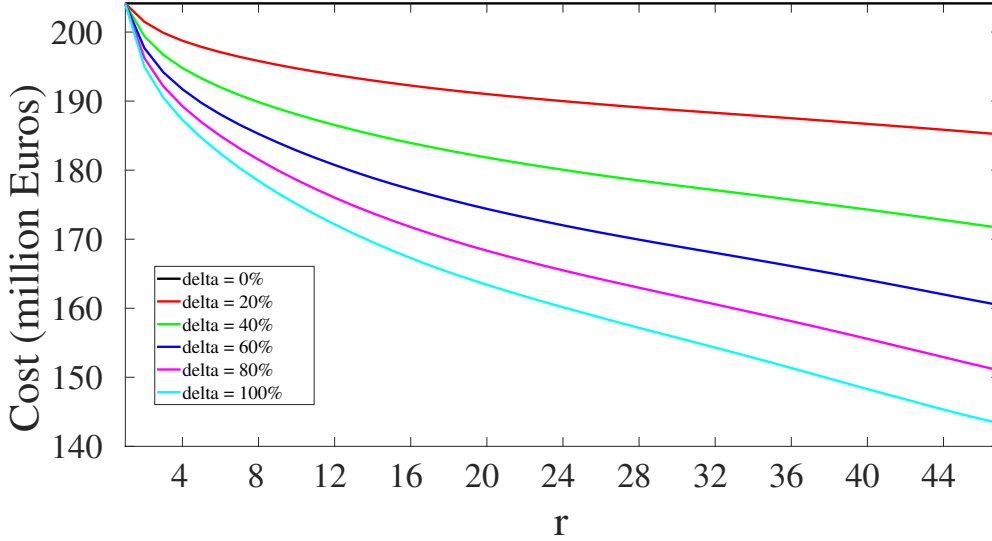
**Results and discussion** Thus, **Publication I** proposed LP-based methodologies to solve the problem of the optimal sizing and selection of PV–wind–BESS systems and determine the cost-optimal energy mix for a microgrid with PV–wind–BESS and NRES. In the publication, the presented methodologies were applied to investigate whether it is possible to cost-effectively employ 100% RES–BESS systems for producing electricity to meet cities’ full, partial, and flexible loads. For the case study, Kortrijk, a typical Belgian city with around 75,000 inhabitants, was used. From a purely economic viewpoint, it was found that RES–BESS systems are not cost-effective even with flexible loads when reference RES and NRES costs (LCOE) from 2014 were used. This is because NRES were significantly cheaper than RES–BESS systems. RES and BESS costs must decrease to around 40% and 7% (around 0.044 €/kWh and 0.038 €/kWh), respectively, of their reference LCOE to cost-effectively supply the city’s load demand.

Figure 2.3 shows the minimal costs for the PV–wind–BESS scenario with flexible loads. Here,  $r = 48$  implies that the loads can be shifted over maximally 12 h (we considered 15-min time steps). The costs were lowest when the entire load can be shifted, i.e.,  $\delta = 100\%$ . As the maximal amount of time shifting,  $r$ , increases, the costs decrease, but this decrease slows down with higher  $r$ , which suggests that the benefits of shifting the load decreases after a certain time frame. For more results and detailed discussions, please refer to **Publication I** (Narayanan et al., 2019).

## 2.2 Economic benefits of residential microgrids

In **Publication I**, the broad question of the cost-optimal RES-based electricity production mix for a microgrid was considered. This naturally leads to a second question—in a renewable-energy-based microgrid, what is the benefit for the residential customer who installs a PV–BESS microgrid system, especially when connected to an external electricity market?

This question is addressed in **Publication II** that focuses on residential customers installing PV–BESS systems in their houses (Figure 2.4). The microgrid is assumed to be connected to an external grid so that the customers can freely purchase and sell electricity from an open electricity market. The method used in **Publication I** is extended to size the PV system, i.e., to determine the number of PV panels that can be optimally installed on rooftops for maximum economic benefits. The economic benefits are then obtained using this extended method. Fur-



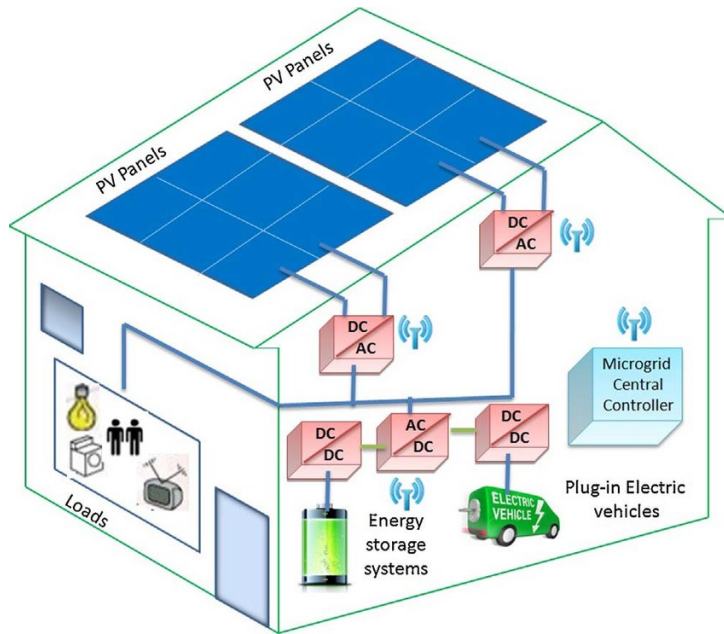
**Figure 2.3:** Variations in the minimal cost in the PV–wind–BESS scenario with flexible loads. The load is shifted with  $r$  varied from 0 to 12 h and  $\delta$  from 0 to 100%.  $r$  refers to the maximal number of 15-min time steps over which the total load can be distributed, and  $\delta$  to the maximal fraction of the load that is shifted to later time steps.

ther, the practical scenario where customers progressively install more PV panels each year, even as PV costs continue to decrease, has also been considered. The problem formulation is an expansion of the concepts and methodologies introduced in Section 2.1.1 and is not presented here (see **Publication II**: Narayanan et al. (2016) for details).

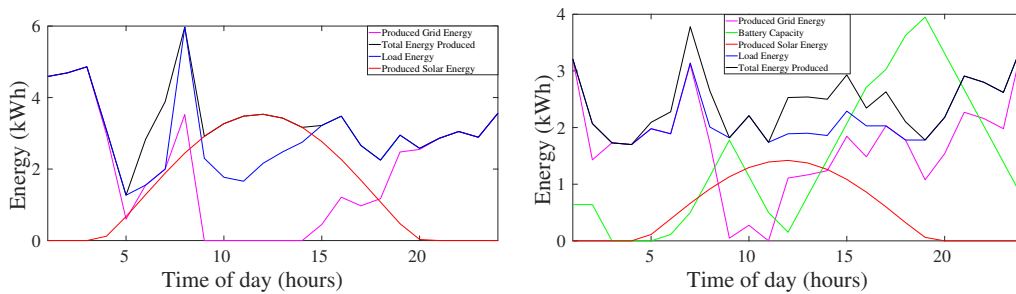
The proposed methodology was applied to the case of a Finnish customer participating in the Nordic electricity market. Note that although the Nordic electricity market was used as the reference in the case study, other price models can also be easily incorporated into the mathematical formulation. In the Nordic market, residential customers pay distribution fees, supplier fees (includes the market prices), and electricity taxes as part of their electricity bill.

The reference PV LCOE value (for 2015) of 0.20 €/kWh was too expensive, and the optimization did not choose even a single PV panel. However, when the LCOE was reduced by half to 0.10 €/kWh, electricity from PV panels were preferred over electricity from the grid. The DERs are sized to obtain the maximum economic benefits for a residential customer. Figure 2.5 shows how the cost-optimally sized DERs—i.e., PV and BESS—meet the load of a single residential customer on a day in April in Finland; Figure 2.5a shows the case for PV systems alone and Figure 2.5b shows the case when the PV system is supported by a BESS.

The presented method makes it possible to evaluate the annual economic benefits for a residential customer and determine an approximate time frame by which the customer can expect investments to be profitable. **Publication II** shows that although residential customers do not have economic benefits at current DER costs, they have long-term benefits from using PV and PV–BESS systems if their costs continue to decrease.



**Figure 2.4:** Publication I focused on the optimal sizing of microgrid systems (with photovoltaic (PV)–wind–battery energy storage systems (BESS) and non-renewable energy sources (NRES)), whereas **Publication II** focused on the economic benefits of a grid-connected microgrid comprising a single residential house with PV–BESS systems, as shown here (Source: Alfergani et al. (2018)).



**(a)** Cost-optimally sized PV systems meeting the load of a single residential customer on a day in April in Finland.

**(b)** Cost-optimally sized PV–BESS systems cost-optimally meeting the load of a single residential customer on a day in April in Finland.

**Figure 2.5:** Cost-optimally sized distributed energy resources (DERs)—PV systems alone and PV–BESS systems—meeting the load of a single residential customer on a day in April in Finland. The DERs are sized to obtain the maximum economic benefits for a residential customer.

### 2.3 Distribution system operator and the microgrid

Publications I and II approached microgrid planning from a customer's perspective. However, microgrids have several stakeholders and the lack of stakeholder co-operation is a great challenge to their implementation (Soshinskaya et al., 2014). An important stakeholder is the DSO who is responsible for distributing electricity in the low-voltage network. In non-liberalized markets, the DSO is also responsible for the retail of electricity. As a result, the microgrid may be owned and operated by the DSO who is then solely responsible for the costs and benefits of microgrid operations. In this case, DSOs may also wish to own the DERs instead of the customer, for example, in the form of centralized PV panels or BESS installations.

In liberalized open markets such as the Nordic market, DSOs are not allowed to interfere or directly participate in electricity trading. However, the increasing penetration of DERs and the resulting business models make it challenging for DSOs to follow all the guidelines directed by regulatory authorities. It is now well recognized that the DSO regulations need to be reviewed and revised (Ruester et al., 2014). In particular, DSOs are obligated by market regulatory authorities to ensure high reliability of power supply by the imposition of regulatory costs (Energiavirasto, 2015). To decrease outages and increase reliability, DSOs traditionally try to build the supplying grid with high-reliability technology, such as weatherproof network structures with meshed network and underground cabling. However, this can often be prohibitively expensive (Haakana et al., 2015).

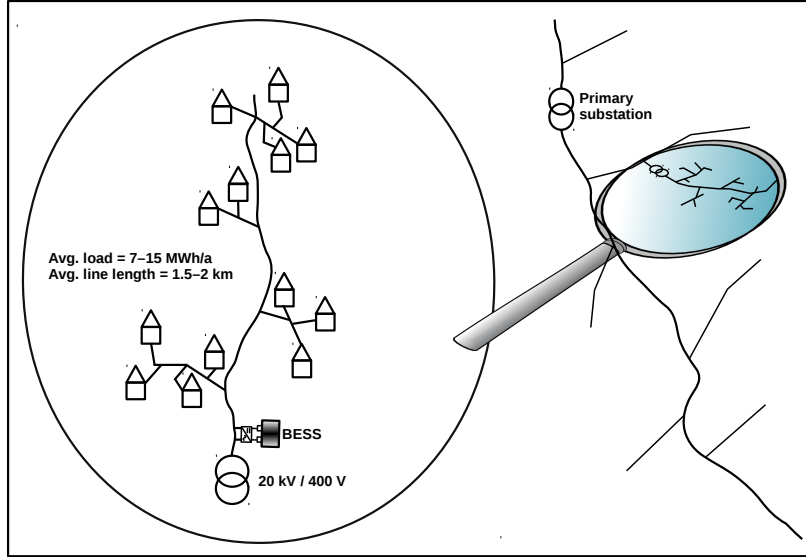
A possible change in regulations is to allow DSOs to use BESS systems to reduce outages. They could either own the BESS themselves or to enter into partnerships with electricity traders, such as retailers or aggregators. The BESS could be physically installed in the networks of local DSOs. Depending on the partnership agreement, DSOs could use the BESS capacity for interruption management, and electricity market traders could use it for market actions such as market-price-oriented peak shaving or power trading. **Publication III** examines this possibility by presenting an innovative MBLP method to cost-optimally size a BESS that is centrally installed at the secondary substation for decreasing outages and achieving peak shaving.

The methodology was applied to a typical Finnish rural electricity network (Figure 2.6) that is characterized by a high forest rate and overhead lines that are vulnerable to adverse weather phenomena. The average number of customers per low-voltage supply area is 10–20, and the residential household loads are spread over a wide area with average line lengths and loads of 1.5–2 km and 7–15 MWh/a, respectively.

The minimum-cost objective to reduce interruptions and achieve peak shaving can be formulated as follows:

$$\min \left[ \sum_{i=1}^T C_g(t_i) \cdot E_g(t_i) + C_b \cdot B_m + \sum_{i=1}^T C_i \cdot k_i \right] \quad (2.11)$$

$C_g(t_i)$  is the cost (€/kWh) of purchasing electricity;  $E_g(t_i)$ , the electrical energy purchased from the grid (kWh);  $T$ , simulation time period (unit of time);  $C_b$ , the total CAPEX cost €/kWh



**Figure 2.6:** A typical rural network in Finland with BESS installed by DSOs at the secondary substation. The residential household loads are widespread with average line lengths and loads of 1.5–2 km and 7–15 MWh/a, respectively.

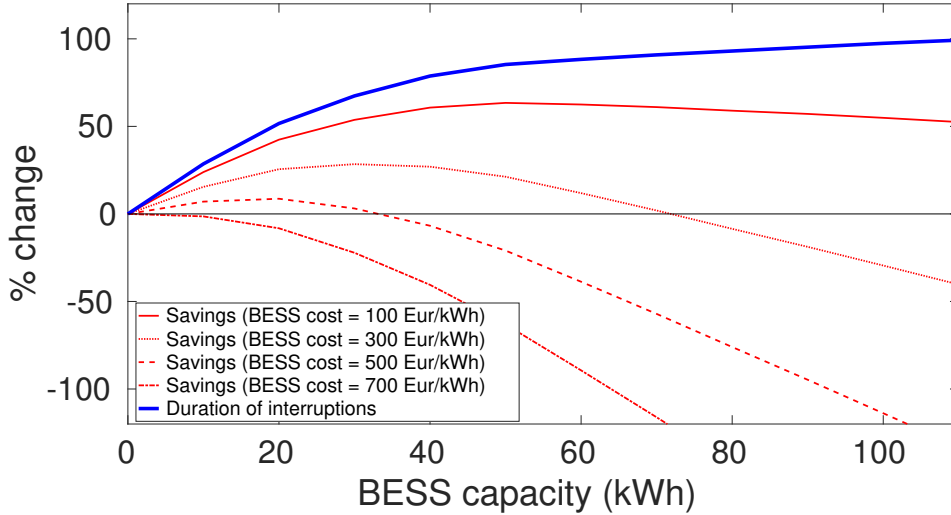
of the BESS; and  $C_i$ , the costs of outages (€/kWh). Binary variables  $k_i$  are used to represent interruption ( $k_i = 1$ ) or no interruption ( $k_i = 0$ ) and other constraints are used for BESS operations, etc. (see **Publication III**: Narayanan et al. (2017)).

By using this MBLP model, any outage costs model can be input into the objective to determine the minimum capacity and optimal schedule of the installed BESS. Moreover, it is possible to determine the tradeoff between improvement in reliability and the costs of BESSs. The BESS can also be used for peak shaving instead of keeping it idle when there are no outages.

Figure 2.7 shows the decreasing rate of the number of interruptions as the capacity of the battery energy storage system (BESS) is increased from 0 to 120 kWh. The number of interruptions decreased slowly and became 0 (decrease = 100%) when the battery capacity was around 112 kWh for this substation. Further, nearly 80% of the interruptions were reduced with battery capacity of 60 kWh. However, this increase in reliability was not always cost-effective. There are no savings with BESS costing  $\geq 700$  €/kWh. The savings are higher and nearly all interruptions are reduced for BESS costs of  $\leq 300$  €/kWh.

## 2.4 Conclusions: limitations and future study

This chapter discussed three important problems that hinder the practical implementation of single microgrids—cost-optimal sizing of DERs; economic benefits to residential customers' PV–BESS renewable-energy-based microgrids; and economic benefits to DSOs from using BESS in



**Figure 2.7:** Decreasing rate of the number of interruptions as the capacity of the battery energy storage system (BESS) is increased from 0 to 120 kWh. For the studied substation, the number of interruptions is 0 (decrease = 100%) when the battery capacity is approximately 112 kWh. The corresponding changes in the cost savings for four BESS costs—100 €/kWh, 300 €/kWh, 500 €/kWh, and 700 €/kWh—are also shown.

microgrids. Using the proposed sizing methodologies, it is possible to plan the usage of 100% RES to meet full, partial, and flexible loads. Further, the partial-loads model can be used to plan at least partial access to electricity. And the proposed two-dimensional flexibility model can be generally applied to analyze the impacts of flexible loads on electricity production resources in microgrids. Residential customers can use the presented methodology in **Publication II** to evaluate their investments into PV–BESS systems; in particular, the size, cost, and charge–discharge schedules of the BESS system can be determined. DSOs can plan the implementation of BESS for decreasing outages and achieving peak shaving, if allowed by electricity market regulations. However, the presented methodologies also have a few limitations.

First, the novel methodology to cost-optimally size DERs in a microgrid has a few drawbacks. An important limitation is that the proposed LP model is *deterministic*, whereas electricity load and production data are *stochastic* in nature especially in the case of weather-dependent DERs. The errors caused by using a deterministic model may be within tolerable limits in the case of long-term planning, but sensitivity analyses are needed to establish the validity of the study further. Moreover, a two-stage stochastic programming model based on previous literature (such as Morales et al. (2009) and Papavasiliou et al. (2011)) could be better than the proposed deterministic methodologies. Advance scheduling decisions can be made in the first stage, and smaller adjustment decisions to cope with any sudden real-time uncertainties can be planned in the second stage.

The presented models should be implemented and tested in different climatic environments for

adaptability, stability, and scalability. For example, it is not clear if the models are scalable to larger microgrids with a more diverse set of DERs. Even in the case study where the models were applied to the loads of a city (in **Publication I**: Narayanan et al. (2019)), only two or three types of DER were used. Moreover, many of the proposed methods are based on MBLP models, but mixed integer LP (MILP) and MBLP models are known to be NP-hard<sup>13</sup>.

The case study in **Publication I** has an important limitation with respect to long-term cost planning because only 1 year was considered, even though the LCOE, which is based on lifetime electrical energy production, was used. As a result, forecasted behaviors of the load and production during longer time frames are ignored. **Publication II** attempts to correct some of these issues by presenting methodologies for 15–20-year periods but variations in costs, production, and load data are not adequately considered in the case study. Further, the algorithm for exploiting flexibility only considered production costs, and other costs such as infrastructure costs for communication and control, socioeconomic costs, and other externalities are missing. However, it should be noted that the methodologies are still valid; models of variations in costs, production, and load data as well as any missing information can be easily included in the algorithm.

A significant result from the three studies is that from a purely economic viewpoint, *RES–BESS systems are not cost-effective for the microgrid system, customers, and DSOs under the cost assumptions*. This agrees with the growing consensus that *smart energy systems* offer better options for the integration of RES (Lund et al., 2016). Moreover, integrating co-production and transportation is crucial for exploiting the flexibility in an electricity system (Kwon and Østergaard, 2014). Clearly, it is very important to integrate several renewable energy sectors—electricity, heat, transport, etc.—to reach high levels of RES penetration.

There are two more ways to make RES–BESS systems cost-effective in a microgrid—electricity aggregation and peer-to-peer (p2p) electricity exchange between customers. The motivation for aggregating or exchanging electricity stems from the fact that a large amount of electricity is often wasted due to over-production or is unprofitably used. By aggregating the capacities of DERs, it is possible to set up a virtual power plant (VPP) that manages the power system and trades with the electricity market (Pudjianto et al., 2007). A VPP provides higher efficiency and more flexibility, which allows the system to react better to fluctuations; however, the increased complexity requires complicated optimization, control, and secure communications. The second approach to reduce renewable energy wastage and improve system efficiency is to enable and exploit p2p electricity exchange between customers, forming the so-called *community microgrids*. The next two chapters will discuss community microgrids in greater detail.

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<sup>13</sup>NP-hard problems cannot be solved in polynomial time. MILP and MBLP problems are typically solved in polynomial time by relaxing them to an LP formulation (for example, with branch and bound or cutting plane algorithms), which make it possible to quickly handle large datasets and variables.



### 3 Community microgrids and microgrid clusters

The previous chapter examined the planning problem in single microgrids and especially focused on the optimal selection and sizing of distributed energy sources (DERs). Due to seasonal variations and relatively high costs, it is currently not cost-effective to supply microgrids using only 100% renewable energy sources (RES) and battery energy storage systems (BESS). In Finland, for example, the size of the BESS required to store and supply electricity in the winter is prohibitively high. Peer-to-peer (p2p) electricity exchanges and microgrid interconnections have been proposed as a method to increase the use of RES and to improve grid independence. This chapter introduces the concept of *community microgrids* in which residential households in a neighborhood microgrid exchange electricity. The benefits of community microgrids as well as the challenges with their implementation are discussed. Subsequently, this chapter discusses *multi-microgrids* or *microgrid clusters* in which several community microgrids interact with each other. A generalized problem statement for microgrid cluster is mathematically formulated. A potential solution design along with descriptions of the solution components that need to be constructed to fully solve the problem is also presented.

#### 3.1 Community microgrids

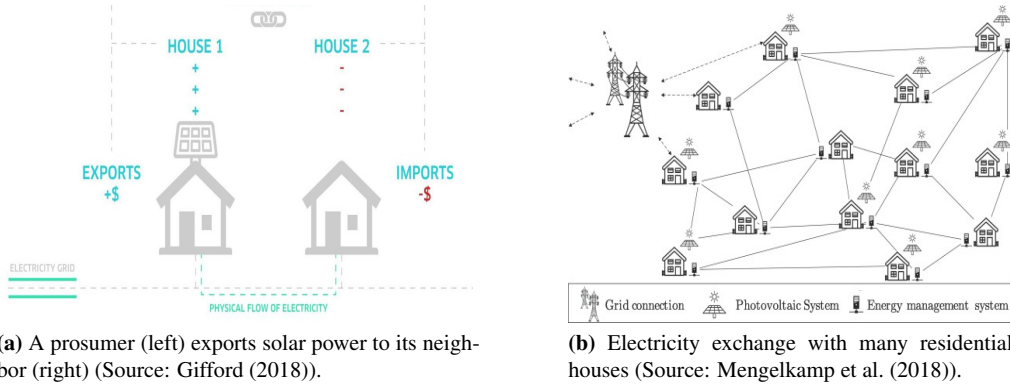
##### 3.1.1 Introduction

As DERs are increasingly integrated into the power system, electricity customers will both consume and produce electricity, i.e., become *prosumers*. However, electricity production by renewable-energy-based DERs is unpredictable and intermittent. Moreover, customer loads are also increasingly unpredictable due to the penetration of newer energy efficient devices and appliances such as electric vehicles (EVs).

Prosumers can use locally produced electricity either for self-consumption, for storing in BESS for later use, or for feeding into the grid at fixed rates (the so-called net metering or feed-in-tariff (FIT) scheme). BESS, as discussed in Chapter 2, is currently relatively expensive (Kim et al., 2019). FIT is not always fair to the distribution system operator (DSO) who has to pay the customer as well as upgrade the network for unexpected high power flows into the system. FIT causes DSOs to lose some financial incomes while still having to maintain quality and reliability of supply electricity (Eid et al., 2014). Many countries have now begun to replace FIT with more market-driven approaches and concepts. It is important to note that throughout this dissertation, we assume that customers do not have the FIT option.

One such market-driven approach is that prosumers can sell the surplus electricity to consumers who have an electricity deficit. Consumers may prefer to buy electricity from neighboring prosumers at a cheaper price rather than from the main grid. In this case, the prosumers and consumers agree upon the price among themselves<sup>14</sup>. Such an electricity exchange or trading among customers is called peer-to-peer (p2p) electricity exchange. Microgrids in which p2p electricity exchanges occur, especially at the residential neighborhood low-voltage (LV) level,

<sup>14</sup>If feed-in-tariffs (FIT) exists, the prosumer will naturally prefer to sell above the FIT whereas the consumer will prefer to buy below the grid price.



**Figure 3.1:** A community microgrid in which many residential houses, which form a low-voltage microgrid, exchange electricity with each other and with the main grid.

are typically called “community microgrids”<sup>15</sup> (Mengelkamp et al., 2017).

In this dissertation, a *community microgrid* is defined as a neighborhood microgrid comprising residential household customers—both prosumers and consumers—that together form an LV distribution network connected to a main grid through a single secondary substation (Figure 3.1). The community microgrid can disconnect from the main grid, if required. The electricity exchanges are typically managed by a central optimization algorithm that interacts with several layers such as the physical layers, communication layers, transaction layers (e.g., blockchain), etc.

A community microgrid has multiple stakeholders, and its planning and implementation processes are complicated by the resulting issues of conflicts of interest, operational mechanisms, and trust. One or many of the following stakeholders are involved in a community microgrid—residential customers; DSOs (also known as utility companies); retailers (also known as suppliers); system operators; governing authorities such as regulators, policy makers, and standardization entities; and non-governmental organizations<sup>16</sup>. Society as a whole can also be considered a stakeholder so that the maximization of “societal benefits” is often an objective of designing and building community microgrids. Since “society” is essentially just a mixture of all the stakeholders, the goal of societal benefits is to achieve a co-optimized balancing of multiple stakeholder objectives.

Community microgrids, and more broadly community renewable energy models, are popular because they not only have many benefits but also several advantages over the traditional isolated distributed energy production model. As early as 2008, Walker (2008) had outlined the benefits of (and barriers to) community-owned means of energy production and use. Based on Walker’s thoughts and other studies, the benefits of p2p community microgrids (Figure 3.2<sup>17</sup>)

<sup>15</sup>Note that some studies refer to the interconnections of several neighborhood microgrids as a community microgrid. In this dissertation, such an interconnection is defined as a *microgrid cluster* (Section 3.2).

<sup>16</sup>This is a non-exhaustive list.

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are listed as follows:

1. *Lower costs and better energy utilization.* Sharing of electricity is a cost-effective method of increasing the energy utilization and lowering the cost of renewables usage, since it avoids wastage of surplus renewables resources. Sharing of electricity is a cost-effective alternative to employing demand-side management (DSM) techniques or expensive storage options to increase the energy utilization and lower the cost of renewables usage. Community microgrids also promote efficient energy balance within the microgrid (Klein and Coffey, 2016; Yuan et al., 2017).
2. *Network expansion.* The efficient usage of electricity internally within the community microgrid reduces congestions in transmission and distribution (T&D) lines, and therefore reduces the need for transmission and distribution asset investments. Further, DSOs can defer expensive network expansions (Ilic et al., 2012; Klein and Coffey, 2016; Mengelkamp et al., 2017).
3. *Reductions in power losses.* Since the customers transfer electricity locally among themselves, electricity is transferred over shorter distances, which reduces power losses. Such a local electricity exchange can also help to avoid the power losses at the level of the substation's transformer (Saad et al., 2012; Chakraborty et al., 2015);
4. *Microgrid independence and autonomy.* Microgrid independence is increased since the power grid can be effectively isolated from the main grid with better power and energy balance (Wei et al., 2014; Yuan et al., 2017). Further, microgrid systems become more autonomous due to decreased reliance on the main electric grid.
5. *Reliable and resilient supply.* The power grid can be seamlessly partitioned into self-sustaining island networks in emergencies (Wei et al., 2014; Yuan et al., 2017). Customer comfort and safety is increased since outages can pose risk to human life. Outages lead to significant revenue losses for DSOs, especially in areas that are prone to storms and inclement weather. DSOs benefit from the increased network resilience and reduced outages, which are important objectives for them (Costa and Matos, 2005). Additionally, the community is engaged to build resilience (Jimenez-Estevez et al., 2017).
6. *Rural upliftment and eliminating electricity poverty.* Worldwide, the problem of electricity deficit is overwhelmingly confined to rural areas. Moreover, rural grid electrification programs are often low priority because of the challenges in connecting less populated remote villages incrementally to the existing grid. As a result, microgrids are seen as a viable option for rural areas. Rural communities are also typically strongly community-oriented. Therefore, they not only stand to benefit from p2p microgrids but are also likely to embrace them. Rural p2p microgrids, in turn, benefit the region and society as a whole.
7. *Local investments and economy.* Consumers are encouraged to invest in RES such as solar panels, especially when government policies disallow net metering or FIT to protect electricity sellers or distributors from unfair transactions and losses. This increases the proliferation of RES-based DERs, which, in turn, improves the society by enabling a clean environment. There are also opportunities for employment creation, especially if the network needs to be newly built.



**Figure 3.2:** Some benefits of community microgrids (Source: Darek Letkiewicz (2015)).

8. *Local participation and ownership.* Consumers can either fully or partially own the network. This encourages them to participate in managing RES, thereby increasing social awareness of environmental issues and concerns.
9. *Servicing electricity markets.* Aggregators can trade the aggregated electrical energy in the main electricity market as well as provide auxiliary services. The revenue generated by aggregating and selling any excess produced electricity can then be shared among the stakeholders.
10. *Permits and licenses.* Some evidences from experiences with community energy projects suggest that projects involving local communities are (arguably) more likely to obtain permissions because of higher acceptability (Walker, 2008).

Despite these benefits, the implementation of p2p community microgrids is not straightforward and faces several barriers that may be classified into the following broad categories (Walker, 2008):

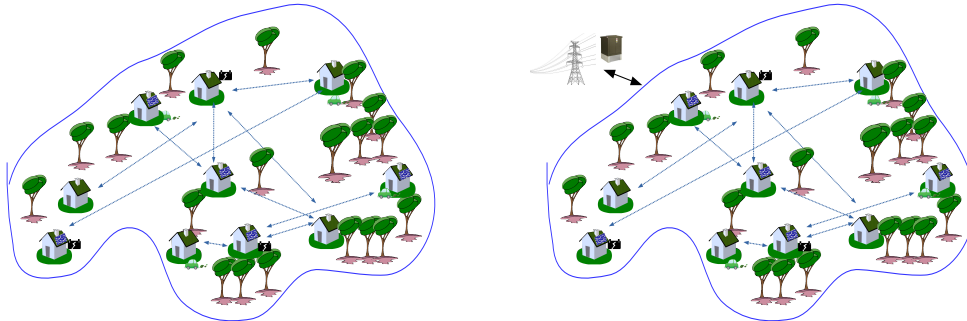
1. *Legal*

- (a) Difficulties in obtaining permissions;
- (b) Lack of governmental regulations and regulatory support;
- (c) Barriers to market entry and network connection;

2. *Economic*

- (a) Insufficient market incentives;
- (b) Revenue adequacy;
- (c) Problems with collective management, billing and metering arrangements;

3. *Technical*



(a) An independent community microgrid operating without connecting to the external grid

(b) A connected community microgrid that is connected to the external grid and therefore to the external market.

**Figure 3.3:** Independent and connected community microgrids with p2p electricity exchange.

- (a) Complications with designing and implementing p2p microgrids keeping the viewpoints of multiple stakeholders, such as requirements, costs, and benefits;
- (b) Integration with existing electricity markets;
- (c) Difficulties with achieving optimal economic and social outcomes, especially due to diverse preferences and behaviors of individual prosumers (Gui et al., 2017);

#### 4. Stakeholder commitment

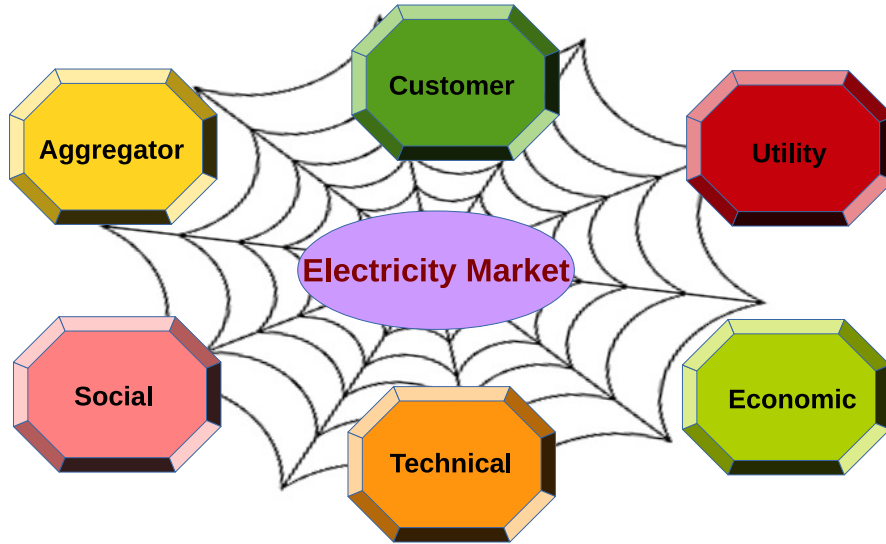
- (a) Unwillingness of customers to co-operate or form a community due to social or other reasons;
- (b) Unwillingness of DSOs/utilities to co-operate and especially to take risks in setting up an uncertain environment that may lead to technical network issues with insufficient compensation;
- (c) Unwillingness of private players to invest in unproven businesses;
- (d) Unwillingness of governments to risk failure, especially if other high-stakes events—such as elections—are impending;

#### 5. Social

- (a) Community acceptance;
- (b) Conflicts with neighbors or electricity providers.

### 3.1.2 Design of local (internal) electricity markets

To successfully implement a community microgrid, it is important to develop a p2p electricity exchange strategy as well as a framework that allows the exchange to take place smoothly. A commonly proposed method to realize p2p electricity exchange is to enable the participating customers to trade competitively with each other. An internal local electricity market should be developed to facilitate the competitive trading. The trading framework and its operations depend on whether the community microgrid is operating independently or is connected to the external

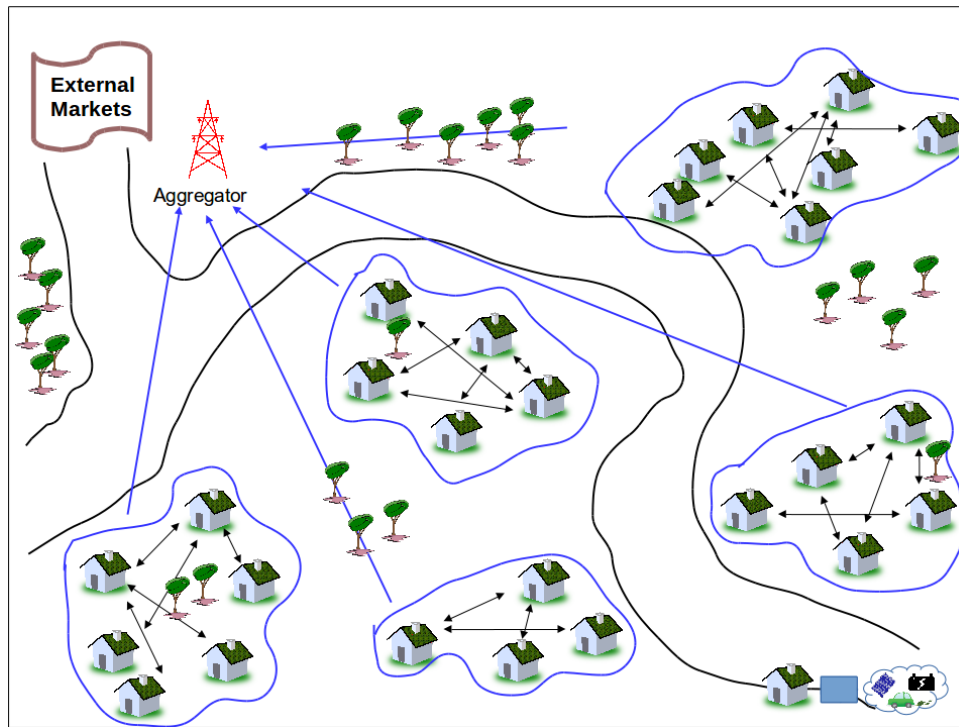


**Figure 3.4:** The local microgrid market design focuses on interconnecting local grid conditions, stakeholder objectives, and microgrid settings with the operational constraints of the external electricity market.

market (Figure 3.3). Figure 3.3a shows an independent self-sustaining local network with p2p exchange of electricity. Figure 3.3b shows a similar network but the community microgrid is now connected to an external grid to meet its internal electrical power and energy balance (and any other requirements). In both cases, each house potentially has intermittent RES such as PV panels, loads including flexible loads such as electric vehicles, and energy storage systems such as BESS.

In the case of an independent community microgrid, the local market can be designed according to the local grid conditions, permissions, stakeholder objectives, and microgrid settings. However, in the case of a connected community microgrid, it is important to efficiently balance the local grid conditions, stakeholder objectives, and microgrid settings with the operational constraints of the external electricity market. Efficiency here primarily implies cost-effectiveness, reliability, and power quality, but there can also be other factors to evaluate it. As shown in Figure 3.4, the local electricity market must balance stakeholder-related legalities, conditions, and objectives (the top row) with social, technical, or economic objectives in a sophisticated and interconnected manner. Further, the design and operation of the internal local market is constrained (and guided) by the regulations in the external market. For example, it may be more practical for the local market to have the same trading time resolution as the external market.

However, researches into achieving such interconnections are relatively nascent. The nature of electricity supply, electricity markets, and regulations vary widely across the world, and it is especially difficult to find a global solution. Researchers have typically tried to develop generalized models for decentralized market design and then try to fit them to local conditions. As



**Figure 3.5:** Many community microgrids separately connected to the external grid and, therefore, external markets. Each coalition of neighboring houses forms a community microgrid. These community microgrids can also cluster and interact with each other to form a *microgrid cluster*.

early as 2001, Kamrat (2001) introduced the conceptual basis for a decentralized market design to model the structure of local energy. A decentralized market design that relies on “random and anonymous pairwise meetings” between buyers and sellers and requires no central authority was proposed by Blouin and Serrano (2001) but they concluded that no equilibrium exists in which both market efficiency and information revelation hold true. Block et al. (2008) established seven requirements for local energy markets, whereas Mengelkamp et al. (2017) trading compared two market designs—a decentralized p2p market and a centralized order book market and analyzed the costs, revenue, self-consumption and the financial outflow for the different market designs. Note that many of the researches so far have focused on designing local internal electricity markets by simply mimicking the external market of that region.

## 3.2 Microgrid clusters

### 3.2.1 Introduction

In Figure 3.5, several microgrids *separately* connect to the external grid to meet their internal electricity requirements. However, it is also possible to imagine several microgrids *clustering* together to interact with each other, and if required, with the external grid (often the MV

transmission line). Such microgrids can collaborate with nearby or farther microgrids to enhance reliability, resilience, operation, and economics. Such a microgrid interconnection is often referred to as *multimicrogrids* or *microgrid clusters* (Saleh et al., 2015; Che et al., 2015, 2017). When connected, both the microgrids and coalitions interact with the grid through the distribution (or MV) substation, buying and selling energy as required. Similar to community microgrids, one of the main objectives to form such microgrid clusters is to reduce interactions with the utility and promote grid independence.

In a microgrid cluster, it is not necessary that every microgrid has to *necessarily* interact with every other microgrid. It is more typical that some microgrids within the cluster collaborate to form coalitions (i.e., partnerships). Thus, a microgrid cluster ultimately consists of numerous coalitions that may also themselves interact with each other. Moreover, these coalitions need not be fixed over the entire time period. Depending on economic (or other) incentives, it is possible that different microgrids come together to form coalitions at different times.

Note that in this dissertation, the term “community microgrid” refers to a neighborhood of residential houses, which may or may not themselves be microgrids, that perform p2p electricity exchange. On the other hand, microgrid clusters refer to a group of community microgrids interconnected to form a cluster.

### 3.2.2 Generalized problem statement

We now present a generalized problem statement for microgrid clusters, i.e., the problem considered in this dissertation at its most general level. Note that the design and operation of community microgrids is a subset of the problem for microgrid clusters. The general microgrid cluster problem can be stated as follows.

**given**

1.  $m$  (community) microgrids each of
  - (a) which is formed by interconnecting  $n_i$  ( $\forall i = 1, \dots, m$ ) *customers* in a low-voltage distribution network, of whom
    - i.  $p_i$  are producers as well as consumers, i.e., *prosumers*, and themselves form (smaller) microgrids,
    - ii.  $n_i - p_i$  are only *consumers*;
  - (b) whose electricity distribution network may be managed by 1 DSO each;
  - (c) which may also have electricity supplied from a main grid by  $r_i$  ( $\forall i = 1, \dots, m$ ) retailers in competition; and
  - (d) which may have one or more governing authorities to oversee their operations, e.g., regulatory (or advisory) bodies,
2. External electricity power market<sup>18</sup>

<sup>18</sup>Either open competitive markets operated and regulated by an external entity such as Nord Pool or vertically integrated markets regulated by regulatory authorities and typically operated as monopolies.

