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TRANSACTIVE ENERGY FRAMEWORKS FOR INCREASED PROSUMER PARTICIPATION IN SMART GRIDS

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Transactive Energy Frameworks for Increased Prosumer Participation in Smart Grids

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In addition, the work in this thesis has contributed to two research projects. Firstly, the research contributed to the UNiTED Project: *Unlocking demand response potential with Next generation innovative optimization Tools Empowering prosumers and Distribution grid benefits — UNiTED*, Ref. POCI-01-0145-FEDER-029803, FCT, Portugal. The work also contributed to the InterConnect Project *Interoperable Solutions Connecting Smart Homes, Buildings and Grids. H2020 European Commission Grant agreement ID: 857237*

Abstract

Historically, consumers of electricity, especially residential consumers, have largely had a passive relationship with the broader energy system. However, the recent and rapid developments in the number and type of distributed energy resources and devices that individual consumers own, has resulted in their being increasingly able to play an active role in electrical power schemes. These new resources are reshaping how consumers interact with the electricity system by allowing them to make more active choices regarding energy use, including generating electricity to meet a portion of their demand and selling any excess to the broader system. This increased flexibility through consumer participation is a foundational element for the success of energy systems that are expected to be decarbonized, decentralized, and digitized.

This reshaping of the role of the consumer as a prosumer presents new challenges and opportunities for the actors who oversee the operations and planning of distribution systems. These challenges and opportunities present important research areas relating to the design of future energy systems. The emergence of active consumers within the energy system affects both the consumer and broader system in various ways depending on factors such as the design of the energy markets, energy regulations, socio-economic status, technology adoption, business model innovation, and the individual preferences of the consumer. These interlinked factors affect the level of participation of consumers in the energy system. Understanding how these factors combine to foster increased consumer participation is the subject of this thesis.

This dissertation presents several innovative conceptual and mathematical models to promote active participation by prosumers in smart grids. Various facets of consumer participation are considered, including technical, economic, thermal comfort and data privacy concerns. These aspects are coordinated and controlled using the concept of Transactive Energy. The thesis presents frameworks that cover both top-down and bottom-up optimization of energy systems as well as both operations and planning impacts to coordinate energy generation and consumption from a diverse set of resources within the smart grid. Therefore, this thesis provides a comprehensive analysis of mechanisms to increase consumer participation in future energy systems as well as detailed investigations quantifying the impacts of this increased participation. The research in this thesis, thus, addresses crucial aspects of the design and operation of future energy systems.

Keywords: Demand Response, Distributed Energy Resources, Prosumers, Smart Grids, Transactive Energy, Virtual Power Plant.

Resumo

Historicamente, os consumidores de electricidade, especialmente os consumidores residenciais, têm tido uma relação passiva com o sistema energético mais amplo. Contudo, as recentes e rápidas inovações em termos do número e tipo de recursos e dispositivos ao alcance do consumidor, permite-lhe cada vez mais desempenhar um papel ativo no sistema de energia. Estas inovações estão a remodelar a forma como o consumidor interage com o sistema de abastecimento de eletricidade, permitindo-lhe fazer escolhas mais ativas no que respeita à utilização de energia, incluindo a produção de eletricidade para satisfazer uma parte das suas necessidades próprias e a venda de qualquer excesso produzido ao sistema geral. Esta maior flexibilidade através da participação dos consumidores é um elemento fundamental para o sucesso de sistemas energéticos descarbonizados, descentralizados e digitalizados.

A alteração do papel do consumidor para “prossumidor” levanta novos desafios e oferece novas oportunidades para os atores que supervisionam as operações e o planeamento dos sistemas de distribuição. Estes desafios e oportunidades oferecem importantes áreas de investigação no que toca à conceção de futuros sistemas de energia. O aparecimento de consumidores ativos no sistema energético afeta de várias formas tanto o consumidor como o sistema, dependendo de fatores tais como o mercado energético, regulamentos energéticos, estatuto socioeconómico, adoção de tecnologia, inovação do modelo empresarial, e as preferências individuais do consumidor. Estes fatores interligados entre si afetam o nível de participação dos consumidores no sistema energético. A presente tese tem por tema, precisamente, compreender como estes fatores se combinam para promover uma maior participação dos consumidores.

Esta tese apresenta vários modelos conceptuais e matemáticos inovadores destinados a promover a participação ativa dos prossumidores em redes inteligentes. Vários aspetos da participação dos consumidores são considerados, incluindo preocupações técnicas, económicas, de conforto térmico e de privacidade de dados. Estes aspetos são coordenados e controlados utilizando o conceito de Energia Transativa. A tese apresenta quadros que cobrem tanto a otimização descendente, do topo para a base, e ascendente, da base para o topo, dos sistemas de energia, bem como os impactos operacionais e de planeamento a fim de permitir coordenar a produção e o consumo de energia a partir de um conjunto diversificado de recursos dentro da rede inteligente. Portanto, esta tese apresenta uma análise abrangente de mecanismos destinados a aumentar a participação do consumidor em futuros sistemas energéticos; apresenta, ainda, a quantificação do impacto desta maior participação que resultou de uma pesquisa detalhada. O trabalho de investigação apresentado nesta tese aborda, pois, aspetos cruciais da conceção e funcionamento de futuros sistemas energéticos.

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The saying goes that it takes a village to raise a child. In my experience, it has taken an international community to raise this PhD student – and it is time for this student to recognize the wonderful people who helped raise him. The PhD has not always been easy, but this community has provided me with incredible support, kindness, and guidance. Over the past five years, I have had the privilege of meeting many wonderful people who, each in their own way, have supported me throughout the PhD program. Meeting and interacting with you all has made this PhD journey all the more worthwhile. Thank you!

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Matthew Gough
Porto, 22 December 2022

*"Let's think the unthinkable, let's do the undoable.
Let us prepare to grapple with the ineffable itself
and see if we may not eff it after all."*

Douglas Adams

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Chapter 1

Introduction

1.1 Context and Background

Recently there has been a rapid increase in the number and type of distributed energy resources (DERs) owned by individual consumers. These resources can include solar photovoltaic (PV) systems, battery energy storage systems (both stationary and mobile in the form of electric vehicles), heating, ventilation, and air-conditioning (HVAC) devices, and electrified water heating devices. These devices are reshaping how consumers interact with the electricity system by allowing consumers to make more active choices regarding energy use.

This reshaping of the role of the consumer presents new challenges and opportunities for the actors who oversee the operations and planning of distribution systems. These challenges and opportunities present important research areas relating to the design of future energy systems. Future energy systems will likely move away from relying on a small number of large generators managed in a top-down manner to transfer electricity across large distances to consumers with relatively inflexible load demands. Instead, future energy systems are likely to be composed of a large number of smaller generation units, using intermittent renewable resources, located much closer to the load point. This will serve consumers who have a much more flexible load demand and can adjust their demand depending on a number of factors such as price, thermal comfort or time of day. These energy systems can be managed using bottom-up approaches, which rely on the devices' increased communications ability and intelligence.

This shift towards decarbonized, digitized, and decentralized energy systems require new operations and planning frameworks to optimally operate and capture the full potential of increased consumer participation using distributed energy resources, especially as electricity is fundamental to modern life.

The emergence of active consumers within the energy system affects both the consumer and broader system in various ways depending on factors such as energy market and retail design, energy regulations, socio-economic status, technology, business model innovation and adoption, and finally, individual preferences of the consumer. These interlinked factors affect the level of participation of consumers in the energy system, and understanding how these factors combine to motivate increased consumer participation is a rapidly expanding research area.

The objective of this thesis is to provide several frameworks to examine consumer participation and better understand its impacts on the consumer and the broader energy system. Various aspects of consumer participation are considered in this thesis, including technical, economic, thermal comfort, and data privacy concerns. This thesis presents frameworks that cover both top-down and bottom-up optimization of energy systems and operations and planning impacts of increased consumer participation. Therefore, this thesis provides a comprehensive analysis of mechanisms to increase consumer participation in the energy system. It presents detailed investigations into the exact impacts of this increased participation which are crucial aspects of the design and operation of future energy systems.

1.2 Research Questions

From the context provided above, this thesis investigates the following research questions. There is one primary research question and six secondary research questions which motivate the research in this thesis. These questions are:

Primary Research Question:

Can smart grids be designed and operated in a manner to increase the active participation of prosumers and fairly account for the impacts of this participation?

Secondary Research Questions:

How has the paradigm of prosumer participation emerged, and what are the key trends in this shift?

What is the role of new information and communications technologies, and novel business models in increasing prosumer participation in smart grids?

How can automation and data-driven control methods allow prosumers to participate in smart grids in a simplified manner while still accounting for their individual preferences?

How best to protect consumer data privacy in transactive energy systems in such a manner that ensures the stable operation of these systems?

Can peer-to-peer energy trading be used to increase prosumer participation while ensuring the efficient technical operation of the distribution system?

Do current planning models, typically using marginal cost pricing, allow for competition between prosumer-owned DERs and traditional grid investments in a transparent and fair manner?

1.3 Thesis Contributions

This thesis presents several conceptual and mathematical models to promote active participation by prosumers in smart grids. The various models allow for the consideration of different regulatory, technological, and consumer preference environments and are adaptable to local contexts.

The original contributions of this thesis are its multi-disciplinary nature and the broad scope of models developed. Thus the contributions of this thesis span several fields and can be separated into both conceptual and methodological contributions. The contributions are listed as follows:

Conceptual contributions

- A consumer-centered version of a transactive energy framework is introduced, and its operation is analyzed.
- The concept of the Technical Virtual Power Plant (TVPP) is expanded to consider thermal comfort and cost allocation mechanisms.
- The literature concerning prosumer participation in smart grids is analyzed and enablers and barriers of prosumer participation are identified.
- The concept of consumer empowerment through the use of distributed energy resources and information and communication technologies is advanced in transactive energy systems.

Methodological contributions

- A privacy-preserving method that ensures the stable operation of a distribution grid while fairly allocating costs and benefits to prosumers is developed.
- A dynamic operational and planning framework that transparently quantifies the tradeoffs between prosumer-owned DERs and traditional grid investments using distributed optimization is shown.
- A data-driven approach for forecasting residential hot water demand and intelligent control of distributed energy resources using only non-intrusive measurements of temperature is developed and validated in a six-month pilot project.
- A prosumer centric peer to peer energy trading framework which incorporates blockchain-based smart contracts and ensures the stable operation of distribution grids.

- Portuguese energy regulations are applied to prosumer energy trading to analyze the role of the agents involved in a transactive energy system and the impact of these regulations on the participation of the prosumers is discussed.

1.4 Publications

During the research that forms this thesis, several scientific peer-reviewed publications have been developed. These publications form the core of this thesis and are classified as Primary Publications or Secondary Publications. There are six primary journal articles, seven primary conference articles, and one primary book chapter. In addition, the research in this thesis contributed to four secondary journal articles and two secondary conference articles.

Thus, this thesis draws upon a total of twenty publications, of which fourteen are primary sources and six are secondary sources. These publications are as follows:

Primary Publications - International Journals

M. Gough, K. Rakhisa, T. Bandeira, H. Amaro, R. Castro, and J.P.S. Catalão, "Design and Implementation of a Data-Driven Intelligent Water Heating System for an Island Community: A Case Study," in *Energy Conversion and Management*.
Q1 Journal, Impact Factor: 11.533
Published: https://doi.org/10.1016/j.enconman.2023.117007

M. Gough, S.F. Santos, M.S. Javadi, J.M. Home-Ortiz, R. Castro, J.P.S. Catalão, "Stochastic Bi-level Energy Trading Model for Technical Virtual Power Plants," in *Journal of Energy Storage*.
Q1 Journal, Impact Factor: 8.907
Accepted with minor revisons.

M. Gough, S.F. Santos, M. Lotfi, M.S. Javadi, G.J. Osório, P. Ashraf, R. Castro, J.P.S. Catalão, "Operation of a technical virtual power plant considering diverse distributed energy resources," in *IEEE Transactions on Industry Applications*. Vol. 58, No. 2, pp. 2547-2558, March-April 2022.
Q1 Journal, Impact Factor: 4.079
Published. https://doi.org/10.1109/TIA.2022.3143479

M. Gough, S.F. Santos, A. Almeida, M. Lotfi, M.S. Javadi, D.Z. Fitiwi, G.J. Osório, R. Castro, J.P.S. Catalão, "Blockchain-based transactive energy framework for connected virtual power plants," in *IEEE Transactions on Industry Applications*. Vol. 58 , No. 1, pp. 986-995, January-February 2022.
Q1 Journal, Impact Factor: 4.079
Published. https://doi.org/10.1109/TIA.2021.3131537

M. Gough, S.F. Santos, T. AlSkaif, M.S. Javadi, R. Castro, J.P.S. Catalão, "Preserving privacy of smart meter data in a smart grid environment," in *IEEE Transactions on Industrial Informatics*. Vol. 18, No. 1, pp. 707-718, January 2022.
Q1 Journal, Impact Factor: 11.648
Published. https://doi.org/10.1109/TII.2021.3074915

M. Gough, S.F. Santos, M. Javadi, R. Castro, J.P.S. Catalão, "Prosumer flexibility: a comprehensive state-of-the-art review and scientometric analysis," in *Energies (MDPI)s*. Vol. 13, No. 11, 2710, June 2020.
Q3 Journal, Impact Factor: 3.252
Published. https://doi.org/10.3390/en13112710

Primary Publications - International Conferences

M. Ilic **M. Gough**, "Interactive Planning and Operations using Peak Load Pricing in Distribution Systems," *CIGRE US National Committee 2022 Grid of the Future Symposium*, 2022,
Published: https://arxiv.org/abs/2212.02145

M. Gough, S.F. Santos, J. Oliveira, J. Chaves, R. Castro, J.P.S. Catalão, "Bidding strategies for virtual power plants in the Iberian electricity market," *21th IEEE International Conference on Environment and Electrical Engineering and 5th IEEE Industrial and Commercial Power Systems Europe — EEEIC 2021 / ICPS Europe 2021*, Bari, Italy, 7-10 September 2021
Published: https://doi.org/10.1109/EEEIC/ICPSEurope51590.2021.9584766

M. Gough, S.F. Santos, P.M.C. Pereira, J.M. Home-Ortiz, R. Castro, J.P.S. Catalão, "Providing flexibility in distribution systems by electric vehicles and distributed energy resources in the context of technical virtual power plants," *21th IEEE International Conference on Environment and Electrical Engineering and 5th IEEE Industrial and Commercial Power Systems Europe — EEEIC 2021 / ICPS Europe 2021*, Bari, Italy, 7-10 September, 2021
Published: https://doi.org/10.1109/EEEIC/ICPSEurope51590.2021.9584698

M. Gough, S.F. Santos, J.M.B.A. Matos, J.M. Home-Ortiz, M.S. Javadi, R. Castro, J.P.S. Catalão, "Optimal scheduling of commercial demand response by technical virtual power plants," *4th International Conference on Smart Energy Systems and Technologies — SEST 2021*, Vaasa, Finland, 6-8 September, 2021
Published: https://doi.org/10.1109/SEST50973.2021.9543463

M. Gough, S.F. Santos, A. Almeida, M. Javadi, T. AlSkaif, R. Castro, J.P.S. Catalão, "Development of a blockchain-based energy trading scheme for prosumers," *IEEE Power Tech 2021 Conference*, Madrid, Spain, June 27 - July 1, 2021
Published: https://doi.org/10.1109/PowerTech46648.2021.9494810

M. Gough, P. Ashraf, S.F. Santos, M. Javadi, M. Lotfi, G.J. Osório, J.P.S. Catalão, "Optimization of prosumer's flexibility taking network constraints into account," *20th IEEE International Conference on Environment and Electrical Engineering and 4th IEEE Industrial and Commercial Power Systems Europe — EEEIC 2020 / ICPS Europe 2020*, Madrid, Spain, 9-12 June, 2020
Published: https://doi.org/10.1109/EEEIC/ICPSEurope49358.2020.9160657

M. Gough, S.F. Santos, M. Javadi, D.Z. Fitiwi, G.J. Osório, R. Castro, M. Lotfi, J.P.S. Catalão, "Optimization of prosumers' participation in energy transactions," *20th IEEE International Conference on Environment and Electrical Engineering and 4th IEEE Industrial and Commercial Power Systems Europe — EEEIC 2020 / ICPS Europe 2020*, Madrid, Spain, 9-12 June, 2020
Published: https://doi.org/10.1109/EEEIC/ICPSEurope49358.2020.9160507

Primary Publications - Miscellaneous

Book Chapter (Elsevier):
M. Gough, R. Castro, S.F. Santos, M. Shafie-khah, J.P.S. Catalão, "A panorama of applications of blockchain technology to energy", in: *Blockchain-based Smart Grids*, Academic Press, 2020, Pages 43-59, ISBN 9780128178621.
Published: https://doi.org/10.1016/B978-0-12-817862-1.00002-6

Secondary Publications - Journal Papers

M.S. Javadi, **M. Gough**, S.A. Mansouri, A. Ahmarinejad, E. Nematbakhsh, S.F. Santos, J.P.S. Catalão, "A two-stage joint operation and planning model for sizing and siting of electrical energy storage devices considering demand response programs," in *International Journal of Electrical Power & Energy Systems*, Vol. 138, 107912, June 2022.
Q1 Journal, Impact Factor: 5.659
Published: https://doi.org/10.1016/j.ijepes.2021.107912

M.S. Javadi, **M. Gough**, A.E. Nezhad, S.F. Santos, M. Shafie-khah, J.P.S. Catalão, "Pool trading model within a local energy community considering flexible loads, photovoltaic generation and energy storage systems," in *Sustainable Cities and Society*, Vol. 79, 103747, April 2022.
Q1 Journal, Impact Factor: 10.696
Published: https://doi.org/10.1016/j.scs.2022.103747

G.J. Osório, **M. Gough**, M. Lotfi, S.F. Santos, H.M.D. Espassandim, M. Shafie-khah, J.P.S. Catalão, "Rooftop photovoltaic parking lots to support electric vehicles charging: a comprehensive survey," in *International Journal of Electrical Power & Energy Systems*, Vol. 133, 107274, December 2021.
Q1 Journal, Impact Factor: 5.659
Published: https://doi.org/10.1016/j.ijepes.2021.107274

M.S. Javadi, **M. Gough**, M. Lotfi, A.E. Nezhad, S.F. Santos, J.P.S. Catalão, "Optimal self- scheduling of home energy management system in the presence of photovoltaic power generation and batteries," in *Energy*, Vol. 210, 118568, November 2020.
Q1 Journal, Impact Factor: 8.857
Published: https://doi.org/10.1016/j.energy.2020.118568

Secondary Publications - Conference Papers

D. Guimarães, **M. Gough**, S.F. Santos, I.F.G. Reis, J.M. Home-Ortiz, J.P.S. Catalão, "Agent-based modeling of peer-to-peer energy trading in a smart grid environment," *21th IEEE International Conference on Environment and Electrical Engineering and 5th IEEE Industrial and Commercial Power Systems Europe — EEEIC 2021 / ICPS Europe 2021*, Bari, Italy, 7-10 September, 2021
Published: https://doi.org/10.1109/EEEIC/ICPSEurope51590.2021.9584767

S.F. Santos, **M. Gough**, J.P.D. Ferreira, M.S. Javadi, G.J. Osório, J.P.S. Catalão, "Financial viability of the aggregators' participation in the regulation reserve market," *21th IEEE International Conference on Environment and Electrical Engineering and 5th IEEE Industrial and Commercial Power Systems Europe — EEEIC 2021 / ICPS Europe 2021*, Bari, Italy, 7-10 September, 2021
Published: https://doi.org/10.1109/EEEIC/ICPSEurope51590.2021.9584599

1.5 Thesis Structure

This thesis tackles the overarching research question of how best to design future energy systems to encourage active participation by prosumers and how to manage the impacts of this participation. The tenet of active participation by prosumers has several distinct aspects, requiring that each aspect be examined in a distinct framework. There are five of these frameworks in this thesis, and each examines the question of prosumer participation from a different viewpoint. Each framework contributes to answering parts of the various research questions presented in the previous section.

There are eight chapters, including the introduction and conclusions. Chapter 2 is an overview of prosumer participation and Chapters 3-7 analyze different aspects of prosumer participation in smart grids. These aspects are addressed by developing five interlinking frameworks. Each separate framework relies upon a different technology, regulatory construct, or modeling approach to address certain aspects of prosumer participation. Thus, each framework has a separate nomenclature section to provide a glossary, abbreviations, mathematical symbols, and formulas used in the chapter.

These frameworks may be viewed as parts of a single, broader framework for increasing prosumer participation, but the frameworks have also been designed to be standalone systems. Therefore the thesis may be read as a single document, or the reader may choose specific chapters which more closely address the reader's particular interests. The chapters are briefly summarized as follows:

Chapter 2 sets out the context of the rise of the prosumer and the emergence of distributed energy resources (DERs). The chapter identifies enablers as well as barriers to increased prosumer participation through a scientometric analysis of the existing literature on prosumers. The relevant Portuguese and European regulations concerning prosumers are also introduced and discussed. This chapter provides an overview of the field of research and grounds the modeling work carried out in the subsequent chapters.

Following the contextualization of the research in Chapter 2, Chapter 3 develops a Peer-to-Peer energy trading framework that relies on smart contracts to automate and record the transactions. This model provides evidence that novel business models and emerging information and communication technologies enable increased prosumer participation in smart grids. Notably, the framework is based on the relevant Portuguese energy regulations concerning self-consumption of electricity by small-scale actors, as was introduced in Chapter 2.

Continuing from Chapter 3, the themes of novel business models and new technologies acting as enablers for increased prosumer participation are prevalent again in Chapter 4. In this chapter, a novel data-driven optimization framework is used to develop a device that can optimally control the operation of electric water heaters. In contrast to Chapter 3, which examines a large energy system, Chapter 4 instead focuses on a single device. The device was installed in a pilot project, and the results of the project were used to examine the potential for prosumer participation in a bottom-up manner.

Moving on from examining the bottom-up effects of novel technologies, Chapter 5 instead focuses on the top-down aggregation of a large number of prosumers to examine the technical, economic, and thermal comfort impacts of increased prosumer participation. This is done by extending the concept of the Technical Virtual Power Plant (TVPP). The impacts of increased prosumer participation are allocated in a fair and efficient manner, using an allocation mechanism from cooperative game theory. The framework explores whether aggregation is an effective means of harnessing the full potential of prosumers to improve the technical operation of smart grids according to transactive energy principles.

The preceding chapters have taken the participation of prosumers as a given, as there are direct economic benefits derived from their participation. However, there are other factors that influence the prosumer's decision to engage in a transactive energy system. Chief among these is the concern for their data privacy, and Chapter 6 utilizes Differential Privacy to preserve the privacy of prosumers' smart meter data to address this concern. The framework developed in this chapter examines the technical and economic impacts of privacy preservation and uses various allocation mechanisms from cooperative game theory to allocate these impacts in a fair and transparent manner.

Chapter 7 again changes the focus of the modeling of increased prosumer participation. In contrast to the other chapters, where the focus is on the impacts on the operation of smart grids, Chapter 7 instead focuses on the long-term impacts of increased prosumer participation by developing a novel dynamic planning model to explore the potential of prosumer-owned distributed energy resources to compete with traditional distribution grid investments. By utilizing this dynamic planning framework, the long-term impacts of DERs can be accurately calculated. This can help incentivize the uptake of DERs in locations of the distribution system which need them the most and fairly reward those prosumers who choose to participate using their DERs.

Finally, Chapter 8 concludes the thesis by using the results and conclusions derived in each of the chapters to answer the research questions in detail. The answers to the research questions are used to derive a set of final conclusions and identify future areas for research building upon the frameworks presented in this thesis, which are presented in Chapter 8.

Chapter 2

Overview of Prosumer Participation in Transactive Energy Systems

The emergence of the prosumer concept (those small-scale consumers of electricity who can use Distributed Energy Resources (DERs) to generate, store or use electricity) has the potential to fundamentally alter the structure of future energy systems, especially when incorporated into Transactive Energy (TE) systems. These prosumers have the ability to provide several major benefits to future energy systems but also introduce some novel challenges to the operations and planning of energy systems. A major benefit that these prosumers introduce into the system is increased flexibility or the ability to alter their generation of consumption of electricity in response to some external signals. This increased flexibility can help system operators plan and manage power systems with high penetrations of intermittent renewable energy sources and can help ensure that the electricity demand begins to follow the generation of electricity, which is a new paradigm as traditionally generating plants are dispatched to meet the forecasted demand. The concept of prosumer-provided flexibility is still a nascent topic, and thus this chapter provides an introduction to the topic of prosumers, the potential for prosumer flexibility as well as the barriers and enablers of large-scale incorporation of prosumer flexibility into transactive energy systems. This chapter gathers 1183 peer-reviewed journal articles concerning the topic of prosumer flexibility and uses them to identify the current state of the art. This body of literature was analyzed with two leading textual and scientometric analysis tools, SAS© Visual Text Analytics and VOSviewer, to provide a detailed understanding of the current state-of-the-art research on prosumer flexibility. In addition, the relevant regulations concerning prosumers at a Portuguese national level as well as at a European level are introduced and discussed.

Chapter Highlights and Novel Contributions:

- Provides a detailed overview of the concepts of prosumer flexibility and transactive energy systems.
- A detailed scientometric analysis of the current state-of-the-art research concerning prosumer flexibility is provided.
- The relevant prosumer legislation at a national and European level is discussed.
- The potential for designing transactive energy systems with a focus on prosumers as a foundational element is presented and the concept of a prosumer-centric transactive energy system is introduced.

Relevant Publications:

M. Gough, S. F. Santos, M. Javadi, R. Castro, and J. P. S. Catalão, "Prosumer Flexibility: A Comprehensive State-of-the-Art Review and Scientometric Analysis" *Energies*, 2020, vol. 13, no. 11, Art. no. 11.
Q3 Journal, Impact Factor: 3.252
Published: https://doi.org/10.3390/en13112710

M. Gough, S.F. Santos, A. Almeida, M. Javadi, T. AlSkaif, R. Castro, J.P.S. Catalão, "Development of a blockchain-based energy trading scheme for prosumers," *IEEE Power Tech 2021 Conference*, Madrid, Spain, June 27 - July 1, 2021
Published: https://doi.org/10.1109/PowerTech46648.2021.9494810

Chapter 2 Nomenclature

Abbreviation	Definition
DR	Demand response
DSF	Demand-side flexibility
DSM	Demand-side management
DERs	Distributed energy resources
ESS	Energy storage systems
FIAD	Flexibility Index of Aggregate Demand
HEMS	Home Energy Management System
MFIAD	Modified Flexibility Index of Aggregate Demand
PFL	Percentage Flexibility Level
RES	Renewable Energy Sources
PV	Solar photovoltaic
vRES	Variable renewable energy sources

2.1 Introduction

2.1.1 Emergence of the Prosumer Paradigm

The current energy system is undergoing a series of profound changes, which by and large, can be described using the three Ds of decarbonization, decentralization, and digitization. With this significant shift occurring in the electrical energy system, new actors and new methods of controlling and organizing the system are emerging. This chapter is an introduction to a new actor, a prosumer, and a new control framework that can be combined to provide numerous benefits to future decarbonized, decentralized, and digitized electricity systems.

The new actor mentioned above is the so-called prosumer, a portmanteau of producer and consumer. These prosumers are consumers of electricity who also have the means to generate and store electricity in such a manner that, during specific periods, they become net producers of electricity and may export or sell the surplus to the existing grid or neighboring consumers [3][4]. These prosumers may have flexible generation or demand, which can be utilized in such a manner to increase the flexibility of the broader electrical system. The flexibility[1] of electricity systems is becoming a pronounced issue, especially with the increasing penetration of intermittent renewable energy generators. Having a multitude of prosumers who can provide flexibility services at the hyper-local level of electrical networks is very beneficial to the operators of the system. While the magnitude of flexibility offered by a single prosumer may be small, the aggregate effect of a group of prosumers may be significant. Driving the increase in the number of prosumers is the increasing digitalization and the use of low-carbon forms of electricity generation, which have enjoyed significant cost declines in recent years. The emergence of prosumers is also helping to add a fourth D to the three D's mentioned above. This fourth D is the decision-making power of the prosumer, as they can begin to choose whether or not to participate in the energy system, and future energy systems may be less hierarchical with more decision-making power given to prosumers [5] [6].

Having an increased number of decentralized prosumers can only benefit the broader electricity system if these prosumers can operate together according to some common coordination framework. The concept of Transactive Energy (TE) provides precisely this framework for the control of a large number of decentralized actors who may have their own objectives [7]. This framework is designed to control and coordinate many DER owned by various entities and users. The TE framework uses market-based approaches to incentivize the trading of both energy and information between participants [8]. TE mechanisms can use price, thermal comfort, technical, and environmental signals to coordinate energy markets across the entire power system infrastructure [9].

[1] In this chapter and in the rest of the thesis, the term flexibility is defined as the ability to alter the generation or consumption of electricity in response to some external signal.

The above sections have introduced the prosumer and transactive energy concepts and briefly discussed how the increased flexibility potential of prosumers may be harnessed using the transactive energy concept. In the next sections, a deeper analysis of prosumer flexibility is carried out, including a scientometric analysis of the existing literature surrounding prosumer flexibility.

The flexibility of electricity systems is becoming increasingly important. This is because one of the more unique characteristics of power systems is that the consumption and production of electricity should occur at the same time. Energy storage systems (ESS), mostly pumped hydro systems and, more recently, battery ESSs have challenged this paradigm, but for the vast majority of the time, the consumption and production of electricity must coincide. Both supply and demand for electricity fluctuate, but until recently, the fluctuations in demand were of primary concern [10][11]. Demand profiles change drastically over different periods, from days to weeks to months. The supply of electricity was thus built around these demand fluctuations with different electricity-generating technologies used to meet various aspects of demand across varying periods [12]. Baseload demand was primarily met by nuclear and coal-fired power plants, while the peaks in demand were met by gas turbines or hydroelectric power plants. This paradigm was based mainly on supply following variable demand. The power system required some flexibility to account for demand deviations, which were met mainly by increasing or decreasing the electricity production from various power plants.