**determine** a *design architecture* and a *management methodology* to interconnect and operate the  $m$  microgrids (and the inner  $p_i$  microgrids and  $n_i - p_i$  ( $\forall i = 1, \dots, m$ ) consumers) with each other and with the external grid and electricity market to ensure that one or more of the following technical services are simultaneously provided:

1. Power and energy balance;
2. Frequency regulation;
3. Interruption management;
4. Reactive power control;
5. Voltage regulation,

**such that** it is *optimized* to meet one or more of the following criteria:

1. *Economic*
  - (a) *Fair* allocation of costs and revenues (and hence, profits) to the relevant stakeholders (customers, DSOs, retailers, governing authorities, etc.);
  - (b) *Just* allocation of costs and revenues (and hence, profits) to the relevant stakeholders;
  - (c) *Maximization* of revenues (or profits) of the stakeholders<sup>19</sup>;
2. *Social Welfare*
  - (a) *Minimization* of carbon footprint;
  - (b) *Minimization* of environmental damage;
  - (c) *Maximization* of privacy;
3. *Technical*
  - (a) *Non-violation* of capacity constraints<sup>20</sup>;
  - (b) *Non-violation* of technical regulations—voltage, frequency, etc.;
  - (c) *Non-violation* of safety standards and protection requirements;
  - (d) *Efficient* distribution of electricity, e.g., with lowest power losses, etc.,

**assuming** that the system is set up under one or more of the following assumptions:

1. Prosumers use only renewable sources of electricity production;
2. Customers may employ electricity storage/management devices;
3. Customers may participate in load control programs (DSM/demand response (DR)); and
4. DSOs and retailers may use (centralized) electricity storage<sup>21</sup>.

<sup>19</sup>This is, of course, equivalent to ensuring that costs are minimized.

<sup>20</sup>For example, overloading of distribution lines or transformers may lead to minor problems in the best case, and major problems with outages in the worst case.

<sup>21</sup>Subject to regulations.

### 3.2.3 Generalized problem formulation

**Problem formulation** The problem statement in Section 3.2.2 is now mathematically formulated. Since there are multiple criteria and (hence) multiple objectives, the mathematical optimization involves many objective functions that should be optimized simultaneously, i.e., co-optimized. Some of these objectives may co-operate whereas some may conflict, and optimal decisions have to be taken after making tradeoffs between conflicting objectives.

At a general level, the co-optimization problem is as follows:

$$\begin{aligned} &\max \{ \text{economic objectives} + \text{social welfare objectives} + \text{technical objectives} \} \\ &\quad \text{such that} \\ &\quad \{ \text{technical services are provided} \} \end{aligned}$$

A possible approach to this co-optimization problem is to maximize one of these objectives and keep the remaining ones as constraints. Let us consider optimizing one of the economic objectives—profit maximization—and keeping the remaining objectives as constraints. There are two possible profit maximization objectives—(1) maximize the profits of each and every stakeholder together; and (2) maximize the profits of the entire system.

First, let us consider a mathematical model to maximize the profits of each and every stakeholder, i.e., *to maximize the profits of each and every microgrid stakeholder (or partner) within the constraints specified by the boundaries of technical and social welfare requirements*. Profit maximization— $\max(\text{profits})$ —is usually also fulfilled when pursuing  $\min(\text{costs})$ , so that profit maximization is equivalent to cost minimization. Then, the problem can be framed as a *general cost minimization problem* with the following objective function:

$$\begin{aligned} &\min(\text{stakeholder}_1 \text{'s cost}) \text{ and } \min(\text{stakeholder}_2 \text{'s cost}) \dots \text{and} \dots \min(\text{stakeholder}_s \text{'s cost}) \dots \\ &\quad \text{and } \max(\text{microgrid revenue}) \end{aligned}$$

where  $s$  is the number of stakeholders. Here, a stakeholder set  $\text{stakeholder}_j$  ( $\forall j = 1, \dots, s$ ) may themselves have many members. Let us confine the problem to three main stakeholder sets—customers, DSOs, and retailers. We then get the following objective function for the *general cost minimization problem*:

$$\min(\text{customer cost}) + \min(\text{DSO cost}) + \min(\text{retailer cost}) - \min(\text{microgrid revenue})$$

i.e.,

$$\begin{aligned} &\sum_{i=1}^m \sum_{j=1}^{n_i} \left( \min \left\{ \int_{t=1}^{t=T} C_{cust_{ij}}(t) dt \right\} \right) + \sum_{p=1}^m \left( \min \left\{ \int_{t=1}^{t=T} C_{DSO_p}(t) dt \right\} \right) + \dots \\ &\quad \sum_{k=1}^m \sum_{l=1}^{r_k} \left( \min \left\{ \int_{t=1}^{t=T} C_{ret_{kl}}(t) dt \right\} \right) + \sum_{q=1}^m \left( \min \left\{ \int_{t=1}^{t=T} -R_q(t) dt \right\} \right) \\ &\quad \forall i, p, k, q = 1, \dots, m; \forall j = 1, \dots, n_i; \forall l = 1, \dots, r_k \end{aligned} \quad (3.1)$$

where  $t = 1, \dots, T$  refers to the time steps  $t$  over the time period  $T$  being considered;  $C_{cust_{ij}}(t)$ , the costs to the  $j^{\text{th}}$  customer in the  $i^{\text{th}}$  microgrid (out of  $m \times n_i$  customers);  $C_{DSO_p}(t)$ , the costs to the  $p^{\text{th}}$  DSO (out of  $m$  DSOs);  $C_{ret_{kl}}(t)$  to the  $l^{\text{th}}$  retailer in the  $k^{\text{th}}$  microgrid (out of  $m \times r_k$  retailers); and  $R_q(t)$ , the revenue obtained by the  $q^{\text{th}}$  microgrid (out of  $m$  microgrids) through the sales of various services, all at time  $t$ . Equation 3.1 is explicated further by the following expansion:

$$\begin{aligned} & \min(\text{customer}_1 \text{'s cost}) \text{ and } \min(\text{customer}_2 \text{'s cost}) \dots \text{and} \dots \min(\text{customer}_{m \times n_i} \text{'s cost}) \dots \\ & \dots \text{and} \dots \\ & \min(\text{DSO}_1 \text{'s cost}) \text{ and } \min(\text{DSO}_2 \text{'s cost}) \dots \text{and} \dots \min(\text{DSO}_m \text{'s cost}) \dots \\ & \dots \text{and} \dots \\ & \min(\text{retailer}_1 \text{'s cost}) \text{ and } \min(\text{retailer}_2 \text{'s cost}) \dots \text{and} \dots \min(\text{retailer}_{m \times r_k} \text{'s cost}) \dots \\ & \dots \text{and} \dots \\ & \max(\text{microgrid}_1 \text{'s revenue}) \dots \text{and} \dots \max(\text{microgrid}_m \text{'s revenue}) \end{aligned}$$

Maximizing the profits of every one of the  $(m \times n_i + m + m \times r_k)$  microgrid stakeholders separately and simultaneously in this manner is a hard and complicated problem due to the often conflicting constraints and regulations. The problem can also be reformulated to *maximize the profits of the entire system* as a whole. Note that it is possible that some individual stakeholders may suffer in this case, thereby reducing their motivation to participate in such collaborative electricity exchanges. Nevertheless, governments or other authorities may have strong reasons to pursue system profits instead of individual profits. In this case, the *max(system life cycle profits)* is again equivalent to *min(system life cycle costs)*, so that the objective function can be written as follows:

$$\min \left\{ \int_{t=1}^{t=T} \left( \sum_{i=1}^m \sum_{j=1}^{n_i} C_{cust_{ij}}(t) + \sum_{p=1}^m C_{DSO_p}(t) + \sum_{k=1}^m \sum_{l=1}^{r_k} C_{ret_{kl}}(t) - \sum_{q=1}^m R_q(t) \right) dt \right\} \quad (3.2)$$

**Customer costs** A single customer's cost  $C_{cust}$ <sup>22</sup> can be further subdivided into

$$C_{cust} = C_{equip} + C_{inst} + C_{main} + C_{grid} - R_{cust}$$

$C_{equip}$ ,  $C_{inst}$ , and  $C_{main}$  refer to the costs paid for purchasing, installing, and maintaining equipment (primarily by the prosumer). For a prosumer installing PV panels, these costs would include the costs of the PV panel as well as related components such as converters, measurement, communication, and protection equipment, and wires and insulation.  $C_{grid}$  refers to the costs paid by the customer to the electricity authorities, including the supplier and the DSO, for obtaining electricity from the grid.  $C_{grid}$  depends on the customer location and regulations. For

<sup>22</sup>For notational simplicity and brevity, we have used  $C_{cust}$  to imply a single customer  $C_{cust_{ij}}$ . We have also extended the same style to other variables mentioned here and in the discussion on DSO and retailer costs. Additionally, we have not indicated time steps  $t$ . In practice, care should be taken to explicitly include all the variables with correct indices, as given in Equation 3.1 (and including additional ones if needed).

example, in the Finnish scenario,

$$C_{grid} = C_{D,m} + (C_{D,e} + C_{spot} + C_{S,a} + C_{S,e} + C_T) \cdot E_g$$

where,  $C_{D,m}$  (€) is a monthly fee and  $C_{D,e}$  (€/kWh) is an electricity usage fee payable to the DSO;  $C_{spot}$  (€/kWh) is the spot price payable to the supplier;  $C_{S,a}$  (€/kWh) is an agreement fee and  $C_{S,e}$  (€/kWh) is an electricity usage fee, which together comprise a monthly fee payable to the supplier;  $C_T = C_{tax} + VAT \times C_{tax}$  €/kWh is the electricity tax plus a value added tax (VAT) on the electricity tax, usually paid to the DSO; and  $E_g$  is the energy consumer by customer (kWh). In addition, the DSO applies a one-time grid connection fee only for new connections.

$R_{cust}$  is the revenue generated by the customer. The revenue generated by the customer may comprise

$$R_{cust} = R_{exch} + R_{DR} + R_{misc}$$

where  $R_{exch}$  is the revenue obtained by selling (or sharing) electricity to (with) other customers;  $R_{DR}$  is the revenue obtained from any incentives offered by DR/DSM programs; and  $R_{misc}$  is the revenue obtained from any other miscellaneous activities, which may include, for example, marketing, consultation, leadership, or other work for the community.

**DSO costs** The DSO costs  $C_{DSO}$  can be further subdivided as follows:

$$C_{DSO} = C_{equip} + C_{inst} + C_{main} + C_{planning} + C_{quality} + C_{efficiency} + C_{reliability} - R_{DSO}$$

where  $C_{equip}$ ,  $C_{inst}$ , and  $C_{main}$  refer to the costs paid by the DSO for purchasing, installing, and maintaining equipment, respectively. These costs would include the costs of creating new networks or expanding old ones as required; costs of protection equipment; costs of installing energy storage if required (or allowed); and costs of any other equipment.  $C_{planning}$  is the expenditure on planning the network.  $C_{quality}$ ,  $C_{efficiency}$ , and  $C_{reliability}$  are the costs required to be paid to the regulator for not meeting quality, efficiency, and reliability targets, respectively. The exact nature of these costs will differ across different regions due to varying regulations. Note that these are costs that are relevant to the electric energy supply itself and DSOs will have other organizational costs, such as salaries, and overheads as well.

In open electricity markets, a DSO's revenues  $R_{DSO}$  are obtained from tariffs set for supplying electricity to the customer using equipment installed by the DSO<sup>23</sup>. In addition, if we assume that regulations allow the DSO to be a stakeholder in a community microgrid, for example, through some form of ownership, DSO's revenues can also include additional revenue from operational, consultancy, and leadership roles.

**Retailer costs** The retailer costs can be subdivided as follows:

$$C_{ret} = C_{risk} + C_{purch} - R_{sales}$$

<sup>23</sup>For a detailed example of how DSO revenues are calculated in open electricity markets such as the Nordic market, refer to Energiavirasto (2015) which describes the electricity distribution regulation methods in Finland.

where  $C_{risk}$  refers to the cost of the risks;  $C_{purchase}$  refers to the electricity purchase costs; and  $R_{sales}$  refers to the revenue from electricity sales. Similar to DSOs, these are costs that are relevant to the electrical energy supply itself. Retailers are usually for-profit organizations and will also have other costs such as salaries and overheads.

**Microgrid revenue** Finally,  $R(t)$  is the revenue obtained by the microgrid through various microgrid services.  $R(t)$  may then consist of

$$R = R_{frc} + R_{react} + R_{pb} + R_{others}$$

where  $R_{frc}$ ,  $R_{react}$ ,  $R_{pb}$ , and  $R_{others}$  refer to the revenues obtained from supplying frequency regulation, reactive power compensation, power balancing, and other services. The allocation of microgrid services to the various ancillary services is a separate problem in itself. One approach is to use binary variables with the objective to maximize revenue  $R$ :

$$\max \left\{ \int_{t=1}^{t=T} \left( \gamma_{frc}(t)R_{frc}(t) + \gamma_{react}(t)R_{react}(t) + \gamma_{pb}(t)R_{pb}(t) + \gamma_{oth}(t)R_{oth}(t) \right) dt \right\}$$

such that

$$\gamma_{frc}(t) + \gamma_{react}(t) + \gamma_b(t) + \gamma_{oth}(t) = 1, \quad \forall t = 1, \dots, T$$

$$\gamma_{frc}(t), \gamma_{react}(t), \gamma_b(t), \gamma_{oth}(t) \in \{0, 1\}, \quad \forall t = 1, \dots, T$$

+ constraints for each service

The binary variables  $\gamma_{frc}$ ,  $\gamma_{react}$ ,  $\gamma_b$ ,  $\gamma_{oth}$  ensure that each microgrid service is “switched on” or “switched off”, i.e., activated, depending on other constraints related to each service as well as the objective to maximize the revenue.

**Constraints** In Equation 3.1, an economic objective—profit maximization—was optimized with the idea that the remaining objectives become constraints. We now list some of the possible constraints to the objective function given by Equation 3.1 as follows:

#### 1. Technical constraints

(a) Energy and power balance should be maintained separately for every customer:

$$E_{res_{ij}}(t) + E_{g_{ij}}(t) = E_{l_{ij}}(t) \quad \forall i = 1, \dots, m; \\ j = 1, \dots, n_i; t = 1, \dots, T$$

$$P_{res_{ij}}(t) + P_{g_{ij}}(t) = P_{l_{ij}}(t) \quad \forall i = 1, \dots, m; \\ j = 1, \dots, n_i; t = 1, \dots, T$$

where  $E_{res_{ij}}$  and  $P_{res_{ij}}$  are the RES energy and power, respectively, produced by the  $j^{\text{th}}$  customer in the  $i^{\text{th}}$  microgrid (out of  $m \times n_i$  customers; for a consumer,  $E_{res_{ij}} = P_{res_{ij}} = 0$ );  $E_{g_{ij}}$  and  $P_{g_{ij}}$ , the electrical energy and power, respectively, taken from the grid by the customer (all the customers are connected to the grid); and  $E_{l_{ij}}$  and  $P_{l_{ij}}$ , the load energy and power demand, respectively.

Electricity shared with another customer can be added to or subtracted from  $E_{g_{i,j}}$  and  $P_{g_{i,j}}$  depending on whether it is received from or given to the customer, respectively. For example, if a customer <sub>$i,j$</sub>  gives electrical energy to another customer,  $E_{g_{i,j}}(t)$  becomes  $E_{g_{i,j}}(t) - E_{s_{i,j}}(t)$ . If a customer <sub>$i,j$</sub>  receives electrical energy from another customer,  $E_{g_{i,j}}(t)$  becomes  $E_{g_{i,j}}(t) + E_{s_{i,j}}(t)$ .

- (b) Constraints to meet other technical objectives such as non-violation of capacity constraints (e.g., transformer overloading); non-violation of technical regulations (e.g., frequency and voltage regulation); and efficient distribution of electricity (minimization of power losses, line losses, outages, etc.). These constraints depend on the setup of the power system and are often numerous and complex; hence, they are not explicitly listed here.
- (c) Constraints that may result from the modeling of additional technical devices in the power system such as BESS:

$$-\eta_B P_{B_{max}}/k_{dch} \leq P_B(t) - P_B(t-1) \leq \eta_B P_{B_{max}}/k_{ch}$$

where  $P_{B_{max}}$  refers to the maximum BESS power;  $P_B$ , the BESS power at time  $t$ ;  $\eta_B$ , the efficiency of the battery; and  $k_{ch}$  and  $k_{dch}$ , the charge and discharge parameters, respectively. This is a simplified and somewhat idealistic model. A more realistic model can be obtained by including more BESS characteristics, e.g. non-linear discharge functions, and BESS chemistries. Note that if the BESS is included, the energy and power balance equations must be modified appropriately by adding terms for battery charge and discharge, e.g.,  $P_{B_{i,j}}(t+1) - P_{B_{i,j}}(t) \forall i = 1, \dots, m; j = 1, \dots, n_i; t = 1, \dots, T$ .

- (d) Load control (DSM/DR) programs to exploit flexible loads in residential households will result in additional constraints. It is difficult to predict the exact formulation of such constraints since it depends on the nature of the load control program and its objectives. A somewhat generalized flexibility constraint (but limited in scope) was presented in Chapter 2 (Equation 2.10).
2. *Economic* constraints: Economic constraints, in general, are still open questions and the subject of active current research. Researchers have, for example, attempted to apply principles of (and approaches in) economic theory to answer questions such as how to divide system costs and revenues (and hence, profits) *fairly* or *justly* or otherwise among the stakeholders; how to define and maximize “societal welfare”; etc.
  3. *Social Welfare* constraints: Social welfare objectives, such as minimization of carbon footprint, minimization of environmental damage, can be set as constraints. These constraints strongly depend on the environment where the microgrid is set up and the priorities of the community.

Note that this is not an exhaustive list of constraints. Depending on the power system, microgrid setting, geographical conditions, and regulations, there could be numerous other constraints. We have only attempted to illustrate one approach to set up the microgrid cluster problem in the form of an optimization problem with some constraints. We believe that this approach and perspective may help future researchers and practitioners to set up their own microgrid cluster problems in this manner and find appropriate solutions.

**Formulation from other viewpoints** It is important to note that the above formulation is from the *profit maximization viewpoint*. However, other objectives can also be used to reformulate the optimization, and profit maximization objectives then become a constraint. For example, the above formulation can also be written from the *social welfare* viewpoint as follows:

maximize (social welfare)

The exact optimization function depends on the definitions of social welfare. One approach in today's context can be for example that maximizing social welfare can be achieved by minimizing emissions, so that the objective function becomes

minimize (CO<sub>2</sub> emissions)

Then the appropriate formula that models the CO<sub>2</sub> emissions caused by each device and element in the system can be included. The profit maximization objectives in Equation 3.1 now become a set of constraints as follows:

$$0 \leq C_{cust_{ij}}(t) \leq K_{cust_{ij}}(t)$$

$$0 \leq C_{DSO_i}(t) \leq K_{DSO_i}(t)$$

$$0 \leq C_{ret_{ij}}(t) \leq K_{ret_{ij}}(t)$$

$$R_i(t) \geq K_{rev_i}(t)$$

$$\forall i = 1, \dots, m; j = 1, \dots, n_i; t = 1, \dots, T$$

where  $K_{cust_{ij}}(t)$  represents the cost limits for the  $j^{\text{th}}$  customer in the  $i^{\text{th}}$  microgrid (out of  $m \times n_i$  customers);  $K_{DSO_i}(t)$  the cost limits for the  $i^{\text{th}}$  DSO (out of  $m$  DSOs);  $K_{ret_{ij}}(t)$ , the cost limits for the  $j^{\text{th}}$  retailer in the  $i^{\text{th}}$  microgrid (out of  $m \times n_i$  retailers); and  $K_{rev_i}(t)$ , the minimum desired revenue from the  $i^{\text{th}}$  microgrid (out of  $m$  microgrids) at time  $t^{24}$ . Summation constraints can be suitably used to express total desired maximum costs and total minimum revenues, e.g.,  $\left( \int_{t=1}^{t=T} \int_{i=1}^{i=m} R_i(t) dt \right) \geq K_{tot.rev}$ , where  $K_{tot.rev}$  refers to the total minimum revenue.

### 3.2.4 Solution methodology design

The problem presented in Sections 3.2.2 and 3.2.3 is quite complicated and requires several components to be solved and interconnected. Here, we describe the features of a general solution methodology. In particular, we present the different components that are required to effectively solve the problem. These components are in accordance with the seven requirements for local energy markets given by Block et al. (2008) who investigated a combinatorial double auction mechanism for the pricing and allocation of locally produced energy.

**Solution components** In general, a practical solution methodology must be designed with the following inter-dependent components (also illustrated in Figure 3.6):

1. **Design component:** The design component is a centrally installed software component and defines the parameters that characterize the problem—e.g., the stakeholders, duration,

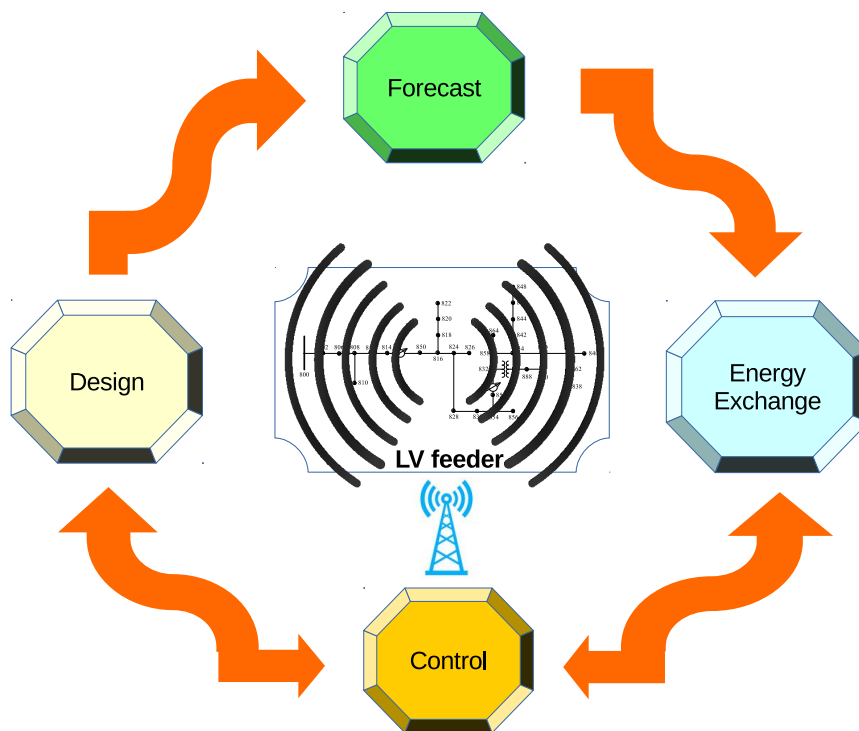
<sup>24</sup>Of course,  $R_i$  will be additionally constrained by other parameters so that it has an upper limit as well.

time resolution, type of interconnections, etc. Many of these parameters are input to the forecast and control components, depending on the requirements. The design component also takes inputs from the control component to update its parameters, if required. In the design component, the parameters that characterize the problem—e.g., stakeholders, type and number of participants, time resolution, interconnections, etc.—are defined, for example, as follows:

- (a) *Stakeholders*: Microgrid cluster stakeholders such as customers, prosumers, DSOs, retailers, governing authority, and regulatory bodies.
- (b) *Participants*: Stakeholders who are willing to participate in the electricity exchange—e.g., customers, producers, retailers, etc.—are typically referred to as participants.
- (c) *System Framework*: The interactions between the participants in a the microgrid cluster can be organized in four different ways—decentralized, centralized, or hierarchical system, or a hybridization of these systems. In all cases, participants can be modeled as intelligent agents with specific goals.
  - i. Decentralized system: Participants are modeled as selfish (i.e., self-interested) non-co-operative agents who aim to maximize their own profits. Large decentralized systems composed of self-interested agents have high levels of efficiency (Vytelingum et al., 2010). Agents are allowed to keep their preferences private and only have a local view of the environment. Stock markets and internet auctions are good examples of building large scale systems in this manner.
  - ii. Centralized system: Participants are modeled as co-operative agents who are managed by a centralized entity based on specific objectives (cost minimization, systemic objectives, societal objectives, etc.). Agents reveal their preferences and other information to the trusted authority that optimizes the state of the entire system.
  - iii. Hierarchical system: Participants can be modeled as a mixture of co-operative or non-co-operative agents but a priority order is established for their objectives.
  - iv. Hybrid system: The above three systems are hybridized by separately modeling different stakeholders and their actions and then connecting them. Such a hybrid system may even be essential because of the differences in stakeholder responsibilities, objectives, and actions. However, this increases the complexity of the solution.
- (d) *Interconnections between internal local market and external market*: If electricity market-based trading is used to solve the problem, it is important to ensure that market parameters such as market time resolution and market products are properly established.

The design component essentially specifies the problem.

2. **Forecast component**: The forecast component is a software that produces forecasts of input time-series data such as electricity production data, consumption (i.e., load) data, and pricing data (e.g., from the external market if considered) that are then input to the energy exchange component. Depending on the time resolution specified in the design component as well as the inputs from the control component, forecasts may be required



**Figure 3.6:** A broad overview of the inter-dependent *software-based virtual components* of a practical solution to operate microgrid clusters. Additional components, such as *communication* and *security* components, are also required for setting up a robust and resilient microgrid clusters. All components need to communicate through either wireless communication (shown here) or using other technology. Some components—or their parts—may be installed locally at customer premises, forming a distributed architecture.

at different time horizons, i.e., forecasting horizons<sup>25</sup>, such as 15-min-, 1-h-, 12-h-, 24-h-, week-, month-, or year-ahead. The forecast component may be either centrally operated or individually operated by each customer.

3. **Electricity exchange component:** In the electricity exchange component, the mechanisms for electricity exchange (or interactions) among the participants are established. These mechanisms should ideally have the following characteristics:

- (a) *Ease of Use*, to enable participants to easily participate in electricity exchanges;
- (b) *Speed*, to allow electricity exchanges to be realized quickly;
- (c) *Scalability*, to allow adaption to increased stakeholders;
- (d) *Fairness*, to ensure that all stakeholders benefit proportional to their contributions;
- (e) *Flexibility*, to ensure adaptation to different environments;
- (f) *Repeatability*, to ensure that the electricity exchanges can be repeated multiple times over a long time period; and
- (g) *Reliability*, to ensure that the repetitions of the electricity exchanges occur without any disparities between the repetitions and are always successful.

The electricity exchange component is a centrally installed software component and its results are input into the control component, which, in turn, sends feedback signals to the electricity exchange component for additional optimization, if required.

4. **Control component:** The control component is a software component that acts as the engine of the solution methodology, driving the other components by interacting with them and co-ordinating their tasks. The control component interacts with all components<sup>26</sup>, taking inputs from them and sending control signals for their operation. The control component is extremely important in a practical system because it controls the sequence and timing of operations. Note that the control component also exchanges information with electric devices such as inverters and phasor measurement units (PMUs), forming the *technical component* (mentioned below). As an example, a typical planning operation by the control component at a time  $t$  is as follows:

- (a) *Step 1:* Obtain all design parameters from the design component. For example, obtain the following parameters: customers are the only traders, and at time  $t$ , the electricity exchange is planned for 24 h from 00:00 the next day.
- (b) *Step 2:* Obtain 24-h day-ahead forecasted price information from the forecast component.
- (c) *Step 3:* Send 24-h day-ahead forecasted price information to the customer.
- (d) *Step 4:* Request customers to send their 24-h day-ahead required/available electricity and bid prices to the forecast component.<sup>27</sup>

<sup>25</sup>Length of time into the future for which forecasts are to be prepared.

<sup>26</sup>Only indirectly with the forecast component.

<sup>27</sup>Based on the assumption that electricity market price forecasts are centrally calculated, whereas electricity production and consumption forecasts are locally generated.

- (e) *Step 5*: Send all information from design and forecast components to the electricity exchange component.
- (f) *Step 6*: Receive market clearing information from the electricity exchange component.
- (g) *Step 7*: Send appropriate control signals to the relevant electricity infrastructure to perform the electricity exchange (e.g., supply electricity from customer 1 to customer 9) in accordance with the market clearing information.

In addition, in the real-time operational phase, the control component resends control signals<sup>28</sup>, records the actual electricity production and exchanges, and calculates the customer incomes based on the real-time electric exchange. Note that the control component may also be decentralized so that there may be multiple control components installed at customer premises that together interact with a central controller to co-ordinate the electricity exchange.

5. **Auxiliary components:** These software components form a virtual layer and play supporting roles. For example, a *communication component* facilitates the information exchange process, whereas a *security component* protects sensitive information.
6. **Technical component:** The abovementioned five components are “virtual” layers comprising software components. In addition, a technical component forming a physical layer consisting of the LV network lines as well as equipment such as protection equipment, relays, cables, etc., and devices such as inverters and PMUs is required to install and operate an electricity grid network. A robust and efficient technical layer is critical to achieve the desired features of the abovementioned “virtual” components.

These components are extremely broad topics that require comprehensive analyses and detailed discussions that, in some cases, are beyond the scope of this dissertation. In particular, the technical and auxiliary components are hardly discussed in this dissertation.

### 3.3 Conclusions: limitations and future study

This chapter examined p2p electricity exchanges and microgrid interconnections as a method to increase the use of RES and improve grid independence. First, the concept of *community microgrids* in which residential households in a neighborhood microgrid exchange electricity was introduced. Their benefits and the problems facing their implementations were then discussed. Subsequently, the chapter introduced *multi-microgrids* or *microgrid clusters* in which several community microgrids interact with each other. We also presented a generalized mathematical formulation of the microgrid cluster problem along with a description of the solution components that can be constructed to fully solve the problem.

The general problem presented here requires in-depth research and co-ordination between many solution concepts and methodologies. Many researchers have addressed specific components of the problem and proposed methods to address them. For example, forecasting has a rich scientific literature. In some cases such as control algorithms, there are numerous researches but

<sup>28</sup>Because forecasts may not be accurate.

no conclusive solutions to the unique problems presented by clusters interconnecting with electricity markets. Additionally, many utility companies as well as communities have attempted to practically build and deploy limited versions of community microgrids as well as microgrid clusters.

The mathematical formulation presented here is a very generalized formulation that may be incomplete for some operating conditions. It will certainly require additional changes in order to be adapted to different environments. In addition, concrete methodologies and potential researches to solve the problem and its sub-components are not presented here. The integration of electricity markets is considered but the analysis is narrow. The chapter also does not consider many diverse market structures, components, and other factors that influence the power system design.

Nevertheless, the concepts presented here along with the problem statement and solution design form building blocks for constructing a complete solution in the future. By incrementally solving all the problems related to building and implementing microgrid clusters, we hope that a final all-encompassing solution will be ultimately achieved. We believe that the problem statement and formulation give a useful bird's-eye view for future researchers to visualize and approach the microgrid cluster problem. The solution design offers a bigger perspective on the various challenges and solutions that will need to be interconnected and enmeshed to obtain the final solution. A complete solution to such a complicated problem is beyond the scope of this dissertation. Instead, in the next chapter of this dissertation, we present a methodology to solve an important problem in one of the components mentioned in Section 3.2.4—the electricity exchange component.

## 4 Electricity exchange and profit allocation in community microgrids

### 4.1 Introduction

The general *microgrid cluster problem*, i.e., the problem of collaborations between community microgrids, which was discussed in Section 3.1, is very challenging and its complete solution is beyond the scope of this dissertation. Instead, we consider a subset of this problem here. We consider a single low voltage (LV) microgrid distribution network comprising prosumers and consumers, i.e., a *community microgrid*, which has been introduced and discussed in detail in the previous chapter (Section 3.1).

In this chapter, we will first describe the community microgrid problem and then present our proposed methodology to solve a part of the problem, i.e., how to achieve *fair* electricity exchange among the customers in a community microgrid. Our solution pertains to the electricity exchange component described in Section 3.2.4 in the previous chapter. We then theoretically prove that our methodology is fair and will achieve higher profits as compared to the case when electricity is not shared. We also show the results from applying the methodology to two locations with different environmental conditions—an LV network in Finland and a neighborhood in Austin, Texas, USA—and compare the results. In addition, we compare and contrast the results of applying our methodology with the case when electricity is not shared as well as with the case when a conventional auction-based approach is applied to the electricity exchange.

Additionally, we consider two tariff structures—the historical and typical energy-based tariffs (EBTs) and the newly proposed power-based tariffs (PBTs). **Publication IV** (Narayanan et al., 2018) compared the profits of applying EBTs and PBTs to community microgrids using a conventional auction-based approach for the electricity exchange. This chapter expands upon the publication by also comparing the impact of the newly proposed methodology with the non-collaborative case and with the conventional auction-based case, when PBTs are used to bill customers.

### 4.2 Community microgrid problem

#### 4.2.1 Introduction

In Chapter 3.1, a *generalized problem statement for microgrid clusters* was expressed by the following equation (Equation 3.1):

$$\begin{aligned} & \sum_{i=1}^m \sum_{j=1}^{n_i} \left( \min \left\{ \int_{t=1}^{t=T} C_{cust_{ij}}(t) dt \right\} \right) + \sum_{p=1}^m \left( \min \left\{ \int_{t=1}^{t=T} C_{DSO_p}(t) dt \right\} \right) + \dots \\ & \sum_{k=1}^m \sum_{l=1}^{r_k} \left( \min \left\{ \int_{t=1}^{t=T} C_{ret_{kl}}(t) dt \right\} \right) + \sum_{q=1}^m \left( \min \left\{ \int_{t=1}^{t=T} -R_q(t) dt \right\} \right) \\ & \forall i, p, k, q = 1, \dots, m; \forall j = 1, \dots, n_i; \forall l = 1, \dots, r_k \end{aligned} \quad (4.1)$$

where  $m$  refers to the number of community microgrids;  $n_i$ , the number of customers within each microgrid;  $r_k$ , the number of retailers servicing each microgrid;  $t = 1, \dots, T$ , the time steps  $t$  over the time period  $T$  being considered;  $C_{cust_{ij}}(t)$ , the cost to the  $j^{\text{th}}$  customer in the  $i^{\text{th}}$  microgrid (out of  $m \times n_i$  customers);  $C_{DSO_p}(t)$ , the cost to the  $p^{\text{th}}$  DSO (out of  $m$  DSOs);  $C_{ret_{kl}}(t)$  the cost to the  $l^{\text{th}}$  retailer in the  $k^{\text{th}}$  microgrid (out of  $m \times r_k$  retailers); and  $R_q(t)$ , the revenue obtained by the  $q^{\text{th}}$  microgrid (out of  $m$  microgrids) through sales of various services, all at time  $t$ .

In this chapter, we consider a component of the microgrid cluster—a *community microgrid*—so that  $m = 1$ ,  $n_i = n_1 = n$ ,  $r_k = r_1 = r$ , and  $R_q = R_1 = R$ . Further, in this dissertation, we simplify the problem by splitting it and considering only one stakeholder, the customer<sup>29</sup>. Therefore, Equation 4.1 reduces to

$$\sum_{i=1}^n \left( \min \left\{ \int_{t=1}^{t=T} C_{cust_i}(t) dt \right\} \right) + \min \left\{ \int_{t=1}^{t=T} -R(t) dt \right\} \quad (4.2)$$

where  $C_{cust_i}(t)$  refers to the cost to the  $i^{\text{th}}$  customer in the microgrid ( $i = 1, \dots, n$ ) at time  $t$  and  $R(t)$  the revenue earned by the microgrid at  $t$ .

Moreover, we deal with the interactions *between the customers inside* a single community microgrid. The nature and impact of potential services provided by a community microgrid to an external grid or entity<sup>30</sup> are ignored here and will be studied later. Hence, Equation 4.2 becomes

$$\sum_{i=1}^n \left( \min \left\{ \int_{t=1}^{t=T} C_{cust_i}(t) dt \right\} \right) \quad (4.3)$$

Further, as described in the previous chapter in Equation 3.2.3, the  $i^{\text{th}}$  customer's costs can be further subdivided into

$$C_{cust_i} = C_{equip_i} + C_{inst_i} + C_{main_i} + C_{grid_i} - R_{cust_i}$$

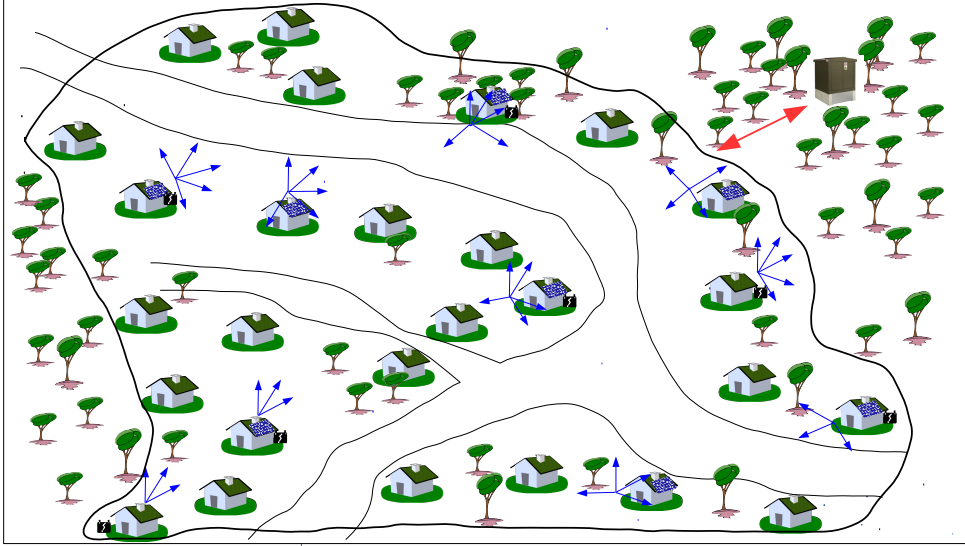
where  $C_{equip_i}$ ,  $C_{inst_i}$ , and  $C_{main_i}$  refer to the costs paid for purchasing, installing, and maintaining equipment by the  $i^{\text{th}}$  customer (typically the prosumer);  $C_{grid_i}$ , the costs paid by the customer to the electricity authorities, including the supplier and the DSO, for obtaining electricity from the grid; and  $R_{cust_i}$ , the revenue generated by the customer.

$$R_{cust_i} = R_{exch_i} + R_{DR_i} + R_{misc_i}$$

where  $R_{exch_i}$  is the revenue obtained by exchanging electricity with other customers by the  $i^{\text{th}}$

<sup>29</sup>By splitting the bigger problem into smaller problems in this manner, we hope to obtain simpler problems. These smaller and simpler problems can then be solved independently. Subsequently, their solutions can be creatively combined to obtain a comprehensive full solution. This dissertation is confined to treating only the customer as a stakeholder; the remaining tasks for DSOs, retailers, etc., are beyond its scope and set as future work.

<sup>30</sup>For example, we can consider a community microgrid to be a single electrical element (generator/load) in a distribution grid, similar to a BESS, and explore the nature and impact of the services that it can provide to the stakeholders in the grid, such as power balance, frequency regulation, etc. This is an active area of research currently.



**Figure 4.1:** A community microgrid. Here,  $p$  prosumers and  $c$  consumers form an LV distribution network that is connected to a main grid through a single secondary substation. A prosumer exchanges excess electrical energy with a consumer who has an electricity deficit.

customer;  $R_{DR_i}$ , the revenue obtained from any incentives offered by demand-side management (DSM) programs; and  $R_{misc_i}$ , the revenue obtained from any other miscellaneous activities, which may include, for example, marketing, consultation, leadership or other work for the community.

Now, consider such a community microgrid (Figure 4.1) comprising  $n$  residential household<sup>31</sup> customers— $p$  prosumers and  $c$  consumers ( $p + c = n$ )—who together form an LV distribution network connected to a main grid through a single substation. The RES installed in a prosumer  $i$  ( $i \in p$ ) generates electrical energy  $E_{p,i}$  to meet its own electrical load demand  $E_{l,i}$ . Then,  $E_{e,i} = E_{p,i} - E_{l,i}$  is either excess energy that can be sold ( $E_{e,i} > 0$ ) or deficit energy that has to be bought ( $E_{e,i} < 0$ ). If  $E_{e,i} = 0$ , the prosumer is able to exactly meet its demand. In the classical case, if  $E_{e,i} < 0$ , the balance energy  $E_{e,i}$  is bought from the main grid, and if  $E_{e,i} > 0$ , it is either wasted or sold to the main grid (net metering). In a community microgrid, the customers collaborate so that  $E_{e,i}$  can either be sold to or bought from consumers or prosumers in the microgrid, respectively, provided electrical constraints and conditions are met.