This paradigm has started to shift with the awareness that the power system needs to decarbonize, and this has mainly been done by the introduction of a large amount of variable renewable energy sources (vRES), mainly wind and solar photovoltaic (PV) [13, 11]. The power produced from vRES cannot be dispatched and is subject to significant variation and uncertainty. This has increased the power system's complexity and requires new sources of flexibility as the existing sources are no longer sufficient. The changes being experienced by the power system are shown in Figure 2.1. This figure shows three drivers of change: the need to decarbonize the energy system by increasing the penetration of Renewable Energy Sources (RES), the need to reduce system costs, and the need to increase the flexibility of the system. These drivers are met by four enablers of the energy transition: novel technologies, new business models, innovative market design, and new system optimization and operation methods. The combination of drivers and enablers produces an ideal opportunity to develop prosumer flexibility into a critical aspect of future power systems.

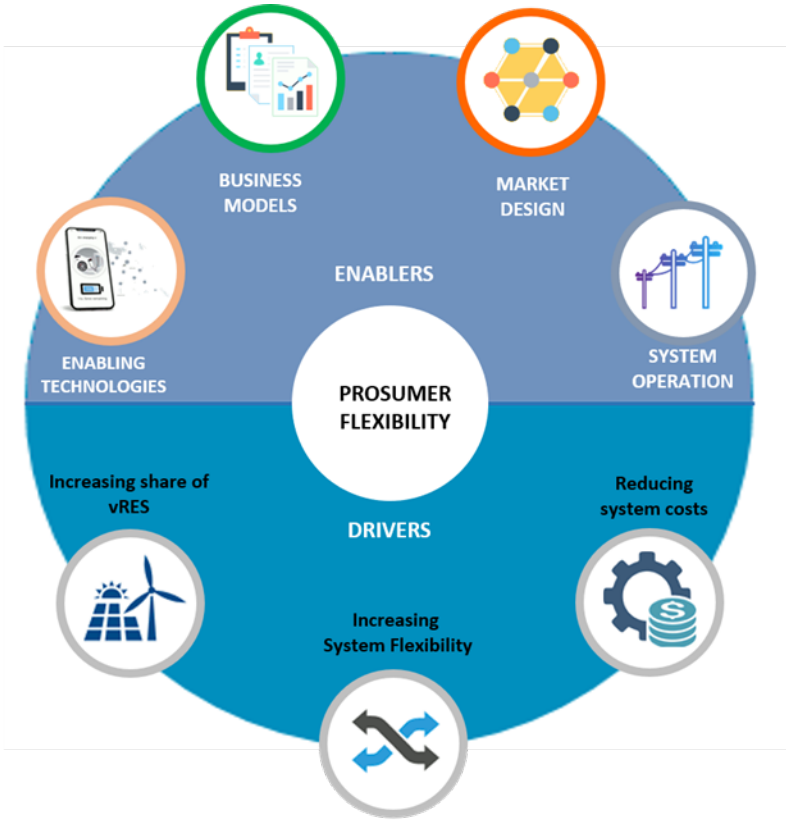

Figure 2.1: Changing energy landscape.

Apart from helping to match supply and demand, sources of flexibility can also assist in various ancillary services such as frequency and voltage profile control and help to defer certain costly investments in network infrastructure [14]. Historically, flexibility sources have been provided by the supply side of the power system, and this was done by changing the level of electricity produced (either increasing or decreasing), investing in more flexible technologies, regional integration of power systems, or curtailing RES production. Also, methods to increase the flexibility of the system from the demand side include demand response programs and energy efficiency initiatives, while grid-side measures to increase flexibility have included optimal network reconfiguration, incorporation of smart grid technologies, and dynamic altering line ratings [12]. In addition, ESS can provide flexibility, and efficiently designed markets and regulations can help incentivize the uptake of flexible technologies [15]. Flexibility resources on a large scale (industrial, commercial, and wholesale measures) have been widely used for grid management in the past. There has been an effort to increase the flexibility of the demand side of the power system as well. Recently, there has been discussion around the increased utilization of flexibility provided by prosumers, but these measures have largely failed to take root. These difficulties can be explained mainly by technological shortcomings as well as issues related to developing markets for prosumer flexibility. In the preceding years, developments in technology have primarily solved these issues, and there is a concerted effort to introduce incentives and markets to increase the impact of prosumer flexibility [15, 16].

In recent years, demand-side measures to increase flexibility have become more common and are now thought to be the least costly and most viable means of adding flexibility to the power system, especially with large amounts of RES generation. This has meant a shift away from the traditional paradigm of supply following demand to a paradigm of demand being altered to meet the available supply of electricity. The potential of the demand side to contribute flexibility has been widely discussed, and the potential for demand-side flexibility is thought to be significant. Methods to change the demand profile of consumers (through either monetary or non-monetary incentives) have been used. These methods could involve a permanent modification of consumption, such as energy efficiency initiatives, or more temporary measures, such as time-of-use tariffs [15].

This shift has also meant that consumers are becoming more active in the energy system. They are transforming from passive agents to prosumers who can take an active role in future electricity systems. One of the major resources that have been used for modulating demand in terms of both magnitude and timing has been demand-side management (DSM) [17]. The most common strategies of DSM may include load shifting, valley filling, conservation efforts, planned load growth, and peak clipping. DSM is still primarily operated by the utility but involves higher customer participation. Increasing the level of customer participation is vital in building future energy systems where customers are placed at the heart of the system. Prosumer flexibility can increase the level of involvement and allow the energy system to be more customer-centric [18]. Genuine customer participation will occur when the customer can decide how, when, and why they interact with the broader energy system. Customers should be allowed to utilize their resources in a manner that, first and foremost, benefits them.

To maximize the societal welfare delivered by an energy system, it will be essential to maximize the welfare of all participants in the system, including prosumers. The key to maximizing the benefits that prosumers can offer will be providing them with the necessary knowledge and decision-making frameworks [19],[20]. Additionally, effective control and operational frameworks will be essential to utilize the potential of prosumer flexibility fully.

In addition to providing consumers with the necessary technical knowledge, the political and regulatory issues relating to the market design and incentives for the energy system to embrace prosumers must be also resolved. This is most evident in the European Commission's Clean Energy for all Europeans initiative which is designed to put the consumer at the heart of the energy system and leads to a decentralized energy system based mainly on RES and allows customers to actively participate in the energy system using various assets and resources. This Clean Energy package requires the member states of the European Union (EU) to begin the process of removing barriers that currently prevent demand-side resources from actively participating in wholesale and retail markets.

This has meant that there is considerable interest in quantifying the potential for flexible services to be provided by the demand side of the power system, with a clear focus on the provision of these services by prosumers. This chapter summarizes the current literature surrounding prosumer flexibility and applies a scientometric analysis to the body of literature to better understand the trends, key aspects, opportunities, and challenges within the body of knowledge for this emerging and rapidly growing area of research.

2.1.2 Prosumer Flexibility

Prosumer flexibility is essential for the cost-effective and efficient integration of RES into the energy system [21],[22]. Increasing the flexibility of the system through prosumer engagement can help to better manage the fluctuations not only in demand but also in increasingly fluctuating supply. Prosumers can help with the idea of balancing supply and demand at a local level, which can help with the reliability and resilience of the energy system. There are concerns that increasing customer participation may not be desirable from a customer's point of view if this increase in involvement leads to increasingly complex decisions about their energy use at various times throughout the day [23]. This concern can be alleviated by the automation of DSM programs through smart grid technologies of Home Energy Management Systems (HEMS) [24] or novel Information and Communications Technologies (ICT) such as blockchain-based smart contracts [25].

While the potential for prosumer-provided flexibility has been widely discussed, a clear distinction needs to be made between the theoretically available potential for prosumer flexibility provision and the realizable amount of flexibility that prosumers may offer. This depends on the technologies considered in the analysis as well as the type of flexibility program studied. In addition, the amount of flexibility available largely depends on the behavior of the customer, and the analysis of this behavior has been difficult to forecast and then modify [26],[19]. Changing the behavior of customers is a crucial problem to solve if the potential for DSF is to be realized [27].

In addition, it is difficult to reliably determine the energy demand and flexibility resources available to a certain prosumer at a given time [28]. There is significant uncertainty about these issues, and aggregators of flexibility services could play an essential role in resolving these concerns [29, 30]. The aggregation of various types of devices (each with its own flexibility profile) requires a detailed understanding and modeling of that specific device [31]. Some studies have raised concerns about the collection of a large number of private consumers' data as well as issues relating to the communication overheads that such systems require [32]. Points are also raised about the effect of a large number of prosumers carrying out coordinated actions within a small geographic area, for example, when a large number of electric vehicles (EVs) are charging at a certain location in the distribution grid [33, 34].

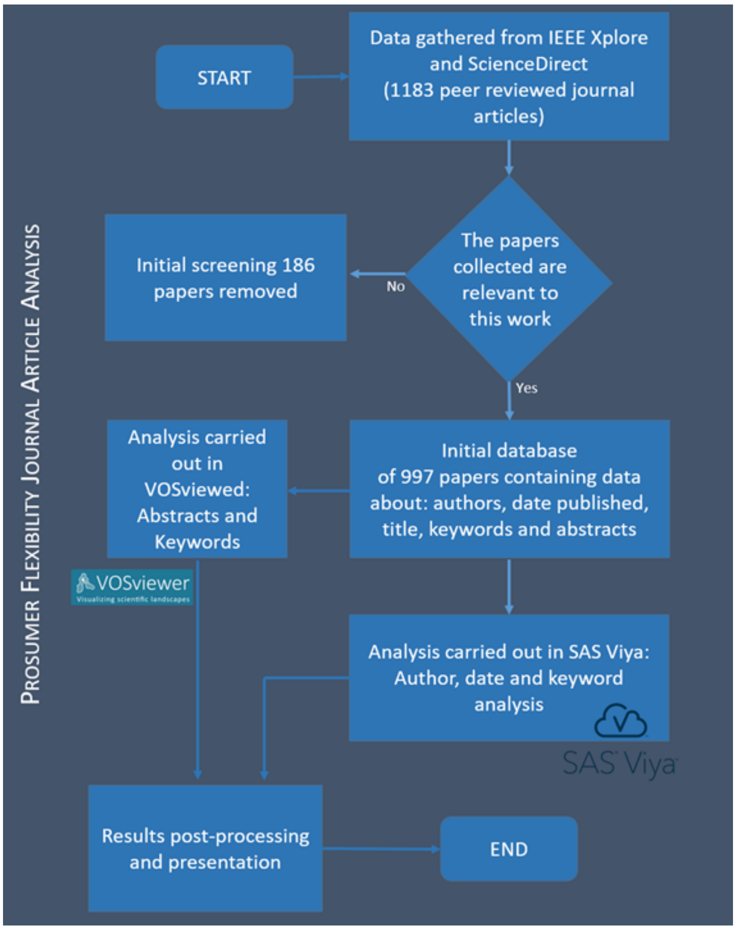

Figure 2.2: Workflow used to carry out the scientometric analysis

2.2 Scientometric Analysis

2.2.0.1 Textual Analysis

A detailed scientometric analysis was carried out to present a thorough review of the current literature around prosumer flexibility. There has been a rapid increase in the amount of literature concerning prosumers and flexibility; however, a detailed analysis of this literature has not been presented. This chapter uses a combination of two tools that use natural language processing, machine learning, and various linguistic rules and applies them to a large dataset containing over 1000 peer-reviewed academic articles concerning prosumer flexibility. The results of this analysis are used to inform the remainder of this chapter, and the thesis in general, as they provide a structure of the most relevant terms used in the literature surrounding prosumer flexibility. The methodology used in the scientometric and text analysis, which was carried out to examine the data associated with the collected 1183 peer-reviewed journal articles, is presented in Figure 2.2.

2.2.1 Tools and Datasets Used

A combination of two well-known tools was used in this analysis. The first tool used was SAS Visual Text Analytics in SAS Viya (version 8.5) and the second was VOSviewer (version 1.6.15). Both tools are designed to extract information from a large textual database and these two tools were chosen to evaluate the differences that might occur and to produce a complete assessment of the body of literature. The statistical and linguistic methods of SAS© Visual Text Analytics were used to extract information about the authors, keywords, and dates of publication of the various papers.

VOSviewer is software designed to carry out a scientometric analysis of bibliometric networks. The text mining functionality of VOSviewer was used to construct and determine the co-occurrence networks of the abstracts of the various papers, where co-occurrence is defined as the network of links between terms in the keyword lists of the studied papers [35]. VOSviewer was developed by Nees Jan van Eck and Ludo Waltman at the Centre for Science and Technology Studies at Leiden University [35].

In total, 1183 distinct papers were analyzed. The metadata of the papers was extracted from the ScienceDirect and IEEE Xplore portals with the keywords 'prosumer' and 'flexibility' in November 2019. The existing literature concerning flexibility was surveyed and a number of reviews focused on flexibility services, especially from the supply side, were found [12, 11]. Thus, the decision was made to focus on a specific aspect of flexibility provision, with a clear focus on the demand side provision of these services. Existing literature reviews were found on the following search terms: demand-side flexibility [36], residential flexibility [37], and local flexibility markets [38]. It was seen that there had not been a thorough review of the flexibility provided by prosumers, and thus this research sought to chart the rise of the active participation of prosumers in electrical networks by examining the current state of the art of research concerning this topic.

The searches were limited to journal articles and thus the papers analyzed in this study are peer-reviewed and of a high standard. The first step of the analysis was an initial screening to ensure that the papers concerned the electricity system and dealt with flexible services provision by active customers within distribution networks. Of these 1183 papers, 186 papers were removed at this stage as they were not relevant to the topic of prosumer flexibility.

The metadata of each paper was then extracted from the relevant database, either ScienceDirect or IEEE Xplore. The data extracted included the title, authors, keywords, date of publication, and the full paper abstract. The information was then put into a database that was fed into either SAS Viya or VOSviewer depending on the type of analysis carried out.

During the analysis, a minimum threshold of occurrences of a specific term was used and the threshold used was a minimum of 10 occurrences of the term. This corresponds to the term appearing in approximately 1% of the 997 articles studied. A total of 26 terms met this requirement. A relevance score was calculated by VOSviewer to highlight the most relevant terms. As a default option, 60% of the most relevant terms were included in the network plots. The 60% most relevant terms were then verified and added to the network plots.

2.3 Scientometric Analysis Results

The results of the scientometric analysis are divided into four subcategories, year, author, keyword, and abstract. Each of these subsections provides some relevant information relating to the body of literature surrounding prosumer flexibility.

2.3.1 Prosumer Flexibility Over Time

From the available papers, the frequency of papers dealing with prosumer flexibility published during the years between 2008 and 2020 is shown in Figure 2.3 below. The first use of the term prosumer appeared in [39] in their discussion surrounding uncertainties in the design and operation of distributed energy resources (DERs).

As can be expected, there are very few papers published dealing with prosumer flexibility up until 2016, when there is a noticeable increase in publications. There were 134 papers published in 2016 that dealt with prosumer flexibility, which was slightly less than all of the papers published from 2008–2015.

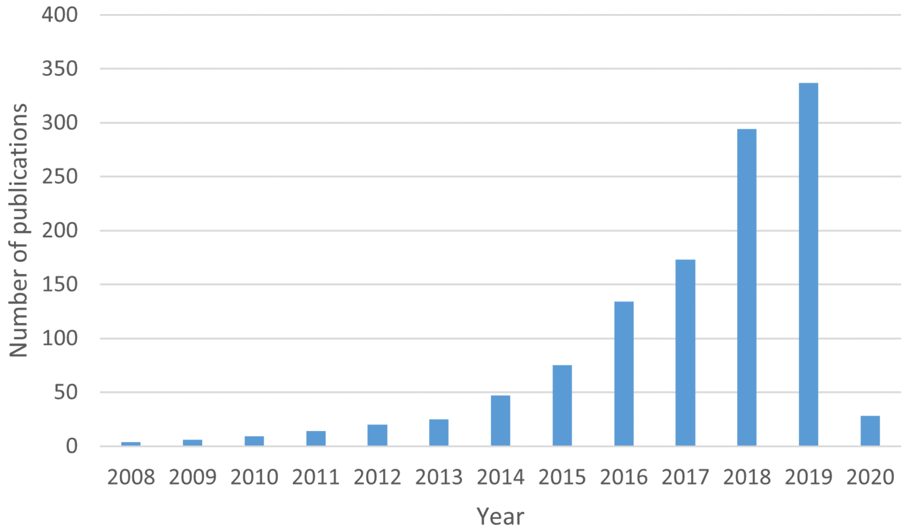

Figure 2.3: The number of articles on "prosumer flexibility".

2.3.2 Abstract Analysis

The full abstracts of all 997 papers were studied using VOSviewer to provide a detailed scientometric analysis of the papers [35]. VOSviewer allows for two types of counting methods for words within abstracts. These two methods are full counting and binary counting. Full counting means that each occurrence of a word within an abstract is counted, whereas with binary counting, the number of times that a word occurs within an abstract is not counted, all that is counted is if that word appears within the abstract. Full counting is used in this study as it can provide a more detailed description of the frequency of words used in an analysis. Two images are presented, dealing with the analysis of the abstracts using the full counting methodology. These images are the network and density plots from the VOSviewer tool. The network plot shows the interrelation between certain terms and this is shown in Figure 2.4. The different colors represent the clustering of the terms with each other. The size of the circle is related to the frequency of the word within the abstracts and the links show the words that occur most frequently with the chosen word. As can be expected from an abstract that aims to give a brief overview of the work, including the motivation behind the research and a summary of the results, the words identified by VOSviewer are quite generic, with the most frequent words being cost, research, and problem. Business model, load, and power system are the next most frequently used words that are more closely related to the energy system. The words are clustered into groups of words that most often appear together, and, in this research, two major clusters emerge, these are the 'Red' cluster, which is more closely associated with power systems, for example, 'electricity', 'microgrid', and 'battery', and the 'Green' cluster, which is more associated with the general planning of academic research and contains words such as 'research', 'innovation', and 'information'.

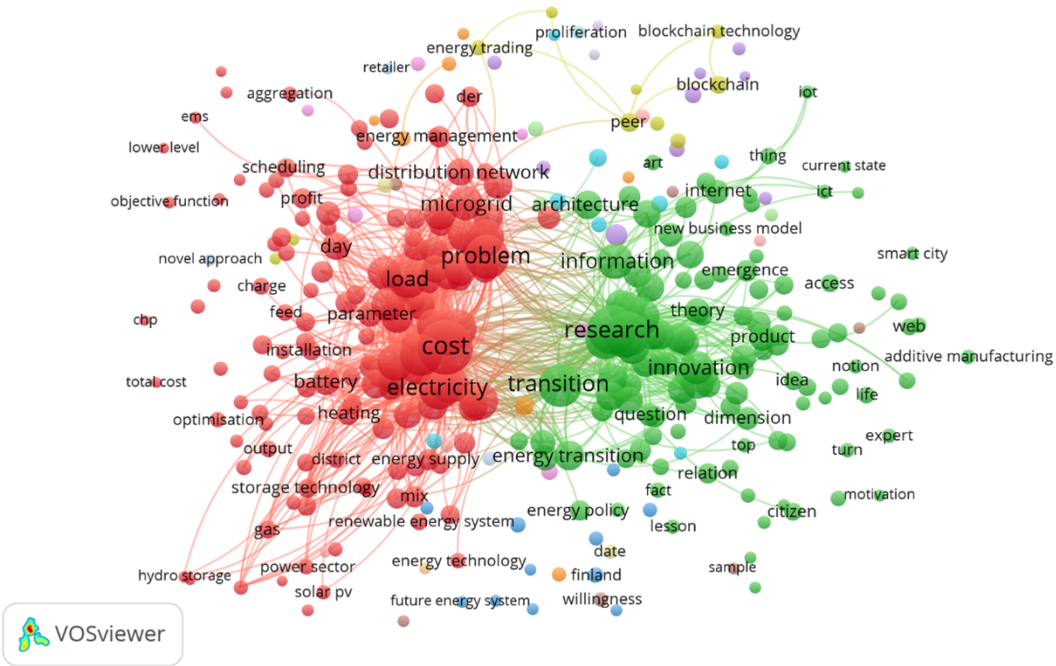

Figure 2.4: Connections between the abstracts through the full-counting analysis from VOSviewer.

The density plot represents the number of times that a word is used within the abstracts and is shown in Figure 2.5. For the full counting methodology, the three most common words were research, cost, and problem.

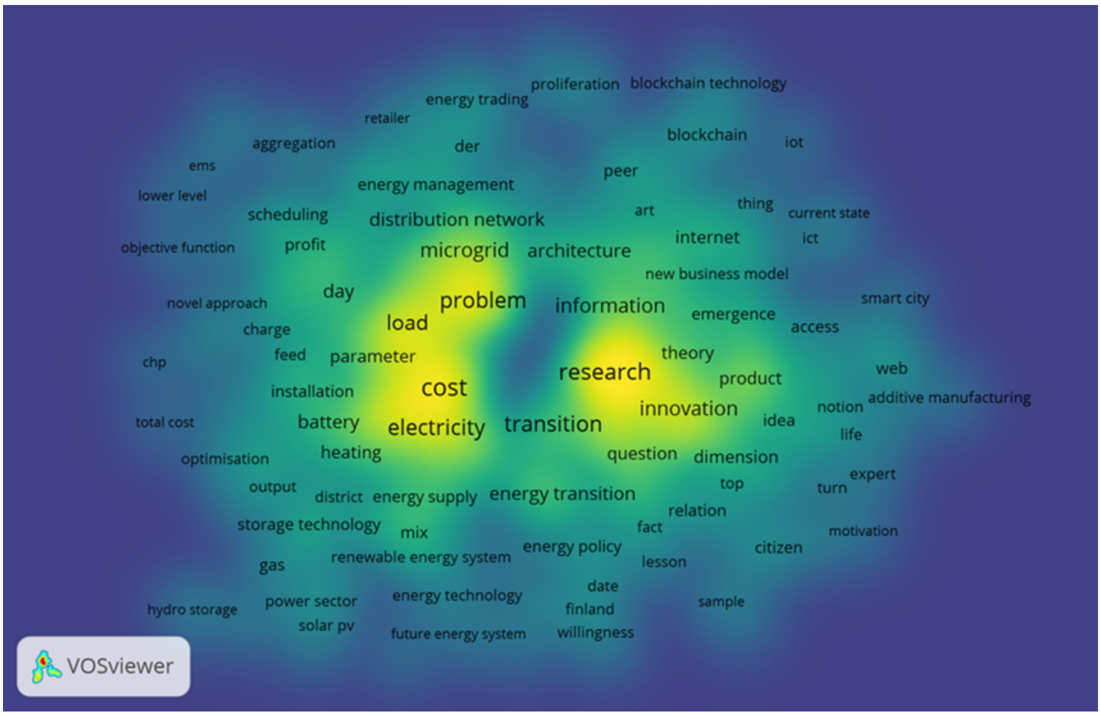

Figure 2.5: Density plot of full counting analysis of abstracts by VOSviewer.

2.3.3 Keyword Analysis

The final section of the analysis was done on the keywords of each of the 997 journal articles. For this analysis, both SAS Viya text analysis and VOSviewer were used. This was done to compare and contrast the results of the two methods. The results of the keyword analysis conducted by VOSviewer are presented in Figure 2.6, where the size of the circle represents the frequency of occurrence. The lines show the links between the keywords. The colors of the keywords represent clusters of terms that most often appear together.

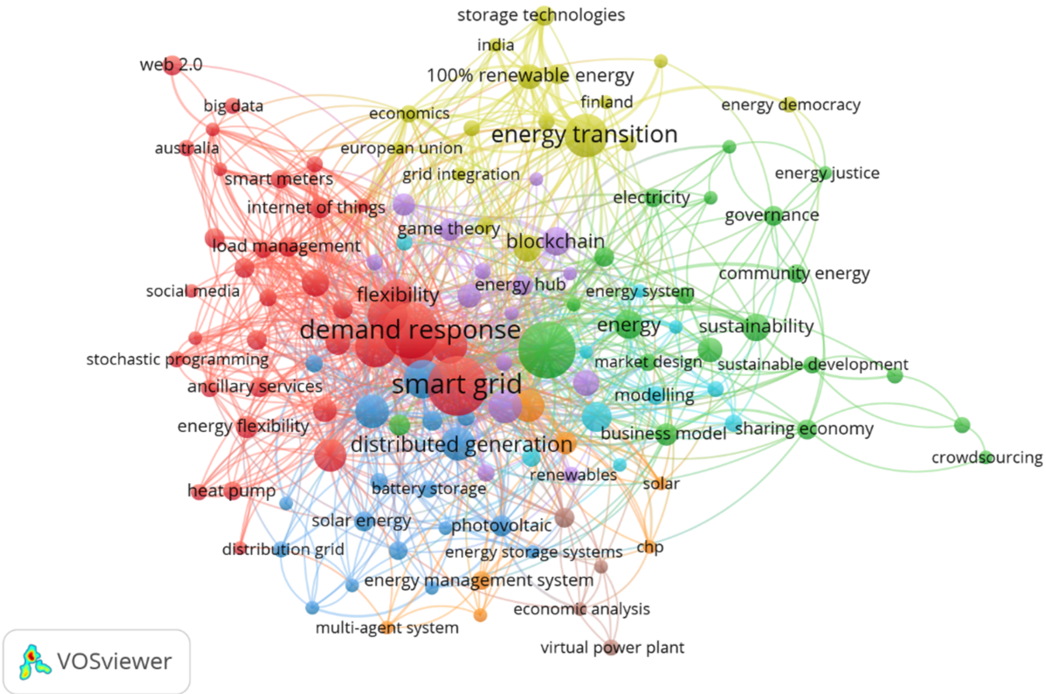

Figure 2.6: Keyword analysis by VOSviewer.

The term flexibility is found to occur in two separate ways, which are 'flexibility' and 'energy flexibility.' This splitting of the term helps to explain why flexibility is not the most common keyword in the body of literature. However, each of these terms has been isolated, and thus the connections between them can be studied in depth. Firstly, 'flexibility' is isolated, and the resulting connections are shown in Figure 2.7. Within its cluster, the most strongly associated words with 'flexibility' are 'demand response' and 'smart grid' with 'prosumer,' 'market design,' 'load management', and 'power systems'.

Secondly, the term 'energy flexibility' is isolated and studied in Figure 2.8. Like the 'flexibility' figure, there are strong connections to 'smart grid' and 'demand response', but also strong connections to 'renewable energy' and 'energy management'.

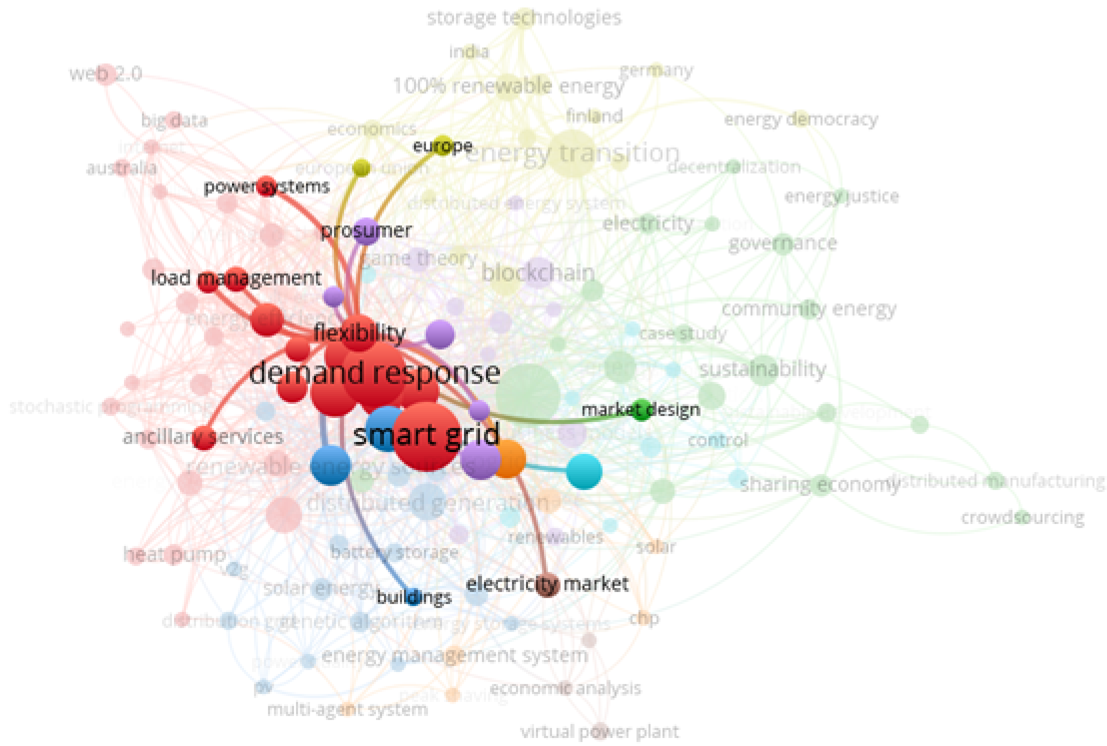

Figure 2.7: Connections from the term 'flexibility.'

The keyword analysis conducted in SAS Viya is highlighted in Figure 2.9. The word cloud shows the most common keywords in all 997 papers. The size of the word represents the frequency of occurrence with the term 'smart grid,' occurring 196 times in the papers studied. This shows that 'prosumer' and 'flexibility' are often used alongside the much more widely used terms 'smart grid' and 'demand response.' This trend may begin to change as more research is conducted on both 'prosumer' and 'flexibility.'

The top five most frequent terms used in the keywords, as analyzed by SAS Viya Text analysis, are presented in the following sections to provide a complete overview of prosumer flexibility. These keywords are smart grid, demand response, microgrid, prosumer, and distributed energy resources. In each of the following sections, the term is described in detail, and its relation to the concept of prosumer flexibility is presented.