#### 4.2.2 Problem statement

We assume that prosumers have already installed RES at their home and are now ready to collaboratively exchange electricity for some benefits, instead of acting independently. This means that we can ignore the cost of equipment and installation. The marginal costs of RES such as

<sup>31</sup>This study has focused on residential customers, but some community microgrids may also include industrial customers. When including industrial customers, care must be taken to ensure that the formulations adhere to relevant regulations.

photovoltaic (PV) panels is practically nil, and we also ignore maintenance costs. Further, revenue from DR and miscellaneous services are also ignored. As a result, Equation 4.3 becomes

$$\sum_{i=1}^n \left( \min \left\{ \int_{t=1}^{t=T} (C_{grid,i}(t) - (R_{exch,i}(t))) dt \right\} \right) \forall i = 1, \dots, n \quad (4.4)$$

This is the main objective of the problem—to *minimize the total cost of electricity purchased from the grid over a time period  $t = 1, \dots, T$  for each and every customer  $i = 1, \dots, n$* . Two constraints are further applied to the minimization objective. The first constraint maintains the energy balance as follows:

$$E_{res,i}(t) + E_{exch,i}(t) + E_{g,i}(t) = E_{l,i}(t); \forall t = 1, \dots, T; \forall i = 1, \dots, n \quad (4.5)$$

where  $E_{res,i}(t)$  is the renewable energy produced by a customer  $i$  prosumer ( $E_{res,i}(t) = 0$  for a consumer);  $E_{exch,i}(t)$  is the electrical energy exchanged by a customer  $i$  with another customer in the community microgrid ( $E_{exch,i}(t) > 0$  if the energy is purchased and  $E_{exch,i}(t) < 0$  if the energy is sold);  $E_{g,i}(t)$ , the electrical energy taken from the external grid; and  $E_{l,i}(t)$ , the load energy demand of a customer  $i$ , all at time instance  $t$ .

The second constraint ensures that the revenue from the electricity exchange is *fair*:

$$R_{exch,i}(t) = \phi_i(t) \quad (4.6)$$

where  $\phi_i(t)$  is a function that expresses *fairness* in an interaction between the participants in a microgrid.

In summary, the problem statement expressed by Equations 4.4–4.6 is as follows:

**given** one connected community microgrid formed by interconnecting  $n$  customers in a low-voltage distribution network, of whom  $p$  are *prosumers* and  $c$  are *consumers*; one DSO; one retailer; day-ahead electricity prices; and day-ahead forecasted electricity production and consumption, **minimize** the electricity costs paid by a customer to access electricity under the **constraints** of *fair allocation, energy balance, and 100% electric supply*.

#### 4.2.3 Assumptions

As mentioned previously, we assume that the electricity distribution network is managed by one DSO. Further, we assume that the community microgrid is connected to a main grid that supplies any extra electricity that may be required to maintain power and energy balances. We also assume that this additional electricity is sold to the customers by one retailer in competition in the external electricity market. This simplifying assumption that there is only one retailer selling electricity in the grid is in agreement with practical trends, for example, in Nordic markets, where the tariffs paid by the customers to a retailer are closely aligned with the market prices<sup>32</sup>. As a result, historically, only a minority of electricity consumers in the Nordic region have

<sup>32</sup>Modern, open competitive electricity markets usually have an hourly day-ahead physical trading mechanism that forms a credible reference price for the traded electricity. In the Nordic market, the day-ahead market is called Elspot, and it specifies the electricity market prices called spot prices.

changed their electricity supplier.

#### 4.2.4 Tariff systems

In the conventional tariff system, the electrical energy consumed by a customer is used to bill the customer. However, in recent years, energy management methods and devices such as ESS, heat pumps, and electric vehicles are significantly reshaping customers' load profiles. The volume of transmitted energy is decreasing due to the increasing energy efficiency of renewable hardware technologies. At the same time, the momentary peak powers in the smart renewable energy grid are increasing. Such increases in peak power are problematic for DSOs who maintain the grid. Since DSO incomes are primarily energy dependent, they will lose revenue from customers. But, on the other hand, their network investment costs will increase since network dimensioning is dependent on the highest peak powers (Tuunanen et al., 2016).

Due to these issues and to ensure that DSO revenues reflect their true network costs, some researchers have proposed PBTs to bill customers (Tuunanen et al., 2016; Haapaniemi et al., 2017). In the PBT scheme, customers pay for their peak load ( $\text{€}/kW$ ) instead of consumed energy ( $\text{€}/kWh$ ). The PBT scheme is also motivated by the recent introduction of smart automatic meter readers (AMR), which has made it possible to record real-time consumption at very fine resolutions. Thus, AMR-based meters enable the implementation of the more equitable PBT scheme.

The implementation of PBTs has important implications for community microgrids, because peer-to-peer (p2p) trading can increase the peak power when prosumers transfer electricity to other consumers. Hence, our proposed methodology has also been applied to PBTs.

### 4.3 Prior literature

#### 4.3.1 Introduction

The idea of electricity exchange in a power grid to increase energy efficiency and cost savings is not new, especially for utilities (Ruusunen, 1992). For example, in 1991, Ruusunen et al. (1991) considered a group of utility companies, each owning a generator, connected together to form a power pool and showed that energy exchange results in the efficient use of electricity. However, it was not until the mid-2000s that electricity distribution researchers started considering renewable microgrids as a way to increase the proliferation of RES (Lasseter and Paigi, 2004). Thereafter, from around the late 2000s, researchers began to examine the problem of interconnecting several microgrids to form coalitions or clusters (Saad et al., 2012). And, by around 2015, p2p electricity exchange within microgrids began to be considered seriously (Giotsas et al., 2015).

To enable and optimize electricity exchange among the participants in a community microgrid, researchers have employed three basic approaches—optimization-based, market trading-based, and game-theory-based methods.

### 4.3.2 Optimization-based methods

Several optimization-based methods have been proposed in the literature, including convex optimization, stochastic optimization, particle swarm optimization, mixed-integer linear programming, and agent-based methods (Jogunola et al., 2017). Here, for brevity, we do not discuss these methods in detail and the interested reader can refer to review papers such as Jogunola et al. (2017).

Our aim (Section 4.2.2) is to optimize (minimize) the objective function (Equation 4.4) when it is constrained by a fairness function (Equation 4.6) to ensure that all participants receive fair remuneration from participating in the community microgrid. Therefore, we need to first define a fairness function and then possibly use optimization tools to solve the problem.

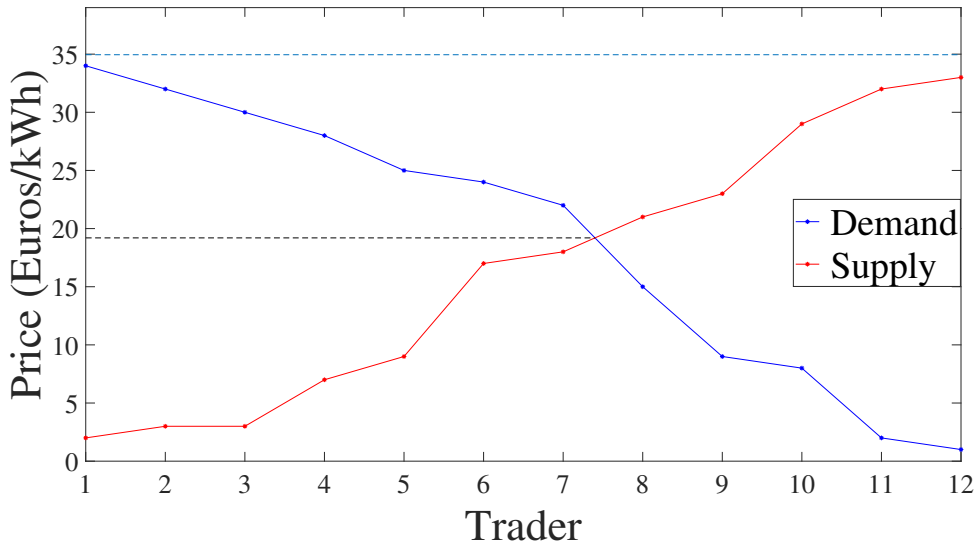
In many traditional approaches, a customer's profit maximization is indirectly achieved by making the participants themselves participate in trading electricity as a commodity. In this case, the customer themselves determine their revenue since their choice sets the price. Local product exchanges by establishing markets and trading principles have been extensively investigated in economic theory. Hence, many researchers have adapted market trading-based methods to accomplish local electricity exchanges in community microgrids by establishing a *local electrical energy exchange market* (Saad et al., 2012).

### 4.3.3 Market trading-based methods

One way to accomplish local energy exchanges is to establish a *local electrical energy exchange market* that provides participants with a market platform to trade locally generated energy within their community. A highly flexible market platform allows for efficiently co-ordinating self-interested consumers, prosumers, suppliers, and any other stakeholders.

P2P markets were first examined in economics literature—in a seminal article on pairwise matching environments, Wolinsky (1990) considered a game with decentralized, bilateral trading in which a constant population of traders enter and exit the market in each period. Blouin and Serrano (2001) proposed a detailed p2p local market mechanism with decentralized, randomized buyer and seller matching for local energy markets. For the pricing strategy, they assumed that the value of the product is binary so that buyers and sellers offer only two values (high or low) to each other. However, this bargaining process (taken from Wolinsky (1990)) is not practical for electricity customers who wish to trade their production or demand since they would desire to price their electricity over a range of values. Further, there existed no equilibrium in which both information revelation and market efficiency hold true (Blouin and Serrano, 2001). Golosov et al. (2014) examined the Pareto efficiency of the allocation of a similar model but with perfectly divisible goods. Moreover, the traders can choose the price to trade, and they have private information about the value of the assets traded. Nevertheless, it continues to be a challenging task to apply the advances in economic theory to establish decentralized local electricity markets.

The most common local energy markets design is to establish a centralized approach using **auctions**, especially continuous double auctions (CDAs). Typically, a moderator conducts double auctions based on bids—buy and sell orders—from the participants via a public order book.



**Figure 4.2:** Zero intelligence pricing for a community microgrid connected to the external grid. The supply-demand curve for 24 traders—12 buyers and sellers each—who bid after pricing their resources using the ZI strategy at a time  $t$  is shown. The spot price at  $t$  is assumed to be 34.95 €/kWh. In this case, the market price—where the supply and demand curves intersect—is 19.2 €/kWh.

Auction theory has a rich literature in economic theory, and numerous models have been examined (Kalagnanam and Parkes, 2004; Mochón and Sáez, 2015). Block et al. (2008) investigated a combinatorial double auction mechanism for the pricing and allocation of locally produced energy, and Vytelingum et al. (2010) presented a continuous double auction that takes congested transmission lines into consideration by accordingly pricing the flow of energy. However, their capacity constraints model punishes residential users because of their location, which may not be fair.

An important problem in auctions is the pricing of the product, in this case, electricity. Several non-strategic and strategic **electricity pricing strategies**—especially for bidding to a centralized double auction market—have been presented previously (Mengelkamp et al., 2017). The baseline pricing strategy for any product bought and sold in a double auction market is the so-called *zero-intelligence (ZI)* bidding strategy, which was first generally proposed in a seminal paper by Gode and Sunder (Gode and Sunder, 1993). Gode and Sunder (1993) used “zero-intelligence” programs to replace human traders and submit random bids and offers to an auction. Their market experiments demonstrated that imposing budget constraints<sup>33</sup> increases the allocative efficiency of double auctions<sup>34</sup> to almost 100%. Their results suggest that aggregate market rationality can be generated not only from individual rationality but also from *individual irrationality* (or randomness).

A ZI trader is basically a trader with no “intelligence”—it does not attempt to maximize profits,

<sup>33</sup>These constraints ensure that the random traders trade only at a profit.

<sup>34</sup>In Gode and Sunder (1993), the allocative efficiency of markets is defined as the actual total profit earned by all the traders divided by their maximum *possible* total profit (i.e., the sum of producer and consumer surplus).

and it does not observe, remember, or learn. The ZI strategy essentially ignores all market decisions to make random uninformed decisions and has the simplest behavior. A ZI trader simply generates random bids or offers that are distributed independently, identically, and uniformly over a given feasible range of the trading price. The value of the ZI strategy lies in the fact that it provides a lower bound on the system efficiency (Vytelingum et al., 2010). Moreover, their allocative efficiency is fairly close to that obtained by human traders, which means that they can be used as a substitute for human traders for analysis purposes (Gode and Sunder, 1993).

The ZI bidding strategy has been adapted to electricity trading analysis previously (Vytelingum et al. (2010); Mengelkamp et al. (2017)). Figure 4.2 illustrates the ZI bidding for a community microgrid. Assume that the microgrid is connected to the external grid and the electricity buyer can choose from either a seller within the microgrid or the external supplier who supplies at the spot price. Figure 4.2 shows the supply-demand curve for 24 traders—12 buyers and sellers each—who bid using the ZI strategy at a time  $t$ . Assuming that the spot price at  $t$  is 34.95 €/kWh, the limits are [1, 34].

Several other strategies have also been used in the literature, especially agent-based strategies, where an agent simply means a semi-autonomous entity that acts upon an environment based on observations with the objective of achieving some defined goals<sup>35</sup> (Weidlich and Veit, 2008; Mengelkamp et al., 2017). These strategies include a continuous learning strategy that adapts the probability of choosing a certain strategy after every trade (Nicolaisen et al., 2001); a bidding strategy that is based on an agent's utility function and combines current and historic market information, agent and environmental information (Lamparter et al., 2010); and others (Bower and Bunn, 2000; Ramachandran et al., 2011; Bessa et al., 2012). Some strategies are not explicitly designed for local energy markets, but the bidding mechanisms can (at least partly) be transferred.

Many intelligent bidding strategies have been employed to increase the market's efficiency. Vytelingum et al. (2008) presented an adaptive-aggressiveness (AA) strategy for bidding in CDAs, which is based on the aggression of its agent. They then adapted the method to electricity markets (Vytelingum et al., 2010). Mengelkamp et al. (2017) used Nicolaisen et al. (2001) to formulate intelligent bidding strategies where agents update their willingness to place certain orders according to their income obtained as prosumers and costs incurred as consumers.

Although market-based methods are attractive, the profits of a customer strongly depend on the cleverness of bidding strategies. The development analysis of bidding strategies is a complicated research area in itself. In addition, market-based auctions by bidding may not efficiently utilize the microgrid resources because of under-bidding due to which the market price may be set too low. Low market prices may also be unfair to prosumers. As a result, researchers have also applied theories and concepts from the science of game theory that models strategic interactions between rational decision makers.

<sup>35</sup> Agents have many other definitions depending on their goals and modes of operation. Sometimes, agents are fully autonomous and sometimes "rational," as defined in economics. Agents can be rather simple or sometimes very complex. Intelligent agents may also learn or use knowledge to achieve their goals.

#### 4.3.4 Game theory-based methods

Game theory broadly deals with models and analyses of *how self-interested participants would behave in strategic interactions* and *about how those interactions should be structured*. Since game-theoretic tools can closely imitate and model interactions among independent rational players, game theory-based methodologies have a natural application to analyze interactions among electricity grid stakeholders and have been explored extensively. Game theory has attracted attention as a key analytical tool in the design of the future power grid, including microgrids, (Rasmusen, 2006; Shoham and Leyton-Brown, 2009).

Several open problems in microgrids have been successfully treated using game theory (Saad et al., 2011; Fadlullah et al., 2011; Saad et al., 2012; Ramchurn et al., 2012; Chakraborty et al., 2014). Game theory is a vast field, and it is beyond the scope of this dissertation to introduce all its sub-fields and their specific applications to microgrid and community microgrid problems. In particular, local electricity exchange between microgrids can be realized by applying concepts from *non-co-operative game theory* in which either there is no communication or co-ordination of strategic choices among the players, or *co-operative game theory* in which the players exchange information and co-operate actively. Note that the abovementioned market trading-based methods are also a type of non-co-operative game-theoretic approach because the participants act in competition with each other.

#### 4.3.5 Problems with optimization and market trading-based methods

Optimization methods suffer from the disadvantage that their implementations can be complicated and not easy to scale, especially when there are multiple actors and parameters. If we consider fine time resolutions over a long time period, the number of variables can become large and the solution can become computationally expensive. Moreover, unless the objective function is convex, it is not easy to determine the global optima. Further, optimization theory alone is insufficient to define a *fairness* constraint. The fairness function can be defined using other tools and then imposed on the problem as a constraints, as discussed earlier in Section 4.2. The complexity of the optimization method then depends on the complexity of the fairness function. Hence, it is preferable to find a simpler and more easily applicable tool.

The market trading-based approach is attractive if we assume that the participants are non-co-operative and compete against each other. As a result, it has been extensively studied for many problems involving the exchange of products, including electricity. Auctions and bidding have been implemented in some on-field community microgrids as well (LO3 Energy and Brooklyn Microgrid, 2019). However, such implementations are still at the experimental stage. It is impractical to expect human participants to bid regularly and it is not easy to automate bidding behavior to maximize profits. This is because it is difficult to accurately model or predict the bidding behavior of participants. At the same time, a customer's bidding strategy is dependent on the bidding strategy of the other participants who are in opposition. In addition, microgrid resources may not be fully utilized because of under-bidding which may set a low market price. Such low market prices may be unfair to prosumers. It is not clear how to establish fairness and equity in such transaction systems. As a result, a customer may not necessarily get fair remuneration from participating in the community microgrid.

To build a fairer system, it is necessary to examine another popular approach to model interactions among participants—coalitional game theory in which the participants co-operate instead of competing. Many researchers have applied co-operative (or coalitional) game theory to realize collaborative energy exchange mechanisms in microgrids because of the way fairness, stability, etc., can be modeled using this approach (Saad et al., 2011; Alam et al., 2013; Wei et al., 2014; Chakraborty et al., 2015; Zhang et al., 2015c,b). In this dissertation also, we have chosen the co-operative game-theoretic approach using which we have constructed a fairness model that can be used to maximize a customer's profits. Our approach differs from the previous studies in the way a traditional fairness model is applied to the electricity exchange problem and reconstructed to solve the profit allocation question.

#### 4.4 Co-operative game theory

In game theory, a **game** is any set of circumstances with a result that depends on the actions of two or more decision makers. These decision makers who make strategic choices are called **players**. A **payoff** is the payout or benefits that a player receives from reaching a particular outcome (Zagare, 1984; Fujiwara-Greve, 2015).

In co-operative game theory, we assume that the participants are willing to co-operate with each other and work in tandem to increase the welfare of the community (Peleg and Sudhölter, 2007). In such a case, it is important to ensure that none of the participants are at a disadvantage from the co-operation and do not suffer any losses themselves. Moreover, the benefits must be fairly allocated, based on some assumption of what constitutes fairness. The co-operative approach has been examined extensively and offers an attractive approach to realize a relatively simple but scalable and fair solution (Peleg and Sudhölter, 2007). We will first introduce a few relevant concepts from co-operative game theory. We will then demonstrate how the co-operative approach can be used to solve the problem in Section 4.2.2.

##### 4.4.1 Co-operative games

In a co-operative game with a finite set of players  $N$ , the groups of players that can be formed—called *coalitions*—and their payoffs are determined. A coalitional game with transferable utility<sup>36</sup> is defined as follows.

*A coalitional game with transferable utility is a pair  $(N, v)$ , where  $N$  is a finite set of players, indexed by  $i$ ; and  $v : 2^N \rightarrow \mathbb{R}$  associates with each coalition  $S \subseteq N$  a real-valued payoff  $v(S)$  that the coalition's members can redistribute among themselves. We assume that  $v(\emptyset) = 0$  (Peleg and Sudhölter, 2007).*

For every coalition  $S$  that could form, up to and including all the players in the game,  $v(S)$  is the payoff that the coalition  $S$  can achieve and divide among its members<sup>37</sup>.  $v(\emptyset) = 0$  is a

<sup>36</sup>A *utility* is considered *transferable* if a player can (losslessly) transfer all or some part of their utility to another player. Such transfers are possible, for example, if all the players have a common currency that is valued equally. When transferable utility is assumed, payoffs may be redistributed among a coalition's members using some rule.

<sup>37</sup>Note:  $2^N$  refers to the power set of  $N$ ; the power set of any set  $S$  is the set of all subsets of  $S$ , including the empty set and  $S$  itself.

normalizing assumption that the value of the empty set is 0.

Co-operative game theory attempts to answer two fundamental questions:

- **Which coalition** will form?
- How should every coalition that forms **divide its payoff** among its members?

In co-operative coalitional games, all players benefit by forming a grand coalition  $N$ , since superadditivity makes its overall payoff  $v(N)$  to be at least as large as the sum of the payoffs received by any disjoint set of coalitions (Çetiner, 2013). Hence, we make the (standard) reasonable assumption that *rational players* will form a *single grand coalition* of all players. The question then is—*how can the profits  $v(N)$  be divided among all the players?*

#### 4.4.2 Allocation methods

Co-operative game theory offers several methods for dividing the resulting total profits among the participants. These methods are based on some principle such as stability, fairness, etc. For example, the *core* allocation method models stability by trying to ensure that no player has an incentive to form a different coalition. The *core* is a set of feasible allocations that cannot be improved upon by any other coalition of players. However, the core is not necessarily unique. In non-unique scenarios, the players may not know their profits in advance. As a result, they may be reluctant to participate in the game without clear knowledge of available profits (Peleg and Sudhölter, 2007).

Let us consider *fairness* as a criteria to allocate the profits. But, what does fairness imply? An equal distribution of the profits among all the players is not necessarily fair since different players may have contributed differently to the profits. On the other hand, it is possible that the contributions of some players are limited by circumstances beyond their control. This is especially true when modeling social issues where the economically disadvantaged may need to be supported rather than punished by the distribution of combined resources or profits. Two solution concepts—Shapley value and nucleolus—offer *unique* solutions that attempt to model *fair* allocations, where fairness is defined by a set of properties.

The nucleolus allocation method models *social justice* by adopting the principle that “the least well-off group in a society should be made as well-off as possible” (Gillman and Housman, 2019). On the other hand, the Shapley value models *merit* by making fair allocations on the basis that the players should be allocated as much as they deserve in terms of their contributions to the coalition (Gillman and Housman, 2019). Another way of looking at this approach is that in a coalition, the Shapley value looks at how much a player needs other players as compared to how much they need him/her. In other words, *who needs whom more?*

#### 4.4.3 Fairness properties

According to Gillman and Housman (2019), the following properties have been defined for fairness: efficiency, player rationality, unbiasedness (also called symmetry), subsidy-free (also called “dummy player”), scale invariance, consistency, coalition rationality, additivity (also

called linearity), and coalition monotonicity<sup>38</sup>. However, the Coalition Game Impossibility theorem states that no allocation method for co-operative games with four or more players can satisfy all the fairness properties (Gillman and Housman, 2019). In particular, no allocation method can be simultaneously *rational*, *efficient*, and *coalition monotone*. The Shapley value lacks consistency and coalition rationality, whereas the nucleolus lacks additivity and coalition monotonicity (Gillman and Housman, 2019).

Therefore, we need to choose either the nucleolus or Shapley method based on which properties are the most important and pertinent for the considered problem. In this dissertation, we choose the Shapley method for the following reasons. Consistency and coalition rationality are important only if the players are free to form and break collaborative agreements. If co-operation is enforced in some manner, for example, by the government, the violations are not as objectionable. Since we have assumed that rational players form a grand coalition, we assume that they will not freely break their agreements. The formation and continuation of such a grand coalition could be self-driven or enforced by an external driver such as a governing agency.

Moreover, an important aim is that the method must reward RES proliferation. This means that prosumers who spend money to install PV panels should be rewarded more than consumers who consume electricity. The Shapley method is more suitable than the nucleolus method since it essentially allocates the payoffs in proportion to the value that the player brings to the coalition. This means that prosumers will be rewarded more than consumers; we prove this later in Section 4.5.3.

#### 4.4.4 Shapley value

The most well known and widely used method to both *fairly* and *uniquely* distribute the total surplus generated by the co-operation of all players in a coalition (game) among all the players is the **Shapley value**  $\phi_i$  ( $\forall i = 1 \dots N$ ) (Shapley and Roth, 1988). In his PhD dissertation written in 1953, Lloyd Shapley<sup>39</sup> axiomatized the concept of fairness by proposing the following axioms to describe fairness in co-operative games (Shapley, 1953):

1. *Efficiency*— $\sum_{i \in N} \phi_i(N, v) = v(N)$ . The entire payoff of a grand coalition must be shared among all the players.
2. *Symmetry*—If  $i$  and  $j$  are equivalent in the sense that  $v(S \cup \{i\}) = v(S \cup \{j\})$  for every coalition  $S$  not containing  $i$  and  $j$ , then  $\phi_i(N, v) = \phi_j(N, v)$ . In other words, for any coalition payoff  $v$ , if  $i$  and  $j$  are interchangeable, then their allocations must be identical.
3. *Dummy player*—For any  $v$ , if the amount that  $i$  contributes to any coalition is 0 ( $\forall S : v(S \cup \{i\}) = v(S)$ ), then  $i$  is a *dummy* player and  $\phi_i(N, v) = 0$ . In other words, a player who neither helps nor harms any coalition should not be allocated at all.
4. *Additivity*—For any two  $v_1$  and  $v_2$ ,  $\phi_i(N, v_1 + v_2) = \phi_i(N, v_1) + \phi_i(N, v_2)$  for each  $i$ , where the game  $(N, v_1 + v_2)$  is defined by  $(v_1 + v_2)(S) = v_1(S) + v_2(S)$  for every coalition  $S$ . In other words, if a game can be separated into two parts  $v = v_1 + v_2$ , then the payments should be able to be decomposed.

<sup>38</sup>For definitions of all the properties and more details, see Gillman and Housman (2019).

<sup>39</sup>Winner of the Nobel Prize in Economics, 2012 (with Alvin E. Roth).

Shapley's famous achievement was to define a value—the Shapley value—that is the *only* division scheme in a coalition that meets these four desirable properties. The Shapley value remarkably is thus not only *fair* but also *unique*<sup>40</sup>.

The Shapley value is based on the idea that profits can be allocated fairly by considering the relative importance of each player to the overall co-operation. And to calculate the contribution of a player to the co-operation, the concept of **marginal contribution (MC)** can be used. Given a set of players  $N$  and a player  $i \in N$ , let  $N \setminus \{i\}$  denote the subset of  $N$  consisting of all players except player  $i$ . Then the MC is defined as follows:

**Definition 4.1** *The marginal contribution of player  $i$  is  $v(N) - v(N \setminus \{i\})$ .*

The Shapley value captures the MC of a player. For a given coalition (game)  $(N, v)$ , the Shapley value of a player  $i$ —i.e., the amount that player  $i$  is allocated—is given by

$$\phi_i(N, v) = \frac{1}{N!} \sum_{S \subseteq N \setminus \{i\}} |S|!(|N| - |S| - 1)! [v(S \cup \{i\}) - v(S)] \quad (4.7)$$

Here,  $[v(S \cup \{i\}) - v(S)]$  represents the MCs of a player  $i$  to a coalition  $S$ , i.e., what does a player  $i$  add to  $S$  that do not already have  $i$ ? The MCs are then weighted by the different possible ways the coalition  $S$  could have been formed prior to  $i$ 's addition— $|S|!$ —and by the different possible ways the remaining players (after  $i$  has been added) could be added— $(|N| - |S| - 1)!$ . Finally, all possible coalitions  $S$  before  $i$  are summed and averaged by dividing by  $N!$ , the number of possible orderings of all the agents.

The Shapley value thus captures the MCs of a player  $i$ , averaging over all the different sequences according to which the grand coalition could be constructed<sup>41</sup>. Thus, the players receive payoffs that are proportional to their MC. A player's Shapley value is designed to be proportional to the contribution made by a player to the coalition as its member, and it increases as the contribution increases.

## 4.5 Proposed profit allocation methodology

We will present the proposed methodology in this section. We make the standard assumption that all the participants—i.e., prosumers and consumers—willingly form a single grand coalition  $N$ . We then use the MC concept to make a fair allocation to all the consumers and prosumers in the grand coalition.

Let  $C_g$  be the price of electricity offered by the external market (i.e., the price offered by the retailer);  $E_p$ , the total electricity produced by the coalition;  $E_{p \setminus \{i\}}$ , the total electricity produced by the coalition without a customer  $i$ ;  $E_l$ , the total electricity consumption of the coalition; and  $E_{l \setminus \{i\}}$ , the total electricity consumption of the coalition without  $i$ . The coalition savings depend on whether  $E_p \geq E_l$  or vice versa. When  $E_p \geq E_l$ , the coalition savings is  $E_l \cdot C_g$  since the

<sup>40</sup>Uniqueness is important because if there is only one possible solution, then the players can know their gains.

<sup>41</sup>The grand coalition can be constructed with different sequences—for example, if there are 3 agents 1, 2, and 3, the coalition can be built with the order [1, 12, 123] or [1, 13, 123] or [2, 12, 123] or [2, 23, 123] or [3, 13, 123] or [3, 23, 123].

remaining production is wasted, and otherwise, it is  $E_p \cdot C_g$ .

The MC of a customer  $i$  is the amount by which the coalition savings will decrease if the customer were no longer a part of the coalition. As a result, the MC of a customer  $i$ ,  $\rho_i$ , in a community-microgrid grand coalition is as follows:

$$\rho_i = \begin{cases} E_l \cdot C_g - E_{l \setminus \{i\}} \cdot C_g & \text{if } E_p \geq E_l \text{ and } E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}} \\ E_l \cdot C_g - E_{p \setminus \{i\}} \cdot C_g & \text{if } E_p \geq E_l \text{ and } E_{p \setminus \{i\}} < E_{l \setminus \{i\}} \\ E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g & \text{if } E_p < E_l \text{ and } E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}} \\ E_p \cdot C_g - E_{p \setminus \{i\}} \cdot C_g & \text{if } E_p < E_l \text{ and } E_{p \setminus \{i\}} < E_{l \setminus \{i\}} \end{cases} \quad (4.8)$$

Note that when considering that a customer  $i$  is not in the coalition, the new total production ( $E_{p \setminus \{i\}}$ ) needs to be newly compared with the new total load ( $E_{l \setminus \{i\}}$ ). We will now expand  $\rho_i$  by considering all the possible cases for the consumer and prosumer separately:

1.  $E_p \geq E_l$

(a) Consumer:  $E_{p \setminus \{i\}}$  has to be  $\geq E_{l \setminus \{i\}}$  since the customer has no production. Therefore,

$$\rho_i = E_l \cdot C_g - E_{l \setminus \{i\}} \cdot C_g = E_{l,i} \cdot C_g$$

where  $E_{l,i}$  is the load of a customer  $i$ .

(b) Prosumer: If  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ , then

$$\rho_i = E_l \cdot C_g - E_{l \setminus \{i\}} \cdot C_g = E_{l,i} \cdot C_g$$

else if  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ , then

$$\rho_i = E_l \cdot C_g - E_{p \setminus \{i\}} \cdot C_g$$

2.  $E_p < E_l$

(a) Consumer: If  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ , then

$$\rho_i = E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g$$

else if  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ , then

$$\rho_i = E_p \cdot C_g - E_{p \setminus \{i\}} \cdot C_g = 0$$

(b) Prosumer: If  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ , then

$$\rho_i = E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g$$

else if  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ , then

$$\rho_i = E_p \cdot C_g - E_{p \setminus \{i\}} \cdot C_g = E_{p,i} \cdot C_g$$

where  $E_{p,i}$  is the load of a customer  $i$ .

In summary, for a consumer  $i$ ,

$$\rho_i = \begin{cases} E_{l,i} \cdot C_g & \text{if } E_p \geq E_l \\ E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g & \text{if } E_p < E_l \text{ and } E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}} \\ 0 & \text{if } E_p < E_l \text{ and } E_{p \setminus \{i\}} < E_{l \setminus \{i\}} \end{cases} \quad (4.9)$$

and for a prosumer  $i$ ,

$$\rho_i = \begin{cases} E_{l,i} \cdot C_g & \text{if } E_p \geq E_l \text{ and } E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}} \\ E_l \cdot C_g - E_{p \setminus \{i\}} \cdot C_g & \text{if } E_p \geq E_l \text{ and } E_{p \setminus \{i\}} < E_{l \setminus \{i\}} \\ E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g & \text{if } E_p < E_l \text{ and } E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}} \\ E_{p,i} \cdot C_g & \text{if } E_p < E_l \text{ and } E_{p \setminus \{i\}} < E_{l \setminus \{i\}} \end{cases} \quad (4.10)$$

The coalition savings— $E_l \cdot C_g$  or  $E_p \cdot C_g$ —are now allocated to the customers by dividing it in proportion to the MC made by  $i$  (Equation 4.8). Thus, the share of the coalition savings allocated to a customer  $i$ , i.e.,  $i$ 's Shapley value—is as follows:

$$\phi_i = \begin{cases} \frac{\rho_i}{\sum_{i=1}^n \rho_i} \cdot E_l \cdot C_g & \text{if } E_p \geq E_l \\ \frac{\rho_i}{\sum_{i=1}^n \rho_i} \cdot E_p \cdot C_g & \text{if } E_p < E_l \end{cases} \quad (4.11)$$

The Shapley value  $\phi_i$  models the  $R_{exch,i}(t)$  term in the objective function (Equation 4.4 in Section 4.2.2). Since  $\phi_i \geq 0$ , this profit allocation methodology optimizes the objective by maximizing the  $\int_{t=1}^{t=T} (R_{exch,i}(t))$  term under the fairness constraint.

It is important to note that the electrical load is always met in all cases since the community microgrid is *connected* to the external microgrid. Hence, bookkeeping for the distribution of coalition savings is straightforward since the bookkeeper only has to record the savings and then redistribute it in accordance with Equation 4.11. The profit redistribution can be done periodically, for example, monthly or annually. In practice, customers are billed the amount that they would have paid normally to the retailer minus their allocated savings.

#### 4.5.1 Player rationality

The proposed Shapley value must ensure that none of the coalition players lose from joining the grand coalition, because, otherwise there is no incentive to join the grand coalition. This property is called *player rationality*.

**Definition 4.2** “An allocation  $x$  for a coalition game  $v(N, w)$  is player rational if  $x_i \geq w(i)$ ,  $\forall i \in N$ ” (Gillman and Housman, 2019).

In other words, a player should receive a payoff at least as much as the player would get without collaborating with any other player.

If Equation 4.11 is correctly set up, it is intuitive that none of the coalition players lose from joining the grand coalition. Consumers never lose because their worst-case scenario is to purchase electricity at the spot price. Prosumers never lose because their worst-case scenario is that they share electricity for free. Therefore, collaboration and sharing of electricity can only increase customers' profits. A formal proof of this is given below separately for the two cases—consumer and prosumer.

**Proposition 1.** *A consumer  $i$  will earn at least as much from joining the community-microgrid grand coalition, with the allocation given in Equation 4.11, as the consumer will make without joining the coalition.*

*Proof.* Without the coalition,  $i$ 's savings is  $-E_{l,i} \cdot C_g$ , i.e.,  $i$ 's electricity bill. Now, let us consider the cases in Equation 4.9 one by one:

1.  $E_p \geq E_l$ : From Equation 4.9,  $\rho_i = E_{l,i} \cdot C_g \geq 0$ .
2.  $E_p < E_l$  and  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ : Consider the equation:  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ . Since  $E_{p \setminus \{i\}} = E_p - E_{p,i}$  and  $E_{p,i} = 0$ ,  $E_{p \setminus \{i\}} = E_p$ . As a result,  $E_p \geq E_{l \setminus \{i\}}$  and  $E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g \geq 0$ . Therefore,  $\rho_i \geq 0$ .
3.  $E_p < E_l$  and  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ :  $\rho_i = 0$ .

In all three cases,  $i$ 's MC,  $\rho_i \geq 0$ . This means that according to Equation 4.11,  $i$ 's share of the coalition savings,  $\phi_i \geq 0$ . Thus,  $i$ 's savings is  $-E_{l,i} \cdot C_g + \phi_i$ , where  $\phi_i \geq 0$ . Therefore,  $i$ 's savings are at least as much as  $i$ 's savings without the coalition ( $-E_{l,i} \cdot C_g$ ).

Hence, QED.

**Proposition 2.** *A prosumer  $i$  will earn at least as much from joining the community-microgrid grand coalition, with the allocation given in Equation 4.11, as the consumer will make without joining the coalition.*

*Proof.* Without the coalition,  $i$ 's savings is  $E_{l,i} \cdot C_g$  if  $E_{p,i} \geq E_{l,i}$  and  $E_{p,i} \cdot C_g$  if  $E_{p,i} < E_{l,i}$ . Now, let us consider cases one by one:

1.  $E_p \geq E_l$  and  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ : According to Equation 4.10,  $\rho_i = E_{l,i} \cdot C_g$ . From Equation 4.11,  $\phi_i = E_{l,i} \cdot C_g$ , since the denominator  $\sum_{i=1}^{i=n} (E_{l,i} \cdot C_g) = E_l \cdot C_g$ . Thus,  $i$ 's savings is the same as  $i$ 's savings without the coalition.
2.  $E_p \geq E_l$  and  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ : From Equation 4.10,  $\rho_i = E_l \cdot C_g - E_{p \setminus \{i\}} \cdot C_g$ . Ignoring  $C_g$ , this is equivalent to  $E_l - E_{p \setminus \{i\}} = E_{l,i} + E_{l \setminus \{i\}} - E_{p \setminus \{i\}}$ . Since  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ ,  $E_{l,i} + E_{l \setminus \{i\}} - E_{p \setminus \{i\}}$  is equivalent to  $E_{l,i} + \delta$ , where  $\delta \geq 0$ . Thus,  $\rho_i = (E_{l,i} + \delta) \cdot C_g$ . This means that  $\phi_i \geq 0$ , and  $i$ 's savings— $E_{l,i} \cdot C_g + \phi_i$ —will be at least equal to  $i$ 's savings without the coalition.

3.  $E_p < E_l$  and  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ : From Equation 4.10,  $\rho_i = E_{p,i} \cdot C_g$ . From Equation 4.11,  $\phi_i = E_{p,i} \cdot C_g$ , since the denominator  $\sum_{i=1}^{i=n} (E_{p,i} \cdot C_g) = E_p \cdot C_g$ . Thus,  $i$ 's savings is the same as  $i$ 's savings without the coalition.
4.  $E_p < E_l$  and  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ : We use essentially the same argument as in (2). From Equation 4.10,  $\rho_i = E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g$ . Ignoring  $C_g$ , this is equivalent to  $E_p - E_{l \setminus \{i\}} = E_{p,i} + E_{p \setminus \{i\}} - E_{l \setminus \{i\}}$ . Since  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ ,  $E_{p,i} + E_{p \setminus \{i\}} - E_{l \setminus \{i\}}$  is equivalent to  $E_{p,i} + \delta$ , where  $\delta \geq 0$ . Thus,  $\rho_i = (E_{p,i} + \delta) \cdot C_g$ . This means that  $\phi_i \geq 0$ , i. e.,  $i$ 's savings— $E_{p,i} \cdot C_g + \phi_i$ —will be at least the same as  $i$ 's savings without the coalition.

Hence, Q.E.D.

#### 4.5.2 Fairness properties for proposed method

As mentioned previously, the Shapley method meets seven fairness properties: it is efficient, player rational, unbiased, subsidy free, scale invariant, additive, and coalition monotonic (Section 4.4.3). Further, as described in Section 4.4.4, historically, the Shapley method was constructed as an efficient, additive, symmetric, and dummy-player-satisfying method. We will now check whether the proposed methodology satisfies these properties, and discuss the implications if it does not satisfy them. Note that the definitions of efficiency, symmetry, dummy players, and additivity are not restated here since they were defined earlier in Section 4.4.4.

1. **Efficiency**: In Equation 4.11,  $v(N) = E_l \cdot C_g$  if  $E_p \geq E_l$  and  $v(N) = E_l \cdot C_g$  if  $E_p < E_l$ . Since  $\sum_{i \in N} \phi_i(N, v) = v(N)$ , the allocation is efficient.
2. **Symmetry/Unbiased**: Since we form a single grand coalition, for the payoff given in Equation 4.11, the two players  $i$  and  $j$  are interchangeable (their allocations will be identical).
3. **Dummy players/Subsidy free**: From Equation 4.11,  $\rho_i = 0 \implies \phi_i = 0$ , thereby satisfying this property.
4. **Additivity/Linearity**: Additivity is satisfied when  $\phi_i(N, v_1 + v_2) = \phi_i(N, v_1) + \phi_i(N, v_2)$  for each  $i$  and any two  $v_1$  and  $v_2$ . In the Shapley method, the MC of a player in the game  $v_1 + v_2$  is the sum of the MCs of that player in the game  $v_1$  and  $v_2$ , thereby making the allocation additive. However, this does not hold true in our allocation method due to the way the MC is set up ( $\rho_i$  in Equations 4.9 and 4.10). Therefore, the proposed allocation method is not necessarily additive.
5. **Player rationality**: Player rationality was shown earlier in Propositions 4.5.1 and 4.5.1.
6. **Scale invariance**: For a grand coalition, scale invariance implies that  $\phi_i(N, M \cdot v) = M \cdot \phi_i(N, v)$ , where  $M$  is a multiplying constant (adapted from Definition 8.2.5, pg. 251, in Gillman and Housman (2019)). From Equation 4.11, assuming that  $E_p \geq E_l$  (the argument remains the same for both cases),

$$\phi_i(N, v) = \frac{\rho_i}{\sum_{i=1}^{i=n} \rho_i} \cdot E_l \cdot C_g$$

$$\phi_i(N, M \cdot v) = \frac{\rho_i}{\sum_{i=1}^n \rho_i} \cdot M \cdot E_l \cdot C_g$$

$$\implies \phi_i(N, M \cdot v) = M \cdot \left( \frac{\rho_i}{\sum_{i=1}^n \rho_i} \cdot E_l \cdot C_g \right) = M \cdot \phi_i(N, v)$$

And, therefore, the method is scale invariant.

7. **Coalition Monotone:** *An allocation is coalition monotone if increases (decreases) in a single coalition's worth (among many coalitions) do not result in a decrease (increase) in the payoff of any player in the coalition (Gillman and Housman, 2019).* In our case, we only consider a single grand coalition. According to Equation, 4.9, 4.10, and 4.11, it is possible that increases (decreases) in the coalition savings result in a decrease (increase) in the payoff of any player. This is because such a change could revise the savings from  $E_l \cdot C_g$  (if  $E_p \geq E_l$ ) to  $E_p \cdot C_g$  (if  $E_p \geq E_l$ ) or vice-versa, which then changes  $\rho_i$ . Therefore, the method does not satisfy coalition monotonicity.

Thus, the allocation method satisfies five out of seven fairness properties. The violation of the additive property is not serious because we have enforced a grand coalition. Further, because coalition monotonicity is violated, players can no longer unilaterally manipulate their gains by using BESS or other production and load control methods. This is advantageous because from the system perspective, it is better to have centralized production and load control. Another advantage is that the coalition can then bargain or trade with other nearby coalitions as well, thereby creating larger coalition clusters.

#### 4.5.3 Proliferation of renewable energy sources

In Section 4.4.3, we stated that a reason for choosing the Shapley approach was that it will encourage RES proliferation. Our basis for this was that prosumers will necessarily gain more profits since the allocation is proportional to a player's MC and prosumers are likelier to have higher MC. Now, let us examine if this is actually true with our proposed allocation.

Consider the allocation in Equation 4.11, which is essentially proportional to the MCs in Equations 4.9 and 4.10. Let us consider the four cases as before.

1. Case 1:  $E_p \geq E_l$  and  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ . The customer and prosumer have the same  $\rho_i$ .
2. Case 2:  $E_p \geq E_l$  and  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ . The prosumer's  $\rho_i$  is  $E_l \cdot C_g - E_{p \setminus \{i\}} \cdot C_g = (E_{l,i} + E_{l \setminus \{i\}}) \cdot C_g - E_{p \setminus \{i\}} \cdot C_g = E_{l,i} \cdot C_g + (E_{l \setminus \{i\}} - E_{p \setminus \{i\}}) \cdot C_g$ . This is greater than consumer's  $\rho_i$  of  $E_{l,i} \cdot C_g$  since  $E_{l \setminus \{i\}} > E_{p \setminus \{i\}}$ .
3. Case 3:  $E_p < E_l$  and  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ . In the case of both the prosumer and customer,  $\rho_i = E_p \cdot C_g - E_{l \setminus \{i\}} \cdot C_g$ .
4. Case 4:  $E_p < E_l$  and  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ . The prosumer's  $\rho_i$  of  $E_{p,i} \cdot C_g$  is greater than the consumer's  $\rho_i$  of 0.

Thus, when  $E_p \geq E_l$ , the prosumer has at least the same  $\rho_i$  as the consumer. And when  $E_p < E_l$  and  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ , the prosumer's  $\rho_i$  is greater than the consumer's  $\rho_i$ . However, when  $E_p < E_l$  and  $E_{p \setminus \{i\}} \geq E_{l \setminus \{i\}}$ , it is possible that the consumer's  $\rho_i$  is greater than the prosumer's  $\rho_i$ . Here,  $E_{p,i} < E_{l,i}$ , i.e., the prosumer is not producing enough to satisfy its own load, which is an undesirable situation. This gives the prosumer great incentive to increase its production, especially since  $E_p < E_l$  and  $E_{p,i} \geq E_{l,i}$  leads to  $E_{p \setminus \{i\}} < E_{l \setminus \{i\}}$ , i.e., Case 4, and higher profits.

#### 4.5.4 Example illustration of methodology

To illustrate the methodology, Tables 4.1 and 4.2 give the MCs and allocated savings for 5 customers (3 consumers and 2 prosumers) for two cases, when  $E_p \geq E_l$  and vice-versa.  $C_g$  is assumed to be 1 €/kWh.

**Table 4.1:** Marginal contributions (MCs), percentage MCs, and allocations using Equation 4.8, when the total production is greater than (or equal to) the total load ( $C_g = 1$  €/kWh).

Customer	Load (kWh)	Production (kWh)	MC (kWh)	%MC (%)	Allocation (€)
A	9	0	9	13.43%	5.24
B	5	20	19	28.36%	11.06
C	8	0	8	11.94%	4.66
D	5	20	19	28.36%	11.06
E	12	0	12	17.91%	6.99
<b>Total</b>	<b>39</b>	<b>40</b>	<b>67</b>	<b>100%</b>	<b>39.00</b>

**Table 4.2:** Marginal contributions (MCs), percentage MCs, and allocations using Equation 4.8, when the total production is less than the total load ( $C_g = 1$  €/kWh).

Customer	Load (kWh)	Production (kWh)	MC (kWh)	%MC (%)	Allocation (€)
A	11	0	2	4.65%	1.86
B	30	20	21	48.84%	19.53
C	2	0	0	0%	0.00
D	5	20	20	46.51%	18.60
E	1	0	0	0.00%	0.00
<b>Total</b>	<b>49</b>	<b>40</b>	<b>43</b>	<b>100%</b>	<b>40.00</b>

## 4.6 Results and discussion

### 4.6.1 Experimental data

**Load** We used real metered annual hourly load data from customers behind a substation transformer in an actual LV Finnish distribution network. There were a total of 53 customers belonging to the following 6 customer categories:

1. Category **110** (36 customers)—detached family house with direct electric heating and hot water accumulator  $< 300$  L;
2. Category **120** (7 customers)—same as 110 but hot water accumulator  $> 300$  L;
3. Category **220** (2 customers)—detached, semi-electric storage heating;
4. Category **601** (5 customers)—detached house with no electric heating<sup>42</sup> and no electric sauna;
5. Category **602** (2 customers)—same as 602 but with electric sauna;
6. Category **910810** (1 customer)—administration building.

**PV** We assumed that randomly chosen 30% of all the residential customers in the microgrid installed PV systems in their houses; thus, there were 17 prosumers. Moreover, at least 1 customer of each type was assumed to have a PV panel. In all these cases, we assumed a PV system size of  $5 \text{ kW}_p$ , which is the typical average PV size installed by a Finnish residential customer. Further, we used identical real annual metered hourly PV production data obtained from a  $5\text{-kW}_p$  south-facing PV panel (tilt angle of  $15^\circ$ ) in 2016 for all the prosumers. Identical data was used since all the houses in a neighborhood microgrid are likely to have near-identical PV production for same panel sizes. We also assumed that the administration building (910810) installed a PV system with a larger size of  $15 \text{ kW}_p$ . In this case, the PV production data obtained from the  $5\text{-kW}_p$  panel was multiplied by 3.

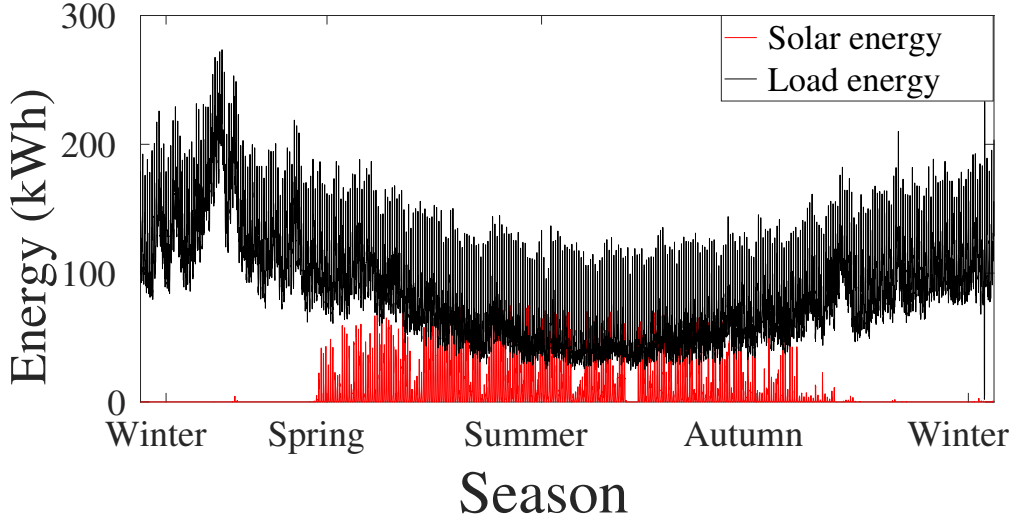
Figure 4.3 shows the total load data and total PV production data for the 53 customers and 17 prosumers, respectively, in 2016 for the Finnish location.

**Prices** For the spot prices, we used day-ahead electricity market prices—Elspot Finnish area prices—from 2016. The DSO and supplier prices were taken from actual data.

**Customer costs** In Finland, residential customers have the following components in their electricity bill:

- **Distribution fees:** A monthly fee  $C_{D,m}$  (€) and an electricity usage fee  $C_{D,e}$  (€/kWh).
- **Supplier fees:** Spot prices  $C_{spot}$  (€/kWh) and a monthly fee that consists of an agreement fee  $C_{S,a}$  (€/kWh) and electricity usage fee  $C_{S,e}$  (€/kWh). There is also a one-time grid connection fee only for new connections, which is neglected here.

<sup>42</sup>Relies on district or wood-based or oil-based heating.



**Figure 4.3:** Total load data for 53 customers and total PV production data for 17 prosumers in 2016 for a microgrid in a Finnish neighborhood.

- **Electricity tax:** Electricity tax as well as a value added tax (VAT) on the electricity tax,  $C_T = C_{tax} + \text{VAT} \times C_{tax} \text{ €/kWh}$ .

Therefore, the total electricity price is obtained as follows:

$$C_{g,var} = C_{D,m} + C_{D,e} + C_{spot} + C_{S,a} + C_{S,e} + C_T \quad (4.12)$$

#### 4.6.2 Profit allocation with energy-based tariffs

In the case of EBTs, we assume that the distribution fees and taxes will be entirely paid by the customer as before, except for the PV used for self-consumption. On the other hand, the supplier fees will be paid by the customer only for the electricity actually bought from the external grid to supplement the electricity taken from a prosumer.

The total annual costs paid by all the 53 customers in the microgrid when there was no PV production was 172,650 € (an average of 3,257.5 € per customer). The total annual costs paid by all the 53 customers in the microgrid when the prosumers behaved independently and themselves consumed their production was 166,940 €. In other words, installation of PV panels in some customers' houses led to a total savings of 3.3% for the microgrid (of course, only the prosumers benefited.). When the customers collaborated and exchanged electricity, the total costs was 159,080 €; thus, the microgrid saved  $\approx 8\%$  compared to the “no-PV-production” situation and  $\approx 5\%$  compared to when PV panels were installed.

All the individual customers profited from the transaction. Figure 4.4 compares the annual savings for all 53 customers without electricity sharing and with electricity sharing using the proposed MC-based profit allocation. Among the 53 customers, 17 were prosumers with identical 5-kWp PV panels (customer nos. 2, 5, 10, 11, 14, 15, 16, 21, 32, 35, 38, 39, 41, 42, 45,

49, and 51), and the remaining were consumers. Customer no. 35, who had the biggest savings, was the administrative building (910810) with a 15-kWp PV panel. The biggest beneficiaries were clearly the prosumers.

We also implemented a conventional trading-based electricity and profit allocation to compare the results with a traditional methodology. For the trading, we employed the ZI bidding strategy described in Section 4.3.3 as the participants' bidding strategies. Traders submitted random bids and offers with a bid price drawn from a uniform distribution between two limit prices. The sealed-bid double auction was used to set the market price. In this type of auction, a central authority first organized the buy and sell bids in descending and ascending orders, respectively. The intersection was then determined and set as the market price. The orders were matched at discrete market closing times  $t$ . To maximize the usage of locally generated electricity, all the sellers were allowed to sell their electricity as long as there was demand from any buyer. Finally, the uniform-price rule was used to clear the market: all the buyers paid the same price for the acquired items<sup>43</sup> (Mochón and Sáez, 2015).

With the conventional trading-based methodology, the total annual costs paid by all the 53 customers was 163,000 €. This means that when using the proposed MC methodology instead of the conventional methodology, the coalition benefited by 3,924 € (2.4%).

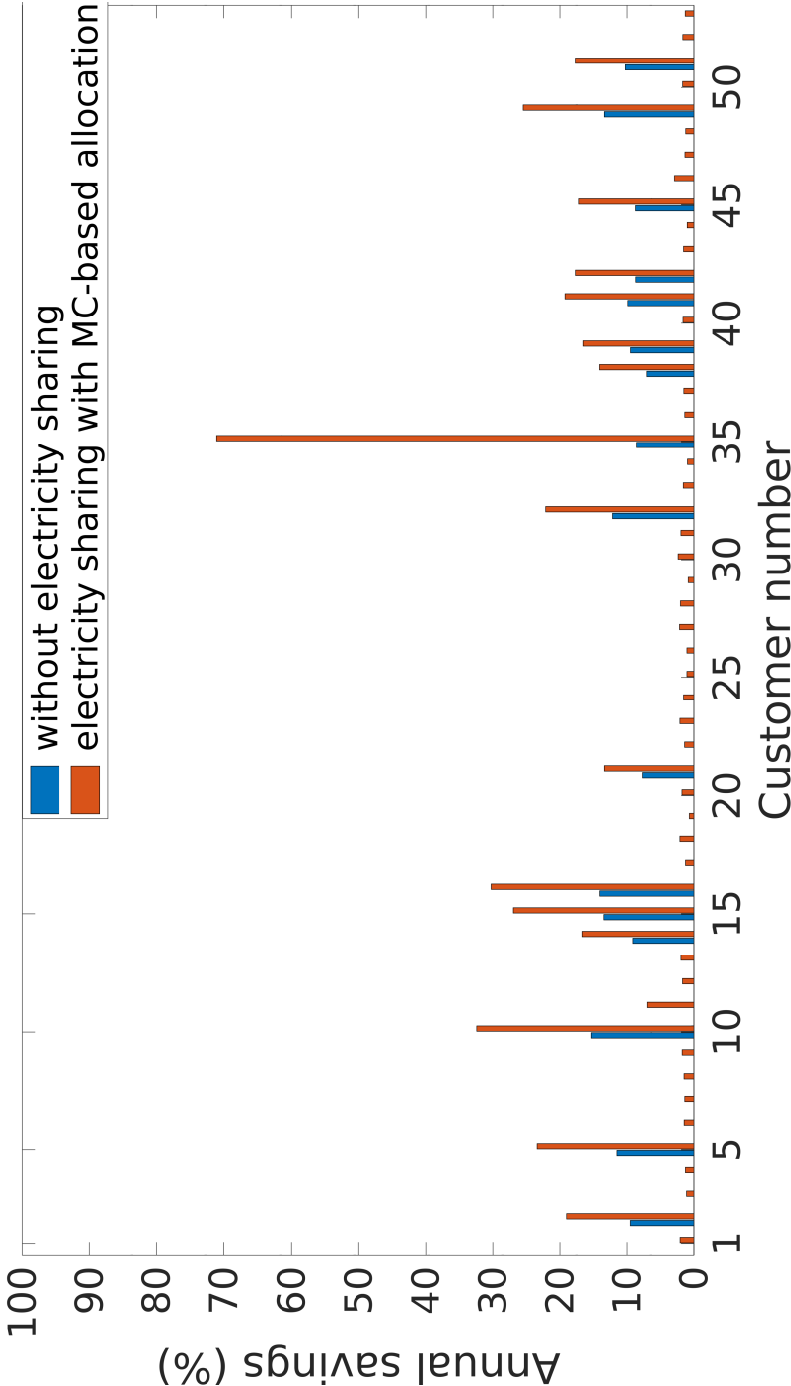
In the trading-based methodology, prosumers sell their electricity at the market price that is set after bidding. Since the maximum bid of a consumer is  $(C_g - 1)$  €/kWh, the market price will always be less than  $C_g$  €/kWh. This means that the maximum price that prosumers can expect through trading is  $(C_g - 1)$  €/kWh. On the other hand, in the proposed MC-based methodology, the prosumers sell their electricity at  $C_g$  €/kWh. This means that the prosumers will always gain from using the MC-based methodology. Figure 4.5 shows the savings for prosumers with MC-based methodology as compared to trading-based methodology. As expected, prosumers benefit from using the MC-based methodology. The administrative building that is a prosumer with a 15-kWp PV panel has the biggest savings at nearly 60%.

On the other hand, consumers need not necessarily benefit from using the MC-based methodology instead of the trading methodology. This is because in the former case, consumers buy the electricity at  $C_g$  €/kWh but in the latter case, they buy at a maximum value of  $(C_g - 1)$  €/kWh. Figure 4.6 shows the savings for consumers with MC-based methodology as compared to trading-based methodology. As expected, consumers lose from using the MC-based methodology. However, the losses are small, with a maximum loss of around 2%.

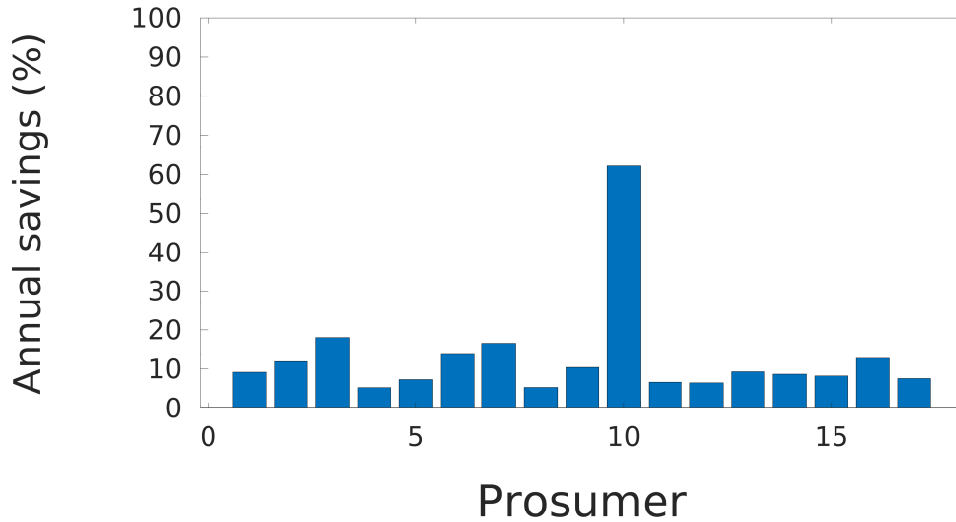
The question then is why should the proposed methodology be used if the customers are going to get less profits than with the trading-based methodology? The reasons are as follows:

1. Because the proposed methodology incentivizes and rewards the prosumer, it encourages the proliferation of RES (proved in Section 4.5.3), which is an essential social objective.
2. As discussed and developed in 4.3, the proposed methodology is *fairer*. It rewards the customer who has spent money to invest in PV and whose contribution to the community is higher.

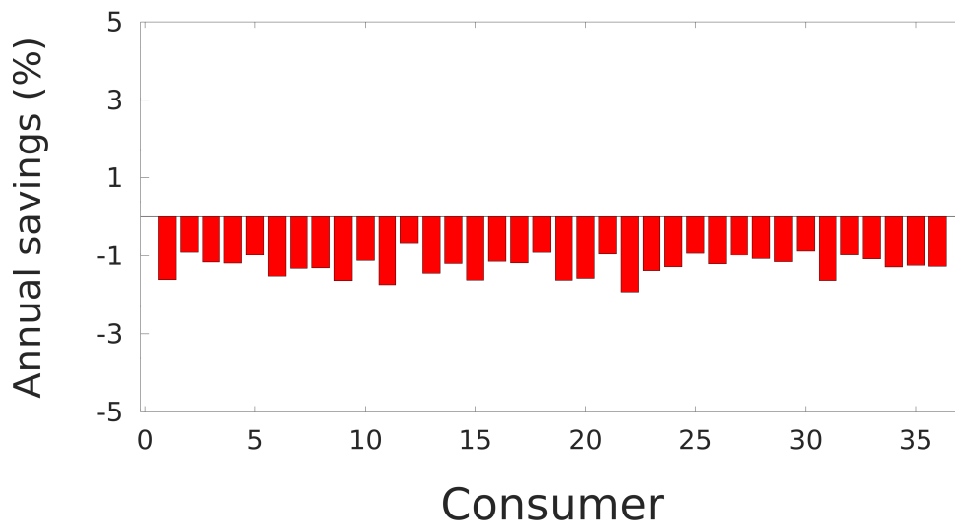
<sup>43</sup>This is fairer for centrally generated random bids (instead of, for example, the pay-as-you-bid rule).



**Figure 4.4:** Comparison of savings for 53 customers without electricity sharing and with electricity sharing using the proposed marginal contribution (MC)-based profit allocation (in a low-voltage network in Finland). 17 customers (nos. 2, 5, 10, 11, 14, 15, 16, 21, 32, 35, 38, 39, 41, 42, 45, 49, and 51) are prosumers with identical 5-kWp PV panels, whereas the remaining are consumers. Customer no. 35, who shows the biggest savings, is an administrative building and a prosumer with 15-kWp PV panel.



**Figure 4.5:** Savings for the 17 prosumers in a community microgrid in Finland when conventional trading-based methodology is replaced with the MC-based profit allocation. 16 customers are prosumers with identical 5-kWp PV panels, whereas 1 customer (No. 10 in the figure) has a 15-kWp PV panel.



**Figure 4.6:** Savings for the 36 consumers in a community microgrid in Finland when conventional trading-based methodology is replaced with MC-based profit allocation. Consumers lose from using the MC-based methodology. However, the losses are small, with a maximum loss of around 2%.

3. Customers provably benefit from sharing electricity as opposed to not sharing it.
4. Trading forces customers to actively participate (unless automated), which enforces additional costs.
5. Finally, customers' profits also depend on the operational environment such as environmental conditions.

We will now demonstrate the validity of point 5. In the example above, the location was a Finnish neighborhood. Finland is one of the world's northernmost countries and has long winters (4–7 months) with very short days (0–6 h); in contrast, summer days are very long (18–24 h). As shown in Figure 4.3, the electricity consumption is the highest during periods of very low to nil PV production. On the other hand, more southern countries have more consistent sunshine over the entire year.

To examine the influence of the operational environment and to demonstrate consumer profits under different environmental conditions, we obtained real consumption and PV production data from a neighborhood in Austin, Texas, USA for 2018<sup>44</sup>. There were 17 customers in the microgrid, of whom 6 were prosumers. Unfortunately, electricity pricing data for the customers were not available due to privacy issues. Hence, we assumed an average price of 9.4 cents/kWh based on data available online for all the customers (Vault Energy Solutions, 2019).

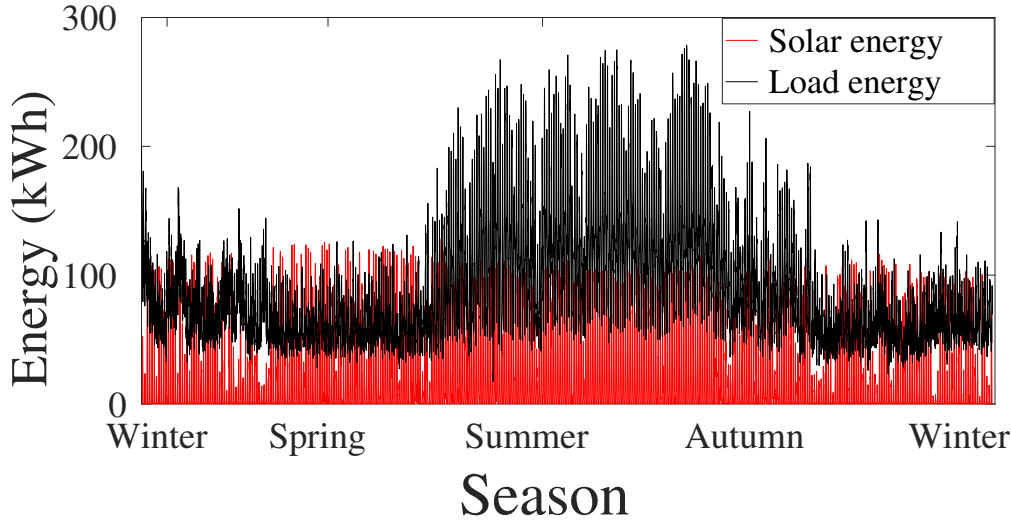
Figure 4.7 shows the total load data and total PV production data for the 17 customers and 6 prosumers, respectively, in 2018. A comparison of Figures 4.3 and 4.7 clearly shows the differences in the environmental conditions in the two locations. The Finnish location had very little production in the winter months when the load was the highest. In contrast, the neighborhood in Austin had nearly consistent PV production throughout the year. In some cases, the total PV production was even greater than the total load demand (even though only 6 out of 17 customers were producing electricity).

We then applied the MC-based methodology and performed the same comparison analyses as above. Here, the installation of PV panels in the 6 customers' houses led to a total savings of 10.255% for the microgrid (of course, only the prosumers benefited). When the customers collaborated and exchanged electricity, the microgrid saved  $\approx 32.59\%$  compared to the “no-PV-production” situation and  $\approx 24.89\%$  compared to when PV panels were installed.

All individual customers profited from the transaction. Figure 4.8 compares the savings for all 17 customers with and without electricity sharing using the proposed MC. Among the 17 customers, 6 were prosumers (customer nos. 1, 2, 14, 15, 16, and 17), and the remaining were consumers. The biggest beneficiaries were clearly the prosumers.

Further, the coalition benefited by 13.21% when using the proposed MC methodology instead of the conventional methodology. Figure 4.9 shows the savings for prosumers with MC-based methodology as compared to trading-based methodology. As expected, the prosumers once

<sup>44</sup>This research was conducted using data from Pecan Street Inc.'s Dataport site. Dataport contains unique, circuit-level electricity use data at one-minute to one-second intervals for approximately 800 homes in the United States, with PV production and EV charging data for a subset of these homes.



**Figure 4.7:** Total load data for 17 customers and total PV production data for 6 prosumers in 2018 for a community microgrid in Austin, Texas (Data Source: Pecan Street (2019)).

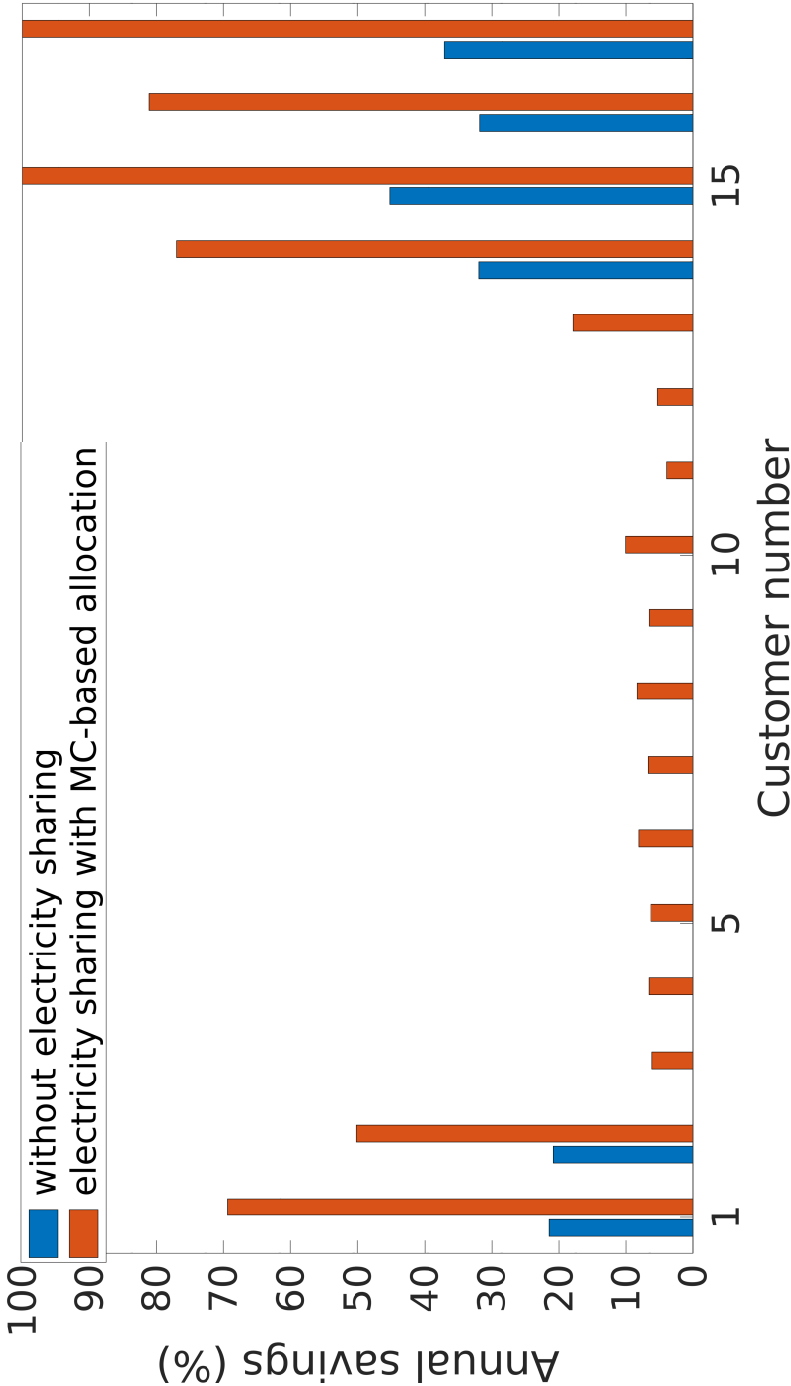
again strongly benefit from using the MC-based methodology. Figure 4.10 shows the savings for consumers with the MC-based methodology as compared to trading-based methodology. Interestingly, only some consumers now lose from using the MC-based methodology. 7 consumers benefit from the MC-based methodology, and only 4 have small losses (maximum loss of around 2%).

These results clearly indicate that environmental conditions play a big role in the proposed MC methodology, offering greater profits over the conventional methodology. In regions with more regular sun hours and solar insolation, the proposed MC methodology gives greater profits. Hence, the abovementioned characteristics should be carefully weighed before the community microgrid operations are established.

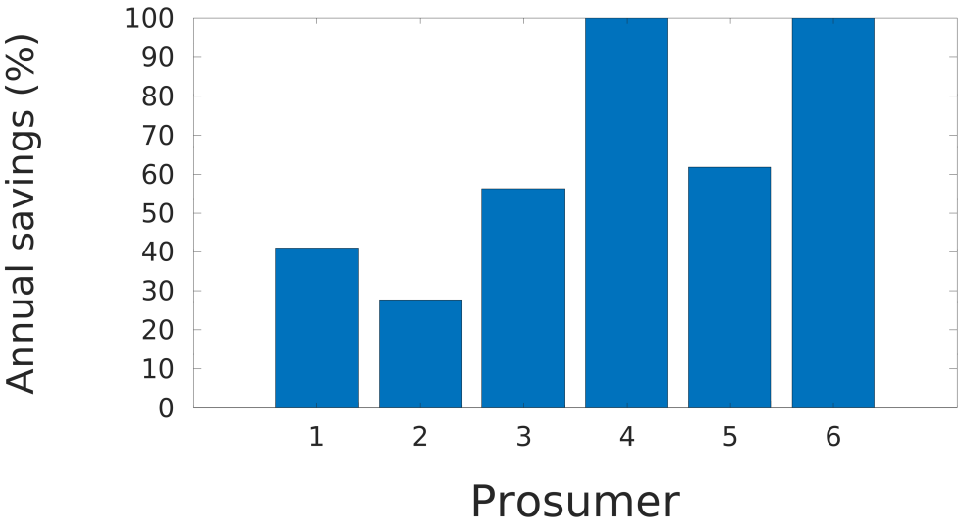
#### 4.6.3 Profit allocation with power-based tariffs

Conventionally, residential customers who invest in PV or other DER installations and participate in p2p community electricity projects consider EBT (€/kWh) schemes when calculating their profits. If the PBT (€/kW) scheme is implemented, their profits can be adversely affected. In Haapaniemi et al. (2017), the authors analyzed the PV profitability of residential customers when PBTs are introduced to replace EBTs. The changes in customers' PV profitability were compared under different DSO tariff structures. They showed that changing the DSO tariff system from EBTs to PBTs will *decrease* the profitability that most customers would achieve by producing electricity using PV-based systems.

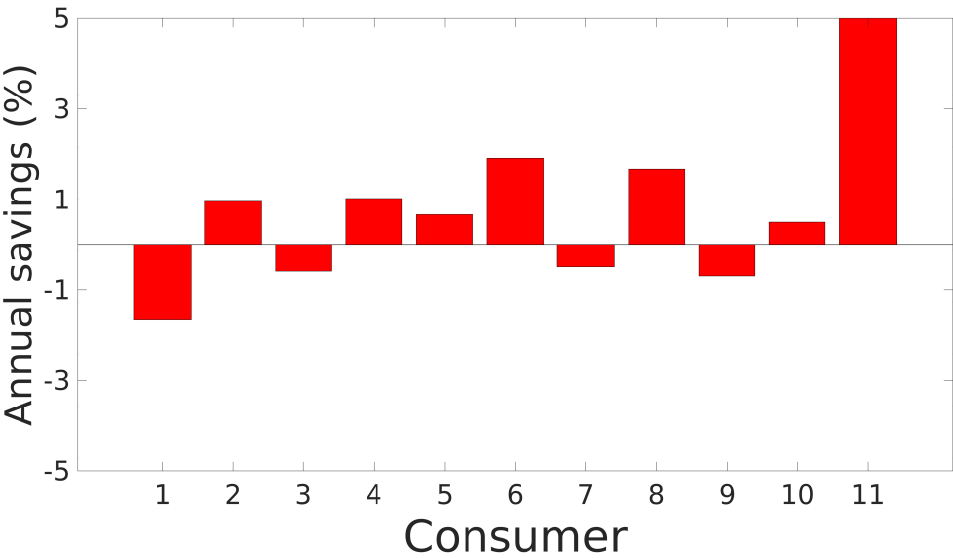
Intuitively, p2p electricity exchange can be expected to increase the customer profits even in the case of PBTs. However, in the p2p scenario, the PBT scheme should be applied not only to the load but also to the power supplied by the prosumers into the grid. As a result, the amount of produced PV power might impact the profitability. Prosumers may then reduce (or stop) trad-



**Figure 4.8:** Comparison of savings for 17 customers without electricity sharing and with electricity sharing using the proposed MC-based profit allocation (in Texas, USA). 6 customers (nos. 1, 2, 14, 15, 16, and 17) are prosumers, whereas the remaining are consumers (Data Source: Pecan Street (2019)).



**Figure 4.9:** Savings for the 6 prosumers in a community microgrid in Austin, Texas, USA when conventional trading-based methodology is replaced with MC-based profit allocation (Data Source: Pecan Street (2019)).



**Figure 4.10:** Savings for the 11 consumers in a community microgrid in Austin, Texas, USA when conventional trading-based methodology is replaced with MC-based profit allocation. Most consumers gain from using the MC-based methodology (Data Source: Pecan Street (2019)).

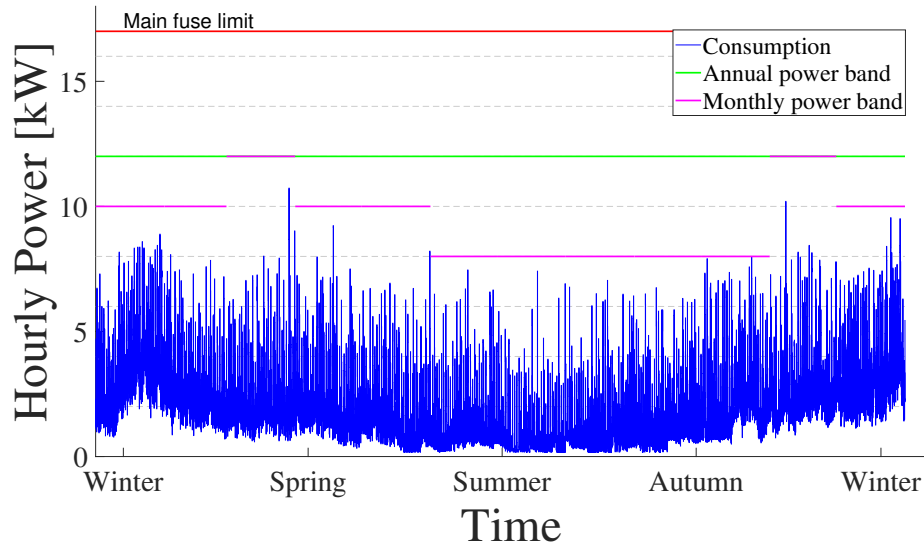
ing, thereby wasting the excess production, which is not desirable. Hence, in Narayanan et al. (2018), we evaluated the economic impacts of shifting from EBTs to PBTs (both annual and monthly PBT schemes) on the customer in the case of p2p community microgrids. Narayanan et al. (2018) demonstrated that the tariff change from EBTs to PBTs did not significantly affect customers' profits from electricity exchange.

In Narayanan et al. (2018), we conducted our analysis at hourly resolutions for a year. We used metered annual hourly load data of 36 different customers taken from an actual Finnish distribution network, assuming that 30% of randomly chosen customers in the microgrid have installed PV systems in their houses. As mentioned previously, Finnish customers are classified into several categories that are typically used in load models in utility applications. We considered three such categories of Finnish customers—Category **110** (*detached family house with direct electric heating and hot water accumulator (< 300 L)*); Category **300** (*detached family house similar to 110, but with electric storage heating using a boiler*); and Category **602** (*detached family house with no electric heating, but with an electric stove (sauna)*). We considered each category separately and also together as **mixed** since a microgrid will have a mixture of categories.

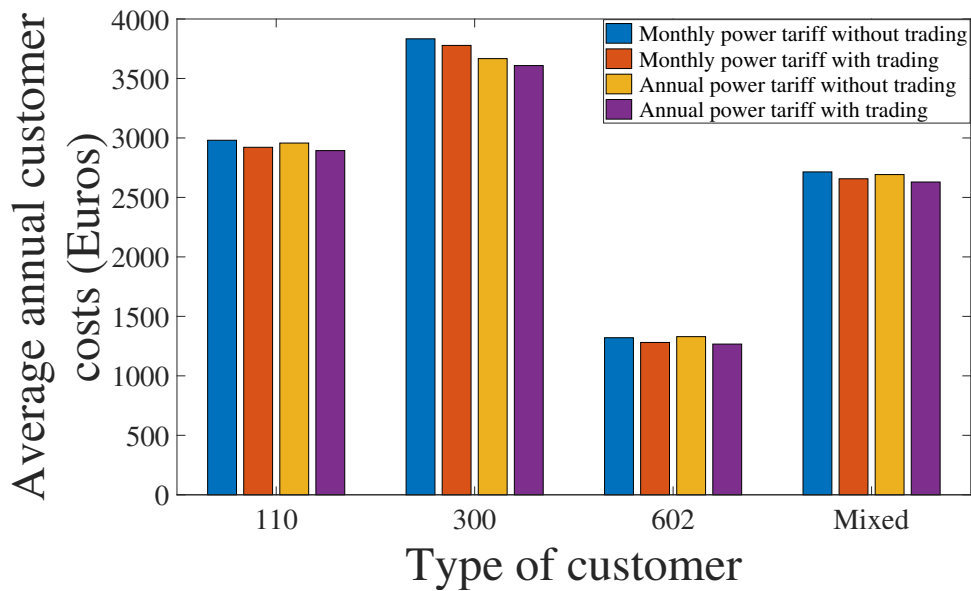
In all cases, we assumed a PV system size of 5 kW<sub>p</sub>, the typical average PV size installed by a Finnish residential customer. We used identical real annual metered hourly PV production data from 2016 for all the prosumers. The data was obtained from a 5-kW<sub>p</sub> south-facing PV panel (tilt angle of 15°) installed close to the neighborhood. For the spot prices, we used day-ahead electricity market prices—Elsport Finnish area prices—from 2016. The DSO and supplier prices were taken from actual data. For the PBTs, we converted the DSO's share of the electricity bill into unit power costs of 6.84 €/kW/month and 9.75 €/kW/month for the annual and monthly cases, respectively.