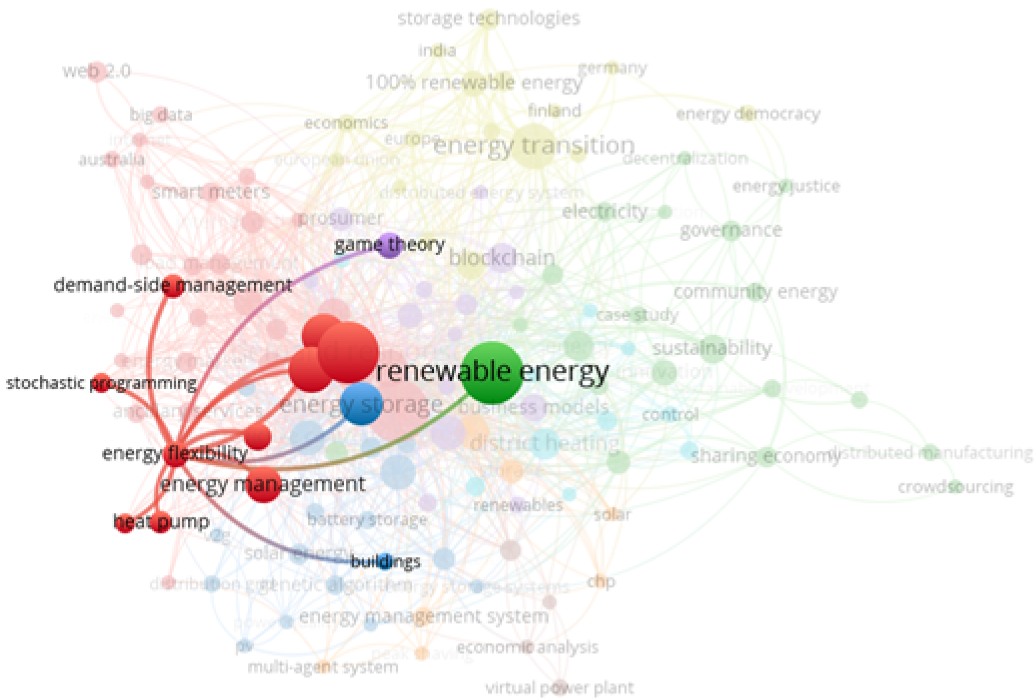

Figure 2.8: Connections from the term 'energy flexibility'.

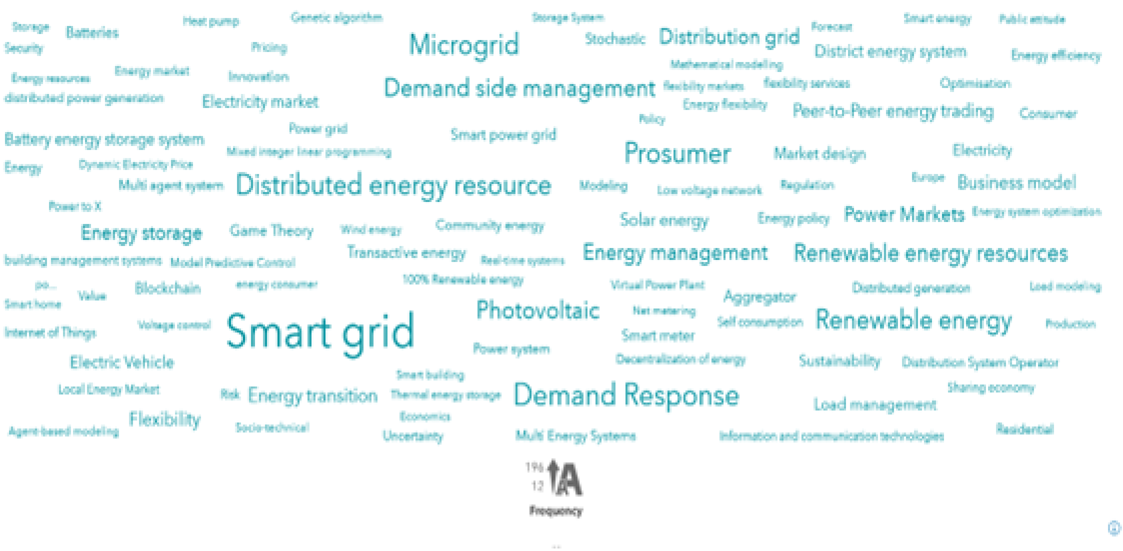

Figure 2.9: Keyword analysis by SAS Viya

2.4 Key Issues Identified from the Literature

This section will discuss each of the top five most frequently-used words, as identified in the text analysis conducted with SAS Viya. Each of the identified issues is important enough to have a whole field of dedicated research behind them, but the interactions between them, and other issues, are essential for the concept of prosumer flexibility. The cyclical interaction between the terms is shown in Figure 2.10 below, where the prosumer owns the DERs which participate in demand response (DR) programs enabled by smart grids and microgrids, who have prosumers as their participating members.

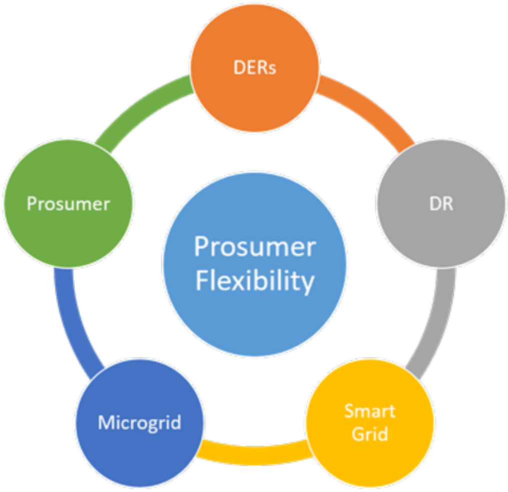

Figure 2.10: Key issues identified from the literature.

2.4.1 Smart Grid

The term ‘smart grid’ was the most used keyword of the 997 papers analyzed. Despite the term occurring 196 times in the literature, there is no agreed-upon definition of a smart grid. Through VOSviewer, the term ‘smart grid’ was isolated, and the connections to other words are shown in Figure 2.11. As can be expected, it forms a central part of the keyword analysis with solid connections to several essential topics in this research field. Although the smart grid is the most commonly used keyword in the body of literature analyzed, a consensus exists about the concept, the technologies needed, and the requirements of a smart grid [40],[41]. This clear consensus is best described by the definition of a smart grid provided by [42] as an advanced digital power system using bidirectional power flows, which is capable of self-healing while also operating in a resilient, adaptable, and sustainable manner using forecasting techniques to manage various types of uncertainties. Another widely used definition is provided by the European Commission’s Strategic Energy Technologies Information System. In their document, entitled “Strategic Deployment Document for Europe’s Electricity Networks of the Future”, they define a smart grid as an intelligent electric network that incorporates the actions of all agents who use the grid to efficiently provide electricity that is sustainable, economic, and secure [43]. In these definitions, ’smart’ applies to the use of technologies and software that increases the ability of the grid to operate autonomously. This can benefit the grid and the users in both a short-term operational time frame as well as in the long term. Various technologies and software, such as supervisory control and data acquisition systems, Energy Management systems (including Home Energy Management Systems), and Demand Management systems can be utilized. These technologies are used to allow the grid to incorporate more active participation from its users [44].

Relating to prosumer flexibility, the advanced technologies and software of the smart grid can be used to track, measure accurately, and predict the demand of customers in a very granular manner [45]. This information can then be used to estimate the customers’ demand response or flexibility potential. Also, these smart grid technologies can be used to increase the ease and speed of communication of customers, not only with the centralized system operator but also with other customers as well [45]. Smart grids can also play a leading role in increasing the penetration of RES (including several types of DERs). Shortages or surpluses of electricity can be rapidly quantified, and actions (such as demand response) can be activated to balance the grid [46]. Several other smart grid systems and technologies can be used (such as Advanced Metering Infrastructure, Substation Automation, and Preventive/Self-Healing Mechanisms) [42].

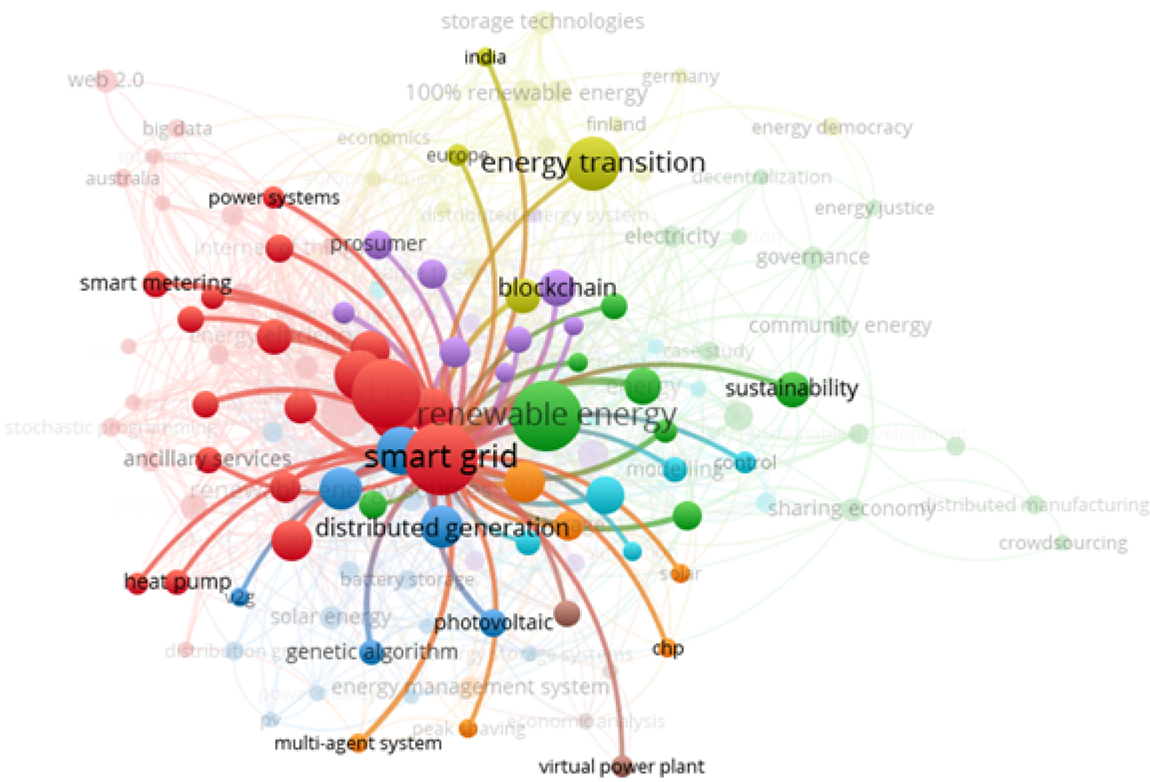

Figure 2.11: Highlighting the connections around ‘smart grid’.

Prosumer flexibility sits within the broader area of demand-side flexibility. Demand-side flexibility (DSF) can cover a wide range of flexibility operations, including resources owned and operated by a wide variety of agents (including prosumers, system operators, and utilities) [47]. Prosumer flexibility deals with the flexibility of resources of individual customers actively participating in the distribution system. These customers can use a variety of tools and technologies to participate, but the critical aspect is that they own and operate the technologies and are actively choosing to engage with the distribution system for a variety of reasons—for example, for financial gain or environmental consciousnesses.

As can be expected, with smart grids being the most frequently used keyword in the literature on prosumer flexibility, smart grids are seen as a critical enabler of increased prosumer flexibility. Smart grids can assist in providing access to flexibility markets for a variety of different actors [48]. Despite the potential of smart grids to enable prosumer flexibility, there are still many concerns and challenges that smart grids need to overcome [42]. Ensuring the security of the supply of energy with a RES-based system is a significant obstacle to overcome. However, there are a host of potential solutions to this issue, including Energy Storage Systems (ESS), small modular generators, and multi-energy systems [49, 50].

A critical smart grid technology for unlocking prosumer flexibility is the smart meter. These devices can measure, record, transmit and receive information about a customer's energy use with very fine granularity and can help provide rapid feedback to customers about their energy use and thus potential energy costs [51].

System operators and utilities can also use these devices to dynamically alter the price according to the demand and supply of electricity which can help to either incentivize load curtailment or increase the use of flexibility resources. Information about the real-time supply and demand of energy across a system will be essential for any energy system of the future and smart meters can help to record and spread this information [52].

Another technology, or more specifically a group of technologies that can help to harness the potential of prosumer flexibility, are Home Energy Management Systems (HEMS). Broadly speaking, HEMSs are composed of a collection of controllable appliances whose energy use can be altered to meet the needs of the occupants optimally [53, 24]. HEMS, like smart meters, provide valuable information on the energy usage profiles of various technologies and can manage these profiles to suit the needs of the inhabitants. HEMS can also incorporate DERs to manage the production and consumption of electricity more effectively within a household. The overarching goal of a HEMS is to ensure that the energy needs of the inhabitants are met as efficiently as possible, but there are other goals that the HEMS may be required to achieve, such as lowering the energy bill, increasing the self-consumption of electricity from the household's DERs or actively participating in DR programs [54, 55].

While HEMS can assist in unlocking the potential for prosumer flexibility, there are some concerns and obstacles to its widespread adaptation. The primary concern is providing connectivity to a wide variety of devices that are manufactured by different suppliers, and thus the interoperability of devices will be a crucial obstacle to overcome [56]. Again, the issue of data privacy and security is of great concern to the users of HEMS. Methods to safeguard this data will need to be developed before HEMS can become widely used [57]. A concept that is linked to HEMS is the idea of smart buildings. Smart buildings can offer similar characteristics to HEMS but with commercial and office buildings as the primary focus rather than residential buildings [58].

2.4.2 Demand Response

The second most frequent keyword within the studied literature was 'demand response'. Demand response provides flexibility to the electric system as it can alter electricity consumption through changing prices or by offering incentives to customers to alter their load at certain times or during specific events [59]. The connections surrounding the term 'demand response' are shown in Figure 2.12.

The official definition of DR is given by the US Federal Energy Regulatory Commission, and it defines DR as the following "*changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time or to incentives payments designed to induce lower electricity use at the time of high wholesale market prices or when the system reliability is jeopardized*". This definition covers prosumer flexibility and as such, prosumer flexibility can be thought of as a tool that can be used in DR programs. The results of effective DR programs are to increase the electric system's flexibility, responsiveness, and adaptability according to various signals (for example, changing costs of electricity) [60, 61].

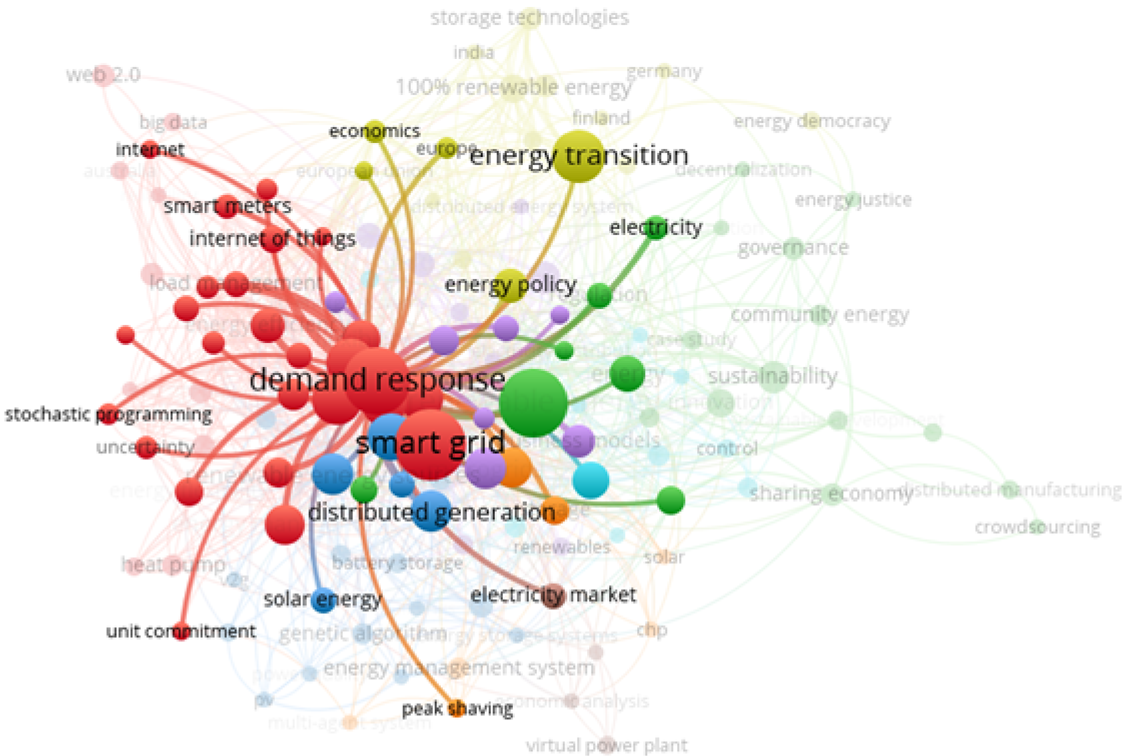

Figure 2.12: Highlighting the connections around 'demand response'.

There exists a split between price-based and incentive-based DR. Price-based DR, as the name suggests, uses changes in the price of electricity to alter the demand of customers, whereas incentive-based DR programs use incentives (either financial or non-financial) to alter consumption patterns. Effective DR programs can deliver increased flexibility to the electricity system as well as reduced costs for the consumer, amongst other benefits [59, 62]. Demand response programs have existed for numerous years, but it is recently where the majority of interest in DR programs has occurred [63, 64]. DR programs can reduce electricity costs for customers and increase the penetration of RES [65, 51]. One exciting application of DR programs to prosumer flexibility is the use of aggregators to combine a large number of individual customers to gather significant flexibility to participate in existing markets. DR, through aggregation, can utilize incentive-based or price-based DR programs. Incentive-based programs can include direct load control, load curtailment, demand bidding, or emergency demand reduction programs, while price-based DR can utilize changing electricity tariffs to induce the required behavior from consumers [59]. The use of a direct control mechanism provides the aggregator with direct control of an individual's resources and thus allows the aggregator to be sure of the timing and quantity of energy available to participate in any market. As mentioned previously, smart meters are an essential technology not only for smart grids but also for effective DR programs. Meters will need to be able to receive and send dynamic price signals to both the operator as well as the prosumer [66].

Moreover, aggregators will need to gather sufficient information about the consumer's power usage to participate effectively in DR programs. The different effects of DR programs on the load profiles are shown in Figure 2.13. These include peak clipping which is a reduction in the peak load; valley filling, which incentivizes power use in low demand periods to reduce the peak-to-average load ratio; Load Shifting, which incentivizes load being moved over time from high to low periods of demand; and Flexible Load Shaping, which helps to smooth out the load profile over time. In addition, energy efficiency measures can reduce the magnitude of the entire load profile and strategic load growth, which aims to do the opposite, i.e., to increase the load demanded.

Despite these clear benefits, there are still some issues and challenges surrounding DR programs. These issues are the lack of appropriate DR markets, policies, effectual forecasting techniques, appropriate control methods, as well as issues relating to communication [12, 59]. A further challenge to the effective use of DR by prosumers emerges from the prosumers themselves. Consumer behavior is incredibly difficult to predict [26, 67]. Individuals have a wide variety of priorities that change over time, age, income level, and weather conditions and are often not consistent [68, 26, 18]. This is made more challenging when more than one individual lives in a household. Another significant challenge is associated with privacy and data security. Participants' data used in a DR program will need to be kept safely and securely [69, 70].

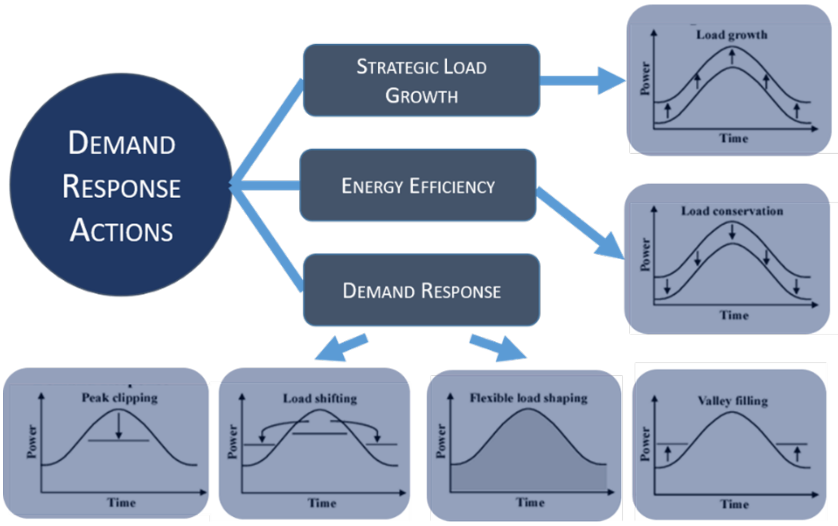

Figure 2.13: Types of demand response actions.

2.4.3 Microgrid

The term microgrid was the third most frequent keyword in the studied literature. There is more consensus about the definition of microgrid compared to the smart grid but there still exist several different definitions of the term microgrid. As with the term 'flexibility', there are two different ways that microgrid is used in the literature. The first is 'microgrid' and the second is the plural 'microgrids'. The connections between each of the two terms are shown in Figure 2.14 and Figure 2.15 respectively.

In this paper, the definition of a microgrid follows the definition used by the Department of Energy of the United States is used and it defines a microgrid as the following: "*A group of interconnected loads and distributed energy resources within a clearly defined electrical boundary which acts as a single controllable entity with respect to the grid. A microgrid can disconnect from the grid to enable it to operate in both grid-connected or islanded mode*" [71]. [72] further generalize this description to have three requirements of a microgrid. These three requirements are

1. It must be possible to identify the part of the distribution system to which the microgrid is connected.
2. The resources used within the microgrid should be used together in a coordinated manner rather than in coordination with distant resources.
3. The microgrid can operate regardless of if it is connected to the wider grid.

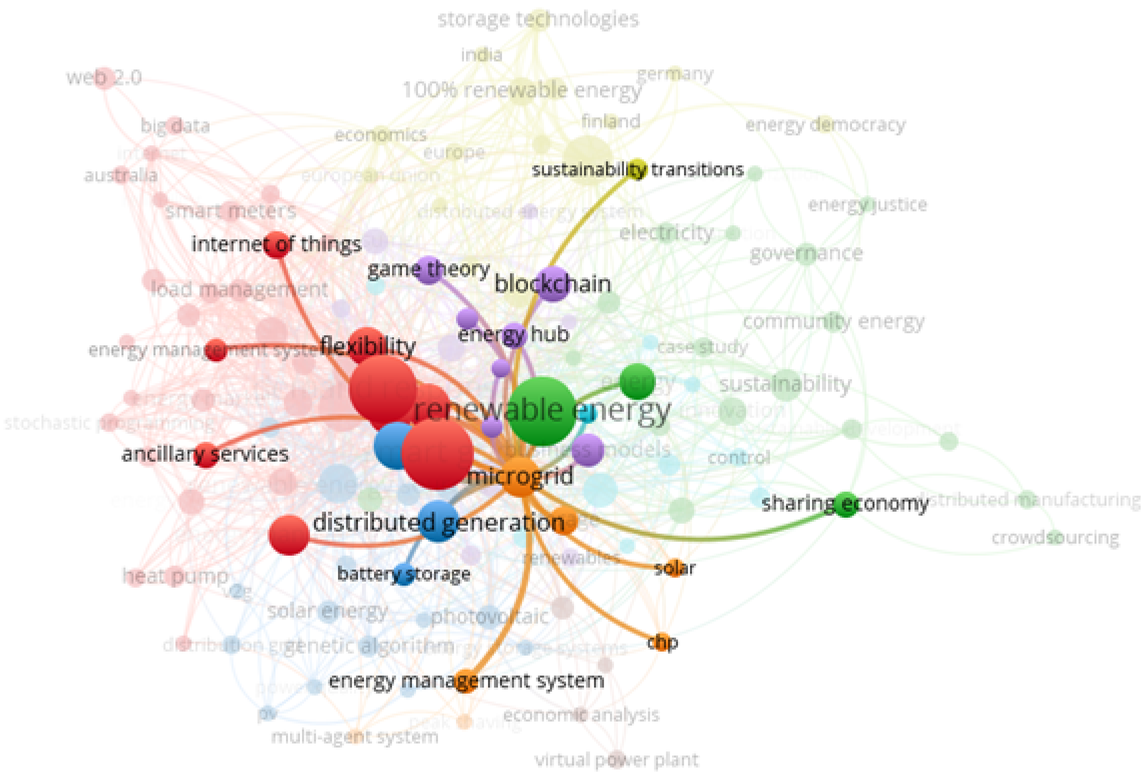

Figure 2.14: Highlighting the connections around 'microgrid'.

Researchers in [73] define a microgrid as a cluster of loads and DERs and these microgrids can have a variety of objectives. Generally, microgrids are composed of a variety of renewable energy sources, combined heat and power plants, energy storage systems, and controllable loads [74, 75]. The microgrid can also disconnect itself from the larger network and operate in islanded mode to supply energy to meet the local demand [76, 77]. Microgrids can optimize the local resources to meet several criteria, such as minimizing the energy cost to users or minimizing the amount of energy imported from the wider grid, and this can then increase the amount of flexibility within the microgrid [78, 79]. Aggregations of several smaller distributed energy resources to participate in energy markets can be done through microgrids and this is needed as these markets usually have some thresholds on the minimum size required for their participation [80]. Using microgrids to offer flexibility services through the forecasting and balancing of local supply and demand, which reduces the burden on distribution system operators, is also possible. Microgrids can be seen as an additional layer in the hierarchical control system, sitting between prosumers, community energy systems, and DSOs, for example, [81].

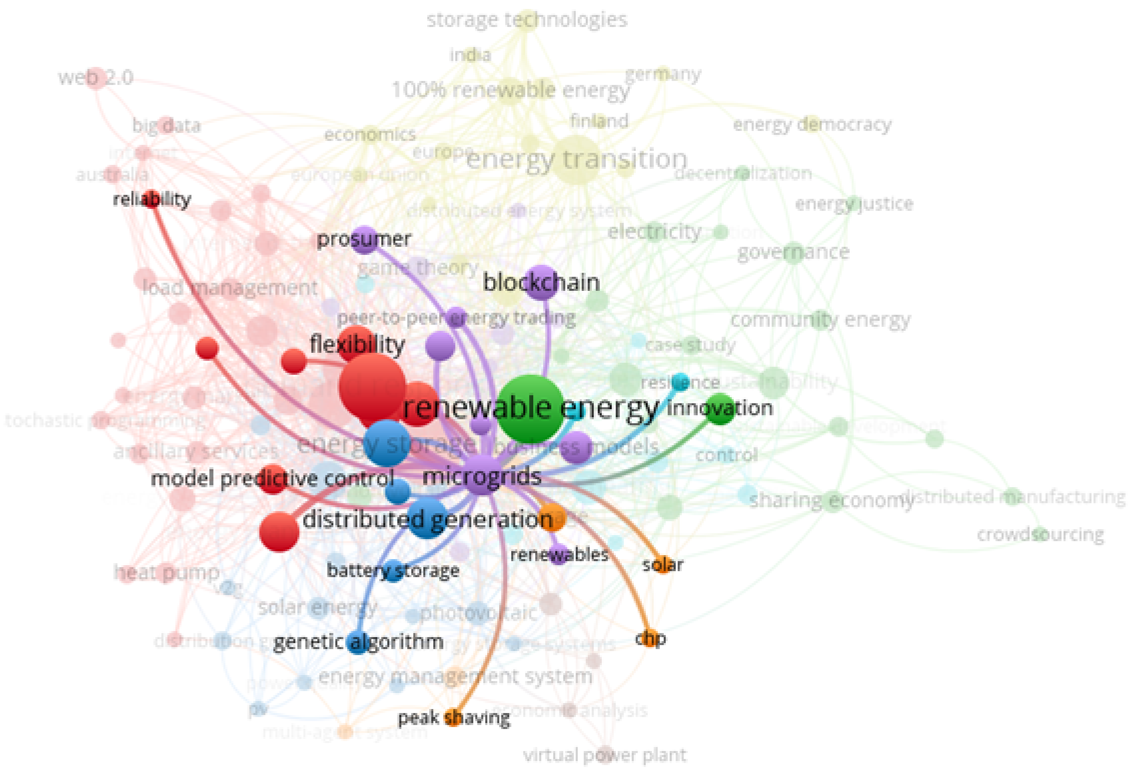

Figure 2.15: Highlighting the connections around 'microgrids'.

2.4.4 Prosumer

The fourth most used keyword in the 997 papers studied was prosumer. The connections associated with this term are shown in Figure 2.16 with 'smart grid', 'energy transition', and 'renewable energy' among the strongest connections. 'Smart meters', 'blockchain', and 'energy hubs' are technologies used to enable the growth of prosumers, so it is reasonable for them to have relatively strong connections. A review on the topic of prosumption is provided by [82]. The authors show the origins of prosumer and prosumption are an article in 1980 by Alvin Toffler, but that the concepts behind the terms extend back to perhaps the age of hunter-gatherers. A major shortcoming that the authors point out is the view that consumption or production occurs as binary activities and that both production and consumption have always had elements of prosumption embedded within them. The authors highlight the role that technological change can play in the rise of prosumption. This role is discussed in depth in this current chapter.

It is proposed by [83] that prosumption, rather than production or consumption, has always played a dominant role in capitalist economies. A key point of the article is that prosumer capitalism is largely reliant on the abundance and effectiveness of the means of production, rather than valuing production based on scarcity and efficiency. This is important for prosumers using PV systems in distribution networks. The PV systems generate electricity which is based on an abundance of natural resources (sunlight) rather than a scarce resource (generally coal or natural gas) even if the efficiency of the PV system is lower than the traditional fossil fuel-generating unit.

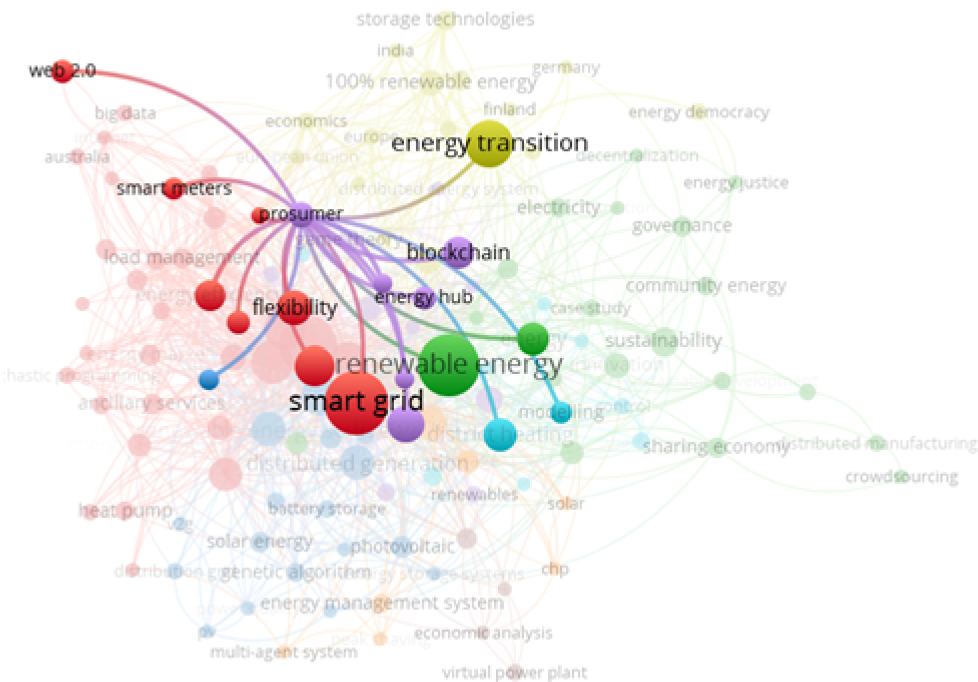

Figure 2.16: Highlighting the connections around ‘prosumer’.