For the PBTs, we employed a power-band pricing in which customers choose a power band in advance. They can then use electricity without additional payments to the DSO if they do not exceed their chosen power limit. The power-band steps can vary, but we assume 2-kW power band steps (Figure 4.11). Further, the distribution fees— $C_{D,m} + C_{D,e}$ —are converted into PBTs of  $C_p$  €/kW, i.e., a DSO's entire income is collected with only the power component. In addition, we have considered two cases: (1) **Annual PBTs**: Customers pay for their *annual peak load*; and (2) **Monthly PBTs**: Customers pay for each month separately based on their *monthly peak load*. Note that in the EBT case, trading only impacts supplier fees, whereas in the PBT case, trading also impacts the distribution fees because the power transmitted by a prosumer into the grid is the peak power if it is higher than their peak load power.

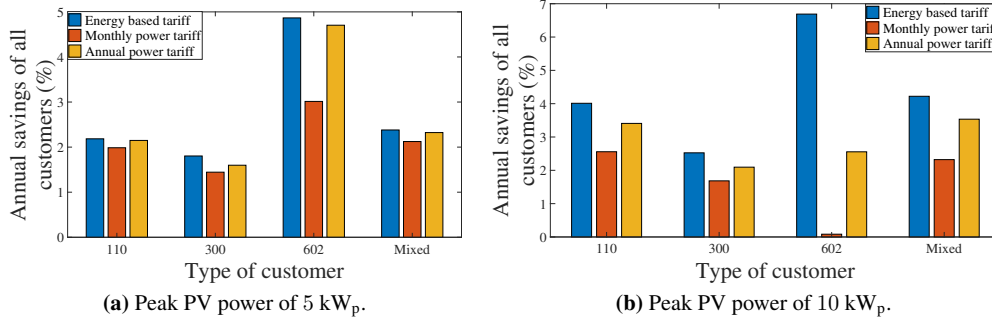
Here, we only show some results of our analysis, and a more detailed analysis can be found in Narayanan et al. (2018). Figure 4.12 shows the annual *average* customer costs when the PBT scheme was implemented with and without trading. In all cases, the annual PBTs with trading were the lowest. The profits increased for nearly all the customers individually as well with trading (not shown). Thus, trading is beneficial for the community microgrid even with PBTs. This is probably because the excess PV production (which is sold) rarely exceeds the monthly or annual peak power of the customers.



**Figure 4.11:** Principle of power-band pricing with 2-kW steps.



**Figure 4.12:** Annual *average* customer costs when the power-based tariffs (PBT) scheme was implemented with and without trading for 36 Finnish customers each in customer categories 110, 300, and 602, and “mixed.”

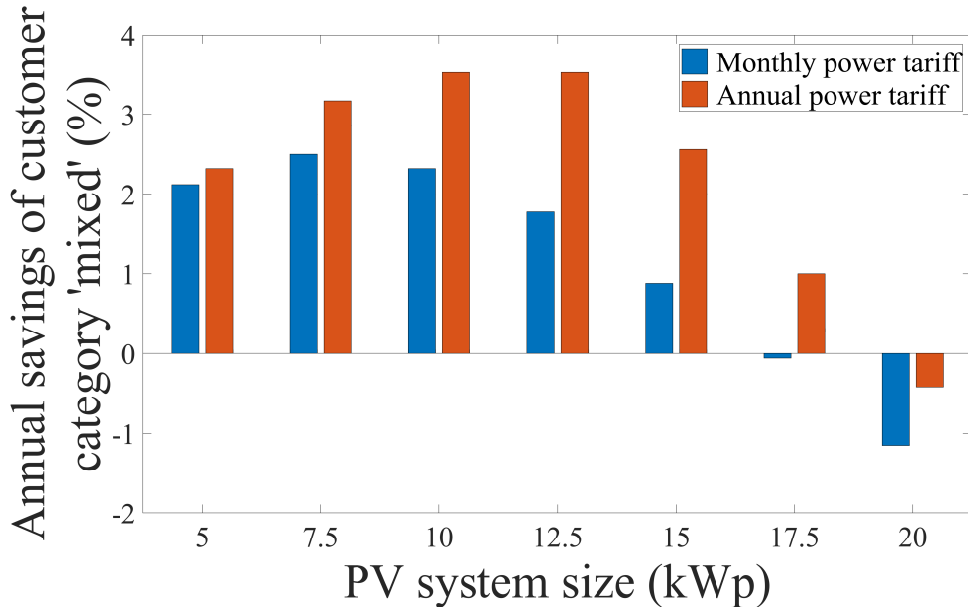


**Figure 4.13:** Annual customer *savings* when the energy-based tariff (EBT) and PBT schemes were implemented with and without trading for 36 Finnish customers each in customer categories 110, 300, and 602, and “mixed” for peak PV power of 5 and 10 kW<sub>p</sub>.

To test this assumption, Figure 4.13 shows the annual customer *savings* with and without trading when the PBT scheme was implemented for the four customer categories with PV sizes of 5 kW<sub>p</sub> and 10 kW<sub>p</sub>, respectively; the savings when trading with EBTs is also included. Due to higher solar energy production, the customers were able to gain higher profits from trades. In three cases (110, 300, and mixed), the annual peak load power was still higher than the power supplied to the grid. Hence, they were not excessively penalized for high power supplied into their grid, and their savings increased especially in the annual case, sometimes nearly doubling. On the other hand, the category 602 had a smaller annual peak load power, and their profits reduced considerably. In the monthly case, there was a dramatic decrease in the savings, implying that the p2p trading was hardly profitable. Finally, the profits from trading in both the EBT and PBT cases are similar, especially in the typical 5 kW<sub>p</sub> case. This suggests that the *tariff change from EBTs to PBTs does not significantly affect profits from electricity exchange*. This result is promising because the PBT scheme can encourage DSOs to implement community microgrids while not affecting the customers significantly.

Note that this does not imply that increased PV system sizes *will always* lead to higher profits. After a certain size, prosumers’ PBTs become higher than the trading profits. Figure 4.14 illustrates this for the mixed category of customers. Trading profits increase until a PV size of 10 kW<sub>p</sub>, but subsequently, the profits begin to reduce. Trading becomes unprofitable for a PV size of  $\sim 20$  kW<sub>p</sub>.

We also analyzed if our proposed MC-based methodology (Section 4.3) is more beneficial than conventional auction-based approaches in the case of PBTs. Figure 4.15 shows a comparison of the profits for both the monthly and annual PBTs. As expected, the profits were significant for prosumers but the consumers had losses. This result is expected for the Finnish case, as discussed earlier in Section 4.6.2. Because of the lack of data regarding DSO (or utility) costs and pricing in Austin due to privacy issues, we were unable to perform an analysis for the Austin case. However, we expect the results to be similar to the EBT case.



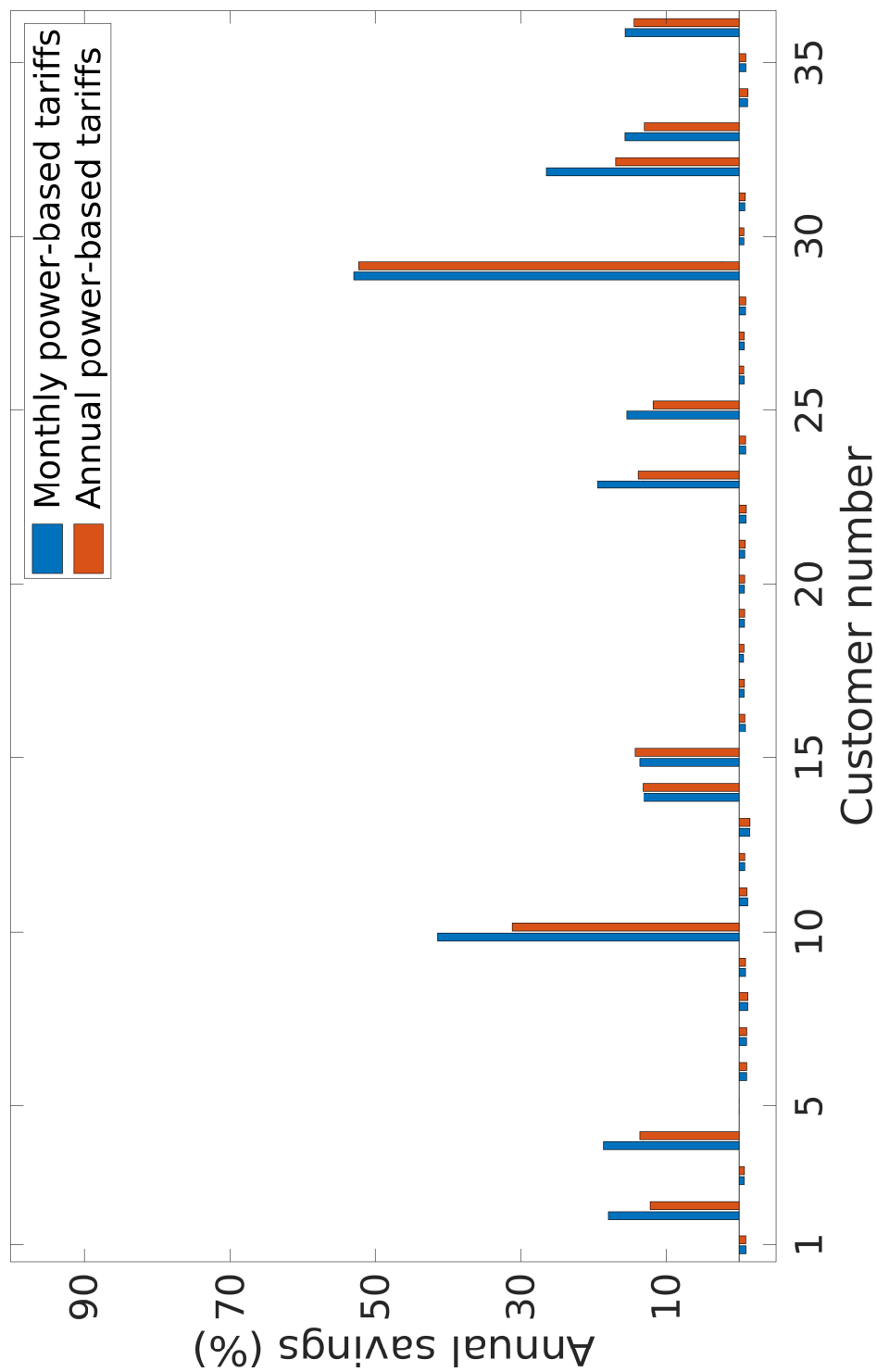
**Figure 4.14:** Annual customer *savings* when the PBT scheme was implemented with and without trading for 36 Finnish customers in the mixed customer category. In this case, the peak power of PV was varied from 5–20 kW<sub>p</sub>.

#### 4.7 Conclusions—limitations and future study

In this chapter, we considered one component of the general *microgrid cluster problem*—the problem of collaborations between community microgrids, which was discussed in Chapter 3. We considered a *community microgrid*, i.e., a single low voltage (LV) microgrid distribution network comprising prosumers and consumers. We first developed a novel methodology to achieve fair allocation of profits to customers exchanging electricity with each other. We then analyzed the effects of tariff design transition from EBTs to PBTs in community microgrids with p2p exchange.

The proposed methodology to realize a fair exchange of electricity in a community microgrid is a relatively simple and effective solution to the problem stated in Section 4.2. As expected, all customers were able to profit from the transactions as compared to the case without any collaborations. This is important because otherwise, customers will not have any incentive to participate in the community microgrid. Moreover, it is relatively easy to scale this profit allocation methodology. The MC-based methodology is also more profitable for prosumers than the conventional trading-based methodology. At the same time, the MC-based methodology is not always more beneficial for consumers whose profits depend on the environmental conditions of the microgrid location. Nevertheless, the proposed methodology is *fairer* and promotes RES proliferation.

However, this methodology has some limitations. First, the methodology addresses a narrow problem in the community microgrid since the role of the retailer and DSO is completely ig-



**Figure 4.15:** Comparison of savings for 36 customers when our MC-based profit allocation was used instead of the conventional trading-based methodology with PBTs in an LV network in Finnish. 11 customers (2, 4, 10, 14, 15, 23, 25, 29, 32, 33, 36) are prosumers with identical 5-kWp PV panels, whereas the remaining are consumers.

nored. In effect, the electricity exchange methodology only solves a small part of the larger microgrid cluster problem discussed in Chapter 3 and presented as a generalized formulation (Equation 3.1). The DSO and retailer are important stakeholders in modern electric power markets, and their profits as well as other requirements must also be considered. In some ways, the DSO is not affected by the electricity exchanges since they happen through its network and DSOs can continue to bill the customers as it has done previously. However, retailers face reduced profits and should be included or compensated in the solution methodology.

Second, the approach is highly deterministic, whereas many input parameters—production, load etc.—are highly stochastic in nature. This could cause many errors in the actual implementation. Third, the impacts of BESS or DSM programs are not investigated. Customers could use BESS or DSM to manage their loads, and this affects the profit allocation. Methodologies to manage such additional DERs must be studied in the future.

Another problem is that the methodology focuses on energy and ignores technical problems with peak power. As a result, potential implementation problems with protection, finer control regimens, and equipment are not considered adequately. In particular, it should be noted the chapter focus on how electricity exchange between customers can be achieved in a fair manner; as a result, it does not focus on how such an electricity exchange can be physically realized in the power system.

Moreover, microgrid economics is not discussed from a broader perspective of ownership and operational issues. This ignores important practical problems that today are a barrier to the wider implementation of community microgrids across the world. Finally, important components such as communication, security, and privacy must also be considered in future studies.

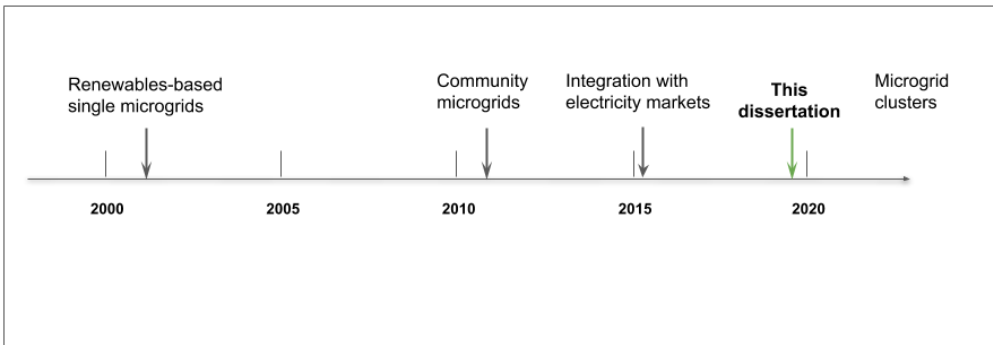
An interesting area of future research is the time resolution in the local markets and interchanges. The local electricity market could have finer time resolutions, for example, 15 or 30 min. The primary motivation for finer time resolutions is to reduce the impacts of increasing volatility in the system caused by higher RES penetration. Cost-benefit analyses of finer time resolutions is a relatively nascent research area, and current studies are primarily focused on shortening the imbalance settlement period (Bo Westh Hansen et al., 2017). The Nordic Finer Time Resolution project was established to evaluate the consequences of moving to finer time resolutions in electricity markets, as well as to develop a potential implementation plan in accordance with the European Electricity Balancing Guideline (GL EB) (Bo Westh Hansen et al., 2017). The possible benefits of lower time resolutions for the day-ahead market requires an in-depth study.

Nevertheless, despite these limitations, the proposed methodology as well as the PBT analyses lay a very important preliminary groundwork for further extensive analyses. Even though a problem with reduced scope has been solved, it represents a building block toward solving the bigger problem of community microgrid control. Future researchers could continue these investigations by including additional stakeholders, such as DSOs and retailers, as well as by solving the larger microgrid cluster problem.

## 5 Conclusions: contributions, limitations, and future research

Worldwide electrification with *electricity access for all* is a global ambition as well as a huge challenge. Today, we also recognize the increasing impacts of environmental degradation by conventional energy sources that threaten to adversely affect all lifeforms. Hence, it has become critical to promote and increase the use of renewable energy sources (RES) of electricity production. At a broad level, this dissertation aims to enhance the proliferation of RES in the electricity grid on the basis of the widely accepted hypothesis that *renewable energy-based microgrids can lead to sustainable electrification and improvements in electricity access to communities*.

Electrification began in the late 19<sup>th</sup> century with the deployment of small autonomous microgrids that were later interconnected through long-distance transmission lines to centralized large generators. Over the last 20 years, microgrids started getting renewed interest because of the potential to implement RES-based distributed generators (DGs). Around 2001, Lasseter proposed the microgrid concept as a new paradigm for operating DGs, and the deployment of renewable-energy-based microgrids in the electrical power system began to be seriously investigated (Lasseter, 2001, 2002; Lasseter and Paigi, 2004).



**Figure 5.1:** Microgrid research timeline over the last 20 years; this dissertation’s position in the microgrid research trends is also marked.

Figure 5.1 shows the progress in researches into renewable-energy-based microgrid implementations over the last 20 years, as well as the position of this dissertation in the microgrid research trends. By the early 2010s, conceptual studies such as sizing and planning; local control and energy management systems; islanding issues; and historically well-understood fields such as protection and reliability had been especially well studied for single microgrids<sup>45</sup>. Researchers then began to shift their focus toward the sharing of electricity and microgrid interconnections. Community microgrids started to be strongly studied by the mid-2010s. Today, some versions of community microgrids have already been tested and implemented in several parts of the world. However, studies into microgrid clusters and the tertiary control of microgrids are still limited. In addition, researches on the integration of community microgrids and microgrid clus-

<sup>45</sup>For a brief discussion on this, see Section 1.4, Chapter 1.

ters into electricity markets are comparatively recent and few in number.

As shown in Figure 5.1, this dissertation builds on renewable-energy-based single microgrids to investigate community microgrids and microgrid clusters. This dissertation fits in between the research transition from community microgrids to microgrid clusters, while also focusing on electricity market integration. We will now recap the scientific contributions of this dissertation, revisit their limitations, and discuss possible future researches.

### 5.1 Scientific contributions

This dissertation has taken small steps to solve the broader aim of proliferating RES by setting the following objective—*to develop concepts and solution methodologies for implementing community microgrids and microgrid clusters with the objective of economically and fairly allocating their combined resources to residential customers, retailers, and the DSO, considering local electricity market designs and external electricity market connections*. During the researches conducted to fulfill this objective, the dissertation made the following scientific contributions.

First, novel methodologies were developed to solve the sizing problem in single microgrid planning. The proposed methodologies cost-effectively dimension the distributed energy resources (DERs) in a single microgrid for full loads, partial loads (i.e., load fractions), and flexible loads (i.e., shiftable loads). The presented methodologies can be either directly applied (or extended with slight modifications) to solve the following questions in any microgrid:

- Is it possible to cost-effectively meet the entire load in the microgrid using 100% RES alone?
- Is it possible to cost-effectively meet a part of the load in the microgrid using 100% RES alone?
- Using 100% RES alone, how many hours of electric supply can be guaranteed to the customers in a microgrid?
- How can the availability of flexible resources in microgrid loads be exploited to enable 100% RES-based electric supply?
- Can residential customers economically benefit from installing PV-BESS microgrid systems in the Finnish scenario, i.e., with participation in the Nordic electricity market?

The partial-loads methodology is especially valuable for enabling electricity access for all because planners can plan partial access to RES-based electricity in electricity-deficit areas. Moreover, the proposed two-dimensional generalized flexibility model is a useful tool to analyze and exploit flexible resources in different microgrid systems so that RES production is fully utilized.

Second, using a mixed-binary linear programming (MBLP) model, we showed that DSOs can have economic incentives to use centrally installed BESS to increase their profits and actively participate in renewable-energy integration in microgrids (when the BESS costs decrease further).

Third, we presented a mathematical formulation of the problem of interconnecting and aggregating small neighborhood microgrids to form microgrid clusters with the objective of economically allocating their resources to residential customers, retailers, and the DSO; the requirements, costs, and profitabilities of different stakeholders were considered in the formulation. Further, a potential solution design for solving the microgrid cluster problem was presented.

Finally, we presented a novel marginal contribution (MC)-based methodology to economically and fairly distribute the economic resources of a community microgrid to its customers. Our Shapley-value-based methodology enables the fair allocation of the profits obtained after cooperative p2p electricity exchange between the customers of a community microgrid. We theoretically prove that our methodology is fair and will achieve higher profits as compared to the case when electricity is not shared. We also perform simulations for microgrids in Finland and USA to demonstrate our methodology and its effectiveness. We also compared the benefits obtained by residential customers when they exchanged electricity in a community microgrid with two different electricity tariff designs—the conventional energy-based tariffs (EBTs) and the recently proposed power-based tariffs (PBTs). The benefits of the newly proposed MC-based methodology were also compared with the benefits from the non-collaborative and conventional auction-based cases, when PBTs are used to bill the customers.

## 5.2 Limitations

The methodologies presented in the dissertation are novel but they have several limitations, some of which have been mentioned in the concluding sections of each chapter.

The limitations of the sizing methodologies were detailed earlier in Section 2.4. In summary, the methodologies are deterministic rather than stochastic<sup>46</sup>; untested in different climatic environments for adaptability, stability, and scalability; only address a limited portfolio of DERs; do not consider integrating other smart energy systems; do not fully consider all system costs; and ignore technical issues in microgrid implementations. Nevertheless, the methodologies are a valuable result because although limited in scope, they are robust models that can be extended and expanded to generalize them. This is potentially an important area of future research.

The MBLP model used for the economic analysis for DSOs is a good approximation of the objective, but MBLPs are NP-hard and not very easy to scale. Also, it is important to emphasize that current European and Nordic electricity market regulations do not allow DSOs to install and use BESS to reduce interruptions (European Commission, 2017; Ministry of Trade and Industry, 2013). Today, DSOs are not allowed to interfere or directly participate in electricity trading. As a result, this is an interesting research question, but its actual practical feasibility is unclear at present. We anticipate that in the future, DSOs will enter into partnerships with electricity traders, such as retailers or aggregators and share BESS capacity for interruption management by DSOs with power trading by traders (e.g., by market-price-oriented peak shaving). The exact nature of this partnership should be explored in future studies. However, to reiterate, current regulations do not permit such partnerships.

<sup>46</sup>The world, however, is largely stochastic!

The mathematical formulation presented in Chapter 3 is a very generalized formulation, but it is possibly incomplete for some operating conditions. Because of this generalized nature, it is not clear how well it can be adapted to different environments. In addition, concrete solutions to solve the problem and its facets are not presented. The bigger problem can be split into smaller simpler problems and then their solutions can be creatively combined, but it is not clear how a comprehensive full solution can be achieved in this manner. Further, the integration of electricity markets is considered but the analysis is narrow. The dissertation ignores many diverse market structures, components, and other factors that influence the power system design. Nevertheless, the problem statement and formulation give a useful bird's-eye view for future researchers to visualize and approach the microgrid cluster problem on a step-by-step basis.

Section 4.7 discusses some of the limitations of the profit allocation methodology presented in Chapter 4. The methodology is limited in scope because it only considers one stakeholder—customers. As a result, this is a narrow solution that does not completely consider all the issues connected to the efficient utilization of the economic resources of a microgrid. It is extremely important to consider other stakeholders, such as DSOs, retailers, etc., before a community microgrid is implemented. Additionally, the profit allocation methodology does not consider either BESS or demand-side management (DSM) programs that can be used to modify the load.

A significant limitation of the dissertation is that the methodologies have not been practically implemented in a real power system so that there is no demonstrated proof-of-concept for the solutions.

A complete solution to the complicated microgrid cluster problem is beyond the scope of this dissertation. Instead, we present a solution to a simplified partial problem that can be improved upon by future researchers. The solution concepts and methodologies presented in the dissertation form building blocks for constructing a complete solution in the future. We believe that by solving problems incrementally in this manner, a final all-encompassing solution to achieve 100% RES-based electrification will be ultimately developed.

### 5.3 Future research

**Stakeholders** Besides high costs, the greatest barriers to the implementation of microgrids are the regulatory and market environment and the ability to trade generated power. Further, DSOs are typically conservative about their networks and not often keen to prioritize microgrid integration into the main network. DSOs are particularly wary of power quality and reliability issues arising from bi-directional power flow, and they typically discourage grid feedback and trading. Moreover, any upgrades carried out by the DSO are ultimately passed down to the customer as higher electricity prices (Soshinskaya et al., 2014). Thus, the implementation of microgrids is hindered by interconnected regulatory, market, and stakeholder issues, creating a layer of complexity.

We suggest that future researchers focus on breaking down these barriers and realizing practical microgrid implementations. This dissertation dealt with three stakeholders and briefly discussed a problem statement, but the proposed solutions are confined to treating only the customer as a stakeholder. The remaining tasks for DSOs, retailers, etc., are beyond the present scope, but

they are crucial areas for future work.

**Electricity market integration** The integration of electricity markets into the power system and microgrid collaborations must be analyzed in detail. Electricity markets across the world have a variety of diverse market structures depending on the environment. Their principles, regulations, products, components, and operations significantly influence the power system design. The integration of electricity markets with microgrid operations is a very important future pathway, whose success will determine the success of microgrid implementations in many countries.

Revenues from selling microgrid services to the external electricity market is an important focus area. For example, we can consider a community microgrid to be a single electrical element (generator/load) in a distribution grid, similar to a BESS, and explore the nature and impact of the services that it can provide to the stakeholders in the grid, such as power balance, frequency regulation, etc. The microgrid can be operated as a “microgrid as a service” model, similar to the “software as a service” software licensing and delivery model.

In addition, because of the increasing volatility in the system caused by higher RES penetration, the benefits of implementing finer time resolutions (for example, 15 or 30 min) in the local markets in community microgrids should be investigated.

**Distributed energy resources and paradigms** The installation and usage of additional DERs such as BESS can potentially benefit the community microgrid and microgrid clusters. Electric vehicles (EVs), which are essentially BESS, are becoming increasingly popular in the world today. Such DERs can be interconnected and their characteristics can be leveraged to increase microgrid revenue. For example, unwanted or excess electrical power can be sold to neighbors or to nearby grids, especially when the electricity market prices are high. Theoretical and practical implementations of interconnected BESS and EVs must be studied in greater depth and detail than that conducted by current researches.

Similarly, the benefits of DSM programs and paradigms must be examined. An interesting research area is to develop an efficient DSM algorithm that can maximize the profits of all the stakeholders in a community microgrid or microgrid cluster.

**Microgrid clusters** Although there is significant research focus on aggregating microgrids for optimal energy exchange, most researches focus on the primary and secondary control level and ignore the tertiary level. It is important to also examine the impacts and influence of connecting microgrids at the tertiary level for optimal energy exchange. For example, new independent power producers are important future stakeholders in upcoming deregulated electricity markets. Since renewable producers are wary of real-time risks caused by weather uncertainties, they tend to bid conservatively in electricity markets. The uncertainty in renewable resources can be reduced by interconnecting geographically diverse producers. Many recent researches have addressed the question of aggregating large-scale renewable electricity producers using competitive coalition formations (Zhang et al., 2015a). Such researches need to be supplemented by investigations into the role and impacts of other stakeholders such as society, retailers and transmission system operators. For example, many authors have considered coalitions of wind producers previously but their main focus was on dividing the profits of a grand coalition

among its members and not on the effect of coalitions on the entire system and on other stakeholders. Such researches need to be broadened and more deeply investigated by considering all actors in the power system.

## 5.4 The future

This dissertation was strongly motivated by social factors, especially the importance of increasing global electricity access and improving a community's energy independence, reliability, and security. PV-based microgrids have been proposed and discussed as an effective method to achieve these objectives. The methodologies, analyses, results, and discussions presented in this dissertation are small steps toward this larger goal of *promoting electrification using RES to transform not only the environment but also people's lives*. The dissertation proposes methodologies that, with more improvements, can enable societies customers to access co-operative, independent, reliable, and resilient electricity grids.

In addition, I believe that the electricity exchanges discussed in this dissertation will promote a culture of communal sharing of resources and build togetherness, unity, and harmony. I hope that this dissertation and subsequent researches in the field will continue to improve the state of electricity access as well as the proliferation of RES across the world. I dream of a cleaner unpolluted world with unlimited renewable-energy-based electricity access for all, and this dissertation represents a small step toward realizing this dream.

## Afterword—Personal reflections on engineering research

### Research, n.

*A diligent, systematic, and careful inquiry or investigation into a subject, field, or problem, undertaken to discover or revise facts, theories, principles, applications, etc.*

American Heritage Dictionary (2019)

Scientific research is an art form, akin to music or poetry. Like all art forms, researchers creatively play with logical ideas to make elegant patterns that are limited only by human imagination and natural boundaries. Some patterns are temporary, as if written on sand to be washed away by the next wave of thought. And some patterns are permanent, as if eternally engraved on stone to be built upon by others into a monument.

Among the scientific disciplines, engineering has a primarily utilitarian function so that engineering research is necessarily bounded. Engineers perforce limit their flights of fantasy to material societal problems whose solutions will have concrete practical purposes. But, just like a painter is able to depict a wealth of thought even on a limited canvas, an engineer is able to explore an infinity of ideas on a bounded landscape. An engineer's canvas may be limited, but the brushwork is inventive and the palette unlimited, so that the engineer's creativity remains undimmed and limitless, shaping the world and improving lives in unimaginable ways.

Engineering research can be divided into (at least) two broad categories: scenario-based research and methodology-based research. Scenario-based researches aim to answer questions about scenarios. Here, the researcher usually first finds a scenario whose implications are yet to be examined. These scenarios either model current societal problems or an imagined future and its implications. The researcher then asks relevant questions and tries to find answers. Questions about current scenarios could be, for example, "How many hours of electricity per day can renewable energy resources alone provide a village and what will be the cost?" And questions about future scenarios could be, for example, "Given current cost trends, what will be the electricity bill of a customer thirty years from now, assuming that electricity is supplied solely from renewable energy sources, including battery?" Some questions may be even more imaginative and futuristic, for example, "What is the type, dimensions, and costs of renewable energy resources needed to operate a human base in the most human-friendly area on Mars?" Researchers then collect existing data and data trends, analyze their implications, and present a considered evaluation.

Methodology-based researches, on the other hand, aim to produce new concepts, techniques, and tool sets that can be used to evaluate and solve a wide variety of problems. Here, the researcher usually first finds a problem to solve and then creatively combines known problem-solving techniques to carve a new analytical approach. Often, concepts and procedures from a completely different field are applied to a new problem whose new constraints and conditions

lead to a new class of problem-solving techniques. Or, two disparate fields are skillfully combined to devise a new algorithm much like a weaver intertwines different colorful threads to create a beautiful tapestry. And, sometimes, the new approach is so revolutionary and of such importance that it opens up entire new research fields, as in the case of John von Neumann, among others.

Thus, scenario-based researches deal with analyzing the societal state today or establishing a pathway toward a desired future, while methodology-based researches try to devise algorithms and concepts to build that future. But, which of these categories should an engineering researcher explicitly choose? Should the researcher even explicitly choose an approach or should the researcher simply solve problems? The supervisor's influence plays a major role in a junior researcher's choices and progress, and often, there is less freedom. A senior researcher, however, has much more freedom to choose paths. Unfortunately, neither approach has clear superiority, and so, there are no clear answers; much simply depends on the researcher's aptitude, appetite, and final aims (and funding potential!). After all, both approaches require different skill sets and different ways of working.

Scenario-based researches require the researcher to be meticulous, disciplined, and organized. Data collection and its analysis and interpretation are often the primary challenges. At the same time, the researcher has the significant advantage that the methods needed to collect, evaluate, and interpret data already exist, for example, the Internet, databases, statistical tools, etc. And if a reasonably generalized method already exists to analyze similar questions, the method can be used with few modifications to multiple scenarios, leading to (relatively) easily produced multiple publications. For example, if a generalized method exists to analyze the renewable energy resources on any astronomical body, the method can be used for all known astronomical bodies (with minor variations), leading to different conclusions and new publications. Scenario-based researches also often take the form of technical reports. Scenario-based researches are valuable to the scientific community and especially to society, because they answer important questions that can have high impacts on public decision making. They inform policies and give society a clear understanding of current scenarios and future trends. As a result, scenario-based researches are often highly cited, for example, survey and review papers that present analyses of current state-of-the-art scenarios.

Methodology-based researches rely on creativity and ingenuity to find new techniques that can solve a wide range of problems. Additionally, the researcher must spend time and effort to learn previous methods and concepts so that the researcher is equipped with a wide array of tools. For example, today, the researcher must be aware of mathematical tools, optimization techniques, machine learning and such statistical learning approaches, as well as a host of other problem solving ideas. Unfortunately, this can set limits on the research output in terms of publications. The researcher must also be able to model the problem to make it tractable, but at the same time, close to reality. Sometimes, the problem formulation is more critical than the solution, because a well-formulated problem can not only make it easier to reason about techniques but to find solutions. The researcher must judiciously choose the right tools for the problem at hand, because choosing the wrong tools has the damaging consequences of lots of time wasted in a mathematical jungle. The researcher faces an additional problem here. Because of the difficult nature of this approach, the researcher is forced to make assumptions about the problem

or introduce limitations to the solution methodology. As a result, the impact of new proposed methodologies on the current field and on society can be limited. A quick glance at current literature will confirm this hypothesis. Thousands of research papers solving the same problem (with small variations) using some new methodologies litter an academic black hole, never to be seen again, much less utilized in practice. On the other hand, a brilliant new methodology of a particularly “genius” variety, the holy grail of this research approach, can have a lasting influence on the field, inspiring new fields and a thousand new papers (e.g., the Shapley value or the simplex algorithm).

Scenario-based researches can be identified and distinguished by the “proof test.” It is usually difficult to prove a scenario-based research without access to the same data set. On the other hand, the methodologies in methodology-based researches are typically mathematical and can be proved without needing any underlying data. Since science is constructive, both novelty and superiority are important; a new method has to be better than the previous one for it to be valuable. As a result, methodology-based researches often include scenario-based test results to support the claim of the method’s superiority, which cannot be mathematically proved. Similarly, scenario-based questions often lead to novel methodologies and such researches often contain novel techniques. For example, a question about renewable energy resources on Mars can lead to a novel general method or mathematical insights that can be applied to any planet’s surface or to other problems as well.

In this dissertation, I have primarily focused on the methodology-based approach and I have presented new methodologies rather than scenario analyses. This was not a deliberate decision taken right at the beginning, but a path laid out by the problems I considered during my dissertation. I was also influenced by my first supervisor and co-author Prof. Chris Develder whose approaches to dissecting and solving problems gave me great insights into applied computational techniques. And perhaps I was subconsciously persuaded by my aptitude and internal motivation to create new algorithms and ideas to solve problems rather than analyze implications. As a result, my journey toward a Doctoral degree was a bit like traveling through a tangled forest, with many stumbles through winding paths and unexpected twists. To creatively produce new methodologies, I had to painstakingly study and apply two different problem-solving tools—optimization theory and game theory. Additionally, I also learned statistical (machine) learning and pattern recognition concepts that I hope to apply to my future research endeavors. Although I cannot now say that I know everything in these fields and probably will never be able to, I do know *something*. This I am proud of, mistakes and mis-steps included. In the end, this was a long journey, but a journey full of learnings and therefore, a satisfying journey.

No scientific endeavor happens in a vacuum. If a researcher looks further than others, it is only by standing on the shoulders of other giants who preceded him. And, if I have looked further, it is not only by standing on shoulders but also by joining hands. I have learned from and worked together with many researchers, some who are known and acknowledged earlier, and some who are unknown and faceless, but have brought immense value. Through my innumerable failures and occasional successes, I have been guided and inspired by teachers and researchers who also valiantly persevered on their journeys.

But, now my special, but long and winding journey, seems to come to at an end. And its culmi-

nation, this dissertation, is in your hands. But, no, this is not an ending! This dissertation is a crest of a wave and not its cessation, a pause, not a closure. Much still remains to be done, and many horizons still beckon. For, the methodologies presented are neither perfect nor complete solutions; at best, it is a window to future possibilities and explorations. But, no matter. This is only a first step, an inception, a beginning, and there are many more interesting and fascinating problems to solve, little puzzles stoked by curiosity and driven by creativity. And creativity is a renewable resource. Thus, the journey still continues.

No matter how special the dissertation is from my personal viewpoint, it is but a middling effort from a “humankind science” perspective. Indeed, this dissertation will soon enter the great academic void. Some copies will sleep in a dusty corner in a dusty shelf waiting to be roused by a prying eye. Some copies will rest in servers in lonely cold rooms, waiting to be stirred by an internet ping. But, maybe some future researcher will find a nugget here and there. To such a future researcher, to the future seeker, to the future explorer, I wish good fortune. And I hope that just as I expanded on the thoughts of countless researchers before me and looked just a little further, you may find something worth your attention and time here. Whether this will happen, I do not know and cannot foresee. But, this, I do know: I had a great intellectual adventure, and now, it is time for another expedition...

*The years yet wait upon me*

*and time doth stand still*

*untrodden paths seek my steps*

*warbling thrushes await my ear*

*and rainbows beseech...*

Arun Narayanan  
October 27, 2019  
Lappeenranta, Finland

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## **Part II**



## Publication I

Narayanan, A., Mets, K., Strobbe, M., and Develder, C.

**Feasibility of 100% renewable energy-based electricity production  
for cities with storage and flexibility**

*Renewable Energy*

Vol. 134, No. 4, pp. 698–709, 2019

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Contents lists available at ScienceDirect

Renewable Energy

journal homepage: [www.elsevier.com/locate/renene](http://www.elsevier.com/locate/renene)

# Feasibility of 100% renewable energy-based electricity production for cities with storage and flexibility

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## ARTICLE INFO

### Article history:

Received 2 April 2018  
 Received in revised form  
 21 September 2018  
 Accepted 12 November 2018  
 Available online 16 November 2018

### Keywords:

Renewable energy sources  
 Linear programming  
 Electricity production  
 Partial loads  
 Flexible loads

## ABSTRACT

Renewable energy is expected to constitute a significant proportion of electricity production. Further, the global population is increasingly concentrated in cities. We investigate whether it is possible to cost-effectively employ 100% renewable energy sources (RES)—including battery energy storage systems (BESS)—for producing electricity to meet cities' loads. We further analyze the potential to use only RES to meet *partial* loads, e.g., by meeting load demands only for certain fractions of the time. We present a novel flexible-load methodology and investigate the cost reduction achieved by shifting fractions of load across time. We use it to evaluate the impacts of exploiting *flexibility* on making a 100% RES scenario cost effective. For instance, in a case study for Kortrijk, a typical Belgian city with around 75,000 inhabitants, we find that from a purely economic viewpoint, RES–BESS systems are not cost effective even with flexible loads: RES–BESS system costs must decrease to around 40% and 7% (around 0.044 €/kWh and 0.038 €/kWh), respectively, of the reference levelized costs of electricity to cost-effectively supply the city's load demand. These results suggest that electricity alone may not lead to high RES penetration, and integration between electricity, heat, transport, and other sectors is crucial.

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## 1. Introduction

Climate change concerns and increasing environmental awareness have encouraged governments, industries, and researchers to make considerable efforts to reduce the current dependence on traditional non-renewable energy sources (NRES), such as fossil fuels, by focusing on alternative renewable energy sources (RES) of electricity production, such as solar and wind energy. The European Union (EU), for example, has set ambitious targets for 2030—to reduce greenhouse gas emissions by 40% compared to 1990, to ensure a share of at least 27% of renewable energy, and to achieve at least 27% energy savings compared to business-as-usual scenarios [1].