A thorough examination of the prosumer concept is offered by [84]. In this work, Kotler discusses the prosumer in terms of its impact on marketing, and this is relevant as Kotler discusses the various reasons why a consumer may choose to become a prosumer in some aspects. Understanding this behavior shift will be key to harnessing the full potential of prosumers, especially in the electricity sector. [84] identifies characteristics of activities that are most likely to be taken over by a prosumer. These characteristics are that the activity should promote large cost savings, require low skill levels, require low time and effort and result in significant personal satisfaction. These characteristics are emerging in the electricity sector, especially surrounding the use of small-scale PV systems.

In the context of energy systems, prosumers are those customers who decide to invest in distributed energy resources (mostly solar PV) for a variety of reasons so they can satisfy a portion of their electricity demand and, in some hours, even produce more than they consume, possibly through storing some of the self-generated energy, thus becoming prosumers [3, 4]. This extra electricity can be exported to the electrical grid and/or shared with other consumers within their local area and, in this manner, prosumers can help to meet the environmental, social, and economic issues surrounding increasing energy demand [85]. This energy sharing can take the form of local peer-to-peer markets such as those studied in [86, 87]. Not only can prosumers export excess electricity, but they can actively modify their demand [88]. This active modification of demand, energy trading within the local area, as well as their self-consumption means that prosumers can play a key role in future energy systems [89, 90].

Traditionally, customers had a passive role in the energy system as pure price-taking agents. This role is changing as prosumers can now take a more active role in the energy system, including setting the price of the excess electricity that they might want to sell. This increased decision-making power of prosumers can be based on several criteria such as minimizing costs or maximizing the social welfare of their community [91].

In the past, the major aspects of the interaction between customers and the distribution system operators revolved around technical and economic aspects, but new dimensions are becoming important with the rise of the prosumer. These new dimensions include behavioral, social, and organizational aspects [92]. Prosumers can offer flexibility services in many ways. They can optimize their electricity use and production, and other groups can use this information for supply/demand forecasting and requirements for ancillary services, including flexibility. Prosumers can also relinquish control of their various distributed energy resources to DSOs or aggregators who can use these devices to help manage the grid, for example, the German Energy company, Sonnen, offers residential battery systems which can be controlled by a third party to help manage the electrical grid [93].

The topic of designing energy markets to account for the rise of prosumers was studied by [94]. In the paper, they state that there is a fundamental difference between prosumer-focused markets and traditional platforms for engagement in the energy sector such as demand–response markets. This is because prosumers are not solely price-taking agents but can also actively offer services to other market agents. This active engagement is a key defining trait of prosumers. In the paper, the authors identify three possible market arrangements of prosumers, which include: peer-to-peer markets, prosumer-to-interconnected, or 'island' mode systems or organized prosumer groups. The authors describe these markets in detail. Also, the authors describe several cross-cutting issues that a prosumer-based market may bring. These include technical issues related to control and management strategies of various distributed energy resources, and issues related to the capacity of distribution grids to manage an influx of DERs. The authors also raise concerns about the economic and regulatory impact of prosumers relating to the possible grid defection and associated 'utility death spiral' that may emerge from an uncontrolled and sudden shift to using DERs. Finally, the authors also discuss concerns relating to the social and behavioral changes that prosumers may bring. Chief among these concerns are information asymmetries, range anxiety over EV driving, and issues related to the perceived privacy risks of sharing data [94].

2.4.5 Distributed Energy Resources

The fifth most frequent term found in the text analysis was distributed energy resources (DERs). This is expected, as DERs are the key technologies that allow prosumers to actively participate in the energy system. The connections within the body of literature to 'distributed energy resources' are shown in Figure 2.17. The following terms occur frequently: Smart grid, Energy transition, Distributed generation, Smart meters, Solar PV, Battery storage, and Blockchain.

Generally, DERs are a grouping of various technologies, most commonly solar PV, ESS (both stationary storage and electric vehicles), heating and cooling technologies, and various smart appliances that provide the user some flexibility, and these resources generally bring positive benefits to the electricity system [1]. The following sub-sections will highlight the five most common DER types as identified in the body of literature and present a concise description of each. These five DER types are stationary energy storage systems, thermal loads, heat pumps, electric vehicles, and PV systems.

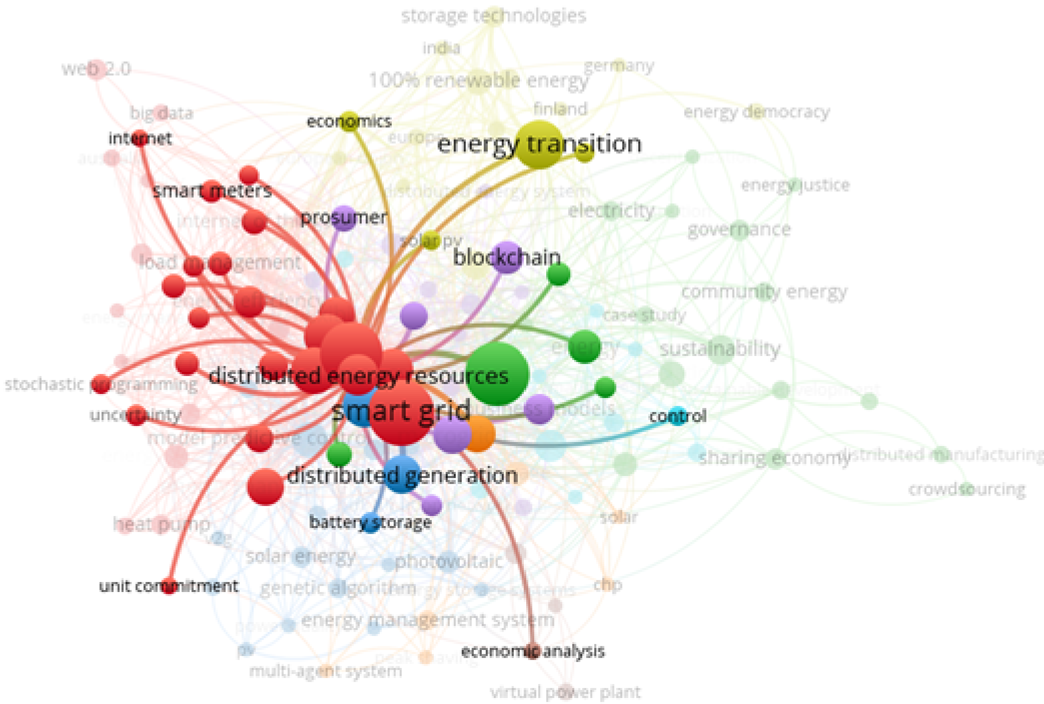

Figure 2.17: Highlighting the connections around 'distributed energy resources'.

2.4.5.1 Energy Storage Systems

Energy storage systems help to shift energy across time (in the case of electric vehicles, the stored energy could also be shifted spatially), typically from periods of high availability and low prices to periods of high demand and high prices and can have significant benefits to the electrical network (especially in the distribution network) [95, 15]. There is a whole suite of available types of ESS and some of them are shown in Figure 2.18. For prosumers, the power required would typically fall below 100 kW and the energy needed would be below 1 MWh, which means the technologies best suited to prosumers would be those in the lower-left section of the figure. Energy storage systems, particularly lithium-ion battery ESS, are becoming widespread in their adoption and use in prosumer portfolios. This has been fueled by the increasing amount of variable renewable energy and the dramatic falling capital costs of these ESS [96, 97].

ESS are especially valuable as they can be deployed in a variety of contexts, both large scale, and small scale, behind the meter or in front of the meter. They can also be used to provide ancillary services to the wider grid due to their fast response times. ESS can be effectively used to reduce a portion of the need for peaker plants, which are the most expensive and often the most polluting plants to run [49]. The variety of ESS also means that as each type of ESS has its advantages and disadvantages, it is possible to develop a portfolio of ESS to optimally suit the needs of a certain location or community [1, 98, 99]. By storing energy for periods of high demand, ESS can provide significant flexibility as the ESS can function as both a source and a sink of energy depending on the requirements of a certain time. ESS can also reduce peak demand and thus postpone costly grid infrastructure upgrades [100, 54]. ESS can provide multiple services to the grid and a number of these services work synergistically, this allows the owner of the ESS to profit from multiple revenue streams (for example, energy arbitrage or frequency control), which helps to make the business case for ESS that often have high capital costs [101].

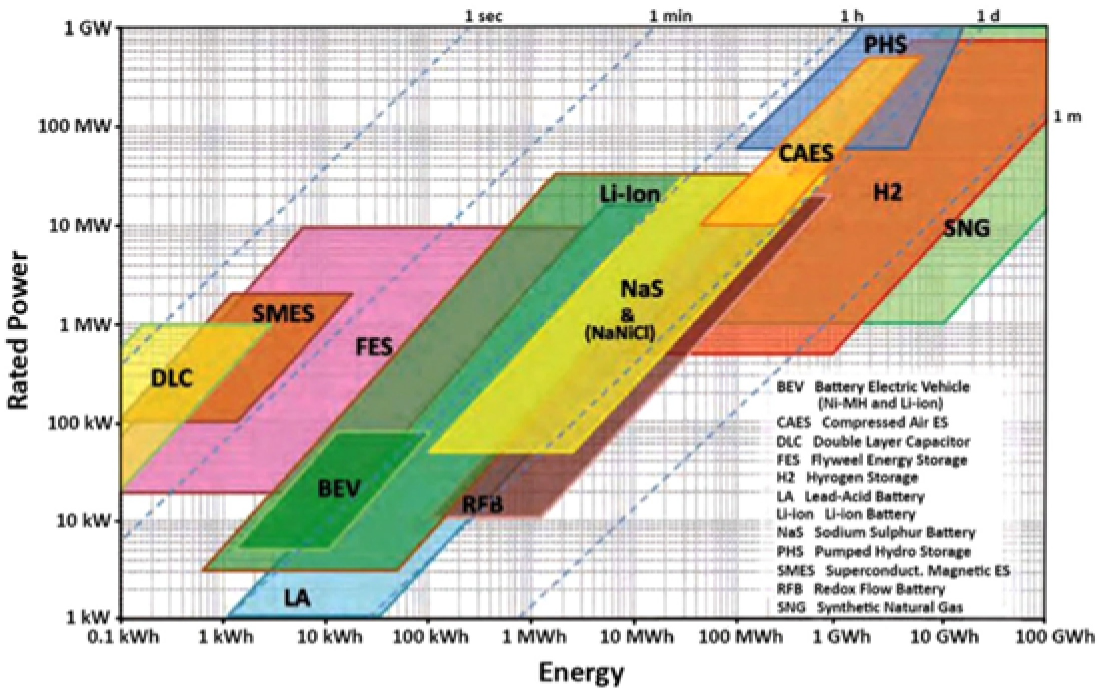

Figure 2.18: Different types of energy storage systems. Reprinted with permission from [1]

In summary, ESS can provide the following main benefits: an increase in the effective use of RES, a reduction in the peak power required at a given time, and an increase in both the reliability and stability of the grid. However, there are a few drawbacks to the use of ESS, which include the costs associated with them, additional infrastructure and management of the assets, and uncertainty around the novel services and business models.

2.4.5.2 Thermal Loads

Another common grouping of DERs is thermal loads. These are generally thermostatically controlled loads with some heat storage capacity and these loads operate within a band of upper and lower temperatures. Domestic hot water boilers are the most common of these types of loads and may be able to provide a significant amount of flexibility to distribution systems but this flexibility may vary significantly with many factors [102].

Another group of devices with a large potential for demand response and flexibility are white goods (these include refrigerators, dishwashers, clothes washers, and clothes dryers). The potential for flexibility will depend on the operating regime and the level of interconnectedness with Home Energy Management Systems [53, 103]. There may be significant potential for flexibility on very short time scales as these devices can be delayed to better suit the needs of the owner.

2.4.5.3 Heat Pumps

Heat pumps may also be able to increase the flexibility resource of prosumers [104]. The operation of these devices can be optimally timed and thermal storage can be used to increase the flexibility offered by the heat pump [105]. There are several issues with this operational regime for heat pumps as the increased cycling could increase the need for maintenance and operating the heat pumps at non-optimal temperatures reduces the efficiency of the device [106].

2.4.5.4 Electric Vehicles

Electric vehicles may provide a significant amount of prosumer flexibility to the electrical grid, but the quantity and timing of this flexibility will be dependent on a large number of factors [107, 108]. Different charging regimes ranging from simple on-off strategies to dynamic vehicle-to-grid regimes may be prevalent in the future and all offer different amounts of flexibility to prosumers and distribution grid operators [109]. Vehicle-to-grid services are archetypal prosumer flexibility services as they involve allowing the distribution system operator to utilize a prosumer-owned DER in exchange for some reward. The number of EVs within a small geographic area will also have a significant impact on the local distribution grid and these effects will need to be managed [110]. Stationary ESS can shift energy across time and EVs (through vehicle-to-grid technology) can also shift energy across the spatial dimension [111, 112]. This may come in handy to help tackle the issue of geographical clustering of EVs due to economic factors as the EVs could be driven away from areas of high concentration to other areas (either from home to work or from work to home), thus helping diffuse the concentration of EVs at a particular location. Optimized charging of fleets of electric vehicles can support the local distribution grid in terms of demand response programs, peak shaving, valley filling, and ancillary services [113].

2.4.5.5 PV Systems

PV Systems are some of the most widely installed DERs. These systems have seen extraordinary cost reductions in the past few years, which have helped to make them a widely accepted technology for generating electricity, either at the utility-scale or the smaller prosumer scale [114, 115]. PV systems are not a traditional DR load, as they generate power, but there is a small degree of controllability to the technology, which means they are well suited to DER installations. PV systems can be used to generate power for self-consumption as well as charging stationary ESS or EVs [116]. PV systems are thus crucial for the prosumer concept as they allow consumers to generate electricity that can be used immediately, stored for later use, or sold either to the local utility or to other consumers.

2.4.5.6 General Issues to Consider

Despite the advantages of DERs that have been discussed in the preceding sections, there remain some significant issues with their large-scale deployment [39, 117]. One identified aspect is the tendency for DERs to cluster in certain areas or neighborhoods for socio-economic or regulatory reasons [26]. This concentrating effect can place a further strain on distribution networks, which may already be operating in a sub-optimal manner and may need extensive infrastructure upgrades to deal with the requirements of the DERs. In addition to this geographic clustering effect, DERs may also create issues relating to new peak demand hours or other synchronization effects, for example, when low-priced electricity is available, there may be a significant increase in demand and many consumers attempt to take advantage of this low-price period. Some non-technical solutions can be deployed to enhance the uptake of DR programs using DERs. These include regulatory and policy mechanisms, as well as the creation of new energy markets, [12, 118].

The authors in [73] raise the issue that the uncontrolled use of distributed energy resources can have significant negative effects on the power system. Thus, efficient control strategies are needed for these DER assets and Transactive Energy has been touted as one such control framework [7].

A major enabler of efficient local energy markets with high penetrations of prosumers is the high forecasting accuracy of both production and consumption [119]. Applying forecasting techniques to individual consumers may lead to significant errors and this can, in turn, be a major barrier to the development of efficient local energy markets. The work done by [119] shows that by aggregating consumers (or prosumers), forecasts for energy demand are significantly improved. Using DERs in local energy markets can bring benefits to the user, as described in [120], where the authors state that there is an inverse relationship between the benefits of using RES and the distance between the RES and the end-user.

In general, a substantial portion of the existing literature on demand side flexibility has mostly focused on the following major types of appliances: heating, ventilation, and air-conditioning (HVAC) systems, washing machines and dryers, and water heaters, as they are widespread, have a relatively large energy demand and can be used in DR programs. A few studies compare residential appliances in terms of demand response potential [66] and these studies generally rely on intensive customer survey data, which is traditionally difficult to obtain from customers.

Various metrics have been proposed to quantify the flexibility offered by DERs. Some studies have classified flexibility according to a more traditional, supply-side definition of flexibility, which includes ramping magnitude (power), ramping cycle frequency, and the response time of an asset [121]. For DERs, additional metrics have been proposed such as minimum power available, the recovery time of the asset after deployment, and the availability of the asset [122]. In addition to these extra metric requirements, the flexibility of DER assets relies heavily on the behavior profile of the owner and this is extremely difficult to predict for individual owners (and assets) but this issue becomes easier to solve with the use of flexibility aggregators [123, 47].

Novel DSF metrics have been proposed. These include the Flexibility Index of Aggregate Demand (FIAD) and the Percentage Flexibility Level (PFL) [91], which statistically analyzes aggregated demand to help define time-varying flexibility resources. These indicators have some drawbacks, mostly around the assumptions relating to the way the fluctuations in load are assumed to be constant, and this has led to the development of the Modified Flexibility Index of Aggregate Demand (MFIAD) [122]. Other metrics suggested include a duration-of-use framework to develop new contracts for flexibility, as proposed by [124]. A metric that included the ability of DR programs to assist the grid is presented by [125]. This metric takes into account a Flexibility Affect Factor which measures the ability of a flexible resource, including demand response programs, to satisfy certain technical characteristics relating to the operation of the power system.

Research has shown that DSF cannot be described in a single indicator but rather should rely on several characteristics to fully describe the flexibility potential of a DER asset and this issue is addressed by [10], who states that to properly estimate the potential of a DER asset to provide flexibility, three aspects should be considered: the ability of the asset to provide flexibility, the wider system's ability to provide flexibility and the system's need for the flexibility. A further key aspect relating to the system's need for flexibility is the variation of demand with temperature and this should include issues like different load curves due to long-term changes in the climate [10].

Like previous terms discussed in this chapter, DERs also suffer from some drawbacks and challenges. This is especially true with DERs as they often provide novel technologies and business models to the electricity system, which has traditionally been very conservative in adopting new technologies [12].

2.4.5.7 Transactive Energy

The Transactive Energy (TE) concept was not one of the top five keywords found in the literature surveyed. This may be because research specifically on prosumer-centric transactive energy frameworks is still at a nascent stage. Currently, DERs are one of the major elements of TE frameworks [126]. This focus on DERs ensures that the technical, economic and communication aspects of TE frameworks are well-designed and can operate efficiently. However, DERs are owned by prosumers who typically make the final decision of whether to use their DER to participate in energy systems. Therefore, by having prosumers as one of the major elements of transactive energy systems, the active participation of prosumer DERs may be increased thus improving the operation of TE systems.

2.5 Trends Identified

While reviewing the existing literature, several key trends emerged. This section will briefly highlight some of these trends associated with prosumer flexibility. Firstly, there is a marked increase in the literature around energy prosumers and their potential roles in future energy systems. There is also a significant regulatory drive to involve active consumers more in energy systems, most notably through the European Commission's Clean Energy for all Europeans framework which could act as a catalyst for widespread investment and adoption of DERs by prosumers.

Associated with prosumer flexibility and aggregation is the concept of community energy systems, where a collection of engaged prosumers works together to integrate DERs to increase the share of self-consumption of electricity and also potentially participate in local energy markets [127]. There exists a knowledge gap in evaluating the flexibility potential of these communities [101]. One of the more pronounced trends is the aggregation of prosumers into collections where they can have a meaningful impact on the wider power system either using commercial Virtual Power Plants or local energy communities. This is done to offer energy or ancillary services to various markets. Key to this trend is the increased temporal and spatial granularity that various markets are beginning to offer [123, 118]. Peer-to-peer electricity trading is one such market design that has the potential to unlock significant prosumer resources [128, 129].

With smart devices and Internet of Things (IoT)-enabled devices becoming more readily available, their potential to provide real-time information to various stakeholders is being explored. This could affect prosumer flexibility by providing incentives to prosumers to increase the level of flexibility to engage further in DR programs in a very granular manner, both in terms of time and location [130]. While this holds promise for increasing the ability of prosumers to participate in energy and/or flexibility markets, there are also drawbacks in terms of privacy of data, communication frameworks, and price signals which will need to be investigated before the full potential of prosumers can be harnessed.

The literature has shown a marked increase in the interest in prosumer flexibility and a clear trend to see is that from a technological level, existing technologies and operational strategies are largely sufficient to fully exploit prosumer flexibility. What is hindering the process is the regulatory and market design [81, 131, 22, 132]. These areas will be key research topics in the coming years if the full potential of prosumers is to be harnessed.

A major trend identified in the literature and the wider field of energy systems is the move towards the increased electrification of end-use sectors such as mobility and heating as the energy system shifts towards a decarbonized and digitalized future [65, 133, 134, 135]. This trend has the potential to radically reshape energy demand, including the demand profiles associated with different types of customers and thus this trend will need to be managed correctly. The increasing digitalization of the energy system also poses challenges around the complexity of managing a grid containing vast amounts of smart connected devices. This digitalization also brings opportunities for the analysis of large data sets by advanced techniques to extract useful information and increase system flexibility.

A final trend identified is the regulatory push for increased participation by consumers in energy systems, especially at a European Union level. This was most prominent in the Clean Energy for all Europeans Package which was completed in June 2019 and gave consumers a prominent role in the so-called Energy Union. This union has the goal of providing clean, affordable, competitive, and secure energy [136]. While there has been this overarching goal at the European Union level to design the energy system with the prosumer in mind, each of the member countries will need to implement the policy nationally [137].

Relating to the European Directives, in October 2019, the Portuguese government released novel legislation relating to self-consumption and energy communities. This was done to align the country's legislative framework with the relevant European Directives as well as the Portuguese National Plan for Energy and Climate (PNEC)[138]. This was enacted through Decree Law 162/2019 on the 25th of October. This law is concerned with the legal framework for the installation and use of small-scale DERs with or without connection to the public electricity distribution system.

The law aims to remove unnecessary burdens from consumers who would like to produce, consume, store, share, and sell electricity. It encompasses peer-to-peer energy trading and renewable energy communities but crucially the law introduces the so-called Market Facilitator (MF) agent. This agent is a supplier or purchaser who is under obligation to buy or purchase energy produced by DERs under market conditions. The concept of MF was included in this legislation as a purchaser of last resort for the surplus from prosumers or larger energy communities. The effects of this agent on the market outcomes will need to be studied. Importantly, this legislation sets the remuneration given to prosumers or energy communities at 90% of the prevailing energy market price. This amount may help increase the financial feasibility of novel business models to increase the number of prosumers in Portugal.

Additionally, this new legislation also increases the size of the DER's installed capacity before a permit from the National Directorate for Energy and Geology is required. Previously, an installer had simply to communicate to the Directorate if the installed capacity was under 1.5 kW and then apply for a permit above this figure. The new legislation means that only installations with an installed capacity larger than 100 kW will need to apply for a permit [137].

2.6 Chapter Conclusions

This chapter has introduced the thesis, provided background to the terminology used, and a review of the literature surrounding prosumer flexibility. This review was done through a textual analysis of relevant academic articles and the results of the textual analysis provided a structure to discuss several key issues surrounding prosumer flexibility. The opportunities and challenges of the different key aspects were discussed, and a holistic view of prosumer flexibility has been provided. This work complements other review papers in prosumer flexibility, demand-side flexibility as well as research concerned with quantifying the flexibility potential of DER assets. Additionally, the relevant legislation for prosumers at a European and Portuguese level was introduced and discussed.

This chapter has shown that most of the research in flexibility has focused on the grid or supply side, but that this is slowly changing as the importance of having engaged consumers is becoming recognized. This chapter has shown a significant rise in the amount of research around prosumer flexibility in recent years and it is expected that the amount of research will continue to increase as the active participation of consumers in the energy system increases.

This chapter has synthesized a large body of research and identified several key trends in the research. The most relevant keyword in the body of literature was 'smart grid' followed by 'demand response'. This can be expected, as these two fields are much more developed research fields. It is expected that as the concept of prosumers gains momentum, the prosumer keyword will be much more widely cited in research.

This work shows that a textual analysis of a large body of related literature can provide interesting information and identify important trends within the chosen body of literature. Tools like VOSviewer and SAS© Visual Text Analytics provide prominent features for scientometric analysis.

There is an exciting mix of technical solutions and novel regulatory frameworks being developed to make full use of the potential for prosumers to provide flexibility services to the electric grid. Most of the technologies discussed in this chapter are commercially available and are cost-competitive when compared to traditional forms of electricity generation. With that being said, there are several barriers or obstacles to the widespread provision of flexibility services by prosumers. Some of these barriers include:

1. Inadequate markets to fully harness the potential of prosumers. Current markets lack both the scale and scope to be fully inclusive to all participants in the energy sector. This will require a notable change in both what products energy markets offer as well as the conditions for entry into these markets. These changes to the market rules are slowly happening as regulators see the significant additional value that prosumers can provide to markets.

2. Tariff and regulatory regimes that do not incentivize DER ownership by consumers. Special attention should be paid to designing regulations that incentivize the adoption of DERs by prosumers in a controlled manner and these incentives should be aware of the behavioral and societal effects that a rise in prosumers may bring. This type of regulation is beginning to emerge, especially in various EU member states as new regulatory regimes are introduced that actively promote consumer participation.

3. Consumers lack the necessary information. Providing easily understandable and accurate information to consumers relating to both the technical and financial aspects of owning DERs is key to allowing consumers to make informed choices.

4. Inadequate business models and financing instruments. With the emergence of prosumers, novel business models and financing instruments are needed to make DER ownership easy and attractive to consumers. In this regard, regulatory agencies have a challenging task ahead. These agencies can spur business model innovation by introducing new regulations, but will still need to ensure that these regulations still protect the best interests of consumers.

5. Privacy and data security concerns. Society is grappling with the issue of personal data use by third parties. The energy sector, with its tight relationship to ICT systems, will also have to devise mechanisms to ensure that consumer data is safe, secure, and only used for the intended purposes. This area will be a key obstacle to overcome if the potential of active consumer participation is to be realized.

The trends and issues identified in this chapter are extensions of those identified in [94] and these trends will be investigated in the following chapters of this thesis. A thorough review of the state of the art of literature concerning prosumer flexibility was needed to identify opportunities, potential bottlenecks, and challenges that a future electricity system may face. The issues raised in this chapter will become more pressing and important as the electricity system undergoes a transition to a decentralized, decarbonized, digitalized, and democratic future where the consumer plays a much more vital role in their energy choices. The remainder of the thesis will take the issues and trends identified here and develop various transactive energy-based frameworks to suggest some solutions to these obstacles facing widespread prosumer integration in the energy system.

Chapter 3

The Role of New Information and Communication Technologies and Business Models in Increasing Prosumer Participation

The previous chapter presented the emergence of active engagement by prosumers in the energy system. Some key drivers of this increased engagement were the combination of novel technical solutions and emerging energy system regulations. This chapter continues this research thread by presenting a transactive energy-based framework combining blockchain-based smart contracts, an innovative Information and Communication Technology, and enabling Portuguese regulations surrounding self-generation and self-consumption of electricity. This framework clusters prosumers into virtual power pools (VPP) and allows for both inter- and intra-VPP energy trading to increase the utilization of prosumer-generated electricity. Additionally, this chapter provides a panorama of the potential applications of blockchain to the energy system. This review of blockchain shows the potential applications of blockchain, including smart contract-based energy trading frameworks. Building on this review, a smart contract layer is incorporated into the transactive energy framework to automate the recording of energy trades between the VPPs. The transactive energy framework is designed to be compliant with novel Portuguese regulations concerning the generation and consumption of electricity from prosumer-owned Distributed Energy Resources to ease the barriers to entry for prosumers and to ensure that this framework can be utilized. This framework shows that blockchain-based smart contracts can be successfully integrated into a hierarchical energy trading model, which respects novel energy regulations. This framework can be used to increase automation of consumer participation, lower energy bills, and increase the penetration of locally generated electricity from renewable energy sources within the Portuguese context.

Chapter Highlights and Novel Contributions:

- A prosumer-centric peer-to-peer energy trading framework that incorporates blockchain and ensures the stable operation of distribution grids.
- Creation of hierarchical VPP trading model to allow for intra- and inter-VPP energy trading and facilitate localized energy balancing.
- Utilize smart contracts from Blockchain technology to automate and record energy transactions amongst the users. This can increase reliability, transparency, and ease of use for consumers.
- Examine the effects of Portuguese energy regulation governing self-consumption on the operation of a VPP.