Global energy demand is expected to increase by nearly 30% from 2016 to 2040, of which electric load demand will account for

almost 40% of the additional consumption until 2040. At the same time, RES will comprise nearly 60% of all new electricity production capacity up to 2040 [2]. RES are also becoming cost-competitive with NRES. From 2009 to 2014, the levelized cost of electricity (LCOE) of wind and solar energy production in the US decreased by 58% and 78%, respectively [3]. Moreover, rapid deployments and considerable research and development are expected to decrease costs further—the average solar PV and onshore wind costs are predicted to reduce by a further 40–70% and 10–25%, respectively, by 2040 [2]. Electricity production is expected to meet the electric load demands of an increasingly *urbanized* world. A large proportion of the world's population already live in urban areas—in 2014, an estimated 54% of the world's population lived in urban areas, which is expected to increase further to 60% by 2030 [4]. Hence, it is important to analyze the potential for utilizing RES to meet the electricity load demand of cities. Such analyses can not only support the utilization of RES in today's cities but also the design, planning, and development of *future 100% RES-based “green” cities*.

In this study, we first address two general electricity-production-capacity mix questions: (1) What is the *cost-optimal electricity-production-capacity mix* to meet a city's load demand when RES—supported by battery energy storage systems (BESS)—

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**Nomenclature**

$\alpha$	Percentage of flexible load shifted across $r - 1$ time steps, %
$b_t = [b_1, \dots, b_T]$	Binary decision variables, $b_t \in \mathbb{Z}_2$
$B_{max}$	Maximum battery energy storage system (BESS) capacity, Wh
$B(t) = [B(t_1), \dots, B(t_T)]$	BESS capacity, Wh
$B_\Delta(t)$	Difference in BESS capacity, $B_t - B_{t-1}$ , Wh
$C_b$	Levelized cost of energy (LCOE) for BESS, monetary unit/Wh
$C_{pv}$	LCOE for photovoltaic (PV) panels, monetary unit/Wh
$C_w$	LCOE for wind turbines, monetary unit/Wh
$C_g$	LCOE for non-renewable energy sources, monetary unit/Wh
$\delta$	Proportion of the load demand that is flexible
$E_t(t) = [E_t(t_1), \dots, E_t(t_T)]$	Load energy, Wh
$E_{fl}(t) = [E_{fl}(t_1), \dots, E_{fl}(t_T)]$	Flexible load energy, Wh

$E_{infl}(t) = [E_{infl}(t_1), \dots, E_{infl}(t_T)]$	Inflexible load energy, Wh
$E_g$	Energy produced by non-renewable energy sources, Wh
$E_{pv}$	Energy produced by PV installations, Wh
$E_w$	Energy produced by wind turbine installations, Wh
$f_{pv}(I(t))$	Function that converts $I(t)$ to solar energy
$f_w(W_s(t))$	Function that converts $W_s(t)$ to wind energy
$I(t) = [I(t_1), \dots, I(t_T)]$	Solar irradiation, Wh/m <sup>2</sup>
$k_{ch}$	BESS charge rate
$k_{dch}$	BESS discharge rate
$r$	Number of time steps across which flexible load can be shifted
$T$	Total time period
$t_i = [t_1, \dots, t_T]$	Time steps
$T_k$	Total time steps with electric power
$W_s(t) = [W_s(t_1), \dots, W_s(t_T)]$	Wind speed, m/s

and NRES are combined? and (2) What is the cost reduction required to enable 100% RES-based electricity production that is competitive with NRES-based electricity production? It is possible that RES-based electricity production cannot cost-effectively meet full electric loads of a city. Nevertheless, it may still cost-effectively meet *partial loads*. Therefore, we then analyze and report the changes in the production costs when supplying electricity for 1–100% (discrete) time steps of the entire time period. Using our proposed methodology, planners can determine their desired RES installation and utilization based on the maximum number of hours that can be supplied by the RES and thus obtain the cost benefits of decreasing the supply security.

Further, we propose a novel methodology to analyze the impacts of exploiting the *flexible resources* present in a city. A resource is considered *flexible* if its electricity production or consumption can be shifted in time within the boundaries of end-user comfort requirements, while maintaining the total electricity production or consumption [5]. A *flexible load* thus constitutes a *shiftable portion* of the total load. Cities have many potential flexible loads such as district heating facilities, electric vehicles, and potentially household devices (e.g., washing machines [6]). Hence, using a novel flexible-load methodology, we analyze the cost-effectiveness of exploiting flexibility by using demand-side management (DSM) to shift flexible loads as the load amounts and load shift durations are varied. Our proposed flexibility model can also be generally applied to analyze the impacts of flexible loads on electricity production resources.

For our analyses, we consider RES-based “green electricity” production infrastructure comprising photovoltaic (PV) panels and wind turbines that are either centrally located outside the city borders or distributed across the city. Solar power is especially attractive as an electricity producer in cities since PV panels can be integrated into the rooftops of buildings, and potentially walls and windows as well [7]. Further, we consider Li-ion BESS, which is a well-known and highly researched solution to mitigate the variability of RES; their prices also have decreased consistently recently [8,9]. NRES supplying “gray energy”, i.e., energy from undesirable fossil fuel sources, are considered to be centralized production infrastructure located outside a city’s borders. To solve these problems, we use linear programming (LP)-based innovative models that take the LCOEs of the production infrastructures, the load data of a city, and RES data—solar irradiation and wind speed—as the inputs.

Some researchers have discussed technical, economical, and political pathways to 100% cost-optimal renewable-energy production and storage for specific regions, e.g., the European Union [10], United States [11,12], Ireland [13], Australia [14], Nigeria [15], North-East Asia [16], as well as some urban regions [17–20]. Some organizations have reported transitions to sustainable energy systems in highly populated urban areas. In 2016, the National Renewable Energy Laboratory reported the potential to reach 66% renewables penetration in California, which included the roles of storage and flexibility from electric vehicles [21]. The International Renewable Energy Agency reported potential approaches toward implementing 100% sustainable urban energy systems [22]. These reports typically make qualitative analyses and focus on the technologies and methods that can be used for the transition. In contrast, our study makes a *quantitative analytical study* into the feasibility of using RES and BESS for supplying electricity to cities and presents effective techniques to analyze their viability from cost-efficiency viewpoints.

Several researchers have also focused on similar electricity generation planning problems, considering renewable energy integration [23]. Dominguez et al. [24] considered investments in both production and transmission facilities using stochastic models. Nunes et al. [25] proposed a stochastic multi-stage-planning mixed-integer linear programming (MILP) model to co-optimize generation and transmission investments under renewable targets. An MILP approach was also used by Bagheri et al. [26] to analyze the feasibility of a transition toward a 100% RES-based power system. The main difference between these studies and ours is our approach toward partial and flexible loads, especially the proposed methodology for exploiting *load flexibility* on the feasibility of large-scale RES adoption and its analyses. Although some studies considered flexible loads, their treatment was indirect, for example, by including an annual cost for load shedding [24]. Moreover, few studies have examined the possibilities of supplying <100% renewable electrical energy (*partial loads*). Supplying partial loads is an essential component of planning electric supply not only for cities but also for small remote villages that have limited access to electricity; here, the planning problem is to offer at least some hours of electricity economically. We have made systematic investigations into how the *electric loads of cities* can be cost-optimally supplied by 100% renewable electrical energy by investigating the *cost impacts of not only full loads but also partial and flexible loads*.

The main contributions of our study are summarized as follows:

- We investigate the reductions in RES (wind and solar energy) and BESS costs required to make it possible for cities to be supplied by 100% RES.
- We present an LP model to determine whether RES, supported by BESS, can cost-effectively replace NRES to supply the *full loads* of cities.
- Since it may be economically feasible and attractive to meet the load demand for a *fraction* of the time period—i.e., *partial loads*—using *only green energy*, we develop a MILP model and analyze the cost-effectiveness of meeting such partial loads.
- We solve the question of analyzing the impacts of exploiting *load flexibility* on the feasibility of large-scale RES adoption by using a *two-dimensional generalized flexibility model*. Our flexibility model is characterized by the load fraction that can be shifted to later time steps as well as the maximal *discrete* time steps across which the load fraction can be deferred. This model can also be generally applied to analyze the impacts of flexible loads on production resources.
- All our models can be universally applied to microgrid planning problems. In this study, we apply our methodology to the city of Kortrijk, Belgium, using realistic data.

Our paper is organized as follows. We first present our mathematical models and methodologies in Sec. 2. In Sec. 3, we report the results of applying our methodology to the city of Kortrijk, Belgium, as a test case. Finally, the paper is concluded in Sec. 4.

## 2. Mathematical model

### 2.1. Renewable energy

Wind energy was calculated from wind speeds using the Tradewind model proposed by the European Wind Energy Association [27]. An equivalent wind power curve was derived to convert wind data to energy data for wind farms across different regions in Europe.

The power production from a solar panel is typically given by the equation  $E_{pv} = \eta \times E \times A$ , where  $\eta$  is the energy conversion efficiency of a solar cell;  $E$ , the incident instantaneous solar irradiance ( $\text{W/m}^2$ ); and  $A$ , a solar cell's surface area ( $\text{m}^2$ ) [28]. We used the solar insolation  $I$  ( $\text{Wh/m}^2$ ), which is the average of  $E$  over a given time period, to calculate the energy production. Standard test conditions (STC) and efficiency  $\eta = 15\%$ —a conventional solar panel's typical efficiency—were assumed [29]. We calculated the energy production at the given location for a solar panel per unit of surface area ( $\text{m}^2$ ).

### 2.2. Battery energy storage systems (BESS)

We considered a simplified, lossless, idealized model of battery cells whose main characteristics are the maximum energy storage capacity  $B_{\max}$  (in Wh) and maximum BESS energy charge and discharge rates,  $k_{ch}$  and  $k_{dch}$  (Wh), respectively. The BESS either charges at  $B_{\max}/k_{ch}$  or discharges at  $B_{\max}/k_{dch}$ .

### 2.3. Costs

The LCOE is a common metric for comparing the cost-effectiveness of electricity generated by different sources at the point of connection to an electricity grid or load [30]. The LCOE considers the initial capital, discount rate, and the costs of continuous operation, fuel, and maintenance, and thus, they represent the

full life-cycle costs of a generating plant per unit of electricity [31]. The LCOE is essentially based on a simple equation—the cost to build and operate a production asset over its lifetime divided by its total power output over that lifetime (monetary unit/kWh). The LCOE can be used to compare the production costs of conventional power plants with those of RES. Hence, we have used the LCOE as the cost parameter for our analyses. Further, we have used LCOEs from 2014 as the reference costs.

### 2.4. Full loads scenario

The problem addressed in this paper is: **given** the LCOEs of green, grey, and BESS energy production, BESS characteristics, and time-series data of load, solar irradiation, and wind speed, **determine** the minimal-cost electricity production infrastructure to meet full, partial, or flexible load demands. To solve this problem, we have used LP models with the objective of minimizing the cost of electricity production.

The objective is to minimize the cost of electricity production. For the full loads scenario, the load demand is met at all time steps. The most general case comprising all the considered production infrastructure—wind turbines, PV plants, BESS, and grey energy installations—is presented here. The decision variables are their produced energies— $E_w$ ,  $E_{pv}$ ,  $B_{\Delta}(t)$ , and  $E_g(t)$ , respectively.  $B_{\Delta}(t) = B_t - B_{t-1}$ , where  $B_t$  is the BESS capacity (Wh) at time  $t$ . The model is as follows:

$$\min \left[ \sum_{i=1}^T C_w \cdot f_w(W_s(t_i)) \cdot E_w + \sum_{i=1}^T C_{pv} \cdot f_{pv}(I(t_i)) \cdot E_{pv} + \sum_{i=1}^T C_b \cdot |B_{\Delta}(t_i)| + \sum_{i=1}^T C_g \cdot E_g(t_i) \right] \quad (1)$$

subject to

$$f_w(W_s(t_i)) \cdot E_w + f_{pv}(I(t_i)) \cdot E_{pv} - B_{\Delta}(t_i) + E_g(t_i) \geq E_l(t_i), \forall i = 1, \dots, T \quad (2)$$

$$-B_{\max}/k_{dch} \leq B_{\Delta}(t_i) \leq B_{\max}/k_{ch}, \quad \forall i = 1, \dots, T \quad (3)$$

$$0 \leq E_w, E_{pv}, B_{\max}, E_g(t_1), \dots, E_g(t_T) \leq \infty \quad (4)$$

where  $C_w$ ,  $C_{pv}$ ,  $C_b$ , and  $C_g$  represent the LCOEs for wind, solar, BESS, and grey energy, respectively;  $f_{pv}(I(t))$  and  $f_w(W_s(t))$ , dimensionless “black box” functions for converting irradiance  $I(t)$  and wind speeds  $W_s(t)$ , respectively, to a fraction of the maximum possible solar and wind energy of a unit installation ( $1 \text{ m}^2$  and  $1 \text{ kW}$  installations, respectively);  $B_{\max}$ , the maximum BESS capacity (kWh),  $T$ , the total time period considered;  $t_i$ , each time step; and  $k_{ch}$  and  $k_{dch}$ , the BESS charge and discharge rates, respectively.

Equation (2) ensures that the load is always met at all time steps; Eq. (3) represents the charging and discharging of the BESS; and Eq. (4) gives the lower and upper bounds of the decision variables.

The other basic scenarios—only green energy; green and grey energy; and green energy with BESS—can be easily deduced from the generalized formulation by neglecting the appropriate variables. For example, for the “green energy with BESS” scenario, the grey energy portion can be dropped from the objective function as follows:

$$\min \left[ \sum_{t=1}^T C_w \cdot f_w(W_s(t_i)) \cdot E_w + \sum_{t=1}^T C_{pv} \cdot f_{pv}(I(t_i)) \cdot E_{pv} + \sum_{t=1}^T C_b \cdot |B_{\Delta}(t_i)| \right]$$

The grey energy variables can either be omitted completely, or  $E_g(t_i) = 0$ ,  $\forall i = 1, \dots, T$  can be enforced.

### 2.5. Partial loads scenario

In the second scenario, only partial load demands are met, which reduces the electrical reliability of the system. We considered a well-known reliability index—the average service availability index (ASAI)—defined as follows [32]:

$$ASAI = \frac{(\sum N_j) \cdot T - \sum (r_j \cdot N_j)}{(\sum N_j) \cdot T}$$

where  $N_j$  is the number of customers at a location  $j$ ;  $r_j$ , the annual outage time for  $j$ ; and  $T$ , the total time period considered [33]. For a single location, this is equivalent to

$$ASAI = \frac{N \cdot T - r \cdot N}{N \cdot T} = \frac{T_k}{T}$$

where  $T_k$  is the total number of time steps without interruptions.  $ASAI \in [0, 1]$ , and in the ideal case,  $ASAI = 1$ .

The production now meets the load demand only during some discrete time steps whose total number is predefined by the ASAI. To solve this problem, the LP model is reformulated as a mixed binary LP (MBLP) model. Binary decision variables  $b_i = \{b_1, \dots, b_T\}$ ,  $\forall b_i \in \mathbb{Z}_2$ , are used to decide whether the load will be met ( $b_i = 1$ ) or not ( $b_i = 0$ ), and they determine the optimum time steps for the given ASAI. The partial loads model is therefore as follows:

$$\min \left[ \sum_{t=1}^T C_w \cdot f_w(W_s(t_i)) \cdot E_w + \sum_{t=1}^T C_{pv} \cdot f_{pv}(I(t_i)) \cdot E_{pv} \right] \quad (5)$$

subject to

$$f_w(W_s(t_i)) \cdot E_w + f_{pv}(I(t_i)) \cdot E_{pv} \geq b_i \cdot E_l(t_i), \quad \forall i = 1, \dots, T \quad (6)$$

$$\sum_{i=1}^T b_i = T_k \quad (7)$$

$$b_i \in \{0, 1\}, \quad 0 \leq E_w, E_{pv} \leq \infty \quad (8)$$

Equation (6) implies that the load is met at some selected ( $b_i = 1$ ) time steps, and Eq. (7) ensures that the loads are always met for the given ASAI.

### 2.6. Flexible loads scenario

In this scenario, we consider the potential cost reductions that can be achieved by shifting flexible loads in time. We characterize flexibility by two parameters: (i) a maximal fraction  $\delta$  of the load that is shifted to later time steps, and (ii) a maximal amount of time  $r$  over which the loads can be deferred. Flexible load energy  $E_{fl}(t_i)$  at time  $t_i$  ( $\forall i = 1, \dots, T$ ) is then defined as  $E_{fl}(t_i) = \delta E_l(t_i)$ , where  $\delta \in [0, 1] \subset \mathbb{R}$  and  $E_l(t_i)$  is the total load. The unshiftable or inflexible load  $E_{inf}(t_i) = (1 - \delta)E_l(t_i)$ .

$\alpha_{i,0}$  is defined as the inflexible load fraction (unshifted load), and

$\alpha_{i,1}, \alpha_{i,2}, \dots, \alpha_{i,r}$  are the flexible load fractions that are shifted from  $t_i$  across the subsequent  $r$  time steps  $t_{i+1}, t_{i+2}, \dots, t_{i+r}$ , respectively;  $\alpha_{ij} \in [0, 1]$ . Thus, at the  $i^{\text{th}}$  time step  $t_i$ ,  $E_l(t_i)$  is distributed across  $r$  time steps:

$$E_l(t_i) = \sum_{j=0}^r \alpha_{ij} E_l(t_i) \quad (9)$$

where

$$\sum_{j=0}^r \alpha_{ij} = 1$$

The load that is shifted away from  $t_i$ ,  $E_{fl}(t_i)$ , is given by

$$E_{fl}(t_i) = \sum_{j=1}^r \alpha_{ij} E_l(t_i) \quad (10)$$

and the unshifted load energy component  $E_{inf}(t_i) = \alpha_{i,0} E_l(t_i)$ . A load cannot be shifted beyond the final time step, and therefore,  $r + t_i \leq T$ . The total flexible load that has been shifted to a time step  $t_i$  from previous time steps,  $E_{fl}^*(t_i)$ , is given by

$$E_{fl}^*(t_i) = \sum_{k=1}^r \alpha_{i-k,k} E_l(t_{i-k}) \quad (11)$$

Here,  $r$  prior loads from  $t_{i-1}, t_{i-2}, \dots, t_{i-r}$  time steps earlier have been shifted to the current time step  $t_i$ . Note that  $i - k > 0$ .

We will first incorporate this flexibility model into an LP formulation.

#### 2.6.1. LP formulation with flexibility

We consider the “green energy with BESS” case for the production. The objective is to minimize the costs for the proposed production infrastructure mix. The LP problem is almost identical to the previous formulation (Sec. 2.4), but additional decision variables  $\alpha_{ij}$  are included. Further, the first constraint—load is met at every time step—now includes the flexible load (Eq. (11)). Two additional constraints—related to  $\alpha_{ij}$ —are also included.

$$\min \left[ \sum_{t=1}^T C_w \cdot f_w(W_s(t_i)) \cdot E_w + \sum_{t=1}^T C_{pv} \cdot f_{pv}(I(t_i)) \cdot E_{pv} + \sum_{t=1}^T C_b \cdot |B_{\Delta}(t_i)| \right]$$

subject to

$$f_w(W_s(t_i)) \cdot E_w + f_{pv}(I(t_i)) \cdot E_{pv} + B_{\Delta}(t_i)$$

$$\geq \sum_{k=0}^r \alpha_{i-k,k} E_l(t_{i-k}), \quad \forall i = 1, \dots, T \quad (12)$$

$$\sum_{j=0}^r \alpha_{ij} = 1, \quad \forall i = 1, \dots, T \quad (13)$$

$$0 \leq \alpha_{ij} \leq 1, \quad \forall i \in \{1, \dots, T\}, \quad \forall j \in \{0, \dots, r\} \quad (14)$$

Equation (12) ensures that the load demand is met at all time steps, and Eqs. (13) and (14) give the bounds for  $\alpha_{ij}$ . The load in Eq. (12) is the sum of  $E_{fl}^*(t_i)$  (Eq. (11)) and  $E_{inf}(t_i)$  ( $\alpha_{i,0} E_l(t_i)$ ). The

remaining constraints pertaining to the BESS and the upper and lower bounds are identical to Eqs. (3) and (4).

The customer's load schedule should contain as few load shifts as possible, since this will cause the least inconvenience or loss of comfort. The presented LP model determines the minimal costs for a given  $r$  and  $\delta$  and yields a new load schedule. However, the LP model can yield multiple solutions with equal (minimal) costs but different sets of  $\alpha_{ij}$  values. Therefore, the solution may not always be the best schedule, i.e., the schedule with the least load shifts. Hence, we implemented an additional schedule optimization step in which we use the newly derived optimum production schedule from the LP model to derive new optimum values for  $\alpha_{ij}$ .

still greater than the total production, the next nearest flexible loads are shifted. This process (lines 10–18) is repeated until the production at least matches the corresponding load. Lines 3–21 are then repeated for all time steps.

Note that we could have attempted to integrate the problem of deriving the best schedule into the LP model and solved a single optimization problem. However, constructing and implementing a model that not only solves the flexibility problem but also chooses the best solution is complicated and slower. Instead, from one of the many possible equal-cost solutions, i.e., the one of the many found by an LP solver, we can derive a solution with minimal shifts using our proposed algorithm (Algorithm 1).

#### Algorithm 1

Flexible load schedule optimization.

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```

1: Inputs: (1) the newly derived production schedule  $E_s$ ; (2) the old (un-
   shifted) load schedule  $E_\ell$ ; (3) total time period  $T$ ; (4)  $r$ ; and (5)  $\delta$ 
2:  $i = 1$ ;  $(\alpha_n)_{i,j} = 0$  ( $\forall i = 1, \dots, T; j = 0, \dots, r$ )
3: while  $i \leq T$  do
4:    $(\alpha_n)_{i,1} = \delta$ 
5:    $E_{infl}(t_i) = (1 - \delta)E_\ell(t_i)$ 
6:    $E_{fl}(t_i) = \sum_{j=1}^r (\alpha_n)_{i-j,j} \delta E_\ell(t_{i-j})$ 
7:   if  $E_s(t_i) \geq (E_{fl}(t_i) + E_{infl}(t_i))$ , then
8:      $(\alpha_n)_{i-1,2}, \dots, (\alpha_n)_{i-r,r} = 0$ 
9:   else
10:    while  $E_s(t_i) < (E_{fl}(t_i) + E_{infl}(t_i))$ , do
11:      for  $j = i-1:i-r+1$  do
12:         $E_x(t_i) = (E_{fl}(t_i) + E_{infl}(t_i)) - E_s(t_i)$ 
13:         $(\alpha_n)_{j,i-j+1} =$ 
14:         $\min\{E_x(t_i)/\delta E_\ell(t_j), (\alpha_n)_{j,i-j}\}$ 
15:         $(\alpha_n)_{(j,i-j)} = (\alpha_n)_{(j,i-j)} - (\alpha_n)_{(j,i-j+1)}$ 
16:         $E_x(t_i) = E_x(t_i) - (\alpha_n)_{(j,i-j+1)} \delta E_\ell(t_j)$ 
17:      end for
18:    end while
19:  end if
20:   $i = i + 1$ 
21: end while
22: Output:  $(\alpha_n)_{i,j}$  ( $\forall i = 1, \dots, T; j = 0, \dots, r - 1$ )

```

---

#### 2.6.2. Flexible schedule optimization

We use the newly derived production schedule from the LP model to obtain new values for  $\alpha_{ij}$ ; the algorithm is presented in Algorithm 1. New  $\alpha_{ij}$  values— $(\alpha_n)_{i,j}$ —are initially set to 0. Line 4 initializes  $\alpha_{i,1}$  to  $\delta$ , which implies that initially, the entire flexible load is shifted to the very next time step. In lines 5–6, the current inflexible and flexible loads are calculated. If the total production is greater than the new total load with  $\alpha_{i,1} = 1$ , it is not necessary to shift the loads anymore—all relevant  $\alpha$  values are set to 0 (lines 7–8). If the total load is greater than total production, the most recent flexible loads are shifted first. If the total remaining load is

### 3. Results

#### 3.1. Experimental data

##### 3.1.1. Data period

We performed our simulations for 1-year data with a data resolution of 15 min.

##### 3.1.2. Location

We considered the city of Kortrijk, Belgium, which is a reasonably sized typical Belgian city with a total population of 75,219 and a population density of 940 inhabitants/km<sup>2</sup> (2013) [34].

### 3.1.3. Wind speeds and solar irradiation

For the solar irradiation and wind speeds, we used 5 min measurement data obtained at Lemcko Labs, Kortrijk, Belgium [35]. Data for an entire year from September 1, 2012 to August 31, 2013 was considered, since this period covers all four seasons and enables us to investigate seasonal variations. Further, since load data was available only at 15 min intervals, we aggregated the 5 min data for wind speeds and solar irradiation into 15 min data.

### 3.1.4. BESS

We considered lithium-ion (Li-ion) batteries because they are among the most promising next-generation batteries for supporting renewable energy-based production [36]. Li-ion cells offer the best cycle efficiency (90%) and durability, lowest self-discharge (5–8% per month at 21 °C), and energy density (up to 630 Wh/l) [36]. Further, Li-ion batteries are expected to become cheaper in the future [9]. We considered charge and discharge rates of 1C, which implies that the BESS charges and discharges at its maximum capacity at every time step.

### 3.1.5. Load

In Belgium, the meter readings of most customers are not recorded continuously, and synthetic load profiles (SLPs) are used to estimate the energy consumption. We used the SLP provided by the Flemish Regulation Entity for the Electricity and Gas market (VREG) for 2012–13 [37]. These SLP profiles model typical user consumption using statistical averages on real life data, as measured by the VREG, and give the amount of energy consumed at 15 min intervals. Fig. 1 shows the input load data and the renewable energy production data (assuming solar and wind power plants with nominal power plant capacity of 1 MW) used in this study for a year.

### 3.1.6. Costs

For LCOE data, we considered a pan-European study conducted by the European Commission that reported energy cost data of different electricity and heat technologies for all countries in the European Union [38]. The LCOEs of small rooftop PV systems, which are popular in Belgium, and onshore wind power were 0.130 €/kWh and 0.110 €/kWh, respectively. The Belgian electricity production infrastructure comprises nuclear (39.54%), natural gas (33.96%), coal (3.14%), liquid fuel (1.5%), water (9.3%), wind (5.93%), and others (6.64%). We calculated the grey energy LCOE as a proportion of their contributions to the total energy as 0.0386 €/kWh.

The procedures for calculating the LCOEs are given in detail in Annexure 4 of the report published in Ref. [38].

Unfortunately, the European Commission study did not include BESS costs. Consequently, we examined scenarios in other countries and concluded that the Li-ion BESS LCOE is currently about 5 times that of wind [3]. Hence, we applied a factor of 5 to the European wind LCOE and arrived at a BESS LCOE of 0.55 €/kWh.

## 3.2. Results

### 3.2.1. Basic scenarios

The “only green” scenario was expectedly infeasible throughout the year. Further, green energy and BESS have no impacts when grey energy is included since they are much more expensive.

Fig. 2 shows the seasonal variations in the total costs for the “green-BESS” case. The average cost per unit of electricity produced was 0.4520, 0.4442, 0.3972, and 0.3720 €/kWh for autumn, winter, spring, and summer, respectively. The costs were lowest in summer due to lower load demand and more renewable resources and highest in the winter. When grey energy was included, it was dominantly selected due to its low costs, and the production infrastructure became cheaper by a factor of  $\approx 12$ —the yearly cost with BESS, for example, was 204.15 million Euro (average cost of 0.4265 €/kWh), while it was 18.47 million Euro with grey energy (average cost of 0.0386 €/kWh, i.e., its LCOE). Note that this can also be predicted from their LCOEs (grey energy is about 14 times cheaper than BESS). When BESS is used with green energy, any excess produced green energy is stored in the BESS to be used at later times with insufficient green energy production (Fig. 3). The curtailment is negligible and the load (dotted blue lines; compare with Fig. 1 showing input data) is almost completely covered by the combined supply from green energy and BESS (black lines). The sizing algorithm is designed to dimension a sufficiently large BESS capacity that ensures that the produced electricity is not wasted due to RES curtailment.

Fig. 4 shows the green energy production, which is directly used without storing in the BESS, and its cost as a proportion of the total. Green energy proportion was highest in summer (nearly 30%) and lowest in winter and autumn, halving to nearly 15%.

### 3.2.2. Cost variations

In the LP solution, grey energy is dominantly selected over the other alternatives due to its significantly lower cost. However, continuous innovations and research and development are making

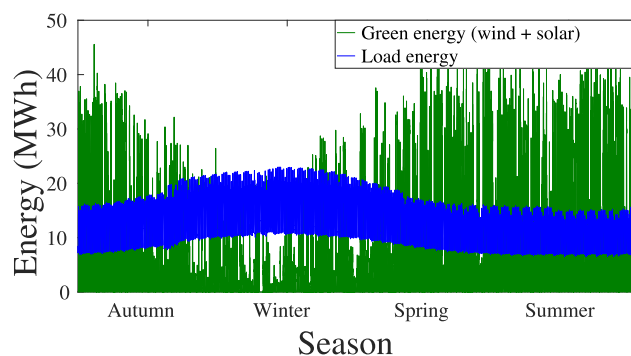
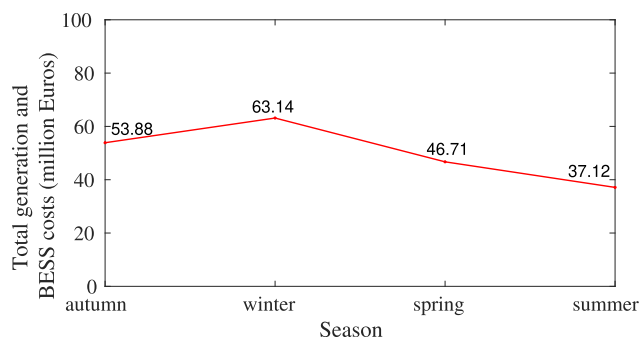
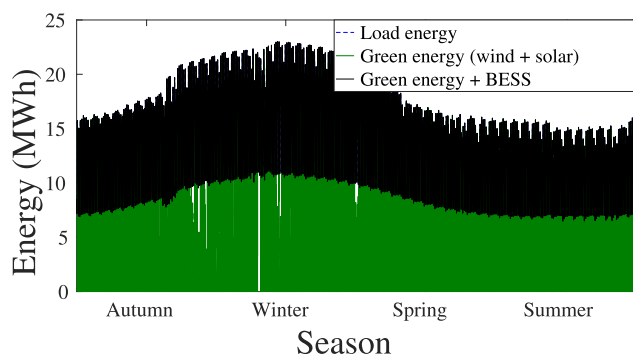


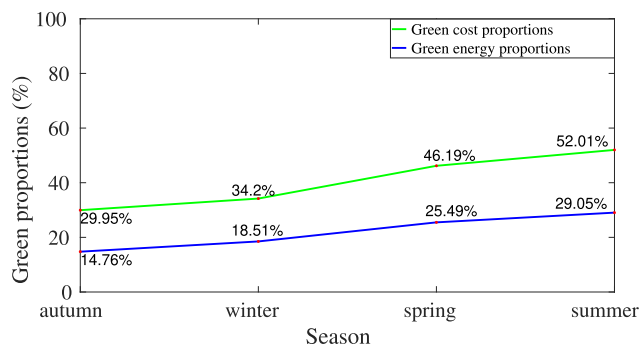
Fig. 1. Input load energy data and renewable (“green”) energy production data (assuming 1 MW solar and wind power plants) for a year at Kortrijk, Belgium (15 min time resolution).



**Fig. 2.** Seasonal variations in the total actual costs for the "green-battery energy storage system (BESS)" case; the costs when grey energy was included were about 4.6, 5.49, 4.54, and 3.85 million Euro for the four seasons, respectively.



**Fig. 3.** Green-BESS energy production meeting the load nearly perfectly. The curtailment is negligible, and the dotted line representing the load (compare with Fig. 1 showing input data) is almost completely covered by the combined supply from green energy and BESS, shown in black.



**Fig. 4.** Green energy production and cost proportions (%)—directly used without storing in BESS—for the "green-BESS" case.

RES increasingly cost-competitive with fossil fuels. Hence, we investigated the increase in green energy proportions, i.e., its participation, as the costs of RES and BESS decrease, when grey energy is included.

Fig. 5 shows the variations in green energy as a proportion of the total energy when green and BESS LCOEs are varied from 0 to 40% and 0–25% of their reference costs, respectively. The green energy includes the energy shifted by the BESS. Green energy participation

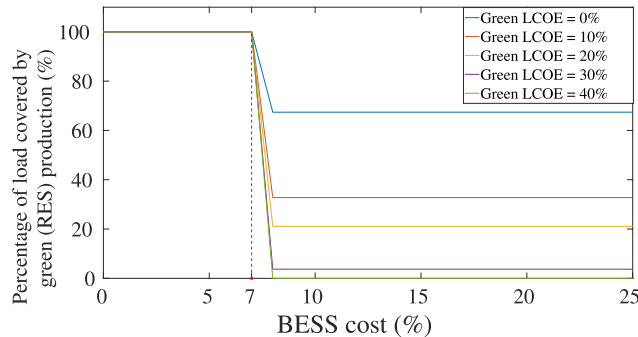


Fig. 5. Variations in the proportion of green energy production in the “green–BESS–grey” scenario, when BESS energy costs were changed from 0 to 100% of its current costs.

is negligible when the green energy costs are  $\geq 40\%$  of the reference costs, i.e.,  $\geq 0.044$  €/kWh. Without the BESS, the maximum green energy proportion is 63%, which is the maximum ASAI (or the maximum amount of load) that can be met by RES alone. With the BESS, the green energy proportion is 100% when the BESS cost is  $\leq 7\%$  of the reference costs, i.e.,  $\leq 0.038$  €/kWh. Thus, the BESS costs must significantly decrease to enable affordable 100% RES.

At the same time, grey energy costs could also increase, for example, if EU emissions trading system (EU ETS) is considered. Fig. 6 shows the variations in green, grey, and BESS energy as a proportion of the total energy required to meet the load when grey energy costs are varied from 1 to 20 times their reference costs. Green energy participation is negligible until around  $3\times$  the grey energy reference costs, i.e.,  $\approx 0.1158$  €/kWh, after which its proportion of the total energy increases. When grey energy costs are  $15\times$  the reference costs, i.e.,  $\geq 0.5790$  €/kWh, it becomes economical to use BESS to support the green energy production. As a result, grey energy is not required any more and it is possible to supply electricity with 100% green energy supported by BESS.

### 3.2.3. Partial loads—ASAI

The maximum ASAI using only RES were 50%, 57%, 73%, and 73% for autumn, winter, spring, and summer, respectively. Unsurprisingly, the summer season had the best electrical reliability (in

terms of ASAI) and lowest costs. The maximum ASAI for the entire year was 63%, which implies that it was possible to meet the entire load for only 63% of the given time period. Fig. 7a shows the changes in the total production cost with the ASAI. The total cost increases nearly exponentially above the ASAI of  $\approx 40\%$  until the maximum ASAI of 63% because of the extreme installation sizes (and thus, costs) required to meet the load at times steps with low wind speeds and solar irradiation. When  $ASAI \leq 50\%$ , the total cost is one-tenth of the cost required to meet the maximum ASAI. For  $ASAI \leq 47\%$ , the total cost of using green energy alone ( $\leq 190$  million Euro) is less than the total cost of using green energy with BESS (204 million Euro). The average cost also exhibits similar trends (Fig. 7b); for an ASAI of 1–30%, the average cost is  $< 0.4538$  €/kWh, increasing to 2.0981 €/kWh at 63%. When  $ASAI \leq 50\%$ , the average cost is less than half the average cost required to meet the maximum ASAI. Moreover, for  $ASAI \leq 28\%$ , the average cost of using green energy alone (0.4238 €/kWh) is less than the average cost of using green energy with BESS (0.4265 €/kWh). On the other hand, the average cost even at  $ASAI = 1\%$  is more than that using grey energy alone. These results suggest that even at the reference costs and with limited installed capacity, it is possible for planners desiring to use only green energy to dramatically decrease the costs if they tolerate meeting the load demand for at least 50% of the time, while using other energy resources for the remaining time.

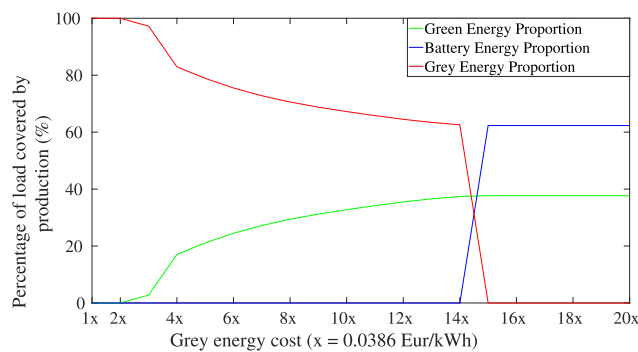
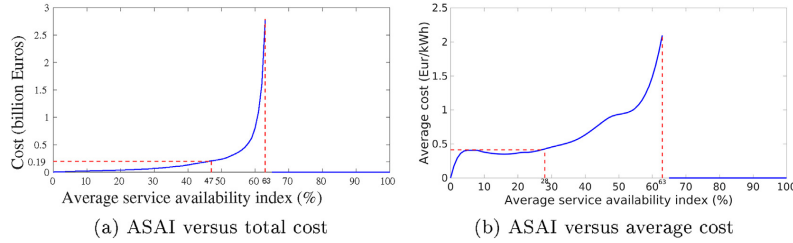


Fig. 6. Variations in the proportion of green, grey, and BESS energy production in the “green–BESS–grey” scenario, when green energy costs were changed from 1 to 20 times of its current reference costs.



**Fig. 7.** Average service availability index (ASAI) versus cost for green energy alone, for the entire year; the maximum ASAI is 63% above which green energy alone cannot meet the load demand. For  $ASAI \leq 47\%$ , the total cost of using green energy alone ( $\leq 190$  million Euro) is less than the cost of using green energy with BESS (204 million Euro); the minimal-cost installation will not use BESS. Similarly, for  $ASAI \leq 28\%$ , the average cost of using green energy alone (0.4238 €/kWh) is less than the cost of using green energy with BESS (0.4265 €/kWh).

Fig. 8a shows the curtailed energy versus ASAI. As shown, a significant proportion of the produced energy is curtailed in this scenario. This is because if the load has to be met for a high proportion of the total time period, the green energy infrastructure must be dimensioned very large to produce sufficient energy at times even when the available green resources (i.e., wind speed and solar irradiation) are very low. Hence, the infrastructure is over-dimensioned and produces excessive energy when the available green resources are plentiful. Fig. 8b illustrates an example of the curtailment of produced energy for ASAI of 25%. At some time steps, the green energy just meets the load energy whereas there is excessive production at other time steps.

### 3.2.4. Flexible loads

Fig. 9 shows the minimal costs for the “green–BESS” scenario with flexible loads.  $r = 48$  implies that the loads can be shifted over maximally  $48 \times 15 \text{ min} = 12 \text{ h}$ . For all flexible load proportions  $\delta$ , the cost was 204 million Euros when there was no shift ( $r = 0$ ), which agrees with the yearly costs for basic dimensioning. Naturally, the costs were lowest when the entire load can be shifted, i.e.,  $\delta = 100\%$ . As the maximal amount of time shifting,  $r$ , increases, the costs decrease, but this decrease slows down with higher  $r$ , which suggests that shifting the load is beneficial only up to a certain time frame. However, the costs do not decrease sufficiently to reach the low costs offered by grey energy installations (about 18.47 million Euro). This suggests that today, load shifting is not competitive with grey energy production to counterbalance intermittent renewable energy production.

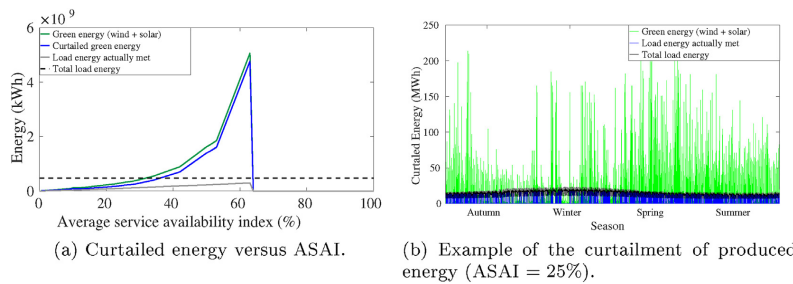
Fig. 10 illustrates the applied (minimal) time shifts for  $\delta = 40\%$  and  $r = 12$  (3 h). At least 60% ( $= 1 - \delta$ ) of the load is unshifted,

whereas maximally 40% of the load can be shifted. A histogram of the fractions of the total load shifted (%) for each of the possible time shifts up to 12 for a year is presented. The scheduling algorithm shifted nearly 35% of the total load to the first time step (15 min), and very few loads were shifted beyond 4 time steps (1 h). This suggests that large time shifts are rarely useful (for balancing).

## 4. Conclusions

In this paper, we investigated the cost-effectiveness of meeting the load demands of cities with 100% RES from PV panels and wind turbines, supported by BESS. We developed an LP-based methodology and applied it to the loads of Kortrijk, a Belgian city with around 75,000 inhabitants.

We first obtained the cost-optimal electricity-production-infrastructure mix to meet a city's full load demand when RES—supported by BESS—and NRES are combined. Since the LCOEs of RES and BESS were higher than the LCOE of NRES, they were *not selected* in the minimal-cost solution for supplying electrical energy to a city. Moreover, with the reference costs, the RES–BESS system costs were about  $10\times$  times *higher* than when NRES were included. The costs were expectedly lowest in summer and highest in winter. Green energy production alone—without BESS—was able to meet 63% of the load demand, but for RES systems to become competitive with NRES, their costs must decrease. Note that green energy alone could meet only 63% of the load because the available green resources (i.e., wind speeds and solar irradiation) were 0 for 37% of the total time period. These results will not only differ for different cities but also be influenced by technological developments. For example, the adoption of low-speed wind turbine technology will



**Fig. 8.** Curtailed energy in the only “green energy” scenario.

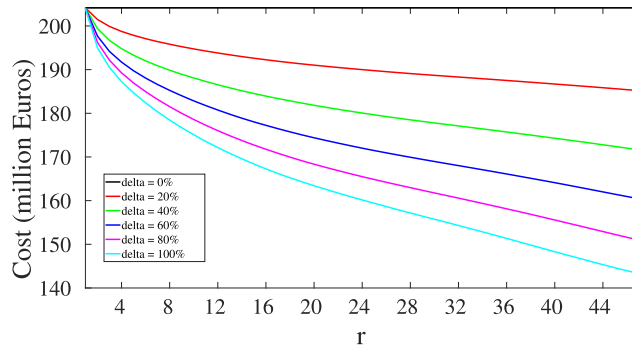


Fig. 9. Variations in the minimal cost in the “green–BESS” scenario when the load is shifted with  $r$  varied from 1 to 12 h and  $\delta$  from 0 to 100%; the cost when grey energy was included was 18.47 million Euro.  $r$  refers to the maximal number of 15-min time steps over which the total load can be distributed.

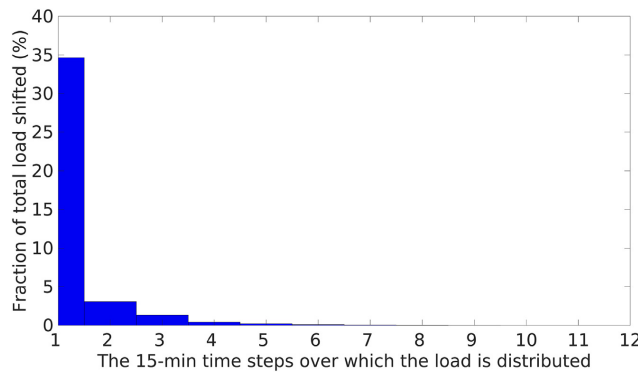


Fig. 10. Histogram of the fractions of the total load (%) shifted across 1– $r$  time steps for a year. Here,  $\delta = 40\%$  and  $r = 12$  were chosen to illustrate the performance of Algorithm 1. About 60% of the total load is unshifted and nearly 35% is now shifted to the first time step (15 min); very few loads are shifted beyond 4 time steps (1 h).

increase the available hours for wind power.

We then analyzed the question of how much the cost must decrease to enable 100% RES-based electricity production to be competitive with NRES-based electricity production. At 40% of the reference costs used in the paper, i.e., at  $\approx 0.044$  €/kWh, RES would meet 63% of the load demand more profitably than NRES. Further, the production cost with RES alone reduces nearly exponentially with lower ASAI and, for ASAI  $\leq 50\%$ , it is one-tenth of the cost with maximum ASAI (63%). Thus, even at the reference cost, it is possible to cost-effectively meet nearly 50% of the load demand using RES alone at 10% of the production costs required to meet 63% of the load demand. Moreover, the total and average costs of using RES alone were less than the cost of using RES with BESS at ASAI of 47% and 28%, respectively. For BESS to be cost effective, its cost needs to reduce to around 7% of the reference costs, i.e.,  $\approx 0.038$  €/kWh. An RES–BESS system with these costs— $\approx 0.044$  €/kWh and  $\approx 0.038$  €/kWh, respectively—will meet 100% of the load demand more cost-effectively than NRES. We also analyzed the effects of increasing the costs of NRES on the adoption of green energy. Green energy participation begins to increase as the grey energy costs become  $\geq 3 \times$  the grey energy reference costs ( $\approx 0.1158$  €/kWh). And, at a  $15 \times$  increase of the reference costs ( $\geq 0.5790$  €/kWh),

grey energy is not required anymore and it is more economical to adopt green energy with BESS.

Finally, we analyzed how exploitation of the flexible resources present in a city improves the cost-effectiveness of RES deployment by investigating the effects of electrical load shifting. We developed and employed a novel two-step flexible-load analysis to explore the changes in the minimal costs with the amount of shifted load fractions ( $\delta$ ) and the maximal discrete time steps ( $r$ ) across which the load fractions can be shifted. As  $r$  increased, the costs decreased by nearly 20% until around 3–5 h, after which they remained nearly constant. Nevertheless, the costs for RES–BESS system with load shifting—around 170 million Euro—were higher than the costs for only NRES system—18.47 million Euro, implying that load shifting with RES–BESS system alone is not competitive with grey costs today. Our results show that it is most economical to not use RES today even when the loads are flexible. However, when the costs of RES and BESS reach around 0.044 and 0.038 €/kWh, respectively, it will become possible to cost-effectively supply the entire load of a city using RES (with BESS).

These results suggest that it is very important to integrate several renewable energy sectors—electricity, heat, transport, etc.—to reach high levels of RES penetration, and they agree with

the growing consensus that *smart energy systems* offer better options for the integration of renewable energy into energy systems [39,40]. Moreover, the flexibility that can be exploited in the electricity system alone is clearly limited without integrating cogeneration and transportation [41]. Nevertheless, the presented methodologies are valuable because they can be simply and effectively used to investigate the utilization and meaningful rate of adoption of RES technologies. The partial-loads analysis shows that the costs required to meet the load demand decrease dramatically with decreasing ASAI. This represents a significant opportunity to meet at least a portion of a city's load at relatively low costs using RES alone. Further, the methodology itself is useful to decide how many hours can be met with RES, given a certain budget. It can also be used in rural areas for providing at least partial access to electricity. Our flexibility model can be generally applied to analyze the impacts of flexible loads on production resources, and it can also be a valuable tool for analyzing the economic value of DSM algorithms. These models can be easily expanded to include flexibilities arising from the integration of other sectors as well.

In the future, we plan to model cost evolutions over a long time period; further, we will incorporate communication costs and other externalities in our algorithm for exploiting flexibility.

### Acknowledgment

We are grateful to the Lemcko research group (Ghent University) for kindly providing us with large data sets for the Belgium test case. We gratefully acknowledge the generous computational resources (Stevin Supercomputer Infrastructure) and services provided by the VSC (Flemish Supercomputer Center), funded by the Research Foundation – Flanders (FWO) and the Flemish Government—department EW, as well as by the CSC—IT Center for Science, Finland.

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## Publication II

Narayanan, A., Kaipia, T., and Partanen, J.

**Economic benefits of photovoltaic-based systems for residential  
customers participating in open electricity markets**

*IEEE PES Innovative Smart Grid Technologies Conference-Europe  
(ISGT-Europe)*

pp. 1–6. IEEE, 2016

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# Economic Benefits of Photovoltaic-based Systems for Residential Customers Participating in Open Electricity Markets

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**Abstract**—Small-scale distributed photovoltaic (PV) generation, in which PV panels are installed on residential customers' rooftops, has been envisaged as an approach to increase renewable energy participation. In this paper, we have presented a method to determine the economic benefits obtained by residential customers who can freely purchase and sell electricity from an open electricity market, when PV panels are installed on their rooftops with and without support from electrical storage. By using our method, the number of PV panels that can be optimally installed on rooftops for maximum economic benefits can be determined. Further, since PV costs are expected to decrease over the next decade, we have extended the methodology to model progressive piecemeal installations of PV panels over many years. We applied our methodology to the case of a Finnish customer participating in the Nordic electricity market. Although installing PV panels is not beneficial for Finnish residential customers today considering the current LCOE prices, customers obtain long-term benefits from using PV panels, and these benefits improve with the inclusion of batteries.

**Index Terms**—Electricity markets, Mixed linear integer programming, Photovoltaics, Renewables, Sizing

## I. INTRODUCTION

Today, we have become increasingly reliant on electric power supply to sustain our economies, daily necessities, as well as comforts. Further, environmental concerns have made it imperative to increase the participation of renewable energy sources (RESs) in the electricity generation infrastructure. In general, two approaches to increase the number of RESs have been explored—large centralized production, typically in the case of wind energy, and small distributed generation, typically in the case of solar energy.

In this paper, we have considered distributed solar installations from the viewpoint of a residential customer who participates in an open electricity market and purchases electricity based on variable hourly prices. We have addressed the question of whether it is economically beneficial for such a customer to install PV panels and to supplement it with energy storage. Moreover, as PV prices reduce, at what point will it become beneficial in the future? This question is important

from the viewpoint of three stakeholders—the customer, the policy-maker, and the distribution system operator (DSO).

Several studies have previously examined these questions as well as the closely related problem of the optimum sizing of PV panels for residential applications [1], [2]. Nevertheless, in this paper, we present a new approach to the estimation of the economic benefits of using PV and PV-battery systems, which considers both short-term annual benefits as well as the long-term economic impacts of using PV-based systems. We consider progressive installations of PV panels over 15–20 years, based on the scenario of a customer who would prefer to cover the rooftop area in small steps to take advantage of decreasing PV prices. Thus, we address the question of the number of PV panels that the customer then installs each year and the long-term profitability of the investments.

In Section II, we will state the problem that we have addressed and the models that we have chosen as inputs to the solution concept. Further, the mathematical formulations of our problem are also presented. Subsequently, we present our results in Section III and discuss them. Finally, we conclude the paper in Section IV.

## II. PROBLEM FORMULATION

### A. Problem Statement

Our fundamental problem is to determine the economic benefits of installing and utilizing PV panels on the rooftop of a residential house both with and without backup by energy storage devices, when the residential user is assumed to purchase electricity from an open electricity market. To do this, we must first determine the optimum number of PV panels that can be set up on a typical rooftop.

Further, we have also extended the analysis to consider multiple years wherein customers can progressively install more PV panels each year, even as PV costs decrease. In this case, our problem is to determine the optimum number of PV panels that should be installed each year for maximum economic benefits. We then determine the benefits to the customer by the end of each year and find out an approximate

time frame by which the customer can expect the investments to be profitable.

To solve these problems, we have implemented a mixed integer linear programming (MILP) model with the objective to minimize the cost of electricity generation of the customer, as described in the subsequent sections.

#### B. PV Power Model

The nominal power, or the nameplate rating,  $P_{PV}$ , of a PV panel is the power output by the panel under standard test conditions (STC) and is given by the equation  $P_{PV,nom} = \eta \times I_{stc} \times A_c$ , where  $\eta$  is the energy conversion efficiency of a solar cell;  $I_{stc}$ , the solar irradiance (1 kW/m<sup>2</sup> under STC); and  $A_c$ , the surface area of the panel (m<sup>2</sup>). Correspondingly, the energy production is given by  $E_{PV,nom} = \eta \times E_{stc} \times A_c$ , where  $E_{stc}$  is the solar insolation (1 kWh/m<sup>2</sup> under STC). In this study, we are interested in the number of PV panels that can be installed cost-efficiently on the rooftop of a residential customer. Therefore, from the equation for nominal power, the energy production of  $n_{PV}$  PV panels

$$E_{PV} = \frac{n_{PV} \times E_{PV,nom} \times \eta \times E \times A_c}{E_{stc}} \quad (1)$$

where  $E$  represents the solar insolation in a given hour on the panels (kWh/m<sup>2</sup>). Note that  $n_{PV}$  is limited by the maximum possible rooftop area,  $A_{max}$ , and is an integer  $\leq \frac{A_{max}}{A_c}$ . Equation 1 can be simply written as

$$E_{PV} = n_{PV} \times k_{PV} \times E \quad (2)$$

where  $k_{PV}$  is the constant part as follows:

$$k_{PV} = \frac{E_{PV,nom} \times \eta \times A_c}{E_{stc}} \quad (3)$$

In this study, we did not consider angles of inclination, directions of PV panels, or any other factors influencing a cell's conversion efficiency.

#### C. Battery Model

We have considered a simplified, lossless battery model that is characterized by the maximum storage capacity  $B_{max}$  (kWh), minimum capacity  $B_{min}$ , charge rate  $k_{ch}$  (kWh), and discharge rate  $k_{dch}$  (kWh). In this model, a battery discharges by  $B_{max}/k_{dch}$  and charges by  $B_{max}/k_{ch}$  at a time instant  $t$ . Further, depth of discharge and related parameters as well as problems such as self-discharge and temperature effects have been disregarded for simplicity.

#### D. Costs

We have considered the following costs incurred by the customer.

1) *PV installation and operation costs:* We have considered the levelized cost of electricity (LCOE) since it represents the full life-cycle per-kWh costs (fixed and variable) of a generating plant per unit of electricity [3]. The LCOE (monetary unit/kWh) is a very useful metric for comparing electricity generation costs since it considers the initial capital as well as the costs of continuous operation, repair, and maintenance.

2) *Energy storage costs:* It is difficult to *a priori* calculate and use the LCOE of a battery since it depends on the actual energy usage and number of battery cycles, which cannot be known beforehand. Instead, in this paper, we have assumed an initial capital expenditure (CapEx),  $C_B$ , for purchasing a battery that is appropriate for residential systems.

3) *Costs for purchasing electricity from grid:* We have considered the typical electricity prices paid by residential customers participating in an open electricity market. The Nordic electricity market is used as a reference for our case study; the exact price distribution might change for other markets, but it can be easily incorporated into the model. In the Nordic market, residential customers have the following components in their electricity bill:

- **Distribution fees:** A monthly fee  $C_{D,m}$  (€) and an electricity usage fee  $C_{D,e}$  (€/kWh).
- **Supplier fees:** Spot prices  $C_{spot}$  (€/kWh) and a monthly fee that consists of an agreement fee  $C_{S,a}$  (€/kWh) and electricity usage fee  $C_{S,e}$  (€/kWh). There is also a one-time grid connection fee only for new connections, which is neglected in this paper.
- **Electricity tax:** Electricity tax as well as a value added tax (VAT) on the electricity tax,  $C_T = C_{tax} + VAT \times C_{tax}$  €/kWh.

In this paper, the variable components in the total electricity price are added as follows:

$$C_{g,var} = C_{D,e} + C_{spot} + C_{S,a} + C_{S,e} + C_T \quad (4)$$

The fixed components are neglected in the formulation, however, since the customer has to pay this amount for electricity connection, unless the house is completely islanded over the entire time period; islanding is not considered in this study.

#### E. Problem Formulation

1) *Single Year:* Only the problem formulation for the PV with battery scenario is given here since the PV alone scenario is a subset. To determine the economic benefits of a residential customer participating in an open electricity market, our objective function attempts to minimize the costs incurred by the customer. The total cost for using PV panels is given by its LCOE  $\times$  energy production, and from Eq. 2, the number of PV panels is a variable. The total cost for using the grid is given by grid costs  $\times$  grid energy  $E_g(t)$ . Here, the grid costs are an input but the grid energy is variable and depends on the PV energy usage. The cost for using a single battery is given by  $C_B$ ; however, a customer may choose to use multiple batteries to increase reliability, and hence, the battery cost is  $n_B C_B$ , where  $n_B$  is the number of batteries. Hence, the decision variables are  $n_{PV}$ , grid energy  $E_g(t)$ , and  $n_B$ . Further,  $n_{PV}$  and  $n_B$  are integers, and our problem is formulated as an MILP with the objective of minimizing the cost as follows:

$$\min \{ C_{PV} k_{PV} \left( \sum_{t=1}^T E(t) \right) n_{PV} + \sum_{t=1}^T C_{g,var}(t) E_g(t) + n_B C_B \}$$

such that

$$k_{PV}(E(t))n_{PV} + E_g(t) + B_{t-1} - B_t \geq E_l(t) \quad (5)$$

$$-n_B B_{max}/k_{dch} \leq B_t - B_{t-1} \leq n_B B_{max}/k_{ch} \quad (6)$$

$$B_0 = n_B B_{max} \quad (7)$$

$$B_{min} \leq B_1, B_2, \dots, B_T \leq n_B B_{max} \quad (8)$$

$$0 \leq E_g(t) \leq E_l(t) \quad (9)$$

$$0 \leq n \leq A_{max}/A_c \quad (10)$$

Here  $T$  refers to the total time period considered;  $t$ , each time instance;  $C_{pv}$ , the LCOE for PV (€/kWh);  $E(t)$ , the solar insolation at time  $t$  (kWh/m<sup>2</sup>);  $\eta$ , the efficiency of the PV panel (%);  $k_{PV}$  from Eq. 3;  $C_{g,var}$ , the grid prices as given by Eq. 4 (€/kWh);  $B_{t-1}$ , battery capacity at time  $t-1$ ;  $B_t$ , battery capacity at time  $t$ ;  $E_l(t)$ , load energy at time  $t$  (kWh);  $B_0$ , the initial battery capacity (kWh);  $B_{min}$ , the minimum battery capacity (kWh);  $B_1, B_2, \dots, B_T$ , the battery capacities at time 1, ...,  $T$ , respectively (kWh); and  $A_{max}$ , the maximum area of the panel (m<sup>2</sup>). Note that  $n_{PV}, n_B \in \mathbb{Z}$ ;  $E_g(t = 1 \dots T) \in \mathbb{R}$ .

Constraint 5 ensures that the load energy demand at each time instant is met by some combination of PV energy, battery energy, and grid energy. Equation 6 represents the charging and discharging of the battery. Equation 7 constrains the initial battery capacity to be the maximum battery capacity in order to ensure that the simulation begins with the battery capacity at its maximum. Equation 8 restricts the battery capacities to be between their minimum and maximum capacities, whereas Eq. 10 places lower and upper bounds on the area of the solar panel. Finally, Eq. 9 restricts the grid energy from exceeding the load energy; this restriction is important because electricity prices are sometimes negative, and without this constraint, grid energy will be unbounded.

Although MILPs are NP-hard, this formulation obtains solutions within reasonable time because the two integer decision variables are positive and have a small upper limit.  $n_{PV}$  is limited by the area of the rooftop of the customer, whereas  $n_B$  is limited by the fact that batteries are relatively expensive and, even when they have low costs, only a limited number of batteries would be required to support the PV installations.

2) *Multiple Years*: The problem formulation given above is now extended to multiple years. Our aim as before is to minimize the installation costs. However, we now assume that the PV panels can be progressively installed across the considered time period; this implies that new PV panels—restricted by the rooftop area—can be installed every year, if it is cheaper to do this. The batteries are still considered to be installed in the first year. The new formulation is as follows:

$$\min \left\{ \sum_{i=1}^y C_{PV,i} k_{PV} \left( \sum_{j=i}^y \left( \sum_{t=1}^{T_i} E_j(t) \right) \right) n_i + \sum_{i=1}^y \sum_{t=1}^{T_i} C_{g,var,i}(t) E_{g,i}(t) + n_B C_B \right\}$$

such that

$$k_{PV} \left( \sum_{i=1}^{j \leq y} E_i(t) \right) n_i + E_g(t) + B_{t-1} - B_t \geq E_l(t) \quad (11)$$

$$0 \leq \sum_{i=1}^y n_i \leq \frac{A_{max}}{A_c} \quad (12)$$

Here,  $y$  is the total number of years and  $n_i$  is the total number of PV panels installed on the rooftop during each year ( $i = 1, \dots, y$ ). In Eq. 11 for load energy balancing,  $j$  refers to the number of years completed so far. The battery and other constraints are identical to Eqs. 6–9. Equation 12 ensures that the total area of the panels is less than the maximum area. In order to explain the objective function, the expanded form of the PV cost minimization for  $y = 3$  years is given as follows:

$$\begin{aligned} & \min \left\{ \sum_{i=1}^3 C_{PV,i} k_{PV} \left( \sum_{j=i}^3 \left( \sum_{t=1}^{T_i} E_j(t) \right) \right) n_i \right\} \\ & \equiv \min \left\{ C_{PV,1} k_{PV} \left( \sum_{t=1}^{T_1} E_1(t) + \sum_{t=1}^{T_1} E_2(t) + \sum_{t=1}^{T_1} E_3(t) \right) n_1 + \right. \\ & \quad C_{PV,2} k_{PV} \left( \sum_{t=1}^{T_2} E_2(t) + \sum_{t=1}^{T_2} E_3(t) \right) n_2 + \\ & \quad \left. C_{PV,3} k_{PV} \sum_{t=1}^{T_3} E_3(t) n_3 \right\} \end{aligned}$$

This objective function implies that  $n_1$  panels produce  $k_{PV} \times E_1, E_2, \dots, E_y$  energies at the LCOE of  $C_{PV,1}$ , while  $n_2$  panels installed in the second year produce  $k_{PV} \times E_2, \dots, E_y$  energies at the LCOE of  $C_{PV,2}$ , and so on. Note that the PV panels installed each year can also have different specifications, and this will make  $k_{PV}$  different for each year; however, different panels have been neglected year since they are dependent on new technologies. The minimization of the grid costs (and battery costs) in the objective is straightforward and reflects the sum of the grid costs over all the years considered.

### III. RESULTS AND DISCUSSION

#### A. Data

We obtained customer load energy data of a Finnish customer located in south-western Finland for the year 2011 and used it in our simulations. Finnish laws prevent accurate data regarding rooftop areas and locations being shared. Hence, based on the statistical averages of floor areas, we considered the maximum rooftop area of an average Finnish residential customer to be 30 m<sup>2</sup> [4]. For the PV panel, we used actual data from SunPower E-Series Residential Solar Panels (E20-327):  $\eta = 20.1\%$ ,  $E_{pv,nom} = 0.320$  kWh, and  $A_c = 1.558 \times 1.046$  m<sup>2</sup>. Further, we obtained modeled solar irradiation data from SoDa service, a web-based service that provides free solar irradiation data [5]. Free data was available only for 2004 and 2005, but since they can be considered reasonably representative average values, we chose the data from 2005. According to Vartainen et al., the PV LCOE for Stockholm in 2015 for residential PV systems was 0.16 (€/kWh); since Stockholm has a lower latitude than Finland and receives more sunlight, we applied a conservative increase of 25% for Finland and used 0.20 (€/kWh) as the current Finnish LCOE [6]. Further, we took Finnish area prices for the year 2011 from historic Elspot market prices [7]. All the data—load, solar, and grid prices—were hourly data.

We considered Tesla Powerwall<sup>®</sup> as the battery used by the Finnish customer. The Powerwall is a rechargeable lithium-ion battery developed by Tesla Motors for home use for supplementing renewable energy production by daily cycling. The battery has a maximum battery capacity of 6.4 kWh and a round-trip efficiency of 92.5%, and it costs approximately 2500 euros [8]. Further, we considered typical charge and discharge rates of C/10.

#### B. Results

The current PV LCOE of 0.20 €/kWh was too expensive, and the optimization did not choose a single PV panel. However, when the LCOE was reduced by half to 0.10 €/kWh, 10 320-W PV panels (out of a maximum of 18) were chosen. Figure 1 shows the energy balance for a random day in spring during which Finland gets  $\sim 16$  h of sunlight. Depending on the availability of solar energy, PV energy production was often preferred over the grid, but the energy produced by the PV panels was sometimes higher than the load and wasted.

For the PV-battery system, the optimization does not choose any battery because of its high costs; hence, in order to demonstrate the battery usage, at least 1 battery was forced into the system by putting  $k \geq 1$  in the model. Figure 2 shows the energy balance in this case for another day in spring; the PV LCOE was 0.10 €/kWh as before. The battery discharged at night, after around 20:00 hours, to reduce the electricity purchased from the grid and charged during the day using the additional solar energy generated by the PV panels. The number of PV panels chosen increased to 17, which suggests that the battery encourages PV energy usage.

The annual costs for a customer to purchase electricity from the grid without any PV-based system was 1684.6 €. Figure 3

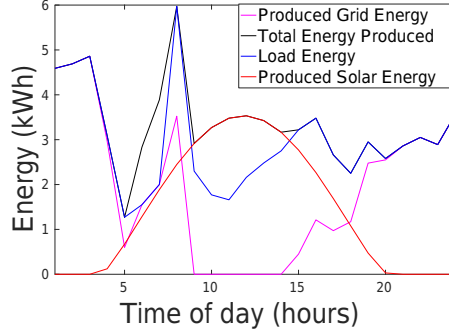


Fig. 1: Energy balance for a residential customer during a day in April in the only PV case. When the PV LCOE was 0.10 (half of the current PV LCOE considered in the study), the optimum number of 320-W PV panels covering the rooftop was 10 (of maximum 18). The resulting PV energy and the electricity purchased from the grid combine to meet the load during daytime; in the night, the load demand is met entirely by the grid electricity alone.

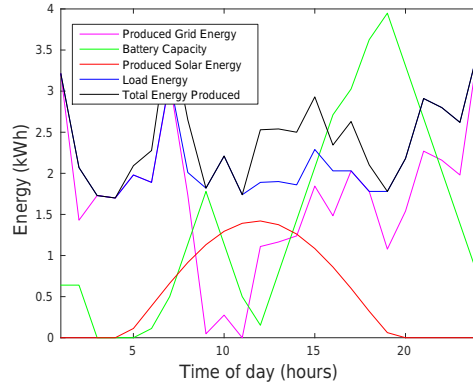


Fig. 2: Energy balance for a residential customer during a day in April in the PV-battery case. The PV LCOE was kept as 0.10 as before (Fig. 1), but the optimum number of 320-W PV panels covering the rooftop increased to 17. The PV energy, which has a smooth curve because it is based on *modeled* irradiation, and grid electricity combined to meet the load during the daytime as well as to charge the battery, if possible; in the night, the load demand was met by the grid electricity and battery discharge.

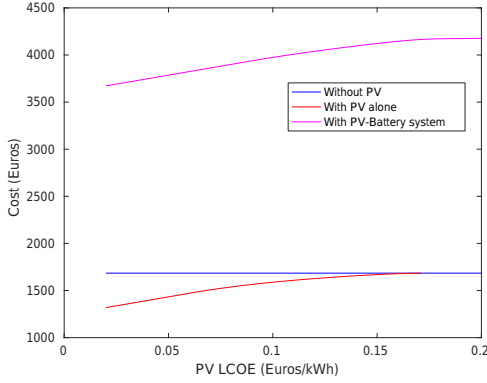


Fig. 3: Variations in the cost to customer when the PV LCOE was varied from its present value 0.2 to 0.2/10 €/kWh. No PV systems were installed for PV LCOE > ~ 0.16 €/kWh. However, as the LCOE decreased, the rooftop was gradually covered with more PV panels, and the total cost decreased.

shows the variations in the annual costs for a customer as the PV LCOE was varied from 0.20–0.20/10 (€/kWh) in the PV alone case as well as for the PV-battery system. At the current solar LCOE of 0.20 €/kWh, installing PV panels is expensive and has no economic benefits. Until ~ 0.16 €/kWh, the customer has lower costs from purchasing electricity from the grid than installing even a single PV panel. However, when the PV LCOE decreased to ~ 15 €/kWh, it became more economical to install PV panels. On the other hand, the costs remained high when the battery was used due to its high CapEx. Thus, batteries do not offer sufficient savings today to justify their short-term investments. Nevertheless, they can be valuable long-term investments with commercial batteries such as Tesla Powerwall® advertising lifetimes of 10 years and 5000 cycles. Thus, if the simulation time frame is increased, the high CapEx costs could be offset by higher savings.

In order to determine the long-term benefits of using PV and battery systems, we first implemented the formulation in Section II-E2 for 15 years and 5% annual reduction in PV LCOE. The model recommended different number of PV panels to be installed each year up to 15 years. For the residential customer with a rooftop area of 30 m<sup>2</sup>, the model recommended no PV panels until the 9<sup>th</sup> year, 4 panels in the 10<sup>th</sup> year, and 1 panel each subsequent year. Since the rooftops of residential customers are too small to adequately analyze the progressive investments, we also investigated the case for 10 customers with a total maximum surface area of 500 m<sup>2</sup> (equivalent to the case of a DSO wishing to install centralized solar production). The optimum PV panel investments from year 1 to year 15 were as follows: [0 0 0 0 0 0 0 19 22 16 12 12 13 12]; in other words, the model recommended no PV

panels till the 8<sup>th</sup> year, 19 panels in the 9<sup>th</sup> year, etc.

Figure 4 shows the total cumulative costs at the end of each year when a residential customer progressively installs PV panels over 15 years; further, the case in which the battery is installed in the first year is also shown. We performed this simulation for five different scenarios: annual PV LCOE reductions of 1%, 10%, 10%, 15%, and 20%. Other PV LCOE evolution models can also be easily considered in the optimization since it only requires the new LCOEs to be plugged into the model.

When the PV LCOE was reduced by only 1%, PV panels were not selected at all by the optimization even after 15 years; hence, this case was omitted from the figure. When the PV LCOE was reduced by 5%, PV installations became slightly more profitable than grid purchases after nearly 12 years, whereas the PV-battery system was never profitable. In the case of 10% reductions, PV systems became more profitable after 8 years, but the PV-battery system still remained expensive. In the case of 15% annual reductions in the PV LCOE, PV systems became profitable after almost 7 years, whereas the PV-battery system were also profitable than the grid after 14 years. Finally, for 20% annual reductions, the profitability of PV systems was similar to 15% but the PV-battery system became more profitable than the grid earlier after around 11 years.

Thus, residential customers have significant long-term benefits from using PV and PV-battery systems. The PV-battery system is still not more profitable than the only PV case because of the high CapEx of the battery. However, battery costs have decreased recently, and hence, alternatively, batteries could be installed into the PV system at a later stage, e.g., after 5 years. The exact profitability of delayed and progressive battery installations will be the subject of a followup study.

Although this paper presents a simple and efficient method to calculate the economic benefits of a customer, the method can be further refined in many ways. First, the battery costs should be integrated in a more comprehensive manner, taking into consideration its actual cycling and energy usage. Moreover, the curtailment of solar energy production or its profitable applications to solve other problems can be considered. The dimensioning could be extended to microgrid clusters wherein several customers can exchange energy with each other optimally, such that not only individual customers but also the entire society benefits. Thirdly, evolutions in the market costs have not been taken into account; this is not realistic since the market prices may vary significantly with higher renewables participation (by all customers) in the future; this change in market prices should be considered.

#### IV. CONCLUSION

We have presented a simple and effective methodology to determine the economic benefits of a residential customer participating in an open electricity market. We have considered two cases—(a) only PV panels are installed; and (b) batteries are installed with the PV panels. By using our method, the optimum number of PV panels that can be set up on a rooftop

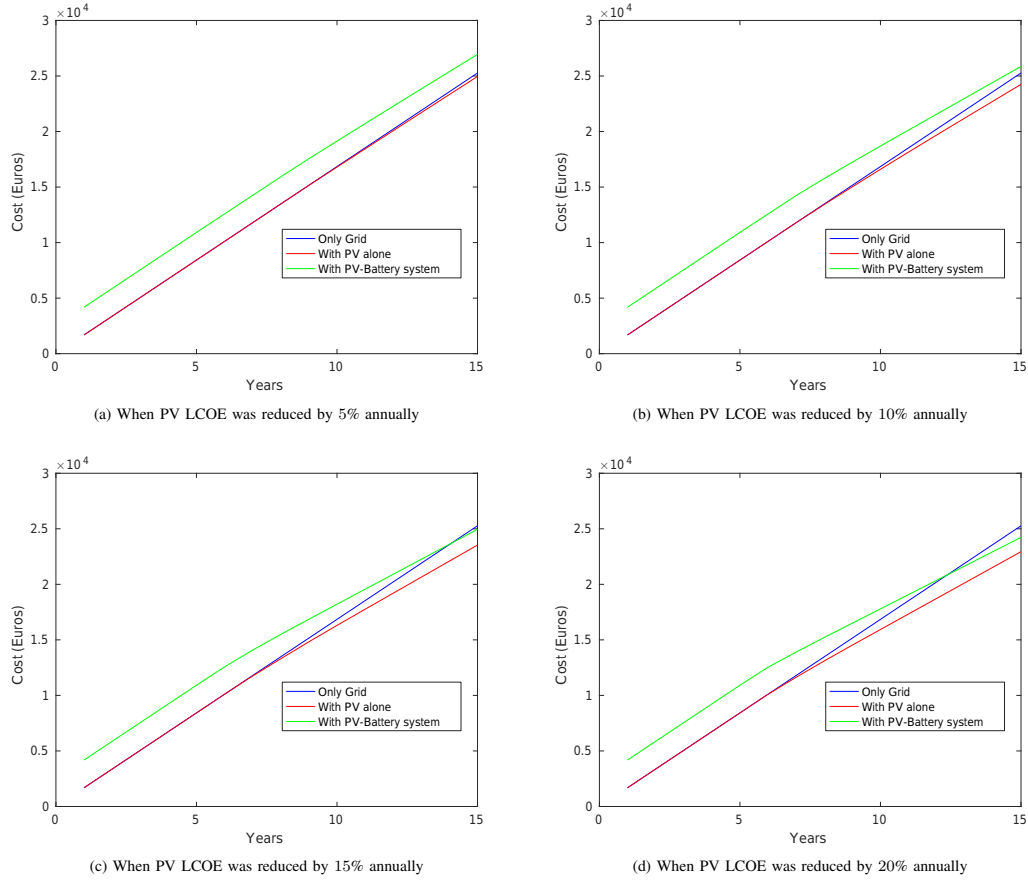


Fig. 4: Cumulative costs of a residential customer at the end of each year from 1–15 years when the PV LCOE was decreased annually for 15 years by a different percentage. In the PV-battery system, a battery was installed in the first year.

can be determined. Further, we have also considered that customers can progressively install more PV panels each year, even as PV costs continue to decrease. Our method makes it possible to evaluate the annual economic benefits for a residential customer and determine an approximate time frame by which the customer can expect investments to be profitable.