Relevant Publication(s):

M. Gough, S.F. Santos, A. Almeida, M. Lotfi, M.S. Javadi, G.J. Osório, R. Castro, J.P.S. Catalão, "Blockchain-based transactive energy framework for connected virtual power plants," in *IEEE Transactions on Industry Applications* Vol. 58 , No. 1, pp. 986-995, January-February 2022. Q1 Journal, Impact Factor: 4.079
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M. Gough, R. Castro, S.F. Santos, M. Shafie-khah, J.P.S. Catalão, "A panorama of applications of blockchain technology to energy," *in: Blockchain-based Smart Grids*, M. Shafie-khah (Editor), ACADEMIC Press (ELSEVIER), London, UK, ISBN: 978-0-12-817862-1, pp. 5-41, May 2020
Published: https://doi.org/10.1016/B978-0-12-817862-1.00002-6

Chapter 3 Nomenclature

Sets	
$t \in \Omega^T$	Time
$s \in \Omega^S$	Scenarios
$w \in \Omega^W$	Prosumers
$n \in \Omega^N$	Neighborhoods
$c \in \Omega^C$	Controllable appliances
$f \in \Omega^F$	Operational phase
Parameters	
$CE^{ESS}_{w,s}$	Charging efficiency of the Prosumer w's Energy Storage System (ESS)
$CE^{EV}_{w,s}$	Charging efficiency of the Prosumer w's Electric Vehicle (EV)
$\eta^{ESS,disch}_{w,t}$	Discharging efficiency of the Prosumer w's Energy Storage System (ESS)
$\eta^{EV,disch}_{w,t}$	Discharging efficiency of the Prosumer w's Energy Storage System (EV)
$InfLoad_{w,t}$	Inflexible load of household w in period t [kW]
$N_{w,s,c}$	Periods of operation for the controllable appliance c of prosumer w
N	Limit on amount of power from grid for prosumer w
$P^{phase}_{w,f,c,s}$	Power consumed by controllable appliance c of prosumer w while in phase f [kW]
$P^{PV,prod}_{w,t,s}$	Available power of the PV system of household w in period t [kW]
$R^{ESS,charg}_{w}$	Charging rate of ESS of prosumer w [kW]
$R^{ESS,disch}_{w}$	Discharging rate of ESS of prosumer w [kW]
$R^{EV,charg}_{w}$	Charging rate of EV of prosumer w [kW]
$R^{EV,disch}_{w}$	Discharging rate of EV of prosumer w [kW]
$SOC^{ESS,ini}_{w}$	Initial State Of Charge (SOC) of the ESS of prosumer w [kWh]
$SOC^{ESS,max}_{w}$	Maximum (SOC) of the ESS of prosumer w [kWh]
$SOC^{ESS,min}_{w}$	Minimum (SOC) of the ESS of prosumer w [kWh]
$SOC^{EV,ini}_{w}$	Initial State Of Charge (SOC) of the EV of prosumer w [kWh]
$SOC^{EV,max}_{w}$	Maximum (SOC) of the EV of prosumer w [kWh]
$SOC^{EV,min}_{w}$	Minimum (SOC) of the EV of prosumer w [kWh]
T^{a}_{w}	Arrival time of the EV of prosumer w
T^{d}_{w}	Departure time of the EV of prosumer w
$T^{dur}_{w,f,c}$	Duration of phase f of controllable appliance c of prosumer w [number of T-hour periods]
$\lambda^{pur}_{t,s}$	Energy buying price [€/MWh]
$\lambda^{sold}_{t,s}$	Energy selling price [€/MWh]
ΔT	Time interval duration [t]
β	Thermal coefficient for prosumer w in scenario s
$COP_{w,s}$	Coeffienct of performance for prosumer w
$R_{w,s}$	Thermal resistance for prosumer w [h.°C/J]

C	Thermal capacity of air [kJ/kg°C]
θ_w^{min}	Minimum indoor temperature for prosumer w
θ_w^{max}	Maximum indoor temperature for prosumer w
Variables	
$P_{w,t,s}^{pur,grid}$	Portion of total power procured from the grid by prosumer w in period t [kW]
$P_{w,t,s}^{pur,local}$	Portion of power procured from the local neighborhood by prosumer w in period t [kW]
$P_{w,t,s}^{pur,neigh}$	Portion of power procured by the local neighborhood from prosumer w in period t [kW]
$P_{n,t,s}^{demand}$	Demand of neighborhood n in period t [kW]
$P_{n,t,s}^{supply}$	Supply from neighborhood n in period t [kW]
$P_{w,t,s}^{pur,T}$	Total power procured by prosumer w in period t [kW]
$P_{w,t,s}^{ESS,charge}$	Charging power of ESS of prosumer w in period t [kW]
$P_{w,t,s}^{ESS,disch}$	Discharging power of ESS of prosumer w in period t [kW]
$P_{w,t,s}^{ESS,used}$	ESS power of prosumer w used to satisfy self-consumption in period t [kW]
$P_{w,t,s}^{EV,charge}$	Charging power of EV of prosumer w in period t [kW]
$P_{w,t,s}^{EV,disch}$	Discharging power of EV of prosumer w in period t [kW]
$P_{w,t,s}^{EV,used}$	EV power of prosumer w used to satisfy self-consumption in period t [kW]
$P_{w,t,c,s}^{mach}$	Power consumed by controllable appliance c of prosumer w while in period t [kW]
$P_{w,t,s}^{PV,used}$	Portion of the PV power of prosumer w used to satisfy self-consumption in period t [kW]
$P_{w,t,s}^{sold,ESS}$	Portion of the ESS discharging power of prosumer w sold in period t [kW]
$P_{w,t,s}^{sold,EV}$	Portion of the EV discharging power of prosumer w sold in period t [kW]
$P_{w,t,s}^{sold,grid}$	Portion of the power injected to grid by prosumer w that flows back to the grid in period t [kW]
$P_{w,t,s}^{sold,local}$	Portion of the power injected to grid by prosumer w that is used in neighborhood in period t [kW]
$P_{w,t,s}^{sold,PV}$	Portion of the PV power of prosumer w sold to the grid or the neighborhood in period t [kW]
$P_{w,t,s}^{sold,neigh}$	Portion of the PV power of sold by the neighborhood to prosumer w in period t [kW]
$P_{w,t,s}^{sold,T}$	Total power injected by prosumer w in period t [kW]
$SOC_{w,t,s}^{ESS}$	SOC of ESS from prosumer w in period t [kWh]
$SOC_{w,t,s}^{EV}$	SOC of EV from prosumer w in period t [kWh]
$x_{w,t,s}^{1}$	Binary variable. 1 if the neighborhood is drawing power from the grid in period t; else 0
$x_{w,t,s}^{2}$	Binary variable. 1 if the power flows from grid to prosumers/if EV is charging for prosumer w in period t; else 0

$x^{3}_{w,t,s}$	Binary variable. 1 if the power flows from grid to prosumers/if ESS is charging for prosumer w in period t; else 0
$x^{phase}_{t,w,c,s}$	Binary variables. 1 if phase f of controllable appliance c in prosumer w is beginning (y)/ongoing(u)/finishing(z) (x = y, u, z) in period t; else 0.
$\theta_{w,t+1}$	Indoor temperature for prosumer w at time t +1
$\theta^{O}_{w,t+1}$	Initial indoor temperature for prosumer w at time t +1
Dw,t^{HVAC}	HVAC demand for prosumer w in time t (kW)
Pw,t^{HVAC}	HVAC power usage for prosumer w in time t (kW)

3.1 Introduction

3.1.1 Aggregation through Virtual Power Plants

The emergence of Distributed Energy Resources (DERs) has created new opportunities and challenges for all stakeholders within the power system [139]. This new paradigm grants consumers the possibility to actively engage in the energy system through the production of electricity through DERs, thus becoming prosumers [140]. Coupled with the rise in the use of DERs, emerging technologies such as blockchain have the potential to broaden the role that active consumers can play [141]. This new role also brings increased challenges in terms of balancing the supply and demand of electricity which is increasingly being generated by intermittent renewable energy sources (RES). This rise in the intermittent supply of electricity combined with the proliferation of small prosumers means that traditional ways of balancing electricity supply and demand are becoming more challenging, especially from a single centralized entity.

To ease these balancing challenges, virtual power plants (VPPs) have been proposed [142]. VPPs have emerged as a concept to aggregate a diverse number of disparate DERs to act as a single entity when participating in energy markets [143]. This helps gather numerous prosumers into a larger entity that can take advantage of the portfolio effect in balancing supply and demand [144]. The VPP combines the separate generation and demand profiles of the underlying DERs to create a single load or generation profile, reducing the complexity associated with controlling a large number of DERs [145]. VPPs can have different structures and operational goals depending on their architecture, which can be based on the transactive energy concept [146]. These VPPs can group consumers into various levels according to scale and location. These different levels are then managed by a designated authority which helps reduce the challenges associated with managing an electric power system with a large number of small-scale intermittent generators [147].

In this chapter, transactive energy concepts were applied to a VPP to create a multi-level energy trading framework using prosumer-owned DERs and this framework is shown in Figure 3.1. At the lower level, the local VPP operators are responsible for intra-VPP energy trading among the different prosumers. At the higher level, the global VPP operator is responsible for inter-VPP energy trading and coordinating with the local VPP operators. The global VPP operator also liaises directly with the system operator, the external grid, and the market facilitator agents, which are incorporated into the model according to the Portuguese legislation on self-generation and consumption discussed in the previous chapter. The figure shows that each VPP is composed of several different consumers, including residential and service buildings with diverse portfolios of DERs and load demand profiles. Within the VPPs, prosumers play a significant role and lead to an increase in the number and type of DERs available [123]. VPPs can reduce the complexity associated with bidding into energy markets, increase consumer participation, improve system reliability and flexibility, and increase the penetration of renewable energy sources within the power system [148, 149].

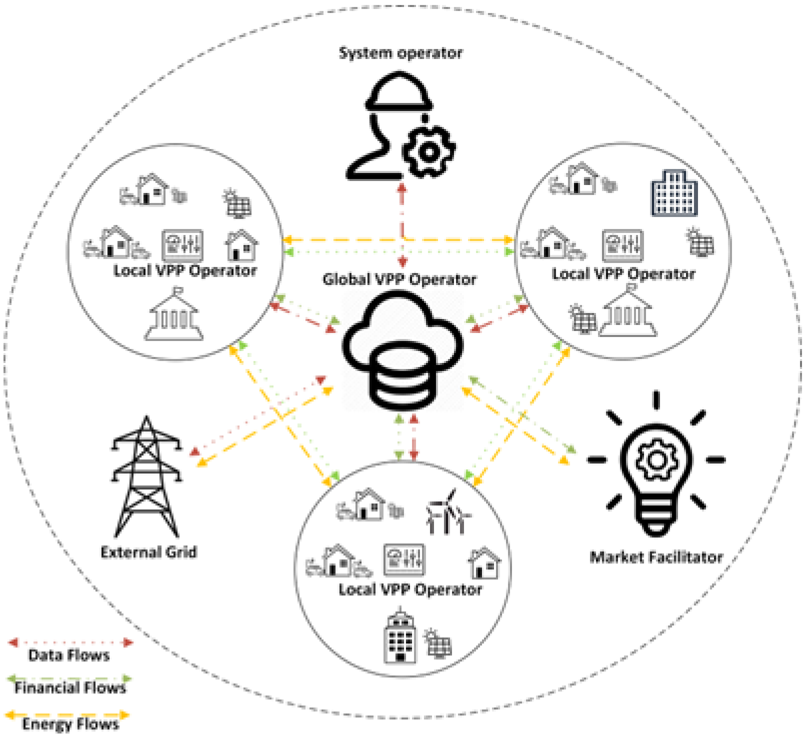

Figure 3.1: Multi-level energy trading market

VPPs increase the number and type of transactions within energy markets, which may also create additional challenges. In order to address these challenges in this model, the transactive energy framework is applied. [7]. This framework is designed to control and coordinate many DERs owned by various entities using market-based approaches to incentivize the trading of both energy and enable sharing of information between participants [8]. TE mechanisms can use price, comfort, technical and environmental signals to coordinate energy markets across the entire power system infrastructure [9]. A thorough review of the TE concept has been presented by [150], where the authors clearly identify the need for multi-layer TE models to maximize the benefits of this control framework. This framework uses the principles of TE to coordinate energy trading both within VPPs and between VPPs. The application of TE to VPPs has been suggested by past work, such as [151], as a number of disparate DERs can be optimized to participate in energy trading.

Within TE systems, there is a large amount of data transfer between the participants. This may raise questions about data privacy and security or even impact the operation of transactive energy markets [152]. Blockchain technology can provide some solutions to these problems and is therefore well suited to TE systems [153]. Within TE systems, multiple interconnected layers transmit information to each other. A blockchain system can, therefore, quickly become part of the network layer of a TE system. Thus, the nexus between VPPs, prosumers, TE systems, and blockchain has emerged as an interesting field of study, both academically and commercially. Despite this increase in interest, there are several areas where more research is needed and these will be presented in the next section. This chapter presents a modeling framework that integrates the four aspects of the nexus between VPPs, prosumers, TE systems, and blockchain.

3.1.2 State of the Art

This section introduces and critically discusses several existing papers which deal with the optimization and scheduling of prosumer-owned DERs in small-scale energy markets. This is done to highlight how the proposed framework addresses specific research gaps and extends the state-of-the-art. The contributions of each of these papers are summarized in Table 3.1, which compares and contrasts existing research with the proposed model.

In the first paper to be analyzed, a decentralized optimization model for energy trading within local energy markets using Hyperledger implementation of the blockchain was developed [154]. The model considered a single layer of energy trading among residential consumers with a variety of DERs, including heat pumps. The authors consider two different trading strategies, namely matching supply and demand and then a strategy that encourages nearby peers to engage in energy trading, thus reducing system losses.

Blockchain was again applied for load and generation aggregation in [25]. Smart contracts were used to record the consumers' energy usage and any potential flexibility the consumer may offer the system. The authors used the Hyperledger blockchain implementation. Optimal scheduling of consumer-owned DERs was not considered.

In [155], a two-stage transactive energy model for the optimization of prosumer's flexibility was developed. This nested market considered several consumer-owned DERs and a local flexibility market to minimize costs for the stakeholders. The model considered 1 million consumers with different participation levels. The model did not incorporate blockchain-based smart contracts.

A model incorporating both transactive energy principles and blockchain was developed by [153]. The model applied a blockchain layer over an energy trading layer to enable the transactive energy mechanism. The model used distributed optimization through ADMM but did not consider nested energy trading among different VPPs.

A model exploring the potential of a network of connected microgrids utilizing blockchain technology to assist in the optimization of both physical and financial operations was developed by [152]. The authors provide several high-level proposals and recommendations for adapting blockchain technologies for transactive energy systems; however, no mathematical formulation or evidence that these proposals are provided. This limits the applicability of these proposals, especially as the authors do not consider emerging energy regulations that can shape the roles and responsibilities of networked microgrids in transactive energy systems.

A standalone blockchain-based energy trading platform using Remix and Ethereum was developed by [156]. This model did not consider the optimal scheduling of consumer-owned DERs or any energy trading. However, a detailed analysis of the processing time and performance of the developed smart contract trading scheme was proposed.

A VPP model considering prosumers and using blockchain was developed by [157]. This model considered ESS and used hierarchical VPP trading layers to minimize the energy cost of prosumers using a knapsack solution algorithm. The blockchain layer was developed in Ethereum to help manage and record energy transactions amongst consumers and VPPS. Uncertainty was not considered, and neither were EVs.

A decentralized energy management platform for prosumers incorporating blockchain was developed by [158]. The system used Ethereum as the underlying blockchain system to support the decentralized optimization of DERs. The model did not consider multi-level trading amongst the VPPs or regulations.

The above paragraphs and Table 3.1 show a large and growing body of literature investigating the optimization of prosumer participation in energy markets, enabled by the new ICT. The table shows that very few papers consider a multi-level trading system. This multi-level system can ease computational complexity and fluctuations in electricity demand and supply. In addition, a research gap that was identified is that none of the papers considered a current regulatory regime of the relevant area. Designing the energy trading system according to applicable legislation and regulations is vital if the trading system is to be successfully implemented.

Table 3.1: Comparison with Relevant Literature

Paper	Type of Optimisation	DERs	Multilevel trading	Blockchain used	Consensus Mechanism	Regulatory framework
[153]	MILP	EES, EV, HVAC, PV	Yes	None	None	No
[150]	ADMM	EES, RES, HVAC	No	Practical Byzantine fault tolerance	Quorum	No
[154]	None	EES	No	Proof of work	Ethereum and Remix	No
[159]	Pure integer non-linear program	EES, PV	Yes	Proof of work	Ethereum	No
[152]	None	None	Yes	Hyperledger consensus	Hyperledger fabric	No
[155]	ADMM	HVAC, BESS	No	None	None	No
[151]	ADMM	BEES, EV, Heat Pump	No	Hyperledger consensus	Hyperledger fabric	No
This chapter	MILP	EES, EV, HVAC, PV	Yes	Proof of work	Ethereum and remix	Yes

3.2 Background Information

This chapter presents a hierarchical energy trading model for several VPPs using blockchain to automate and record energy trading transactions within the VPPs and then between the VPPs. The model is developed according to recent Portuguese energy regulations. In this section, a brief background of blockchain, smart contracts, and the current Portuguese regulations concerning self-generation and consumption are presented.

3.2.1 Blockchain

Blockchain has emerged as an innovative Information and Communication Technology (ICT) with diverse applications, including in the power sector. Within the power sector, blockchain has primarily been used in energy trading applications, especially in decentralized or peer-to-peer energy trading [141]. In short, a blockchain is a collection of distributed databases of records that continually grows as new records are added. These records are secure, transparent, and tamper-proof [160]. Thus this chain of immutable blocks of recorded transactions can provide trust between individuals without the need for a central third party overseeing the market [141].

Within blockchain, smart contracts are electronic contracts that can be automatically executed should specific criteria be met. These smart contracts are simple programs that can be created to suit the needs of the individuals involved in the transaction. Rules and conditions may be written into the smart contracts, which can interact with the underlying blockchain network and structure the transaction without the need for human intervention or third-party authentication. These smart contracts have the potential to enable decentralized energy trading amongst peers based on their preferences. Using smart contracts, this energy trading will be secure, automated, and fairly carried out [160].

There exist numerous definitions for the blockchain but the general definition of the blockchain is given by [161]:

> Blockchain, at its core, is a peer-to-peer distributed ledger that is cryptographically secure, append-only, immutable (extremely hard to change), and updateable only via consensus or agreement among peers. From a business point of view, a blockchain can be defined as a platform whereby peers can exchange values using transactions without the need for a centrally trusted arbitrator. A block is simply a selection of transactions bundled together in order to organize them logically. It is made up of transactions, and its size is variable depending on the type and design of the blockchain in use. A reference to a previous block is also included in the block unless its a genesis block. A genesis block is the first block in the blockchain that was hardcoded at the time the blockchain was started.

Another definition is provided by [141]:

> Blockchains are shared and distributed data structures or ledgers that can securely store digital transactions without using a central point of authority. The data structure is, in other words, a ledger that may contain digital transactions, data records, and executables. Instead of managing the ledger by a single trusted center, each individual network member holds a copy of the records' chain and reaches an agreement on the valid state of the ledger with consensus. The exact methodology of how consensus is reached is an ongoing area of research and might differ to suit a wide range of application domains. Cryptography links new transactions to previous transactions, making blockchain networks resilient and secure. Every network user can check for themselves if transactions are valid, which provides transparency and trustable, tamper-proof records.

3.2.1.1 Smart contracts

A key characteristic of the current Blockchain ecosystem is the smart contract. While these contracts have emerged as a major defining characteristic of the so-called 'Blockchain 2.0' the concept of smart contracts has existed for longer than the Blockchain concept. Nick Szabo first defined smart contracts in 1996 as those types of contractual clauses that could be embedded in various aspects of hardware and software to make the breach of the contract inordinately expensive [162]. These contracts can be self-executing and immutable. Another definition of smart contracts is given by [163], who defines the smart contract as a piece of computer code that, should specific criteria be met, corresponding actions are then carried out. Smart contracts can assist in removing the intermediary part in various use cases, and this may lower transaction costs and allow for low-value transactions to take place [141].

3.2.1.2 Limitations

While there have been many examples of the potential benefits of incorporating Blockchain technology in the energy sector, there are some limitations that need to be addressed before the technology can make a significant impact in this sector.

While not a limitation of the Blockchain technology itself, there is an inherent limitation in applying the technology to the electric sector. The electric sector is often characterized by large-scale, centralized systems which make use of both economies of scale and economies of scope. These factors, combined with the risk-averse nature of many electric utilities, could limit the speed and scale of the blockchain impact in the sector. The fact that there is often a physical transaction coupled with a financial transaction in the energy sector raises some issues with regard to Blockchain's potential impact on the sector. This is especially true in the electric power sector, as once injected into the grid, it is very difficult to control and track the electricity from the supplier to the consumer. Public and permissionless blockchains would allow the highest number of people to join a blockchain system, but the trade off of this increased size is the transaction speed and the high costs of proof of work consensus mechanisms which have dominated the public and permissionless blockchain ecosystem. This trade-off has been termed the 'scalability trilemma,' and it states that a blockchain can only have a maximum of two of the following three characteristics: decentralization, scalability, and security [164].

The self-governance of blockchain systems is also a significant challenge facing developers today. The ideals of decentralized, immutable, and pseudo-anonymity do not generally make for the easy establishment of a robust governance structure. To establish these structures within the blockchain ecosystem without sacrificing the ideals of a project based on open collaboration between a group of core developers can be a difficult issue to overcome.

3.2.1.3 Blockchain enabled energy trading

One of the most widely cited applications of blockchain in the energy sector is its potential impact on the energy trading sector. Blockchain could speed up the payment for various services and allow for payment to follow automatically as soon as the transaction has been completed. This could be achieved by using smart contracts. Traditionally, the payment process has lagged behind delivery quite significantly, and a whole business sector has emerged to deal with the payment and settlement process. The rapid settlement of transactions will become increasingly important because the volume of transactions is expected to grow as more prosumers engage in the energy sector [165]. Currently, the trading process involves numerous transactions between numerous actors, and this means that the process is ripe for the possible disintermediating effects of blockchain technology.

[166] suggests that the initial use case for blockchain technology in this sector could be as part of the communications network handling the trades. This could be especially useful in standardizing the information flow between traders. Should the markets make use of one blockchain to coordinate the transactions, all traders will need to provide the same information for their trades which could increase the transparency of these trades.

Some of the longest lags between the delivery of energy and the associated payment occur within imbalance settlement markets, with payments taking up to 28 months to be settled [141]. Smart contracts could be utilized to automatically carry out the payment once the delivery of the energy has been received and verified. Smart contracts could also create a more transparent market and reduce other inefficiencies within the existing markets.

However, using the blockchain in energy trading markets still has some issues to work out. It may still be challenging to track the flow of electricity in a network so as to verify the transaction between a supplier and consumer of the electricity [167]. Additionally, even if the market allows energy trading agreements to be set up between two parties, these agreements will need to be approved by a central authority once a technical feasibility assessment has been done in order to prove that the network can handle this transaction. Should the network not be able to handle the agreed transaction, it may be difficult to renegotiate the agreement if smart contracts are used.

Using blockchain technology to enable peer-to-peer markets can increase the prosumer's participation in that market and put the customers at the heart of the energy transition. In these markets, individuals could offer to sell their excess generation or market their flexibility to other market participants. This could help increase the penetration of small-scale renewable energy sources and the flexibility of the market. Various use cases for blockchain in energy trading have been presented and include: peer-to-peer trading in microgrids, bilateral agreements between producers and consumers, demand response actions, coordination of Virtual Power Plants (VPPs) (as is shown in this chapter), management of the grid, energy storage management, aiding in the control strategies of DERs, community energy initiatives, and coordinating a power plant portfolio [141]. It is unlikely that the energy system will ever be fully decentralized as there will always be a need for a central authority to manage and control the distribution and transmission grid. Blockchains could also expose consumers to the actual price of energy. This could lead to more rational energy choices or increased participation in demand response activities [141].

The roles played by the different actors in the energy system may also change. The owners of the transmission and distribution (normally the TSO and DSO) will still be responsible for operating and maintaining the physical networks and they will need to be compensated for that plus their roles as system stabilizers. Each node in a peer-to-peer energy market will need to be responsive to the needs of the grid and react accordingly. These grid needs may include network conditions, prices, and balancing supply and demand [168]. This will increase the onus on the owners of the DERs to provide timely and accurate information to the system operator.

These factors combine to make it very unlikely that a fully decentralized electricity network that makes use of peer-to-peer energy trading will develop in the next decade. This is because the existing grid, while flawed, does provide services to its customers that a decentralized network may struggle to achieve [169]. As the roles of actors within the electric power system change and evolve over time, there may be scope for blockchain systems that work with the incumbent utilities to help manage the grid [169]. Blockchain is likely to reduce the barriers to entry for individuals to participate in an energy trading market. This increases both transparency and liquidity of the market. Blockchain also allows for more flexible generation portfolios with a diverse set of resources and numerous transactions occurring between the market participants [17].

3.3 System Development

3.3.1 Model overview

The model used in this chapter has two connected layers. The first deals with energy trading, and the second layer, termed the network layer, sits on top to coordinate and record energy transactions using smart contracts. The first layer uses a stochastic mixed-integer linear programming (MILP) optimization model to investigate the potential for both intra- and inter-VPP energy trading. The second layer is the network layer which automates and records the transactions. The model considers various sources of uncertainty and variability, such as PV production, and departure and arrival times of EVs. The multi-layer approach of this model is shown in Figure 3.2. This shows the interconnected layers which optimize the scheduling of DERs and work together to facilitate and record energy trading while respecting the constraints of the underlying physical infrastructure layer. The figure shows that while each layer can be independent, by utilizing the principles of TE a more complete framework can be developed. This provides a deeper understanding of the functions and roles that the consumers can have.

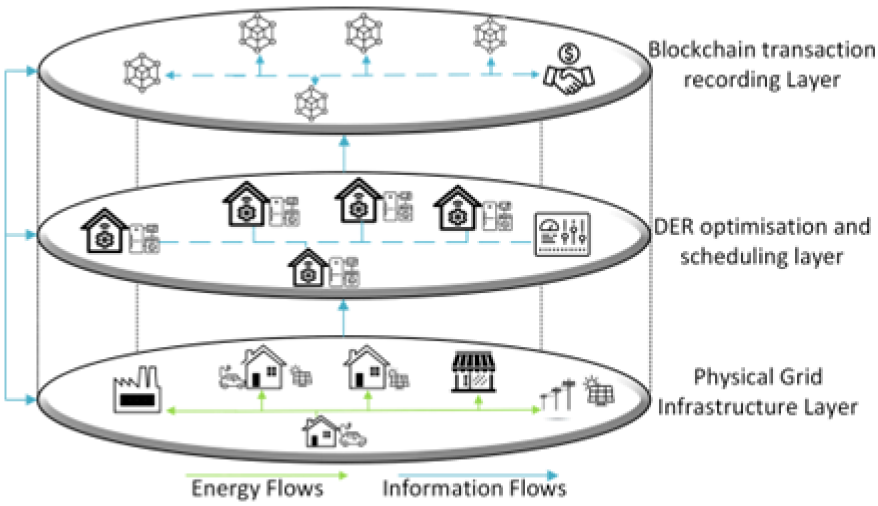

Figure 3.2: Layers within the transactive energy market

3.3.2 Energy trading model

This model is operated using a two-stage optimization approach. Initially, the model is applied to a single VPP (or neighborhood) to optimize the energy trading between connected consumers, prosumers, or producers. The results of this stage are then passed to the second stage of the model which deals with energy trading between connected VPPs (energy trading between neighborhoods). The objective function is to minimize the total costs of prosumers shown in Equation 3.1.

$$Min\ \ total\ \ prosumer\ \ cost = \sum_{s} \rho_s \sum_{w} \sum_{t} (\lambda_{t,s}^{pur} P_{w,t,s}^{pur,T} \Delta T - \lambda_{t,s}^{sold} P_{w,t,s}^{sold,T} \Delta T) \tag{3.1}$$

In Equations 3.2 to 3.4b, the set of restrictions regarding the power exchange in the VPP or neighborhood is shown. The power purchased may come from the grid or a prosumer shown in Equation 3.2, in in the case where inter-VPP trading is allowed, the energy can also be bought from another prosumer in another VPP. In Equation 3.3 the power sold may go to the grid or another prosumer in the neighborhood, or in in the case where inter-VPP trading is allowed, the energy can also be sold to another prosumer in another VPP. The energy balance in the neighborhood is represented by Equations 3.4b. Initially, all energy demand in the neighborhood is met through purchasing power from the grid (Case 1), then energy trading within the neighborhood is allowed (Case 2), and finally in energy trading among the neighborhoods is allowed (Case 3).

$$P_{w,t,s}^{pur,T} = P_{w,t,s}^{pur,grid} + P_{w,t,s}^{pur,local} + P_{w,t,s}^{pur,neigh} \tag{3.2}$$

$$P_{w,t,s}^{sold,T} = P_{w,t,s}^{sold,grid} + P_{w,t,s}^{sold,local} + P_{w,t,s}^{sold,neigh} \tag{3.3}$$

$$\sum_{n} P_{n,t,s}^{demand} = \sum_{n} P_{n,t,s}^{pur,grid} + \sum_{n} P_{n,t,s}^{pur,local} + \sum_{n} P_{n,t,s}^{pur,neigh} \tag{3.4a}$$

$$\sum_{n} P_{n,t,s}^{supply} = \sum_{n} P_{n,t,s}^{sold,grid} + \sum_{n} P_{n,t,s}^{sold,local} + \sum_{n} P_{n,t,s}^{sold,neigh} \tag{3.4b}$$

In Equation 3.5, the power balance equation for each prosumer is presented. Energy transactions between prosumers and the network are represented by Equations 3.6 to 3.8, where parameter N may impose limits on the amount of power coming from the grid.

$$P_{w,t,s}^{pur,T} + P_{w,t,s}^{PV,used} + P_{w,t,s}^{EV,used} + P_{w,t,s}^{ESS,used} = InfLoad_{w,t,s} + P_{w,t,s}^{EV,charge} + P_{w,t,s}^{ESS,charge} + \sum_{c} P_{w,t,s,c}^{mach} \tag{3.5}$$

$$P_{w,t,s}^{sold,T} = P_{w,t,s}^{PV,sold} + P_{w,t,s}^{ESS,sold} + P_{w,t,s}^{EV,sold} \tag{3.6}$$

$$P^{pur,T}_{w,t,s} \leq N * x^2_{w,t,s} \tag{3.7}$$

$$P^{sold,T}_{w,t,s} \leq N * (1 - x^2_{w,t,s}) \tag{3.8}$$

In Equations, 3.9 - 3.15, various flexible appliances such as the dishwasher (DW) and washing machine (WM) are modeled. These are included as they operate in predefined cycles and each prosumer's consumption during an operation is known. However, operational periods may change depending on the energy price and the preferences of the prosumers, for example, the number of times to operate during a day.

$$P^{mach}_{w,t,s,c} = \sum_{f} (x^{phase}_{w,t,f,c,s} * P^{phase}_{w,f,c,s}) \tag{3.9}$$

$$\sum_{f} x^{phase}_{w,t,f,c,s} \leq 1 \qquad x \in [y, u, z] \tag{3.10}$$

$$y^{phase}_{w,t,f,c,s} \leq 1 \tag{3.11}$$

$$z^{phase}_{w,t,f,c,s} = y^{phase}_{w,(t+T^{dur}_{w,f,c,s}),f,c,s} \tag{3.12}$$

$$y^{phase}_{w,t,f,c,s} - z^{phase}_{w,t,f,c,s} = u^{phase}_{w,t,f,c,s} - u^{phase}_{w,(t-1),f,c,s} \tag{3.13}$$

$$z^{phase}_{w,t,f,c,s} = y^{phase}_{w,t,(f+1),c,s} \tag{3.14}$$

$$\sum_{t} y^{phase}_{w,t,f,c,s} = N_{w,c,s} \tag{3.15}$$

The EV model used is presented in Equations 3.16 to 3.21, where the EV discharging power can go either to the network or to the home. In Equation 3.17 and Equation 3.18, the charging and discharging limits are presented. The state-of-charge (SOC) is defined by Equation 3.19 and Equation 3.20.