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## Publication III

Narayanan, A., Kaipia, T., and Partanen, J.

**Interruption reduction using battery energy storage systems in  
secondary substations**

*IEEE PES Innovative Smart Grid Technologies Conference-Europe  
(ISGT-Europe)*  
pp. 1–6. IEEE, 2017

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# Interruption Reduction in Secondary Substations using Battery Energy Storage Systems

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**Abstract**—Reliable electric power supply is extremely important in modern societies. Distribution system operators (DSOs) are obligated to ensure high supply security, especially in deregulated electricity markets. DSOs face penalties or pay compensatory costs when they are unable to supply electricity reliably to customers. DSOs can increase their supply reliability by either employing expensive high-reliability technology or backup power supply such as battery energy storage systems (BESSs) or generators. We have presented a novel mixed integer linear programming model to determine the economic feasibility of installing BESSs at a secondary substation in a medium voltage network. We have also determined the minimum capacity and optimal schedule of the installed BESS. Moreover, we have examined the cost-effectiveness of using BESSs if they are also used for peak shaving instead of remaining idle when there are no outages. We validated our simple but effective methodology by applying it to a substation network in Finland. All the interruptions were reduced with a BESS capacity of 112 kWh, and the savings were significant for BESS costs less than 300 €/kWh. Moreover, peak shaving increased the cost savings. However, the current costs of lithium-ion-based BESSs are nearly thrice as high, and they must decrease further before BESSs can be cost-effectively used for interruption management and peak shaving.

**Index Terms**—Battery Energy Storage Systems, Distribution System Operators, Interruptions, Mixed Integer Linear Programming, Outages

## I. INTRODUCTION

Electric power is an essential and pervasive part of modern society. Supplying electric power reliably is therefore extremely important in electricity distribution, and it is critical for distribution system operators (DSOs) to ensure high security of supply [1]. Even momentary interruptions may lead to significant economic losses for industrial electricity customers, and residential customers also strongly rely on continuous power supply. Power failures are especially problematic at places where environmental safety and public safety are at risk, such as in mines and hospitals. The negative economic impacts of electrical power interruptions on both industrial and residential customers have been extensively studied previously [2].

DSOs are obligated to ensure high reliability of power supply, especially in deregulated electricity markets. Market authorities impose regulatory costs on DSOs either in the form of compensation to customers who pay market prices for the delivered energy or as penalties for failure to meet supply of security standards [3]. At the same time, DSOs must minimize their costs [4]. However, it is often challenging to ensure reliable electric supply, especially in environments that are susceptible to extreme weather. Extreme weather events can cause widespread damage to the power infrastructure, leading to severe outages and interruptions at the customer end [5]. Outages can also occur due to overloading of electricity mains, electric faults at power stations, short circuiting of lines, etc.

In principle, there are two primary methods of ensuring high-level supply reliability for the customer. The supplying grid can be built with high-reliability technology, such as weatherproof network structures with meshed network and underground cabling. However, high-reliability technology, especially underground cabling, is expensive [6]. Alternatively, high reliability can be ensured by employing backup power supply, for example, by using battery energy storage systems (BESSs) or generators. DSOs have two options to install such backup options. They can either install them locally at the customer end, probably in partnership with the customers, or they can install backup options at the substation [7].

In this paper, we have considered that DSOs wish to install BESSs in the medium voltage (MV) network at a secondary substation in order to reduce interruptions at the customer end, which will, in turn, reduce the outage costs that are imposed on them by regulatory mechanisms. We have investigated the following research questions:

- 1) Is it economically feasible to use BESSs?
- 2) What is the minimum BESS capacity with respect to the customer load and reliability of the grid supply?
- 3) If a BESS is able to cost-effectively manage reliability, what is its optimal BESS schedule?
- 4) If the battery performs peak shaving when there are no outages, what are the cost benefits?

Lassila et al. addressed some of these questions using an exhaustive search approach to determine the tradeoff between battery size, cost, and reliability improvement [1]. Using stochastic interruption statistics and Monte Carlo simulations, they determined the possible savings in customer interruption costs. Markkula et al. used an approximate analysis methodology to examine the profitability of three different lithium-ion (Li-ion) batteries as back-up power in a low voltage direct current network [8]. Both assumed that the BESS can be fully charged before each fault in the network, which enables the entire capacity to be used to supply power during the interruptions. However, this assumption is not necessarily accurate and depends on the network conditions.

We have proposed a simple and effective mixed-integer linear programming (MILP) methodology to determine the minimum BESS capacity. In our algorithm, the assumption that the BESS is fully charged before each outage in the network is not required. Further, the presented methodology is independent of the nature of outages in a network and therefore independent of the outage distribution. The algorithm also determines the optimal schedule for decreasing the interruptions, which is useful for planned outages by DSOs. In addition, we present the cost-effectiveness of using the BESS. We also show how the algorithm can be extended to enable the BESS to perform cost-effective peak shaving to enhance its utility and cost-effectiveness. To our knowledge, such a discrete-optimization-based simple methodology to determine the minimum battery size to deal with outages at the substation transformer level has not been published previously. Further, this approach gives DSOs additional opportunities and motivations to use BESSs, increase their profits, and actively participate in renewable-energy integration.

Alternative methods to ensure reliability and quality of supply are especially important to DSOs operating in the Nordic environment, which is characterized by a high forest rate and overhead lines that are vulnerable to adverse weather phenomena. Hence, to validate our methodology, we applied our methodology to an electricity network in a Nordic environment—we used real substation data from a Finnish network. Figure 1 shows a typical rural network in Finland, where the average number of customers per low-voltage supply area is 10–20. The residential household loads are spread over a wide area with average line lengths and loads of 1.5–2 km and 7–15 MWh/a, respectively.

## II. METHODOLOGY

### A. Outage Reduction

The objective is to minimize the interruption costs that are incurred by a DSO when outages occur in a MV network at the secondary substation. The input data consists of the simulation time period ( $T$ , unit of time), total customer loads in an MV substation network for each time step  $t_i = 1, \dots, T$ , ( $E_l(t_i)$ , kWh); the total capital expenditure (CapEx) cost ( $C_b$ , €/kWh) of the BESS; the

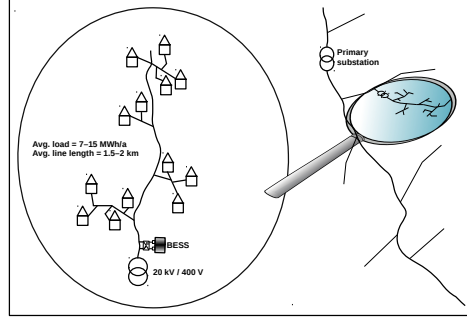


Fig. 1: A typical rural network in Finland—the residential household loads are widespread with average line lengths and loads of 1.5–2 km and 7–15 MWh/a, respectively.

efficiency of the BESS system ( $\eta_b$ ); the maximum charge ( $k_{ch}$ , kWh) and discharge ( $k_{dch}$ , kWh) rates of the BESS; the costs ( $C_i$ , €/kWh) of outages; and the timing of the outages ( $k_i = \{k_1, \dots, k_T\}$ ,  $k_i \in \{0, 1\}$ ;  $k_i = 1$  represents interruption and  $k_i = 0$ , no interruption).

The interruption cost minimization model is given by

$$\min \left[ C_b B_m + \sum_{i=1}^T C_i b_i \right] \quad (1)$$

$$b_i = 0 \text{ if } E_g(t_i) + \eta_b B_\Delta(t_i) = E_l(t_i) \quad (2)$$

$$b_i = 1 \text{ if } E_g(t_i) + \eta_b B_\Delta(t_i) < E_l(t_i) \quad (3)$$

$$-B_{max}/k_{dch} \leq \eta_b B_\Delta(t_i) \leq B_{max}/k_{ch} \quad (4)$$

$$b_i \in \{0, 1\}, 0 \leq B_m \leq \infty \quad (5)$$

$$0 \leq E_g(t_i) \leq \infty, E_g(t_i) = 0 \text{ if } k_i = 1 \quad (6)$$

Here,  $b_i$  is a binary variable that represents interruption ( $b_i = 1$ ) or no interruption ( $b_i = 0$ ) and  $B_\Delta = B_t - B_{t-1}$ . The *if condition* in the interruption constraints—Eqs. 2 and 3—can be satisfied by applying

$$E_g(t_i) + \eta_b B_\Delta(t_i) \leq E_l(t_i)$$

and

$$E_g(t_i) + \eta_b B_\Delta(t_i) \geq (1 - b_i) E_l(t_i)$$

When there is an outage, electricity must be supplied solely by the BESS, and this condition is modeled by enforcing  $E_g = 0$  when  $k_i = 1$  (Eq. 6).

### B. Outage Reduction and Peak Shaving

Further, the above model can be extended to include peak shaving by revising the objective (Eq. 1) as follows:

$$\min \left[ \sum_{i=1}^T C_g(t_i) E_g(t_i) + C_b B_m + \sum_{i=1}^T C_i b_i \right] \quad (7)$$

$C_g(t_i)$  is the cost (€/kWh) of purchasing electricity and  $E_g(t_i)$  is the electrical energy purchased from the grid (kWh).  $C_g(t_i)$  is variable in countries with open electricity markets.

In this model, the BESS is used based on the grid energy costs—the BESS is charged when the grid energy is cheap and discharged when it is expensive, thereby achieving optimized cost-effective peak shifting and peak shaving.

## III. EXPERIMENTAL DATA

### A. Outage Statistics

In order to demonstrate our methodology, we constructed outage data using probabilistic analysis. We conducted simulations using real outage data from 2012–2016 from substations located in a Finnish MV network. We first obtained the annual outage frequencies and durations from nearly 260 substations for all five years. We then combined the data and fitted a lognormal probability distribution to the data. From this fitted probability distribution, we randomly selected an annual outage frequency and using this outage frequency, we randomly selected the outage duration for all outages occurring during the year (given by the annual outage frequency).

Further, outages occur at different times in the year, and some months, for example, in autumn, are especially prone to outages due to the higher probability of storms. We collected the outage timing for all substations across the five years and ordered them from the time when the maximum number of outages occurred to the time when the least number of outages occurred. Based on this, we selected the outage timing from the top of the list—i.e., we started with the time when maximum outages occur and continued until we obtained as many outage timing data as required (given by the annual outage frequency).

### B. Outage Costs

In Finland, DSOs incur two types of revenue losses due to outages—regulatory losses and customer reimbursement. The Finnish Energy Market Authority encourages DSOs to achieve at least the level of security of supply required by the Electricity Market Act by imposing full regulatory outage costs as part of its quality incentive [3]. These regulatory outage costs, which are meant to reflect the disadvantages caused by outages, are calculated on the basis of the number and duration of planned and unplanned outages, the number of high-speed and time-delayed autoreclosers, and the unit prices of outages. In addition, DSOs are expected to reimburse a certain percentage of the annual electricity delivery fee to the

customer [9]. However, this reimbursement is to be given only when the interruption duration of a single event exceeds the maximum allowable duration of single events (typically 12 h). For simplicity, we have only considered regulatory losses in our outage data.

Further, outages can be divided into temporary and permanent outages on the basis of the time taken for the fault clearance. Temporary outages are caused by momentary faults that are typically cleared within short time intervals by high-speed autoreclosers. We have not considered the use of BESSs to clear such temporary outages since a reasonably sized BESS that can alleviate the effects of longer outages can be expected to manage the effects of temporary outages. Nevertheless, the exact mechanism of using a BESS to handle momentary faults should be discussed separately.

The total revenue losses for the DSO due to outages is defined in the regulations as follows [3]:

$$\text{cost} = \frac{E_l}{T_t} \{ t_u C_{ud} + n_u C_{un} + t_p C_{pd} + n_p C_{pn} + n_{hsar} C_{hsar} + n_{dar} C_{dar} \}$$

where  $E_l$  is the volume of annual transmitted energy (kWh);  $T_t$ , the number of hours in the year (h);  $t_u$  and  $t_p$ , the durations of unexpected and planned interruptions, respectively (h/a);  $C_{ud}$  and  $C_{pd}$ , the unit costs for the durations of unexpected and planned interruptions, respectively (€/kWh);  $n_u$  and  $n_p$ , the number of unexpected and planned interruptions, respectively;  $C_{un}$  and  $C_{pn}$ , the unit costs for the number of unexpected and planned interruptions, respectively (€/kWh);  $n_{hsar}$  and  $n_{dar}$ , the number of high-speed and delayed autoreclosings, respectively; and  $C_{hsar}$  and  $C_{dar}$ , the unit costs of delayed and high-speed autoreclosing, respectively (€/kWh).

We neglected temporary faults and planned outages (which have lower unit costs) and employed the following outage cost model:

$$\text{cost} = C_i = \frac{E_l}{T_t} \{ t_u C_{ud} + n_u C_{un} \}$$

The unit costs  $C_{ud}$  and  $C_{un}$  are given by the DSO regulations as 11 €/kWh and 1.1 €/kWh, respectively. Since  $C_{un}$  is much lower than  $C_{ud}$ , and the number of outages  $n_u$  is typically much lesser than the outage duration  $t_u$ ,  $C_{un}$  is neglected in the objective function and only applied retrospectively when making the final calculations. The objective function in Eq. 1 can now be updated to the Finnish scenario as follows:

$$\min \left[ C_b B_m + \sum_{i=1}^T b_i \frac{E_l(t_i)}{T} C_{ud} \right] \quad (8)$$

Note that  $E_l(t_i)$  is the total annual transmitted energy (kWh) transmitted through a substation into the low voltage network to meet the load demand—this energy is not considered to be transmitted during an outage. Moreover, the energy transmitted using the BESS to meet

the load demand is not considered on the basis that the BESS is an additional investment made by the DSO and its usage should not be penalized further.

The Finnish regulation methods calculate the impact of the quality incentive so that the realized regulatory outage costs are deducted from a reference level of regulatory outage costs [3]; however, this reference level is ignored in our calculations. Further, the unit prices are in the 2005 value of money, and we have not adjusted them according to the consumer price index, as recommended by the guidelines.

### C. Electrical Load

We used load data obtained from a Finnish DSO for the same network from which the interruption data was obtained. We selected a substation with 12 customers and total annual load energy of 74.69 MWh.

### D. Battery Energy Storage System

Li-ion batteries are highly promising for grid-scale applications due to their decreasing costs and desirable functionalities such as high power capability, energy density, and efficiency [10]. Hence, we considered Li-ion-based BESSs for our analysis. The cost of losses of the BESS is indirectly considered by using the efficiency of Li-ion batteries. Li-ion battery efficiencies have been reported to range between 85% to 97%, and we selected a mid-level efficiency of 91% [11], [12]. Moreover, for simplicity, we assumed maximum charge and discharge rates of 1C.

In [12], the authors have investigated the capital, operational, maintenance, and replacement costs of various energy storage technologies such as pumped hydropower storage, compressed air energy storage, and electrochemical batteries (e.g., lead-acid, Li-ion, and Ni-Cd). Moreover, their calculations of the total capital costs include power conversion costs as well as costs of other services and assets such as grid connection interfaces. Hence, we have chosen the battery costs  $C_B = 1095$  €/kWh based on their analysis [13].

Since DSOs making a one-time investment into a BESS system will expect to utilize it for multiple years, we also considered the lifespan of Li-ion BESS systems. However, in the absence of long-term utilization and field experiences for the majority of BEES applications, we could only make an approximation based on previous research projections into similar applications such as primary frequency regulation [14]. We considered a lifespan of 5 years, which is a reasonable expected lifespan for Li-ion batteries in terms of both maximum number of cycles and time. In order to consider the lifespan, we extended all the obtained annual data to 5 years and performed the simulations.

## IV. RESULTS

Before the BESS was used, there were 7 annual interruptions with a total outage duration of 45.5 h at the selected substation. We first ran the outage reduction model given

in Section II-A to obtain the minimum BESS capacity required to reduce all interruptions—112 kWh.

Subsequently, we preset the BESS capacity by enforcing a constraint  $B_m = 0$ –120 kWh in the model. From the resulting vector for  $b_t$ , which gives the new time of interruptions, we obtained the new interruption frequency, interruption duration, as well as savings. The results are illustrated in Figure 2. The number of interruptions increased slowly and became 0 (decrease = 100%) when the battery capacity was around 112 kWh for this substation. Further, nearly 80% of the interruptions were reduced with battery capacity of 60 kWh. However, this increase in reliability was not always cost-effective, as shown by the variations in the savings from using the BESS. At the current costs assumed in the study (1095 €/kWh), the savings are very low, reaching nearly –300% to –400% (not shown) when the interruptions are reduced to less than 50%. There are no savings with a 700 €/kWh battery as well, but a 500 €/kWh shows some savings. The savings are higher and nearly all interruptions are reduced for BESS costs of 300 €/kWh and less.

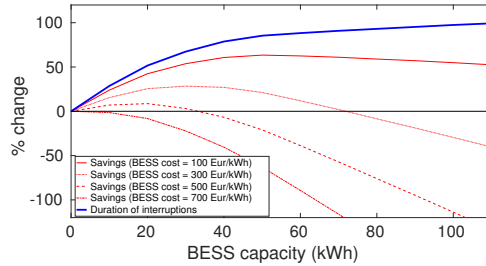


Fig. 2: Changes in the interruption duration as the capacity of the battery energy storage system (BESS) is increased from 0 to 120 kWh; the corresponding changes in the cost savings for four BESS costs—100 €/kWh, 300 €/kWh, 500 €/kWh, and 700 €/kWh—are also shown.

Figure 3 compares the savings when the BESS is used with and without peak shaving. Peak shaving is implemented by using Finnish regional electricity market prices (Elspot prices) for 2015, which are used for all five years of the simulation. A BESS capacity of 70 kWh is used to illustrate the savings; this BESS capacity is sufficient to reduce the interruptions by 88%, which is shown by the red line. When the BESS is used with peak shaving, the savings are clearly higher. The grid power required is actually higher than when there are no interruptions, since more load energy is now met. However, there are cost savings because the BESS shifts the charging periods to the time steps when the electricity prices are lower.

We then performed the outage reduction model simulation for each BESS cost, and derived the minimum BESS capacity, using which we obtained the interruptions and

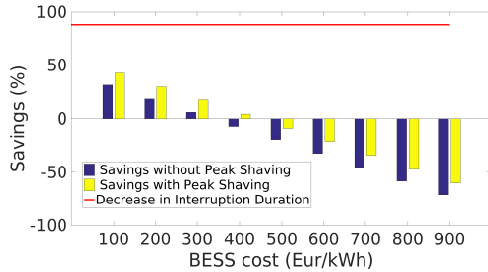


Fig. 3: Comparison of the cost savings when a BESS of 70 kWh is used with and without peak shaving. The decrease in the interruption duration for this BESS was nearly 90%.

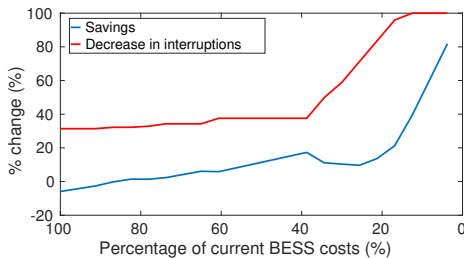


Fig. 4: Savings from using BESS as the BESS cost is decreased from 100% to 10% of current cost. The decrease in the number of outages with the decrease in cost is also given.

savings. Figure 4 shows changes in the savings from using the BESS versus a percentage of its current costs when the battery cost is linearly decreased from 1095 €/kWh to ~10% of its value—100 €/kWh. This figure clearly emphasizes that at the current battery costs, the savings are negative and it is not recommended to use the BESS. In other words, the cost of purchasing the BESS is greater than the savings from using it. However, as the BESS costs decrease, the savings increase. The increase is exponential beyond 20% of the current battery costs.

Figure 5 illustrates how the BESS is charged by grid energy and then supplies electric power when the grid energy is absent ( $= 0$ ). The BESS chosen for this illustration has nearly half the minimum capacity (46 kWh), and the figures show a randomly chosen time frame. In Fig. 5a, the BESS is able to supply energy during many, but not all, time steps. Fig. 5b shows that the BESS gets charged before and after the outage in order to supply energy effectively and with as high reliability as possible, given the maximum BESS capacity.

## V. DISCUSSIONS

In our proposed methodology, the minimum BESS capacities and optimal schedules are calculated based on historical load and interruption data, which may misestimate the benefits from the BESS. The presented methodology to decrease DSO losses is from a planning rather than operational point of view. During the planning phase, the analyses give a reasonable approximation of the potential benefits of using BESS and a probable schedule. In the operational phase, sophisticated algorithms must schedule the available BESS usage such that profitability is highest; this is a trickier problem that will be studied in the future.

In addition, not all outages are unexpected, and DSOs often conduct planned outages for various reasons such as repairs and maintenance. In such cases, it would be useful for DSOs to know the costs of their outages and the potential of BESSs to decrease their costs. Our proposed methodology simplifies and eases these analyses.

This study only considers capital costs of a BESS installation, partly because incorporating cycles per day or depth of discharge parameters into the model is challenging. A potential solution is to use BESS levelized costs (e.g., levelized costs of storage) and use them in the model by, for example, reshaping the objective as a function of the actual energy used by the battery during a time step. Nevertheless, the challenge of incorporating BESS cycles in some manner, for example, to set operating limits remain. Moreover, there is insufficient information regarding long-term practical usage of many BESS technologies, since they are still either in the laboratory phase or their deployment has only recently begun. As a result, most of the operating costs are still fairly uncertain. Incorporating the operating costs of BESS into the model will be a subject of future studies.

It is important to emphasize that under the current European and Nordic electricity market regulations [15], [16], DSOs are not allowed to interfere or directly participate in electricity trading. Nevertheless, electricity traders, such as retailers or aggregators, and DSOs could enter into a partnership, where the electricity traders may use the BESS physically installed in the networks of local DSOs to perform market actions such as market-price-oriented peak shaving. Depending on the ownership of the BESS, its capacity can be rented either for interruption management by the DSOs or for power trading by traders. The exact nature of this partnership and how the two entities can reach a fair price will be explored in future studies.

## VI. CONCLUSIONS

It is critical for DSOs to ensure high security of supply. In this paper, we have presented a novel methodology to determine the economic feasibility for DSOs to increase electrical supply reliability by installing BESSs centrally at secondary substations. By using our algorithm, it is possible to determine the minimum capacity and optimal schedule of the installed BESS. Moreover, it is possible to

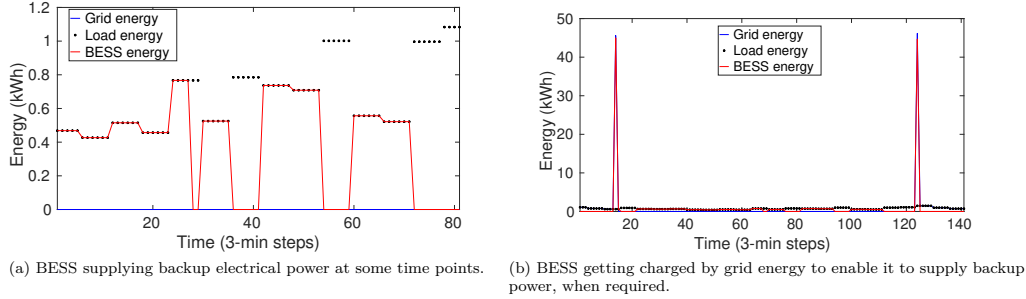


Fig. 5: BESS supplying backup electrical power when grid energy is affected by an outage.

determine the tradeoff between improvement in reliability and the costs of BESSs. We also proposed a method to use the BESS for peak shaving instead of keeping it idle when there are no outages and examined the cost-effectiveness.

Our methodology was validated by applying it to a substation network in Finland. All the interruptions were reduced with a BESS capacity of 112 kWh, and nearly 80% of the interruptions were reduced with BESS capacity of 60 kWh itself. Further, the savings were negligible at BESS costs greater around 500 €/kWh. However, for BESS costs less than 300 €/kWh, the savings improved and nearly all the interruptions were reduced. Moreover, peak shaving increased the cost savings. However, the current costs of Li-ion-based BESSs are nearly thrice as high, and they must decrease further before BESSs can be cost-effectively used for interruption management and peak shaving. Nevertheless, even though the use of BESSs for interruption management should be viewed cautiously today, the current trend of declining Li-ion-based BESS costs is an encouraging sign pointing to their cost-effective and efficient usage in the future.

In the future, we will extend the theoretical model by integrating the operational costs of BESSs and will improve the calculations by considering compensations to customers in their electricity bills for interruptions.

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## Publication IV

Narayanan, A., Haapaniemi, J., Kaipia, T., and Partanen, J.

**Economic impacts of power-based tariffs on peer-to-peer electricity  
exchange in community microgrids**

*15th International Conference on the European Energy Market (EEM)*  
pp. 1–6. IEEE, 2018

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# Economic impacts of power-based tariffs on peer-to-peer electricity exchange in community microgrids

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**Abstract**—Due to the proliferation of renewables-based distributed energy resources, many electricity customers today consume *and* produce electricity. Since prosumers can benefit from supplying surplus electricity to consumers with electricity deficits, (p2p) peer-to-peer electricity exchange has been proposed for low-voltage (LV) microgrids forming “community microgrids.” The distribution system operator (DSO), who is an important stakeholder in LV networks, has an income that is largely energy dependent. However, energy-based tariffs (EBT) do not reflect the true cost of a DSO’s network investment that is highly dependent on the peak power in the network. A power-based distribution tariff (PBT) scheme where customers pay for their peak load (€/kW) instead of consumed energy (€/kWh) has been proposed. In this paper, we evaluate the economic impacts of revising the tariff structure from EBT to PBT on customers participating in p2p community microgrids with photovoltaic (PV) installations. We consider four different Finnish customer types and compare the benefits obtained by 36 customers of each type after their EBT was replaced by PBT. We apply PBT also to the power supplied by prosumers to their peers. Nearly all the customers (expectedly) benefited from electricity exchange especially for the typical PV system size of 5 kW<sub>p</sub>. When the PV system sizes were increased, the benefits decreased and became negative at PV system size  $\geq 17.5$  kW<sub>p</sub>. In particular, the savings in EBT and PBT cases were similar—the tariff change from EBT to PBT did not significantly affect the customers’ benefits from electricity exchange.

**Index Terms**—Power-based tariffs, community microgrids, peer-to-peer trading, distribution system operator, double auction

among the customers in a distribution network is called peer-to-peer (p2p) electricity exchange. Pilot installations of p2p exchanges in off-grid and grid-connected low-voltage (LV) microgrids, typically called “community microgrids” (Fig. 1), have been implemented across the world [1]. Community microgrids have several advantages such as better energy utilization, enhanced microgrid autonomy, and higher penetration of DERs [2]. Moreover, all stakeholders can profit from local trading [3]. Besides prosumers who profit from selling their electricity to consumers, distribution system operators (DSOs) can benefit, for example, by the consequent reductions in expensive grid reinforcement, outages, and power losses.

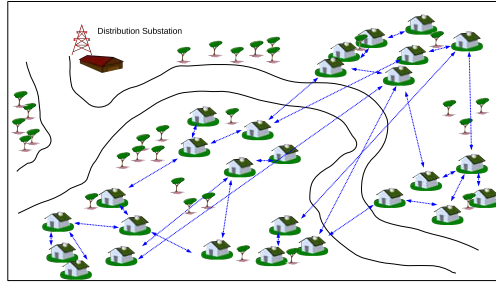


Fig. 1. Abstracted model of community microgrid with electricity exchange.

## I. INTRODUCTION

Today, distributed energy resources (DERs) comprising renewables-based production are being increasingly integrated into the power system. As a result, many electricity consumers are now prosumers, i.e., they both consume *and* produce electricity. However, the electricity generated by renewables-based production is unpredictable and intermittent. Prosumers may produce more electricity than required by their electrical load. Electricity storage systems (ESS) and demand-side management are typical solutions used to match the production. In addition, prosumers producing surplus electricity could supply electricity to nearby consumers with electricity deficits, thereby earning some benefits. Such an electricity exchange

Energy technologies such as ESS, heat pumps, and electric vehicles as well as improved energy efficiencies can reshape customers’ load profiles. The volume of transmitted energy will probably decrease whereas momentary peak powers could increase. P2p trading could also increase the peak power when prosumers transfer electricity to other consumers. Such increases in peak power are problematic for DSOs because their incomes are primarily energy dependent. On the one hand, DSOs will lose revenue from customers, but, on the other hand, their network investment costs will increase since network dimensioning is dependent on the highest peak powers [4]. A power-based distribution tariff (PBT) scheme to bill

customers has been proposed as a solution to ensure that DSO revenues reflect their true network costs [4], [5]. In the PBT scheme, customers pay for their peak load ( $\text{€}/kW$ ) instead of consumed energy ( $\text{€}/kWh$ ). The recent introduction of smart automatic meter readers (AMR) has made it possible to record real-time consumption at very fine resolutions, thereby enabling the implementation of the more equitable PBT scheme.

However, this new tariff structure raises questions about the changes in the investment costs and profitability for the customer. Residential customers who invest in photovoltaic (PV) or other DER installations and participate in p2p community electricity projects consider energy-based ( $\text{€}/kWh$ ) tariff (EBT) schemes when calculating their benefits. If the PBT ( $\text{€}/kW$ ) scheme is implemented, the customers' benefits can be adversely affected. Haapaniemi et al. had previously analyzed the effects of PBT on the profitability of PV systems installed by electricity customers in Finland [5]. In this paper, we have extended the analysis to evaluate the benefits of making the major tariff structure transition from EBT to PBT in the case of p2p community microgrids with PV installations.

Intuitively, p2p electricity exchange can be expected to increase the customer benefits even in the case of PBT<sup>1</sup>. However, in the p2p scenario, the PBT should be applied not only to the load but also to the power supplied by the prosumers into the grid. As a result, the amount of produced PV power might impact the profitability. Prosumers may then reduce (or stop) trading, thereby wasting the excess production, which is not desirable. In this paper, we have examined the economic impacts of implementing the PBT scheme on the customer as compared to the traditional EBT scheme. We apply both annual and monthly PBT structures to a real residential neighborhood LV network in Finland<sup>2</sup>. To our knowledge, this is the first paper to combine p2p electricity exchange with PBT, and we lay the preliminary groundwork for further extensive analyses.

## II. METHODOLOGY

### A. Trading Methodology

P2p exchange was simulated using well-known trading mechanisms. We assume that a centralized authority (e.g., a governing authority formed by the participants) conducts the bidding, trading, and clearing on behalf of all the participants and redistributes the benefits (or costs).

First, a local microgrid market that will facilitate an equitable and reliable balance of electricity production and consumption must be established. We consider that the microgrid is connected to the external grid, and therefore, the electrical load demand is always met. Further, we consider that some (randomly chosen) customers in the microgrid have renewables-based production, specifically PV. Our main objective is to *maximize the usage of PV production*. Therefore,

<sup>1</sup>Indeed, why will the customers trade otherwise?

<sup>2</sup>AMR penetration is especially high in Nordic regions, and further, they currently offer the most suitable conditions for the transition.

we design our market with the aim to first meet the load using local PV production, and, if required, to buy any remaining load demand from the main grid at the spot price  $C_{sp}(t)$  for the current hour  $t$ .

We conducted our analysis at hourly resolutions for a year. The following five scenarios may occur during each hour:

- (1) **No Trade:** There are either no sellers or no buyers (or neither in the rare instance when every trader has a PV installation with production exactly matching their load).
- (2) **Bilateral Trade:** There is exactly 1 seller and 1 buyer in which case they simply trade with each other. We assume that they will trade at a market price equivalent to the integer closest to  $C_{sp}(t)/2$ .
- (3) **Seller Monopoly:** There is only 1 seller but there are many buyers. The market price is set at an upper bidding limit, which is 1 less than the spot price, i.e.,  $C_{sp} - 1$ . The buyers are ordered according to their bids and the highest bidder gets the first opportunity to buy electricity, followed by the next highest bidder, and so on.
- (4) **Buyer Monopoly:** There is only 1 buyer but there are many sellers. The market price is set at the lower bidding limit (1 €). The sellers are now ordered according to their bids with the lowest bidder getting the first opportunity to sell, followed by the next bidder, and so on.
- (5) **Competitive:** There are multiple sellers and buyers, and hence, a competitive market. The sellers and buyers both bid for electricity sales and purchases, respectively. The market price is then set, and the trades are cleared.

The trading mechanisms for the competitive scenario are as follows.

1) *Zero-intelligence bidding:* Several non-strategic and strategic bidding strategies have been presented earlier [3]. We have employed the so-called *zero-intelligence (ZI)* bidding strategy—traders submit random bids and offers with a bid price drawn from a uniform distribution between two limit prices [6]. The ZI strategy essentially ignores all market decisions to make random uninformed decisions and has the simplest behavior. The ZI strategy since it is a baseline strategy that provides a lower bound on the system efficiency [6].

Each trader privately communicates either their electricity demand required for buying or the supply available for selling to the central authority. The central authority then generates buy and sell bid prices for the local electricity by taking pseudorandom integers from a discrete uniform distribution between the lower and upper bidding limits, i.e.,  $[1, C_{sp}(t) - 1]$ . The bid prices are used to set the market price as well as to determine the selling and buying order.

2) *Trading—sealed-bid double auction:* We employed the sealed-bid double auction to set the market price [7]. The central authority matches the orders at discrete market closing times  $t$  by first organizing buy and sell bids in descending and ascending orders, respectively. The intersection is then determined and set as the market price. Since a key objective is to maximize the usage of locally generated energy, all the sellers are allowed to sell their electricity as long as there is demand from any buyer.

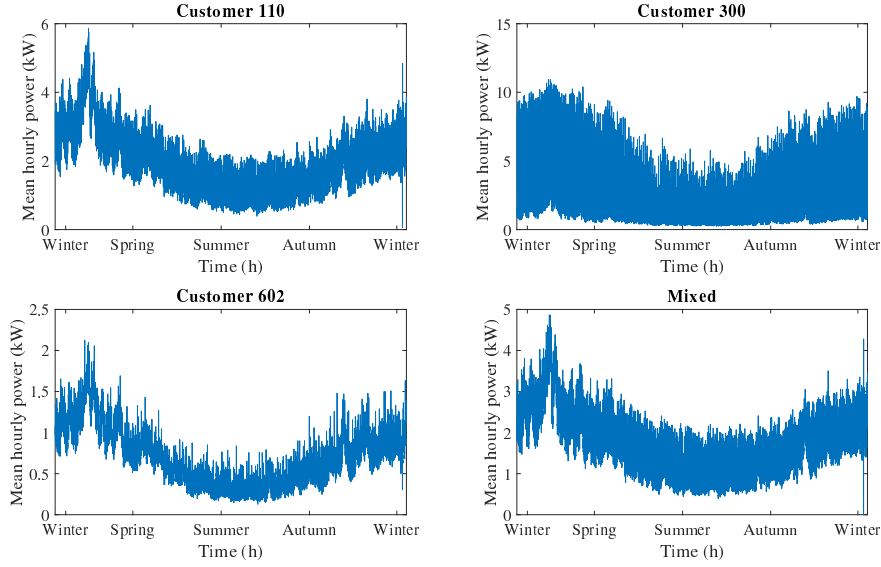


Fig. 2. Average hourly power of all the four customer categories for a year from January to December.

3) *Clearing—uniform price rule* : We used the uniform-price rule in which all the buyers pay the same price for the acquired items [7] since it is fairer to use this method for centrally generated random bids (instead of, for example, the pay-as-you-bid rule). Therefore, all the buyers pay the same price for the acquired items, i.e., the market price.

Thus, in summary, the market is cleared as follows:

- (1) Buyers are ordered from maximum bids to minimum bids.
- (2) Sellers are ordered from minimum bids to maximum bids.
- (3) The first seller sells the extra electricity to the first buyer.
  - a) If there is still excess electricity, the first seller sells to the next buyer, and so on.
  - b) If electricity is still required by the buyer, the next seller now sells, and so on.
- (4) Step 3 continues till either all buyers have received electricity or all sellers have sold electricity.
- (5) Any remaining electricity demand will be bought from the main grid at  $C_{sp}$ .
- (6) Any remaining electricity supply gets wasted.
- (7) Note that the sales in Step 3 are carried out at the market price established by the sealed-bid double auction.

#### B. Analysis Methodology

1) *Customers*: Finnish customers are classified into several categories that are typically used in load models in utility applications. We considered three such categories:

- (1) Category **110**—Detached family house with direct electric heating and hot water accumulator (< 300 l);

- (2) Category **300**—Detached family house similar to 110, but with electric storage heating using a boiler;

- (3) Category **602**—Detached family house with no electric heating, but with an electric stove (sauna).

First, we consider each category separately. However, this is not realistic since a microgrid will have a mixture of categories. Hence, we also consider a fourth category—**mixed**—in which a mixture of categories was taken from an actual Finnish LV network. The average hourly power of all the four customer categories are shown in Fig. 2.

2) *Power-based tariffs*: A Finnish customer's electricity costs are divided into three components—(1) **Distribution fees**: A monthly fee  $C_{D,m}$  (€) and an electricity usage fee  $C_{D,e}$  (€/kWh); (2) **Supplier fees**: Spot prices  $C_{sp}$  (€/kWh) and a monthly fee comprising an agreement fee and a usage fee; and **Electricity tax**: Electricity tax plus a value added tax.

For PBT, we employ power-band pricing in which customers choose a power band in advance. They can then use electricity without additional payments to the DSO if they do not exceed their chosen power limit. The power-band steps can vary, but we assume 2-kW power band steps (Fig. 3). Further, the distribution fees— $C_{D,m} + C_{D,e}$ —are converted into a PBT of  $C_p$  €/kW, i.e., a DSO's entire income is collected with only the power component. In addition, we have considered two cases: (1) **Annual PBT**: Customers pay for their *annual peak load*; and (2) **Monthly PBT**: Customers pay for each month separately based on their *monthly peak load*.

In the EBT case, trading only impacts supplier fees, whereas

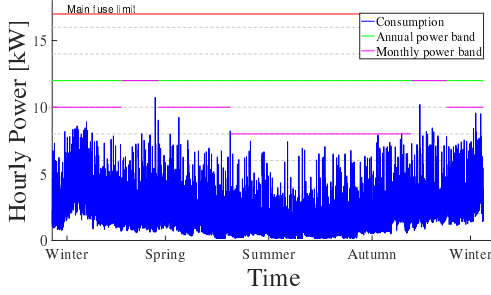


Fig. 3. Principle of power-band pricing with 2-kW steps.

in the PBT case, trading also impacts the distribution fees because the power transmitted by a prosumer into the grid is the peak power if it is higher than their peak load power.

### III. RESULTS

#### A. Data

For the customers' average hourly power, we used metered annual hourly load data of 36 different customers taken from an actual Finnish distribution network for the three customer categories—110, 300, and 602. For the *mixed* category, we took real data from a LV Finnish neighborhood comprising 65 customers with a mixture of the following categories—110, 120 (same as 110, but accumulator > 300 l), 220 (same as 300, but partial storage heating), 601 (same as 602, but no sauna), 602, and 910810 (administration building). For uniformity, we trimmed the data to 36 customers.

We assumed that 30% of the customers in the microgrid, who were randomly chosen, have installed PV systems in their houses. In all cases, we assumed a PV system size of 5 kW<sub>p</sub>, the typical average PV size installed by a Finnish residential customer. We used identical real annual metered hourly PV production data from 2016 for all the prosumers. The data was obtained from a 5-kW<sub>p</sub> south-facing PV panel (tilt angle of 15°) installed close to the neighborhood.

For the spot prices, we used day-ahead electricity market prices—Elspot Finnish area prices—from 2016. The DSO and supplier prices were taken from actual data. For the PBT, we converted the DSO's share of the electricity bill into unit power costs of 6.84 €/kW/month and 9.75 €/kW/month for the annual and monthly cases, respectively.

#### B. Results

We analyzed the cost benefits for all categories when PBT is implemented with and without trading; Table I shows the *total* customer costs, whereas Fig. 4 shows the annual *average* customer costs. In all cases, the annual PBT with trading was the lowest. These results suggest that the total community microgrid profits from p2p trading are higher than the costs of PBT even when PBT is applied for the power supplied to peers. The profits increased for nearly all the customers

TABLE I  
TOTAL ANNUAL CUSTOMER COSTS WHEN PBT WAS IMPLEMENTED WITH AND WITHOUT TRADING FOR 36 CUSTOMERS EACH IN CUSTOMER CATEGORIES 110, 300, AND 602, AND "MIXED."

Cust. Group	No Trading Costs (€)		Trading Costs (€)	
	Monthly PBT	Annual PBT	Monthly PBT	Annual PBT
110	107301	106453	105170	104166
300	137999	132007	136005	129898
602	47540	47866	46107	45614
Mixed	97188	96914	95643	94663

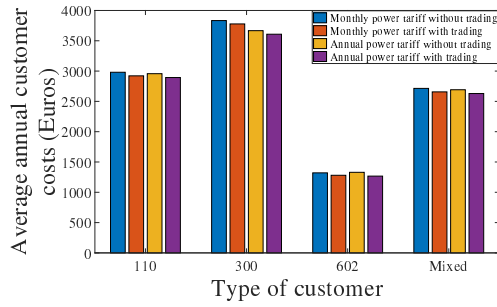


Fig. 4. Annual average customer costs when power-based tariff (PBT) was implemented with and without trading for 36 customers each in customer categories 110, 300, and 602, and "mixed."

individually as well (not shown). Thus, trading is beneficial for the community microgrid even with PBT. This is probably because the excess PV production (which is sold) rarely exceeds the monthly or annual peak power of the customers.

To test this assumption, we calculated the savings from trading in the monthly and annual cases for two PV installations—the 5 kW<sub>p</sub> already considered above and the case of 10-kW<sub>p</sub> PV installed at the same customers. Figures 5 and 6 show the annual customer *savings* with and without trading when PBT was implemented for the four customer categories with PV sizes of 5 kW<sub>p</sub> and 10 kW<sub>p</sub>, respectively. Further, the savings when trading with EBT is also included. In three customer categories, the savings increased especially in the annual case, sometimes nearly doubling. Since the solar energy production was higher now, the customers were able to gain higher profits from trades without being penalized for high power supplied into their grid. This is because in all three cases—110, 300, and mixed—the annual peak load power was still higher than the power supplied to the grid. However, in the case of 602, which had a smaller annual peak load power, the profits reduced considerably. In the monthly case, there is a dramatic decrease in the savings implying that the

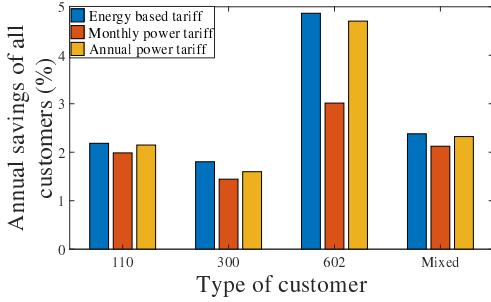


Fig. 5. Annual customer savings when EBT and PBT were implemented with and without trading for 36 customers in customer categories 110, 300, and 602, and “mixed.” In this case, the peak power of PV was 5 kW<sub>p</sub>.

p2p trading was hardly profitable. Moreover, the benefits from trading in both the EBT and PBT cases are similar, especially in the typical 5 kW<sub>p</sub> case. This suggests that the *tariff change from EBT to PBT does not significantly affect benefits from electricity exchange*. In the 10 kW<sub>p</sub> case, the benefits from trading with EBT is higher.

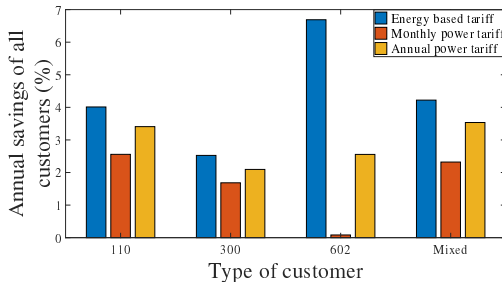


Fig. 6. Annual customer savings when PBT and EBT were implemented with and without trading for 36 customers in customer categories 110, 300, and 602, and “mixed.” In this case, the peak power of PV was 10 kW<sub>p</sub>.

However, it is not necessary that increased PV system sizes will lead to higher profits. After a certain size, the PBT that prosumers have to pay for supplying electricity becomes higher than the trading profits. Figure 7 illustrates this for the mixed category of customers. Trading benefits increase until a PV size of 10 kW<sub>p</sub>, but thereafter, the benefits begin to reduce and trading becomes unprofitable for a PV size of ~ 20 kW<sub>p</sub>. Similar results were observed for the other categories as well.

#### IV. CONCLUSIONS

We examined the impacts of making a major tariff structure transition from EBT to PBT on customers participating in p2p community microgrids. We considered four different Finnish customer types and compared the benefits (or losses) obtained

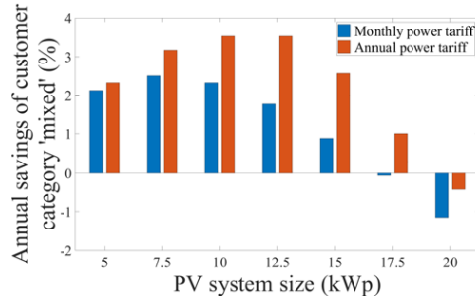


Fig. 7. Annual customer savings when PBT was implemented with and without trading for 36 customers in the mixed customer category. In this case, the peak power of PV was varied from 5–20 kW<sub>p</sub>.

by 36 customers in each type after their EBT was replaced by PBT. The profits from p2p trading was higher than the costs of PBT even when PBT was applied for the power supplied to peers. Nearly all the customers benefited from electricity trading. In particular, for typical PV system sizes of 5–10 kW<sub>p</sub>, as expected, trading *always* decreased the electricity costs to customers. Moreover, the annual PBT with trading was lower than monthly PBT in all cases. Further, the tariff change from EBT to PBT did not significantly affect the benefits from electricity exchange, and the benefits in EBT and PBT cases were similar at the typical PV of 5 kW<sub>p</sub>. For PV system sizes of 15–20 kW<sub>p</sub>, the excess PV production (which is sold) often exceeded the monthly or annual peak power of the customers, thereby adversely affecting the benefits of customers.

In future studies, we will consider the usage of batteries or load shifting by customers to decrease their peak power.

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ISBN 978-952-335-440-1  
ISBN 978-952-335-441-8 (PDF)  
ISSN-L 1456-4491  
ISSN 1456-4491  
Lappeenranta 2019