$$P^{EV,used}_{w,t,s} + P^{EV,sold}_{w,t,s} = \eta^{EV,disch}_{w,s} * P^{EV,disch}_{w,t,s} \tag{3.16}$$

$$0 \leq P^{EV,charg}_{w,t,s} \leq R^{EV,charg}_{w,s} * x^3 \qquad t \in [T^a_{w,s}, T^d_{w,s}] \tag{3.17}$$

$$0 \leq P^{EV,disch}_{w,t,s} \leq R^{EV,disch}_{w,s} * (1 - x^3) \qquad t \in [T^a_{w,s}, T^d_{w,s}] \tag{3.18}$$

$$SOC^{EV}_{w,t,s} = SOC^{EV,ini}_{w,t,s} + CE^{EV}_{w,s} * P^{EV,charge}_{w,t,s} * \Delta T - P^{EV,disch}_{w,t,s} \Delta T \qquad \forall w, sift = T^{a}_{w,s} \tag{3.19}$$

$$SOC^{EV}_{w,t,s} = SOC^{EV,ini}_{w,t-1,s} + CE^{EV}_{w,s} * P^{EV,charge}_{w,t,s} * \Delta T - P^{EV,disch}_{w,t,s} \Delta T \qquad \forall w, sift \in [T^{a+1}_{w,s} > T^{d}_{w,s}] \tag{3.20}$$

$$SOC^{EV,min}_{w,s} \leq SOC^{EV}_{w,t,s} \leq SOC^{EV,max}_{w,s} \qquad \forall w,s,t \in [T^{a}_{w,s} > T^{d}_{w,s}] \tag{3.21}$$

$$SOC^{EV}_{w,t,s} = SOC^{EV,max}_{w,t,s} \qquad \forall w,s \quad if \quad t = T^{d}_{w,s}] \tag{3.22}$$

In Equations 3.23 to 3.28, the ESS of each prosumer is modeled.

$$P^{ESS,used}_{w,t,s} + P^{ESS,sold}_{w,t,s} = \eta^{ESS,disch}_{w,s} * P^{ESS,disch}_{w,t,s} \tag{3.23}$$

$$0 \leq P^{ESS,charg}_{w,t,s} \leq R^{ESS,charg}_{w,s} * x^{3}_{w,t,s} \qquad \forall w,t \tag{3.24}$$

$$0 \leq P^{ESS,disch}_{w,t,s} \leq R^{ESS,disch}_{w,s} * (1 - x^{3}_{w,t,s}) \qquad \forall w,t \tag{3.25}$$

$$SOC^{ESS}_{w,t,s} = SOC^{ESS}_{w,t-1,s} + CE^{ESS}_{w,s} * P^{ESS,charge}_{w,t,s} * \Delta T - P^{ESS,disch}_{w,t,s} \Delta T \qquad \forall w,t \geq 1 \tag{3.26}$$

$$SOC^{ESS}_{w,t,s} = SOC^{ESS,ini}_{w,s} \qquad \forall w \quad if \quad t = 1 \tag{3.27}$$

$$SOC^{ESS,min}_{w,s} \leq SOC^{ESS}_{w,t,s} \leq SOC^{ESS,max}_{w,s} \qquad \forall w,t \tag{3.28}$$

The PV production by the prosumer is presented in Equation 3.29, where PV production can be used by the prosumer or sold to the grid. A simplified heating, ventilating and air conditioning (HVAC) model is presented in

$$P^{PV,used}_{w,t,s} + P^{PV,sold}_{w,t,s} = P^{PV,prod}_{w,t,s} \qquad \forall w,t \tag{3.29}$$

Equations 3.30 to 3.32 based on temperature control. Eq 3.30 relates the temperature in a period to the temperature in the previous period plus any HVAC usage in that period. Eq 3.31 bounds the temperature between the minimum and maximum acceptable temperature limits for that prosumer. Eq 3.32 places limits on the power usage of the HVAC equipment.

$$\theta_{w,t+1} = \beta_{w,s} * \theta_{w,t,s} + (1-\beta_{w,s})(\theta^{0}_{w,t,s} + COP_{w,s} * R_{w,s} * P^{HVAC}_{w,s}) \quad where \quad \beta_{w,s} = e^{\frac{-\delta T}{R_w R_w}} \tag{3.30}$$

$$\theta^{min}_{w} \leq \beta_{w,t+1} \leq \theta^{max}_{w} \qquad \forall w,t \tag{3.31}$$

$$0 \leq P^{HVAC}_{w,t} \leq P^{HVAC,max}_{w} \qquad \forall w,t \tag{3.32}$$

In this model, uncertainty is accounted for using scenario generation. Two sources of uncertainty, solar generation and demand, were considered in the model. Three scenarios for each parameter were developed. This resulted in nine scenarios which were reduced using k-means clustering techniques as described in [170].

The model is programmed in GAMS 24.0 and solved using the CPLEX 12.0 solver. The simulations are conducted on an HP Z820 workstation with two 3.1GHz E5-2687W processors and 256 GB of RAM.

3.3.3 Smart contract layer

The second layer of this transactive energy model introduces the blockchain-based smart contract layer to the underlying MILP model to automate and record the energy transactions both within VPPs and between the connected VPPs. This layer is designed to sit atop the energy management layer and receive data related to the energy trades between consumers and VPPs. This layer helps to increase the automation of energy trading, improves the transparency of trading mechanisms, and increases the security of the system through the immutable nature of blockchain. The system of smart contracts developed for this framework was developed using Ethereum. The contracts were compiled using Solidity version 0.6.6 and deployed using Remix v0.9.4.

The flow of information between a consumer and a prosumer using the smart contract system is shown in Figure 3.3. This flow of information occurs within the network layer specified in Figure 3.2. There were four types of agents operating within the smart contract layer. These are the Administrator, Consumer, Prosumer, and the Market Facilitator. These agents and their actions will be introduced in the following sections:

3.3.3.1 Administrator

This agent is responsible for the functioning of the VPP by allowing consumers to enter and leave the VPP. The administrator agent is responsible for ensuring that the consumers adhere to both technical and market-based requirements. While the presence of the administrator agent negates the promise of fully decentralized energy trading among prosumers, it can be argued that this agent is necessary as the administrator provides security and reliability to the system and may be required by the relevant energy regulation.

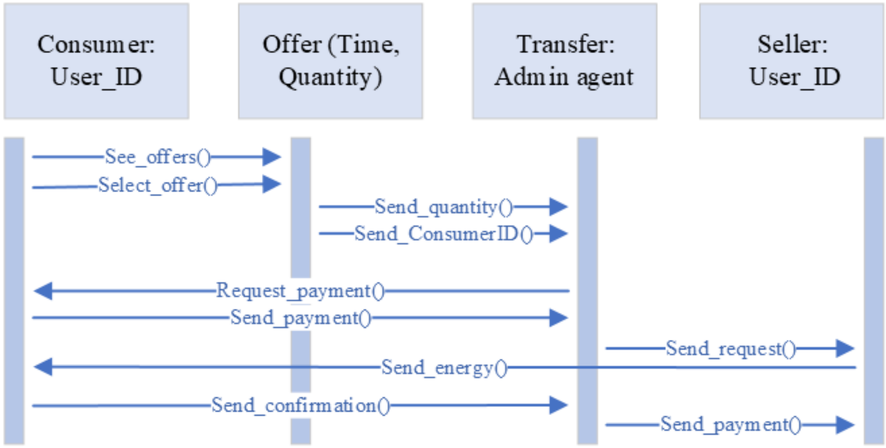

Figure 3.3: Flow of information through the system within the network layer

3.3.3.2 Consumer agent

This agent represents the traditional customer role within power systems. The consumer only purchases energy, either from the external grid or from prosumers.

3.3.3.3 Market facilitator

This agent is authorized to buy and sell energy within the VPP. This agent is a regulatory construct and has emerged from the recent changes to the regulations dealing with self-generation and self-consumption of electricity in Portugal. According to this regulatory framework, the Market Facilitator (MF) acts as a supplier and purchaser of last resort to minimize any shortfalls in electricity supply or demand. Within this model, energy transactions amongst consumers are prioritized, and the MF only intervenes if there is a shortage or excess of electricity within the system. This was done by setting the price charged by the MF at a higher level than the energy traded.

The roles of the various agents and their available actions are shown in Figure 3.4. The figure shows that the administrator sits at the heart of the system. Once consumers are registered by the administrator, they become contract owners and may place supply offers (instances where the agents have surplus energy) or demand requests (instances where the agents have a shortfall) for energy. Once these supply bids or demand requests are matched and approved by the contract owner, they move to the Transfer contract, which may require the participation of the MF agent.

3.3.3.4 Prosumer

This agent represents an active consumer who may generate or store electricity using various types of DERS and then can sell this excess to other agents or the external grid. Prosumers can also buy energy in instances where they have a shortfall. This agent needs to be authorized by the Administrator agent to participate in the market.

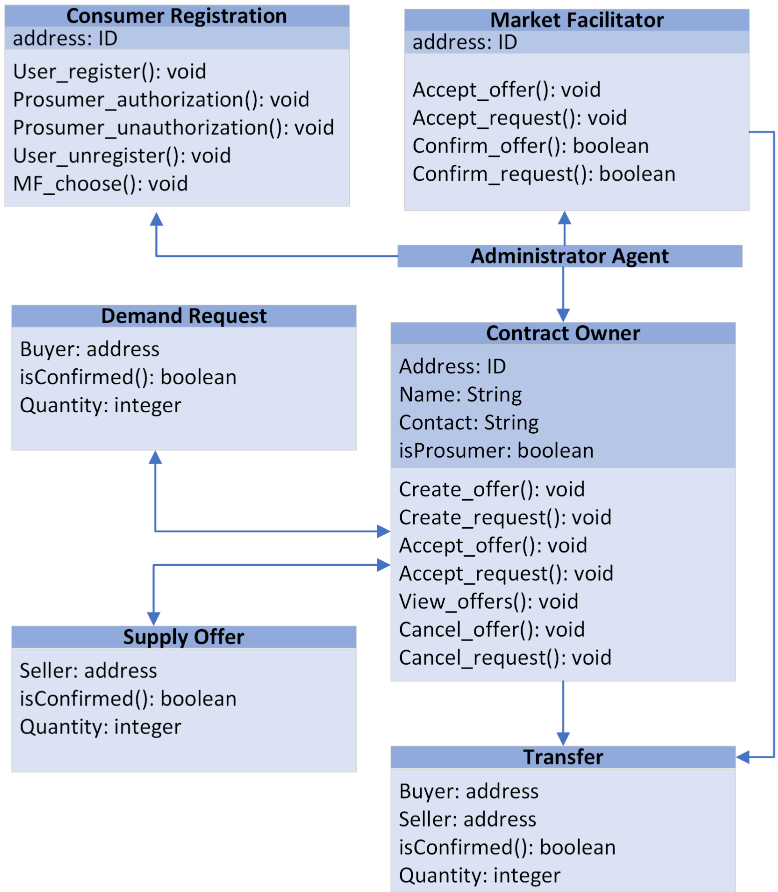

Figure 3.4: Roles of agents within the system

3.4 Case Study and Results

3.4.1 Case study details

This framework used three VPPs to investigate the impacts of transactive energy trading. Each VPP had 10 consumers with a different mixture of residential and service buildings. This diversity of consumer types leads to different load profiles and DER portfolios which helps to increase opportunities for energy trading within the VPP. The allocation of these DERs can be seen in Table 3.2.

The PV systems had a capacity of 1 kW each. The ESSs had a capacity of 3 kWh, maximum charging and discharging rate of 0.6 kW, initial state of charge (SOC) of 80%, minimum SOC of 40%, and charging and discharging efficiency of 90%. The EVs had a capacity of 4 kWh, maximum charging and discharging rate of 0.6 kW and efficiency of 90% [171].

In this paper, three case studies were considered. In each case study, different levels of energy trading were considered. In the baseline case, Case 1, there was no energy trading between consumers. All the energy demand was satisfied by purchasing the energy from the external grid. Case 2 introduced intra-VPP energy trading. This allowed energy trading within the VPP but not between VPPs. Any shortage or excess of electricity was imported or sold to the MF agent. There is a fixed fee for energy trading between peers of €0.03/kWh, taken from [171]. The transaction cost for each P2P energy trade is fixed in this model. However, the question of tariff design for P2P energy markets is an interesting and important field [172]. Numerous factors influence the composition of this tariff including technical (maintenance costs), economic (taxes), or social costs (equity concerns), and these will vary depending on the local conditions. In Case 3, inter-VPP trading was considered. In this case, the model first sought to balance any excess or shortfall from a single VPP by trading energy from the other two VPPs, and only if this excess or shortfall could not be met would the MF agent becomes active.

3.4.2 VPP optimisation results

This section introduces the results of the model for each case study and then compares the operating costs.

Table 3.2: Total Number of DERS in the VPPs.

Device	VPP1	VPP2	VPP3
EV	10	7	13
ESS	7	5	10
PV	9	3	21
HVAC	11	10	10
DW	9	10	8
WM	9	10	8

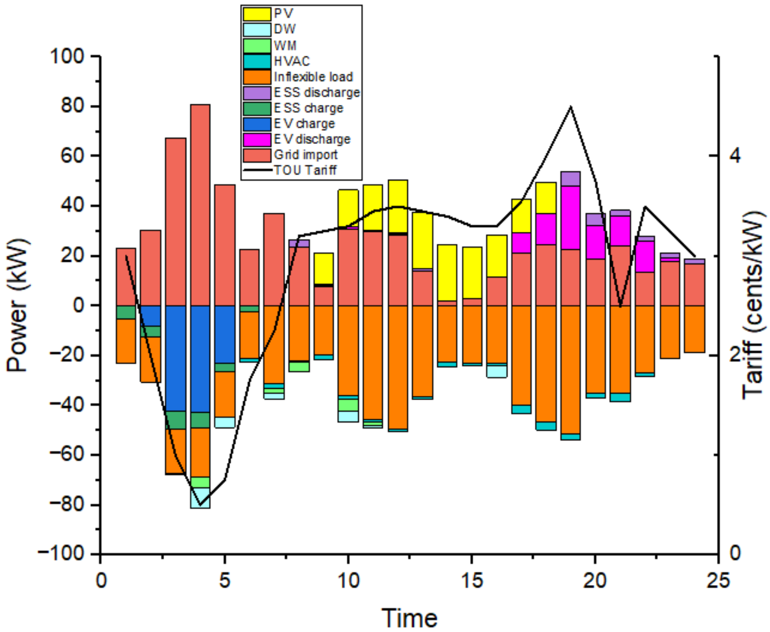

Figure 3.5: Energy mix for VPP 1 in case study 1

3.4.2.1 Baseline

In the baseline model, Case 1, there was no energy trading permitted. This case study provided a baseline for the comparison of the other two cases in terms of the scheduling and operating costs of the DERs. The energy mix for VPP 1 in this first case study as well as the TOU tariff used in this study is shown in Figure 3.5. The negative power values in Figure 3.5 are loads used in the VPP and include flexible and inflexible loads. The energy used to charge the ESS and EVs is also shown. The majority of EV and ESS charging takes place during the early hours of the morning when electricity prices are relatively low. The EVs and ESSs are discharged in the evening peak period to reduce the amount of energy bought from the external grid. The flexible loads are scheduled to occur in periods of low tariffs. In this case study, renewable energy sources accounted for 31.56% of the total load for VPP 1.

3.4.2.2 Intra-VPP trading

This case allowed for intra-VPP energy trading between the consumers. The energy supply of VPP 1 for case study 2 is shown in Figure 3.6. This figure shows that when the TOU tariff is low, between 01:00 and 07:00 power is imported from the grid and used to charge the EVs and ESSs. Energy trading among the peers occurs when the TOU tariff is high, namely from 17:00 to 21:00. It is also during these evening hours when the EVs and ESSs discharge power to help meet the evening peak load. Comparing this case to the baseline, grid imports were reduced by 5.7% as the VPP demands could now also be met through energy trading which helped to reduce the costs of electricity for the VPP. Interestingly, a new peak load period is introduced into the system. This new peak load period, which occurs between 00:00 and 02:00 is due to the charging of the ESSs and EVs. This is an important feature to consider in future distribution grids which may contain a large penetration of EVs or ESSs.

In Case 2, VPP 3 had the most energy trading amongst consumers. These trades can be seen in the chord diagram shown in Figure 3.7. This figure shows the quantity and direction of the energy traded within this VPP during the 24 hours. The numbers and width of the arcs are proportional to the amount of energy traded with other consumers during the 24 hours. Much of the excess energy for trading is generated by Peer 9 and Peer 10. These two peers are the two service buildings within the VPP and have large installed PV systems.

In this VPP there exist different types of consumers, namely those consumers who only consume energy, such as Peer 3 and Peer 4. Some consumers are self-reliant and do not require any additional energy, such as Peer 9 and Peer 10. Then there are some consumers who, depending on the time of day, are either exporting or importing energy, for example, Peer 5 or Peer 1. With intra-VPP energy trading allowed, renewable energy sources accounted for 36.12% of the total load which is an increase of five percentage points relative to Case 1.

In this case, energy trading accounted for 5.7% of the total load for VPP 1 and across the three VPPs, energy trading accounted for 6.97% of the total load which reduced VPP costs.

VPP 3 had the highest amount of energy trading taking place in this case study. This was due to the presence of the two large service buildings with large installed PV systems which is cheaper relative to the electricity from the external grid. This promotes energy trading and the use of electricity generated within the VPP. It is expected that more PV systems will be installed in VPPs therefore this effect will become more prevalent and the scope for energy trading will increase.

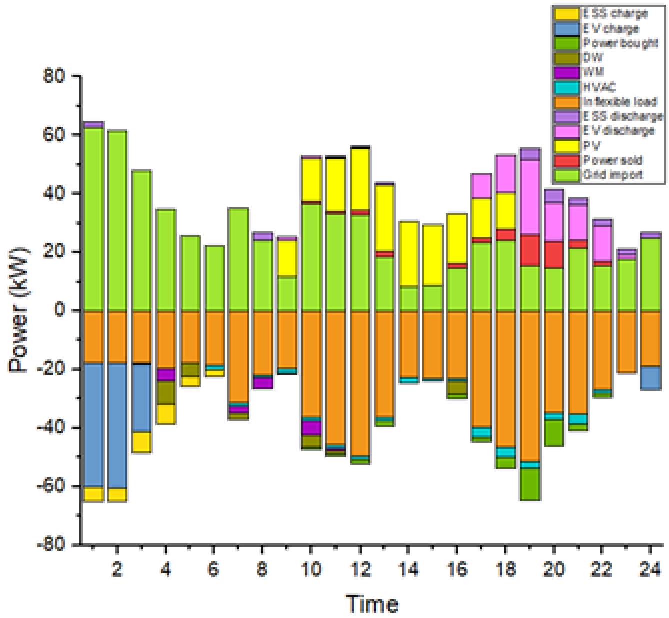

Figure 3.6: Energy mix for VPP 1 in case study 2

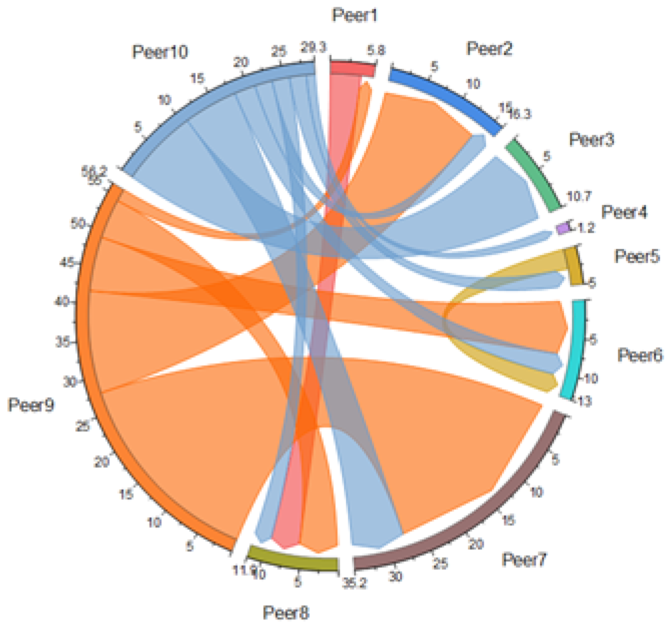

Figure 3.7: Energy trades amongst peers in VPP 3 for case study 2

Table 3.3: Daily operating costs of the VPPs across the case studies

	Case 1(€)	Case 2(€)	Case 3(€)
VPP1	18.446	18.12	18.12
VPP2	24.795	14.794	24.703
VPP3	16.12	15.462	15.381
Total cost	59.363	58.366	58.204

3.4.2.3 Inter-VPP trading

The third case study allowed for the trading of energy between the VPPs. This inter-VPP trading is coordinated by the Global VPP manager as shown in Figure 3.1. The flow of the energy trades was from VPP 3 to VPP 2. This is likely due to the large capacity of PV installation in VPP 3, which produced excess energy and this could be traded with VPP 2. The energy trades occurred between 14:00 and 22:00 and totaled 11.31 kWh. This was 3.5% of the energy used by VPP 2 during these hours. The amount of renewable energy used by the VPPs, in this case, was 38.8% which is an increase relative to Case 2. Across the three VPPs in this case study, energy trading accounted for 8.3% of the total load which is an increase relative to Case 2. Inter-VPP trading further helped reduce costs due to the lower fixed fee for each local transaction.

3.4.2.4 Comparison

Table 3.3 shows the costs of energy for the three VPPs across the three case studies. The operating costs of the VPPs decreased between Case 1 and Case 2, i.e., with the introduction of intra-VPP trading. The cost reduction was a maximum for VPP 3 which saw a 4.3% reduction solely by allowing energy trading among the VPP members. These cost reductions were due to a combination of lower electricity prices for locally produced electricity and the revenue generated by trading electricity within the VPP.

The cost reductions were largest for VPP 3, which had the highest number of EVs, ESSs, and PV systems installed. This allowed the VPP members to optimally schedule their electric demand to avoid periods of high prices and utilize locally generated electricity, which is cheaper during peak periods. This result shows the advantage of having a diverse group of customers within a VPP to take advantage of their different load profiles and DER portfolios.

In terms of the cost reduction between Case 2 and Case 3, there was a 0.72% reduction in overall costs for the VPPs. This was obtained solely by allowing VPP 3 to sell excess generation to VPP 2. This trading reduced costs for VPP 2 and increased profits for VPP 3.

The amount of energy traded between VPPs is relatively small and this is due to the energy balancing of each VPP and the use of EVs and ESSs to store excess energy within the VPP. Additionally, each VPP only has 10 consumers or prosumers. As the number of consumers or prosumers within the VPP grows, it is expected that inter-VPP trading will increase.

```
contract administrator {

    address service_admin;

    event service_in_execution();
    event new_service_admin(address service_admin);

    constructor() public{...}

    modifier only_admin{...}

    function get_admin() public view
        returns (address){...}

    function change_admin(address new_admin) public
        only_admin{...}
}
```

Figure 3.8: Deployed administrator contract

3.4.2.5 Impact of Portuguese energy policy

In this model, the impact of the new self-consumption regulations and the targets laid out in the PNEC was investigated. The significant increase in solar PV systems was modeled and this increase led to an increase in the ability of VPPs to trade excess energy as seen in the differences between VPP 2 and VPP 3.

The main impact of these regulations was the introduction of the MF agent which provided a buyer or seller of last resort for the excess energy generated by the DERs. In Case 1 and Case 2, this agent was not active as the VPPs could balance supply and demand. However, in Case 3, with the introduction of inter-VPP trading, there were several instances where the MF agent bought excess generation from VPP 3. The MF agent bought 2.16 kWh of electricity from Peer 10 in VPP 3, which otherwise, would not have been traded. This value is expected to grow with an increase in the number and greater diversification of prosumers in VPP. This shows the benefit of this new agent. The participation of the MF agent is thought to increase as more self-generation is brought online by active consumers.

3.4.2.6 Smart contracts

In this section, the results of the network layer from the case study are presented. The main results identified in this section are the execution of the various smart contracts and the fact that only certain agents may access certain contracts.

The smart contract for the administrator agent is deployed first as this agent is then responsible for managing the other agents in the system. The deployed administrator contract is shown in Figure 3.8. The figure shows that only the administrator agent can modify this contract which helps maintain the security and integrity of the model.

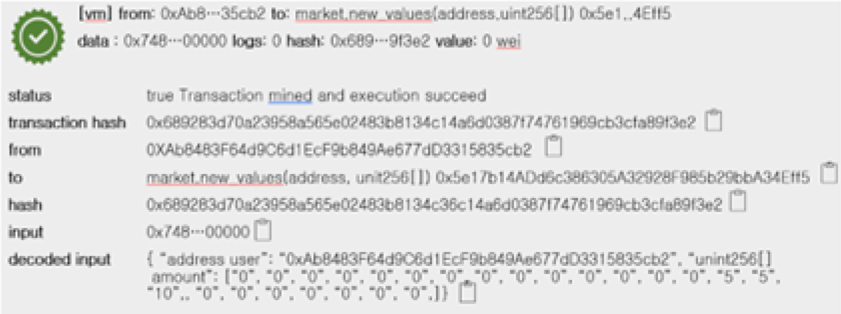

Figure 3.9: Submitted energy requests from Peer 2 in VPP 1

A consumer can submit a request for energy for the following 24-hour period. This request is submitted to the administrator agent for approval. An example of these requests is shown in Figure 3.9. This shows the requests for energy from Peer 2 in VPP 1. The amount of energy is shown in the 'decoded input' section as a vector of values each corresponding to 1 hour for the next day. This request is encoded and only visible to the administrator agent, which helps maintain the privacy and security of the system. Once a transfer has been authorized by the respective agents, the transaction is completed and recorded. An example of a completed transaction is shown in Figure 3.10. This figure shows the details of the transaction such as the hash codes of both the transaction and of the block in which the transaction was included, the address of the contract, and the originator and receiver addresses of the agents involved in the transaction.

Figure 3.10 also shows the acceptance by the administrator agent of an offer of excess generation from Peer 9 in VPP 1 for 1 kWh of energy. The transaction hash ensures that this trade can be tracked and verified by the members of the system which increases the transparency and reliability of the system.

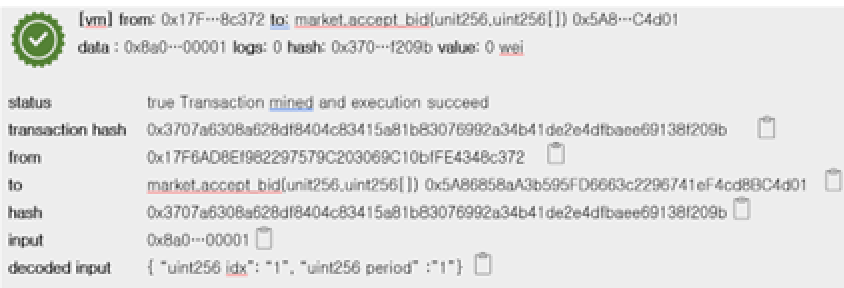

Figure 3.10: Accepted bid from Peer 9 in VPP 1

3.5 Chapter Conclusions

In this chapter, an innovative two-level transactive energy management model for three connected VPPs was developed. This MILP model optimally scheduled and managed the operation of a diverse set of DERs to minimize energy costs. The MILP model operated at two levels within the market and allowed for both intra-VPP and inter-VPP energy trading. A blockchain-based smart contracts layer was utilized on top of the energy management layer to help automate and record energy transactions. This was done to increase the reliability and transparency of the system to incentivize consumer participation. Three different case studies were investigated to show the impact of different trading regimes and the impact of the new agents introduced by the self-consumption regulations in Portugal. Results showed that the operating costs of the VPPs were reduced when both intra-VPP and inter-VPP trading was allowed. Increasing the size and diversity of DERs within a VPP led to more trading and lower prices. This model has shown that blockchain-based smart contracts can be successfully integrated into a hierarchical energy trading model which respects novel energy regulations. This combination of technologies can be used to increase consumer participation, lower energy bills, and increase the penetration of locally generated electricity from renewable energy sources.

This chapter has also presented an overview of the potential impacts of blockchain technology in the energy sector. This chapter has introduced the technology as well as the context surrounding not only the technology but also the ongoing energy transition. The combination of these two events has shown that blockchain technology could play a significant role across numerous sectors in the future energy system. Within the field of blockchain-enabled energy trading, there are clear parallels between blockchain technology and the operation of decentralized energy networks, however, there are still major challenges to overcome. The rise of DERs will cause the energy system to become more decentralized in the future and electricity trading will also become more decentralized. It is unclear just exactly what role blockchain will play in decentralized energy trading. Proactive regulation of both blockchain and the energy regulations surrounding self-generation and consumption by prosumers is key to helping achieve this goal and further research will be key, especially using pilot projects to investigate how the technology works in the real world.

Chapter 4

Data Driven Models for Distributed Energy Resources to Increase Prosumer Participation in Smart Grids

The automation and intelligent use of Distributed Energy Resources (DER) can enable prosumers to participate in transactive energy systems actively. The previous chapter presented a large-scale model where prosumer participation was a given. This chapter focuses on providing evidence to demonstrate how intelligent devices can operate to allow previously passive consumers to play an active role in energy systems. This chapter presents an innovative design and implementation of an easy-to-use device to transform a previously passive Electric Water Heater (EWH) into an active DER for intelligent water heating for residential consumption to benefit both the consumer and the electrical utility. The device relied upon Long Short-Term Memory (LSTM) networks to forecast a consumer's hot water demand and optimize the operation of an EWH. The device was deployed in a six-month pilot project on the island of São Miguel, in collaboration with the Electricidade Dos Açores, S.A., the Azorean electricity utility. Results from this case study show that the LSTM model could accurately forecast hot water demand and the device can optimally operate the EWH to meet this demand. Results show an average reduction of 1.33 kWh/day per consumer. This equates to an average cost-saving of 35.5% for the consumers' water heating costs, which is significant. The qualitative results from the survey importantly show that the device did not affect the consumer's comfort. Indeed, the consumers enjoyed a sense of control over their hot water demand, validating the benefits and efficacy of the proposed device.

Therefore, this chapter provides firsthand evidence showing that new control methods based on artificial intelligence can enable the active participation of consumers in energy systems and creates systems where economic and thermal comfort signals can be used to manage prosumer participation in transactive energy systems.

Chapter Highlights and Novel Contributions:

- Design, validation, and implementation of a non-intrusive device to intelligently control electric water heaters in an easy and user-friendly manner.
- Development of a machine-learning algorithm to forecast residential hot water consumption based on non-intrusive temperature data alone. The model can use temperature data to identify the volume of water used. This was also used as the basis of the control method to intelligently control the device to ensure that the demand for hot water is met in a cost-efficient manner and with no alterations made to the EWH.
- Details and results of a pilot study where the device was implemented in 15 homes on the São Miguel island for a period from July to December 2021 and a database of residential hot water demand and associated EWH demand profiles.
- Results showing the impact of intelligent heating on the consumer's energy bill, providing evidence that the comfort of the consumer was not impacted through a survey conducted on the pilot study homes. This introduces important qualitative information relating to the preferences, behavior, and comfort of the prosumers.
- Quantification of the results shows the impact of the device on consumer costs. Additionally, the benefits provided by the device to the electrical utility in terms of avoided costs of generation, avoided emissions, and impacts on physical infrastructure are shown.

Relevant Publication(s):

M. Gough, K. Rakhisa, T. Bandeira, H. Amaro, R. Castro, and J.P.S. Catalão, "Design and Implementation of a Data-Driven Intelligent Water Heating System for an Island Community: A Case Study," in *Energy Conversion and Management*.
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Published: https://doi.org/10.1049/icp.2021.2095

Chapter 4 Nomenclature

Abbreviation	**Definition**
AdaGrad	Adaptive Gradient Algorithm
CTCL	Caldeirão Thermoelectric Power Plant
DHW	Domestic Hot Water
EWH	Electric Water Heaters
EDA	Electricidade dos Açores
XGBoost	Extreme Gradient Boosting
PEGR	Graminhais Wind Farm
HEMS	Home Energy Management Systems
LSTM	Long-Short-Term-Memory
CGPV	Pico Vermelho Geothermal Plant
CGRG	Ribeira Grande Geothermal Plant

Symbol	**Definition**
$\hat{y}_i$	Predicted value
y_i	True value
$\Omega(f_t)$	Penalty function
x_i	Input vector
T_i	Number of leaves in the decision tree
λ and γ	Square loss function
w	Leaf weight
σ	Gate activation function
g	Input activation function
h	Output activation function
b	Bias weight vector
c^t	Current cell state
z^t	Candidate values
z^t	Block input
f^t	Forget gate

4.1 Introduction

The ongoing shift towards the electrification of energy services, especially at a residential level, is an important step towards the decarbonization of our society. This electrification is being driven by several factors, chief among them is the introduction of smart appliances and Home Energy Management Systems (HEMS) [173]. The increasing ability of previously passive residential loads, especially electric water heaters, to actively participate in the energy system brings several benefits to many actors within the system. This increased ability to intelligently control previously passive loads is being driven by many factors, including increased automation through artificial intelligence and machine learning and the Internet of Things concept has formed the foundation of the so-called Internet of Energy, which allows diverse devices to work together to meet various load demands in an automated and intelligent manner, contributing to the clean energy transition [174].

Electrical Water Heaters (EWHs) have been identified as high potential devices for intelligent operation as they typically have high power consumption, operate in regular bursts of heating, and can store significant energy as hot water [175]. Broadly speaking, these benefits can be allocated either upstream of the device or downstream. Upstream benefits can include reduced peak load through load shifting. This can lead to less energy being demanded at peak periods and intelligent heating during low-demand periods, which can also reduce the need for physical network infrastructure upgrades and an improved peak-to-average ratio [176]. The electrification of heating can lead to increased demand for electricity and the ability to heat during periods of high penetration of renewable energy, thus improving the utilization of these sources. Typically, electricity produced at peak periods is generated by more expensive peaker plants; therefore, the reduction of peak load can have outsized benefits in terms of cost reductions. This is especially relevant for the power systems of islands, as is the case in this chapter. Furthermore, the intelligent electrification of residential water heating instead of gas in islanded power systems can also reduce the need to import costly fossil fuels to the islands, promoting energy security. Upstream benefits of these intelligent devices are accrued by various parties such as distribution system operators (DSOs), energy retailers, and possibly aggregators or virtual power plant operators [177]. The downstream benefits of intelligent electrification of water heating are typically related to reduced energy costs and improved indoor air quality when the electric water heater replaces a natural gas water heater. Using gas to heat water is still very common, especially in Portugal, and thus replacing these gas water heaters with intelligent electric water heaters can even increase access to clean and affordable energy services [178].

Additionally, intelligent EWHs can be used by prosumers to participate in energy systems according to economic signals using transactive energy principles. However, the quantification of both upstream and downstream benefits is somewhat unexplored, especially in small or island power systems, and therefore this is the main contribution of this chapter. This chapter details an innovative design and implementation of an easy-to-use, low-cost device for intelligent heating of water for residential consumption. Results and data from a case study based on a pilot project undertaken on the Azorean Island of São Miguel, in collaboration with the Electricidade dos Açores (EDA) utility, are presented. This smart plug harnesses the newfound ability to intelligently control residential EWHs and provide benefits to both the consumer and the broader grid while ensuring that the consumer's desire for hot water and comfort is maintained.

4.2 Background and Context

4.2.1 Azores Islands

The Autonomous Region of the Azores is composed of nine islands that are widely dispersed and differ significantly in size. An image of the Azorean archipelago is shown in Figure 4.1. These are isolated microsystems with no electrical connection between the islands. The nine islands utilize a wide variety of electricity-generating technologies depending on the endogenous resources and the demand on each island. Due to their characteristics, these islands are generally very dependent on thermal generation using fossil fuels [76]. This dependence on imported fuels is due to various factors such as energy security and cost-effective means of production [179]. Each island has a main fossil-fuel-based generator which typically uses a diesel engine. There is, however, a growing desire to increase the penetration of renewable energy sources in the energy mix of the various islands, as can be seen by the 2030 Energy Strategy (EAE 2030) for the Azores published by the Regional Directorate of Energy of the Açores [180].

The focus of this pilot project was on the island of São Miguel and thus, a more in-depth discussion of its electricity mix is provided using data from the document 'Caracterização das Redes de Transporte e Distribuição, 2019' [181]. As of the end of 2020, there were twelve electricity-generating stations on the island. Chief among these plants is the Caldeirão Thermoelectric Power Plant (CTCL) which has an installed capacity of 98 MW and relies on imported fuel. The two geothermal plants, Ribeira Grande (CGRG) and Pico Vermelho (CGPV) have an installed capacity of 16.6 MW and 13 MW respectively. The single wind farm, Graminhais (PEGR), has an installed capacity of 9 MW. Seven hydroelectric power plants have a combined installed capacity of 5.1 MW. There is also a single plant that relies on biogas for electricity production, the Musami Landfill Biogas to Energy Recovery Plant, and it has an installed capacity of 1.1 MW. In 2020, there was 422.15 GWh of electricity delivered to the grid in São Miguel. Roughly 50% of this was from the thermal power plant, 40% from geothermal power plants, 6% from various hydroelectric power plants, and 4% from the wind farm.

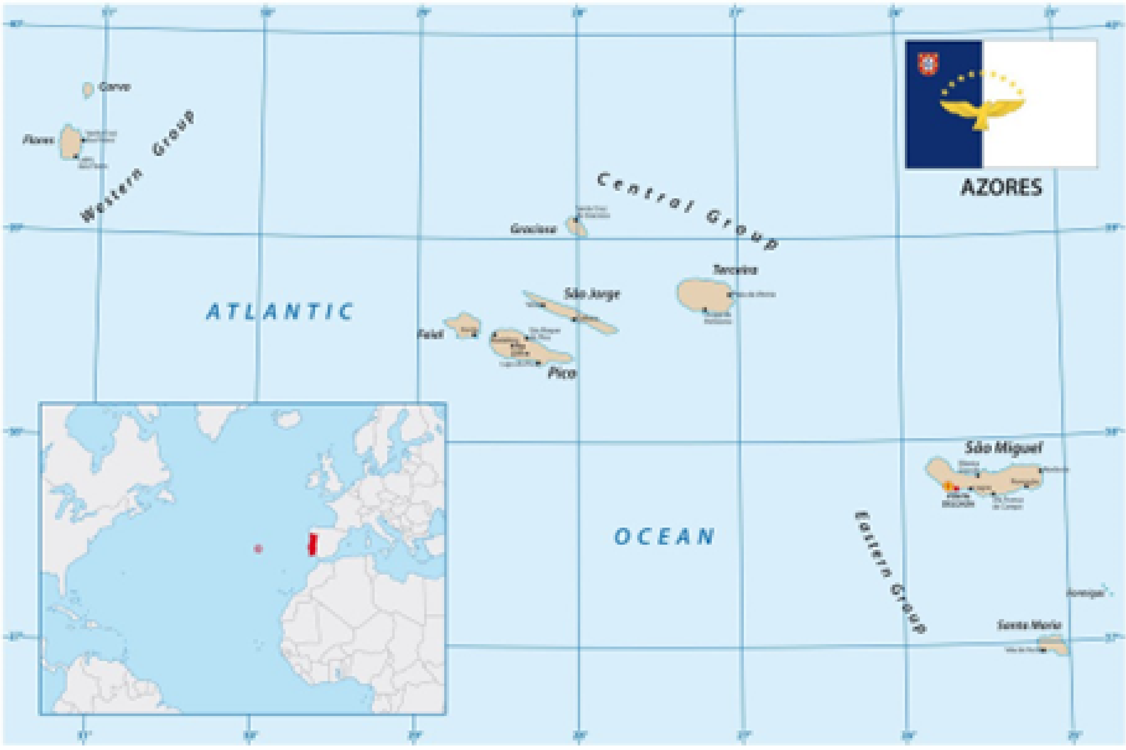

Figure 4.1: Map of the Azores

4.2.2 Klugit Energy

The smart plug was developed by Klugit Energy, a Portuguese start-up based in Aveiro. The device is used to convert a passive electric water heater into an intelligent device that can respond to economic and thermal comfort signals. This device consists of two components: the first component is a smart Wi-Fi-enabled plug that plugs into a regular wall power socket and the EWH is plugged into the other side; the second component is a connected water use detection sensor that clips onto the hot water outlet pipe of the EWH. Therefore, this device can be easily installed and requires no technical knowledge, extra tools, or modifications to the EWH unit. An example of an installed Klugit device is shown in Figure 4.2, where the smart plug and the clip-on water use detection sensor are easily visible.

The Klugit device has been under development since 2018. The prototypes were installed in 2020, and the first small-scale project was carried out in conjunction with E-REDES, the Portuguese DSO, in the town of Aveiro, Portugal. The results of this pilot project were positive and showed both the technical and economic benefits that the Klugit device could bring to both customers and DSOs [176]. The device allowed a reduction of energy use for the consumers and showed the potential to operate as a non-wires alternative to upgrading the physical infrastructure within low voltage networks. Based on this successful first pilot, a second, larger pilot was planned with EDA and commenced in July 2021.

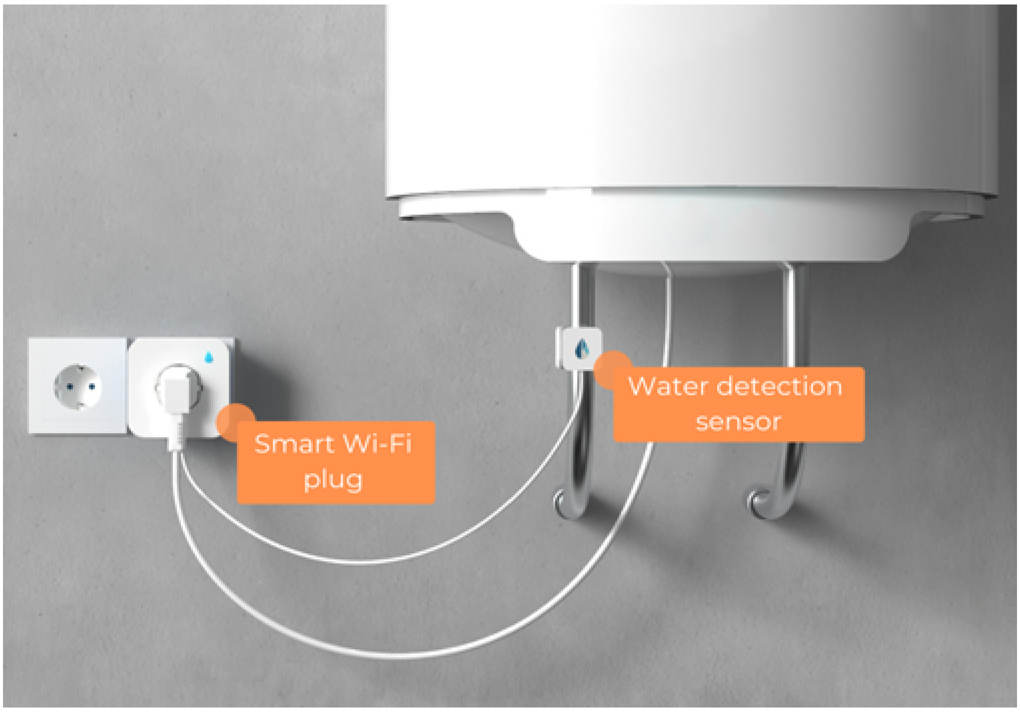

Figure 4.2: Connected Klugit device

4.3 State of the Art

The idea of operating electric water heaters intelligently to provide benefits to both the distribution operator and the consumer has been examined before [178]. However, previous studies tend to rely on intrusive monitoring techniques for water temperature and do not update the operation and control strategy of the EWH depending on the consumer's hot water usage. Moreover, the majority of these studies do not validate and implement their models in a real-world setting.

The potential of EWHs to provide benefits to either the consumer or the DSO has been the subject of significant research in the past years. For example, a data-driven optimization model for the smart scheduling of EWHs was developed [182] to meet several demand-side management requests. The authors utilize model predictive control (MPC) to develop a two-state EWH model and test it on real-world data consisting of 77 EWHs for 120 days. Results showed that costs were reduced by 33.2% and that anticipated domestic hot water demand met 97% of the actual demand during the day. These results were promising, however, there is no real-world testing of this model. In addition, even with the MPC framework, the temperature within the EWH still went below the lower comfort level set by the model. The ability of the model to avoid peak loads or to reduce emissions was not considered either.

A study that did investigate results from a real-world pilot project considering the demand response flexibility from smart appliances, including electric water heaters, was [183]. The study was based on a Belgian research project titled 'Large-scale implementation of smart grid technologies in distribution grids' (LINEAR), which examined residential demand response in the Flanders region of Belgium. The project prioritized user comfort over other technical objectives. The paper considered data from 15 residential EWHs among other appliances. The developed system needed to be attached directly to the EWH and was not controllable by the consumer as is the case in the device in the present chapter.

A study that focused on the benefits provided by intelligent EWH to the grid was conducted by [175]. The authors used virtual devices to emulate real-world EWHs. A thermal model was used for the estimation of the EWH's temperature, and 100 virtual devices were emulated. The key result from this study was the high potential of EWH to engage in both frequency response services as well as peak shaving services. The ability of the EWH to reduce costs by participating in these services or concerns relating to the comfort of the consumer were not considered in their study.

The ability of EWHs to modify residential electricity consumption due to external incentives was investigated by [184]. Their paper used a simplified EWH model and used hot water usage profiles of 450 apartments for 14 months with a 15-minute time granularity. Results showed a reduction in annual consumer costs by 33% and a significant ability to shift the heating load away from peak periods. No validation of the model in a laboratory or real-world setting was considered. In addition, the impacts on the comfort of the consumer were not considered.

The paper authored by [185] demonstrates and validates a simple and low-cost control module for the intelligent operation of an EWH. The authors used this system to minimize the cost of water heating in the home while respecting the user's comfort. Unfortunately, the system relied on a temperature monitoring probe to be inserted into the EWH. This may cause unnecessary complications for the user such as requiring specialist installation or voiding the manufactures warranty. A single EWH is used as a case study in their paper, and the results show that the power used in high-tariff periods is reduced and thus the cost of water heating is reduced significantly while maintaining the user's comfort levels. Another model that uses a heuristic algorithm to optimally schedule EWH under a dynamic pricing tariff is presented by [186].

The papers discussed above show that the concept of intelligent electric water heaters has been studied in the past. However, several shortcomings of these previous studies have been highlighted and Table 4.1 shows how the current chapter addresses those shortcomings in a real case study through several novel contributions using machine learning algorithms (XGBoost and LSTM) and considering consumer costs, peak load, consumer comfort and emissions, relying on a non-intrusive strategy.

Table 4.1: Comparison with Relevant Literature

Paper	Type of control	Consumer cost	Peak Load	Pilot project	Non intrusive	Consumer comfort	Data set used	Emissions considered
[182]	MPC	Yes	No	No	NA	No	77 EWH for 120 days	No
[183]	Linear programming	No	Yes	Yes	Yes	Yes	15 EWH	No
[175]	Thermal model	No	Yes	No	NA	No	Synthetic data	No
[184]	Greedy algorithm	Yes	Yes	No	NA	No	450 EWH for 14 months	No
[185]	Heuristic	Yes	Yes	Yes	No	Yes	1 EWH	No
[186]	Heuristic	Yes	No	No	No	Yes	Authors own	No
This chapter	XGBoost, LSTM	Yes	Yes	Yes	Yes	Yes	15 EWH	Yes

4.4 Data-Driven Model for Hot Water Prediction

This section introduces the methodology used in this chapter. Initially, a section discussing the theoretical background is presented to provide an overview of the methods used. Following this, the details of the implementation of this methodology are given. The Domestic Hot Water (DHW) demand throughout the day depends on several factors, such as the number of people living in the home, the day of the week, and ambient temperature. In addition, at the beginning of the pilot project, minimal data related to the DHW demand was available to be included in the prediction model. As a result, the methodology was split into different periods depending on the amount of data available for the prediction model. Each period used a different technique to forecast the hot water demand of each household. These techniques were simple regression, XGBoost and LSTM networks.

4.4.1 Theoretical background

4.4.1.1 Extreme Gradient Boosting (XGBoost) Algorithm

Initially, there was not sufficient data to develop the machine learning algorithms. Therefore, for the first three weeks of the pilot project, a regression model was used to forecast the DHW demand based on the average water demand from the previous day. Once sufficient data was collected for the household from the clip-on sensor, the Extreme Gradient Boosting (XGBoost) algorithm was used to forecast hot water consumption. XGBoost is a widely used tree boosting system [187]. XGBoost is a highly scalable machine learning system that uses several adjustments to traditional tree boosting algorithms. These adjustments provide the ability to handle sparse data, a proven procedure for handling weights for efficient proposal calculations. These improvements lead to a robust tree boosting solution that has been successfully deployed in many real-world applications. A python interface of XGBoost was used in this project [188].

The XGBoost algorithm is based on several decision trees with each tree being generated through a gradient descent method. The algorithm's objective is to minimize a specific objective function subject to a second-order Taylor expansion of the penalty function. To reduce overfitting, the XGBoost utilizes the complexity function of the tree to represent the objective function's constant term. The mathematical formulation of the XGBoost algorithm is taken from [187]:

$$Object(t) = \sum_{i=1}^{n} l(y_i, \hat{y}_i{}^t) + \Omega(f_t) + C \tag{4.1}$$

$$\hat{y}_i{}^t = \hat{y}_i{}^{t-1} + f_t(x_i) \tag{4.2}$$

$$where \quad \Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \tag{4.3}$$

In the equations above, l is a differentiable convex function that calculates the gap between the prediction y_i^t and the actual value $y_i \Omega(f_t)$ is a penalty function which increases as the complexity of the model increases to reduce overfitting, and C represents a constant. In Equation 4.2, x_i represents the input vector, and the actual value of hot water demand is shown by y_i while the predicted value of hot water demand is shown by $\hat{y}_i{}^t$. In Equation 4.3, the number of leaves in the tree is shown by T_t. The square loss function is represented by γ and λ. w is the leaf weight. Using the Taylor expansion, we can approximate the Object by the following:

$$Object(t) \approx \sum_{i=1}^{n} [l(y_i, \hat{y}_i{}^t) + g_i f_i(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega f_t + C \tag{4.4}$$

Where g_i and $\frac{1}{2}h_i$ represent the coefficients of the linear and quadratic terms of the Taylor expansion, respectively.

4.4.1.2 Long Short-Term Memory Algorithm

After 6 weeks of the pilot project and sufficient data was collected regarding the hot water usage of the consumers, the XGBoost algorithm was replaced by a Long Short-Term Memory (LSTM) algorithm. This was done due to the superior accuracy of the LSTM model [189]. Despite the increase in the predictive ability, this algorithm also required a larger amount of data for training and testing, hence the decision first to use the XGBoost. Seven LSTM models were trained, one for each day of the week.

A typical LSTM model consists of several sub-networks which are recurrently connected [190]. These sub-networks are known as memory blocks. These memory blocks maintain their state over time and regulate the information flow through the non-linear gating units. Conceptually, an LSTM model is composed of several processing blocks and inputs. The interaction between these components is discussed below in Figure 4.3.

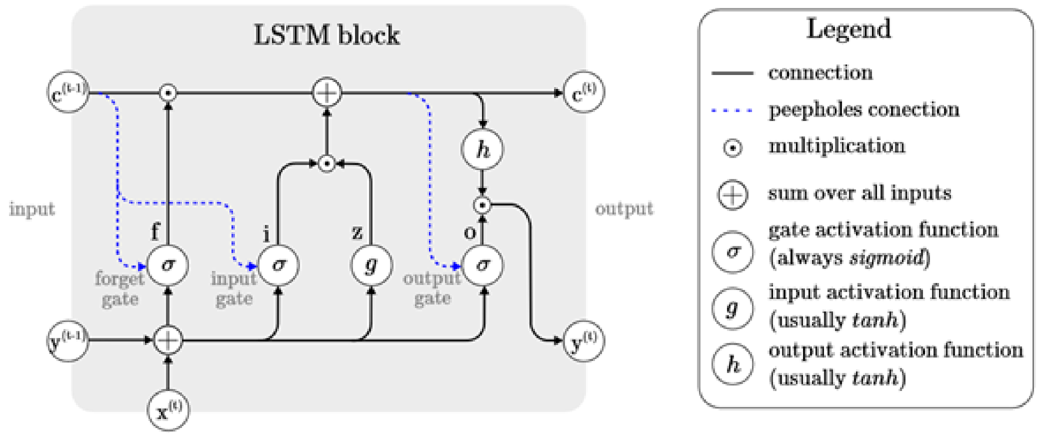

Figure 4.3: Structure of a vanilla LSTM model. After [2]

The initial step is a block input that uses the output of the previous LSTM unit and the current input. This is expressed as:

$$z^t = g(W_z x^{(t)} + R_z y^{(t-1)} + b_z) \tag{4.5}$$

In the above equation, W_z and R_z are weights associated with x^t and y^{t-1} respectively and the bias weight vector is denoted as b_z [2]. The next step is to update the input gate, which combines the current input x^t and the previous LSTM unit with the value c^{t-1} from the previous iteration. This is shown in Equation 4.6.

$$i^{(t)} = \sigma(W_i x^{(t)} + R_i y^{(t-1)} + p_i \cdot c^{(t-1)} + b_i) \tag{4.6}$$

where W_i,R_i and p_i are weights associated with x^t, y^{t-1} and c^{t-1} respectively for this component [2]. The bias weight vector is represented by b_i. The gate activation function is represented by σ. The LSTM layer determines how much information is retained in the cell states c^t from the previous steps. The vectors p^i and c^{t-1} are multiplied using point-wise multiplication. This layer also considers the selection of the candidate values, z^t, which may be added to the cell states as well as the input gate activation values, i^t. The next important aspect of the LSTM cell is the forget gate in which a decision about how much information to remove from the previous cell state, c^{t-1}, is taken. In this step, the activation values, f^t, of the forget gates are calculated using the current input, x^t, the outputs from the previous time step, y^{t-1}, and the previous memory cell state, c^{t-1}, the peephole connection and the terms representing the bias, b_f. This is shown as [2]:

$$f^{(t)} = \sigma(W_f x^{(t)} + R_f y^{(t-1)} + p_f \cdot c^{(t-1)} + b_f) \tag{4.7}$$

where W_f,R_f and p_f are weights associated with x^t ,y^{t-1} and c^{t-1} respectively and the bias weight vector is denoted as b_f. The next step is to compute the cell value. This step uses the outputs of the block input, z^t, the input gate, i^t, and the forget gate, f^t as well as the previous cell value. From [2], this is represented as:

$$c^{(t)} = z^{(t)} \cdot i^{(t)} + c^{(t-1)} \cdot f^{(t)} \tag{4.8}$$

The next output to be calculated from [2] is the output gate which combines the current input, x^t, the result of the last LSTM unit, y^{t-1}, as well as the cell value, c^{t-1}. Visually, this is represented by:

$$o^{(t)} = \sigma(W_o x^{(t)} + R_o y^{(t-1)} + p_o \cdot c^{(t-1)} + b_o) \tag{4.9}$$

where W_o,R_o and p_o are weights associated with x^t ,y^{t-1} and c^{t-1} respectively and the bias weight vector is denoted as b_o. The final step is the calculate the block output. This is a combination between the current cell value and the current output gate [2]. This is represented by:

$$y^{(t)} = g(c^{(t)}) \cdot o^{(t)} \tag{4.10}$$

4.4.2 Deployment

The data was collected by a non-intrusive temperature sensor attached to the hot water outlet pipe of the EWH. In the pilot project in São Miguel, only the temperature data was collected from the various EWHs. In a previous pilot project to validate the proof of concept, water flow data was also collected, and the model was initially validated against this previous data. This was used to train the temperature-to-flow converter model, but in the present pilot project, only the temperature data were collected and utilized.

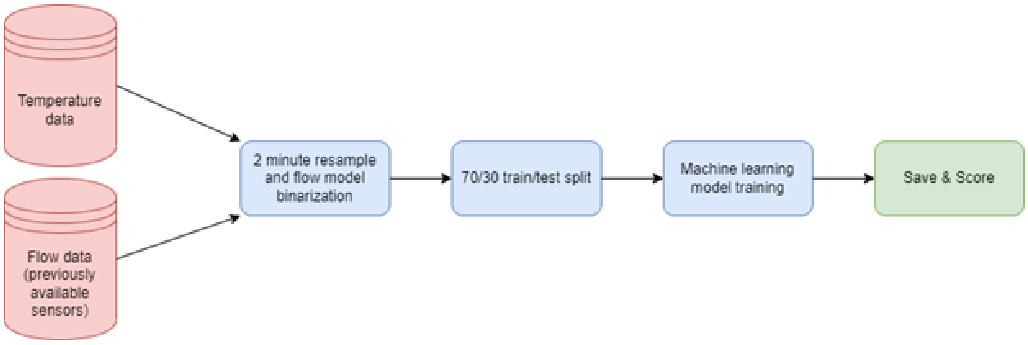

Figure 4.4: Pipeline for the temperature-to-flow converter model.

4.4.2.1 Temperature to flow converter model

The first model uses previously available flow data and the chronologically corresponding temperature data to train a model that predicts whether there was significant flow in a given time interval, outputting a result of either 1 or 0 for a specific moment. The flow and processing of data in this model are shown in Figure 4.4.

The selected sampling rate was two minutes. The issue of whether the ratio between the sampled flow duration and real flow duration was significantly different in the predicted and real flow data was studied and it was concluded that there was only a significant difference if the sampling rate was greater or equal to three minutes, meaning any value lower than three minutes is appropriate. For values of the sampling rate lower than three minutes, there was no significant change in the aforementioned ratio. Interestingly, the results obtained when using two minutes were better than when a sampling rate of one minute was used. The machine learning model uses a neural network with the structure shown in Table 4.2.

Table 4.2: Temperature to flow convertor's neural network structure and parameters

Layer number	Layer type	Parameters
1	1D Convolutional Batch normalization ReLU	Filters: 64, Kernel size: 3
2	1D Convolutional Batch normalization ReLU	Filters: 64, Kernel size: 3
3	1D Convolutional Batch normalization ReLU	Filters: 64, Kernel size: 3
4	1D Global average pooling Dense	Neurons: 2, Activation: softmax

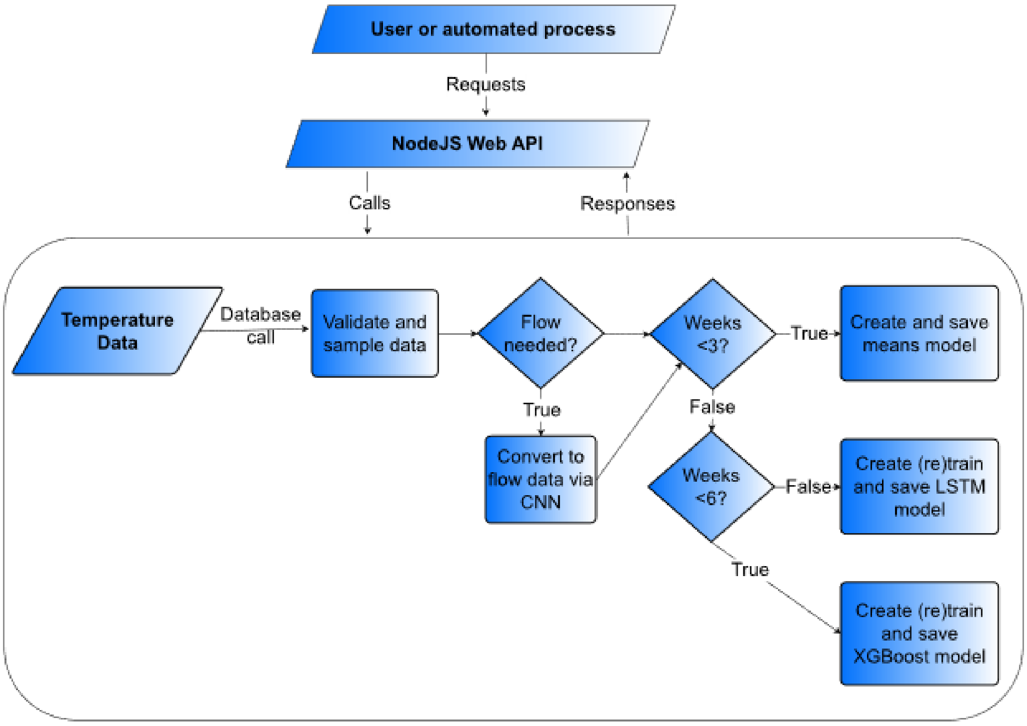

Figure 4.5: Pipeline for training the relevant hot water usage prediction model

The model was trained for 70 epochs, with a batch size of 128. The learning rate was set at 0.0001 and a validation split of 0.2 was used. The loss was computed using a custom function that allows different weights for the two classes to be applied to a typical binary categorical cross-entropy function. The weights applied made the loss function penalize false negatives twice as much, in the best-performing model that was trained. This was done to compensate for the fact that there is a substantial discrepancy between the number of samples of each class.

The performance of various iterations of this model with these and different parameters were tested using the F-Score for the test set. A pseudo-grid search was performed, using different values for all aforementioned parameters and testing the final F-Score for each. The best model obtained an F-Score of 0.77 and was saved to be used in the relevant hot water usage prediction model as shown in Figure 4.5.

Once the model had been created, trained, and saved, it could be used to forecast the periods of hot water demand for the consumers. This is shown in Figure 4.6 where a request would be sent to the application programming interface (API) which in turn would call the relevant model to make a forecast of the hot water demand. The forecast is made and sent back as a response to the API which in turn sends it to the device. Then the decision is taken whether or not to heat the water to meet the forecast demand.

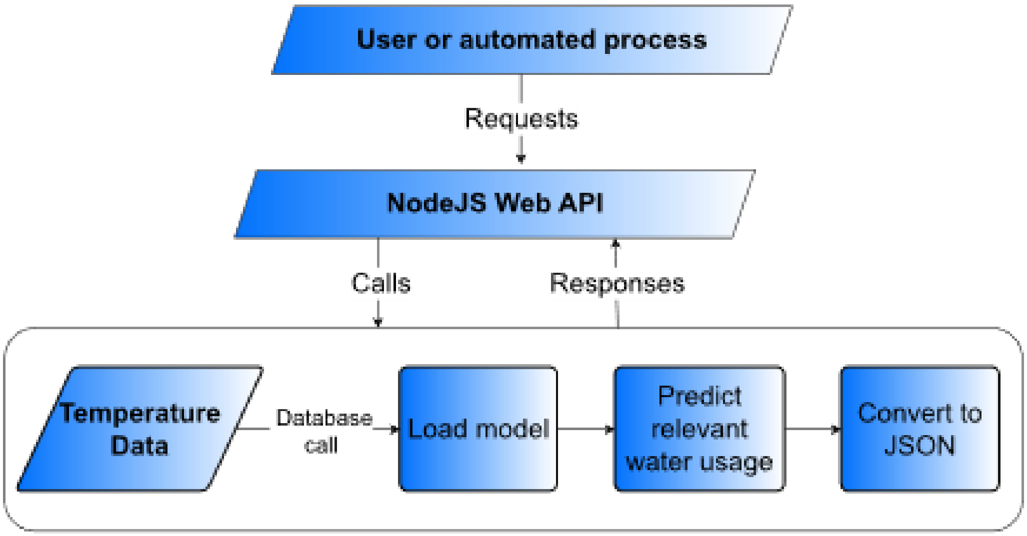

Figure 4.6: Pipeline for obtaining the predicted relevant hot water usages for a period of the day.

Three types of models are used which are: Regression, XGBoost, and LSTM. The regression model is used when there was a low number of samples and the training model is not yet viable. It approximately identifies which hours were relevant hot water usage seen in the last few weeks by using a Mean Shift model. The XGBoost model minimizes the squared error and uses 1000 estimators. The LSTM model comprises seven models, one for each day of the week. Each model is trained individually, but with the same parameters. Each model is composed of 32 LSTM units, followed by a Dropout layer that drops 20% of the results and a final dense layer of 24 neurons (one for each hour) that uses a softsign activation function in the version designed for flow data.

When using temperature data, an activation function is not necessary as the temperature data is normalized before it is used as input into the network. The data is rescaled afterward to reconstruct the temperature data. This approach was not appropriate for the flow data, as it is binary and so an activation function that allowed some progression, such as the softsign was necessary. Both temperature and flow versions were optimized by the Adam optimizer.

The Adam optimizer is an alternative to classical stochastic optimization in deep learning problems. It combines the advantages of two other extensions of stochastic gradient descent. These other two extensions are the Adaptive Gradient Algorithm (AdaGrad) and the Root Mean Square Propagation (RMSProp) [191]. Further details of the Adam algorithm can be found in [192] but, in summary, the Adam algorithm achieves good results quickly and emerged as an excellent overall choice of algorithm for deep learning applications [191].

After the application of these models, the times of significant hot water usage need to be identified. The temperature model identifies these times and the results are evaluated using the Root Mean Square Error Model for the first iterations and afterward, the F-Score model was applied. During the pilot project, the model was under continuous evaluation and improvement. One such improvement is the flow model. The flow model is an extension of the temperature model and in this model, the duration of the flow can also be forecasted. The performance of the flow model was compared to the performance of the temperature model. For this comparison, the ratio of the correct predictions against the total (correct plus the incorrect) predictions was used for all periods where water flow was predicted.

The following two figures, Figure 4.7 and Figure 4.8 show the improvement of the flow duration model for both the XGBoost and LSTM methods respectively across ten experiments. The flow model outperformed the previous temperature model in each experiment and for both machine learning techniques. This new method also provides additional information regarding the total quantity of hot water used which can be reported to the consumers to increase their knowledge of their water usage. The choice of adding an estimation of the flow of water was made during the pilot project and the results show that this choice improves the results of the model.

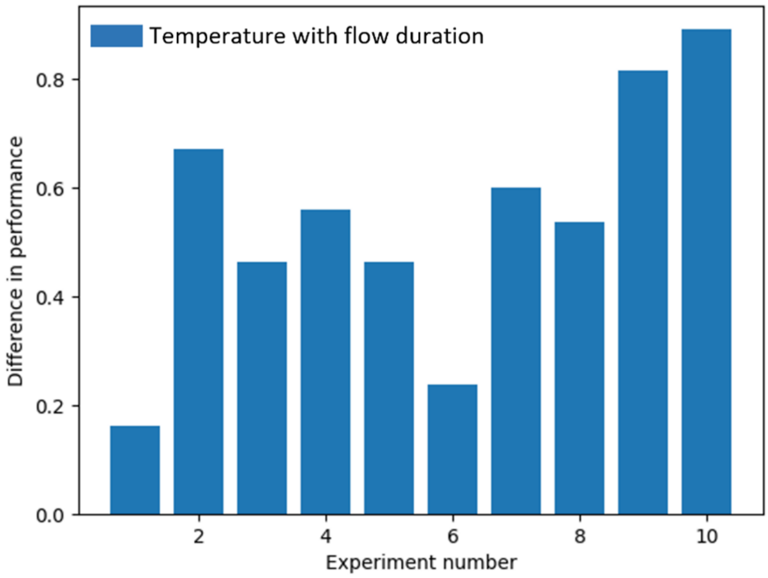

Figure 4.7: Improvement in the performance of the final XGBoost flow model.

4.4.3 System architecture

The models introduced above were incorporated into a larger digital infrastructure that was implemented for the pilot project. This infrastructure allowed the devices to gather the data, communicate this data to the server and receive control signals from the server. The infrastructure used in this system is presented in Figure 4.9. The relevant services and applications are shown with the flow of the information shown via the black arrows. The intelligent EWH is depicted as the 'KLUNIT' in the bottom left of the figure.

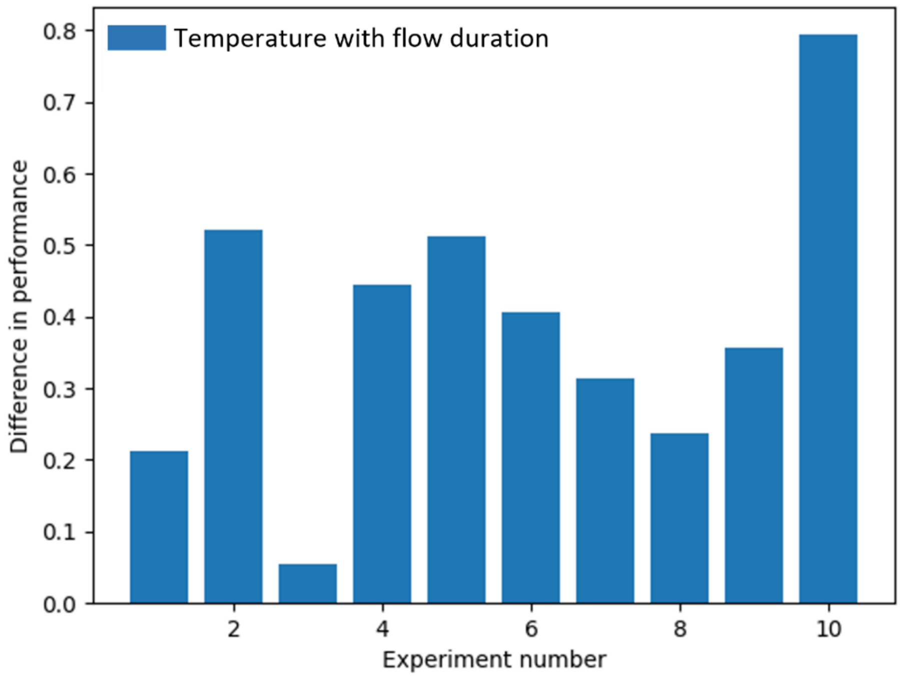

Figure 4.8: Improvement in the performance of the final LSTM flow model.

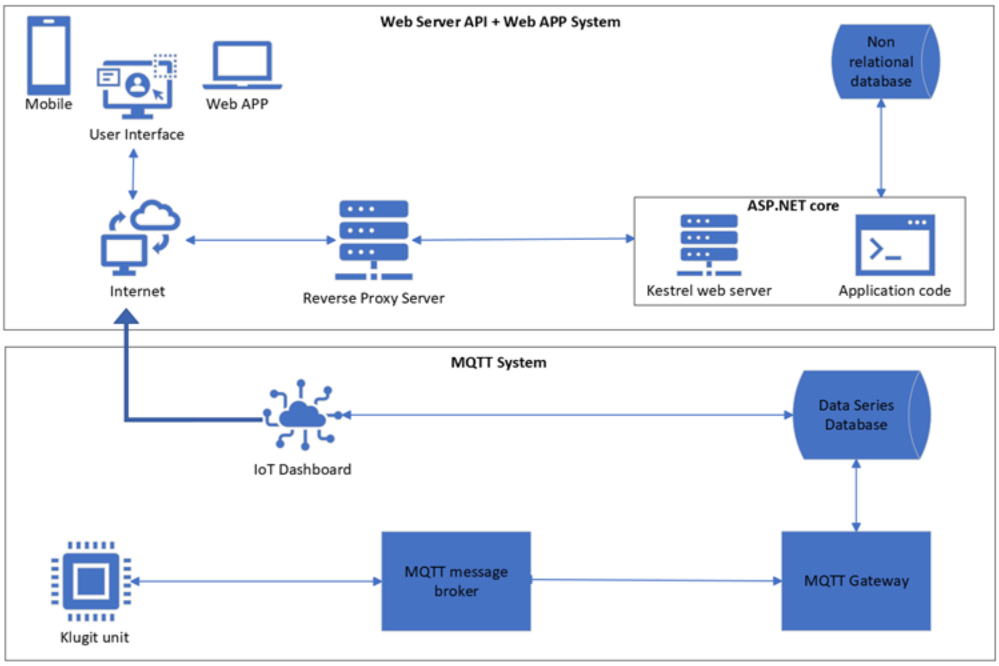

Figure 4.9: Infrastructure layout of the Klugit system.

4.5 Case Study, Results and Discussion

4.5.1 Case Study

This section contains the details of the case study implemented in São Miguel carried out between July and December 2021. The devices were installed in 15 homes and a photo of a typical installation is shown in Figure 4.10 below. The types of homes and equipment installed varied widely across the homes. The number of inhabitants ranged from two to five people in the home while the capacity of the EWH ranged from 80 to 150 l. A standard installation and training process was done for each household. The device was controlled by a smartphone application, which allowed the users to monitor hot water usage and also included a 'heat now' option. A screenshot from the app is shown in Figure 4.11. This option allowed the users to override the algorithm and heat the water in the tank immediately up to a certain set point. This provided the users with increased control and flexibility.

Figure 4.10: Typical installation of a Klugit device.

4.5.2 Results and Discussion

In this section, both the quantitative results of the hot water forecasting, peak load reduction and avoided emissions are presented. In addition, the qualitative results of consumer interviews and surveys are presented. These surveys are included to help evaluate the impact of the devices on consumers' lifestyles and comfort.

Figure 4.11: Screenshot of the Klugit Energy application.

4.5.2.1 Hot water forecasting and intelligent heating

The core function of the device is to forecast residential hot water demand and to activate the EWH to meet this demand intelligently. This intelligent heating can help reduce unnecessary heating cycles of the EWH, thus reducing thermal losses, and shifting the heating periods away from periods of high tariffs. These two benefits accrue to the consumer, but the device can also offer benefits upstream to the system operator. These benefits may include: peak shaving, load shifting, participation in demand response programs, and ancillary services as the EWH functions as a controllable DER. In this pilot project, only the first two benefits were assessed.

In addition to the above-mentioned benefits, there is also the ability of the device to operate during high periods of renewable energy generation. By operating during these periods, the device can help increase the penetration of renewable energy technologies as well as utilize energy that may be curtailed if the device was not operating. To demonstrate the impact of the device on the operation of an EWH, Figure 12 compares the baseline operation for the average of July and August without any intervention for the same months.

In Figure 4.12, the blue line shows the baseline operation of EWH without the operation of the device. The orange line shows the device operating in the smart mode to intelligently heat the water when it is needed, trying to use low tariff periods. From the Figure, it is clear that the heating load has been shifted out to the early morning and late afternoon periods, avoiding the early evening peak. The result of this load intelligent heating is a reduction in the electricity used. There is a significant period of pre-heating done in the early hours of the morning and again between 16:00 and 17:00. This helps reduce the need for heating at other high-peak demand periods.

The heating load was reduced by an average of 1.33 kWh/day per device for all devices, which represented an average reduction in heating demand of 26.43%. The maximum reduction in heating use was 54.4% for a single household while one home saw the heating demand increase by 2.24%. This specific case is discussed in detail in the following paragraphs.

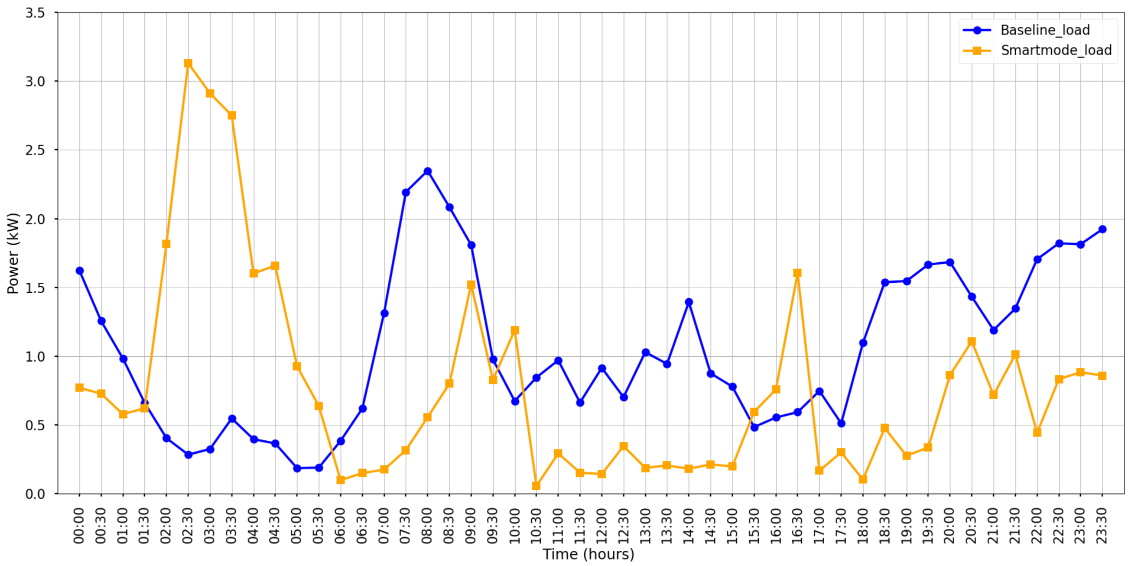

Figure 4.12: Energy use in both smart mode and baseline modes.

The average daily energy use in the baseline and smart mode of the 10 devices with the most recorded data during the pilot period are shown in Table 4.3. The device names have been removed for data privacy reasons. The table shows a considerable reduction in the energy use associated with domestic hot water use.

In addition to reducing the electricity used for water heating, the Klugit device also shifts the timing of the heating to periods with low energy tariffs, which further reduces the energy bill of the consumer. In São Miguel, a three-period tariff regime is available for the clients. There are periods of low, moderate, and high energy tariffs depending on the time of day. These tariffs are shown in Table 4.4 below.

Table 4.3: Energy use differences

Device	Baseline (kWh)	Smart mode (kWh)	Percentage reduction
1	10.09	8.79	12.88
2	2.52	2.22	11.90
3	5.03	3.51	30.22
4	4.61	3.37	27.84
5	2.9	2.14	26.21
6	7.78	4.82	38.05
7	4.23	2.92	31.78
8	5	2.28	54.40
9	4.46	4.56	-2.24
10	3.75	2.41	35.73

These costs are distributed over the entire day, periods of which are related to the demand for electricity in the regulated energy market. The low tariff corresponds to the periods where the electricity demand is less; the moderate tariff corresponds to the periods where there is medium demand; the high tariff corresponds to the periods where the peak load is observed, which means the electricity demand is at the highest.

The tariff is overlaid on Figure 4.13 below which shows the average baseline and smart mode operation for a given home. The green area represents periods of a low tariff, the yellow indicated periods with moderate tariff, and the red denotes the periods with a high tariff. Again, the blue curve represents baseline mode operation, and the orange curve represents smart mode operation.

Figure 4.13 shows that in the smart mode operation, there is more electricity used by the EWH in low or medium tariffs compared to the baseline operation. Combining the effects of reducing energy consumption and switching heating load from high tariff periods to low tariff periods, the smart mode operation reduces the energy cost to consumers. Based on the tariffs in place and Figure 4.13, consumers would pay an average of € 0.754/day in the baseline and € 0.4866/day in the smart mode to satisfy their heating demand. This results in a cost-saving of 35.54% for the consumer. The annual cost savings enjoyed by the consumer equate to € 97.63 without affecting the thermal comfort of the consumer.

Table 4.4: Tariffs in use during the pilot project

Tariff type	Low	Moderate	High
Cost (€/kWh)	0.1	0.16	0.23

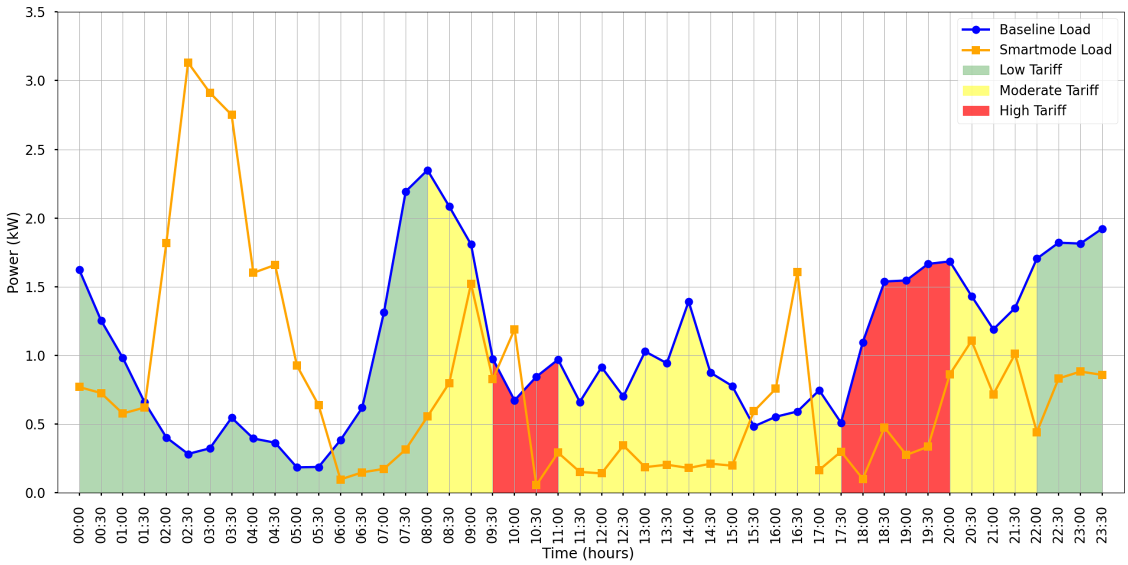

Figure 4.13: Effects of load shifting due to Klugit device.

During the pilot project, one EWH, while operating in smart mode, used more electricity compared to the baseline operation as is shown in Figure 4.14. In this case, the smart mode used an additional 0.05 kWh/day relative to the baseline operation. However, in this case, due to shifting the load from high tariff periods to lower tariff periods, the cost to the consumer was still lower when the smart mode was operating. In the baseline approach, this EWH had a daily cost of €0.33/day, while in the smart mode the cost was reduced to €0.277/day. This result shows the benefit of load shifting and how it can directly benefit the consumer even if more electricity is used to satisfy heating demand in certain specific cases.

Therefore, a considerable amount of savings can be observed when this smart plug is connected to an EWH and operating in smart mode. Importantly, as there were only 15 homes in the pilot project, there was constant communication between the users and the organizers of the project. This allowed the consumers to report any issues with the operation of the smart mode such as inadequate hot water. Therefore, a considerable amount of savings can be observed when this smart plug is connected to an EWH and operates in smart mode while maintaining consumer comfort. These savings in both energy and money are expected to increase with increasing numbers of installed devices. The savings are direct savings accrued to the consumer. A summary of these results is shown in Table 4.5.

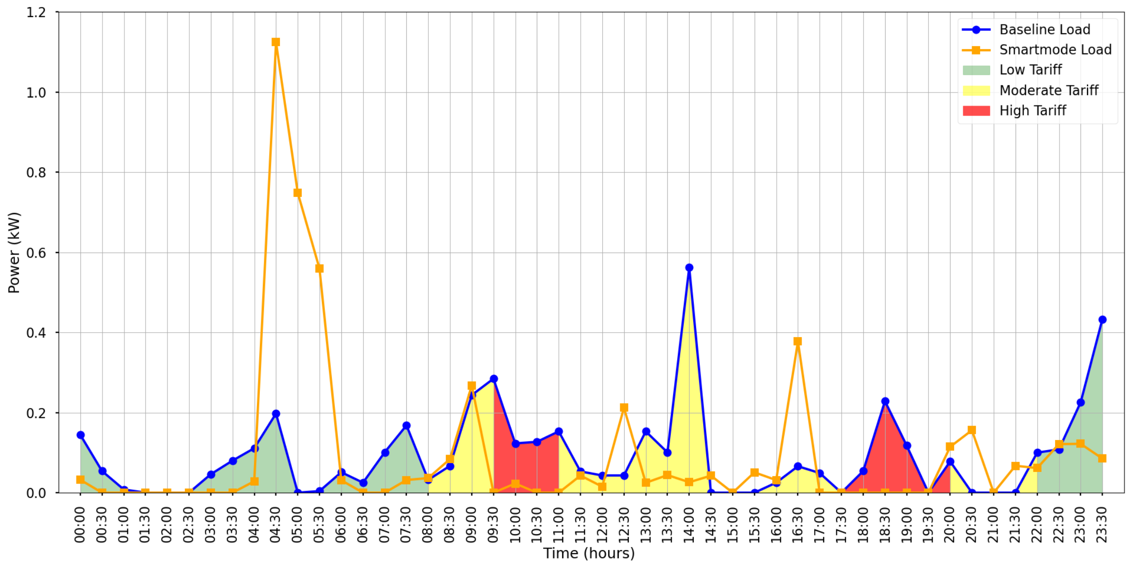

Figure 4.14: Energy use of selected EWH with higher energy consumption in smart mode for device 9.

Table 4.5: Summary of results from the São Miguel pilot

	Average energy saved	**Average energy removed from high tariff period**	**Average energy added to low tariff period**	**Money saved by the customer**
Azores Pilot	1.3 kWh	0.92 kWh	1.26 kWh	€0.267/day
Annual extrapolation	485.45 kWh	335.8 kWh	459.9 kWh	€97.63

4.5.2.2 Peak load reduction

The ability of the installed device to reduce energy consumption and also shift load to periods of lower demand also has important benefits for the system operator. This is especially true in the case of São Miguel Island. As was mentioned previously, the island relies heavily on imported fossil fuel (both diesel and oil) to run the main thermal power plant, the 98 MW capacity Caldeirão Thermoelectric Power Plant (CTCL). This plant uses a combination of diesel and fuel oil to generate electricity. Due to the fuel being imported for this plant, its generating costs are significantly higher than those of other resources in São Miguel. This is shown in Table 4.6 which contains the generating or operational costs of each technology for São Miguel and is provided by EDA.

Table 4.6: Dispatch order of generating technologies

Plant type	**Dispatch order**	**Rate (€/kWh)**
Geothermal	1	0.101
Hydro	2	0.101
Wind	3	0.101
Biogas	4	0.0924
CTCL	5	0.1241

In addition, the operating costs of the CTCL plant are dependent on numerous factors including the global oil price. This can vary significantly. Between January and June 2021, the operational costs for the CTCL plant were on average €0.1241/kWh, but this can change depending on the global oil price which has been especially volatile in the past 12 months. The dispatch order is the order in which the different technologies are used to meet the demand of the system. It depends on numerous factors such as power plant composition, capacity, operational costs, and flexibility (ramping, load following, frequency regulation). The dispatch order is important in this analysis as a collection of installed devices can operate as a flexible resource and thus would be able to partially replace the peaking plants used by EDA to meet the demand. The collection of devices may operate as a Virtual Power Plant and have the ability to respond to certain requests from the system operator in a transactive energy system. The devices were compared to the biogas and thermal plants, which are dispatch orders 4 and 5.

Figure 4.15 shows the average energy mix for São Miguel for July 7th, 2021. It can be seen that both geothermal and hydro act as baseload generators. Biogas (yellow area) has the cheapest operational cost but does not contribute significantly to electricity generation (biogas only produced 0.17% of electricity in São Miguel in 2020) and only produces electricity when there is enough feedstock material. Wind generation has a relatively small contribution on this day but in the late afternoon, it has a larger share. The CTCL plant operates as a mid-merit plant to satisfy the remaining demand. The quantity of electricity generated by each technology and its associated generation costs are reflected in Table 4.7 and the data are provided by EDA [181]. These costs are the commercial costs paid for each unit of electricity generated by the plants under the relevant production agreements. The amounts of energy generated by solar PV and biogas are estimates, as they are independently owned and operated. The amount of energy generated by these two sources is not currently meaningful in the wider energy system of São Miguel. On São Miguel island, there are 64 055 low-voltage clients. Of these clients, 8.3% already use an existing electric water heater and thus this is the initial target market for the intelligent EWH. This provides a currently addressable market of 5317 EWHs in São Miguel. In the future, it is expected that an increasing number of low-voltage clients switch from liquefied petroleum gas (LPG) boilers (currently 88.3% of low-voltage clients in the Açores islands use LPG boilers to heat water) to electric water heaters.

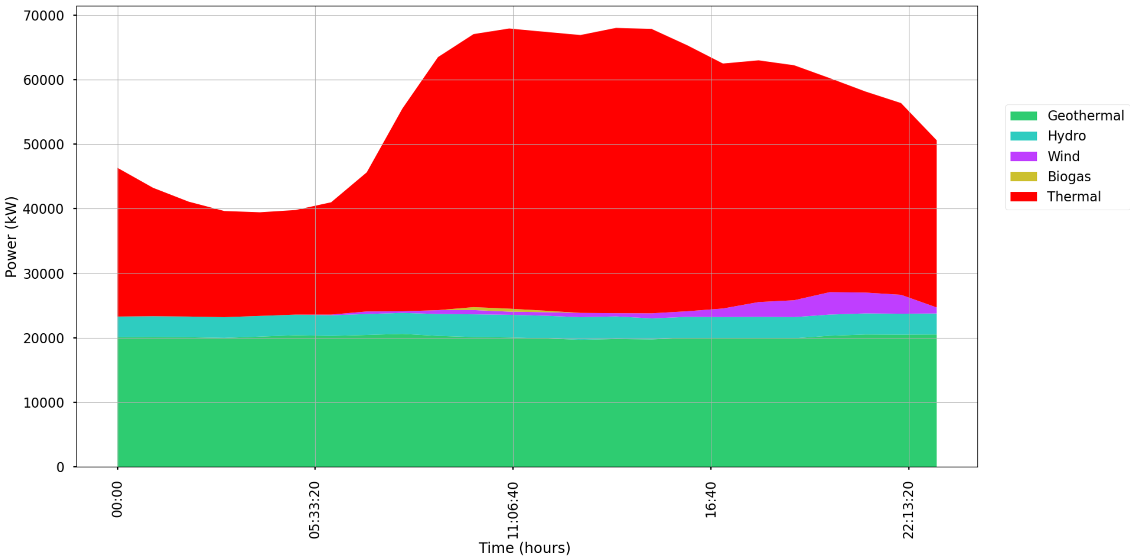

Figure 4.15: Energy mix for 7 July 2021.

To investigate the potential system-wide impact of the devices, various scenarios were considered. These initial scenarios were classified as low, medium, and high uptake scenarios depending on the percentage of clients with an existing EWH who will install a device. These scenarios are the following:

- Low uptake: Klugit devices are installed on 20% of existing EWHs (20% of 5317 EWHs gives 1063 devices).
- Medium uptake: Klugit devices are installed on 40% of existing EWHs (40% of 5317 EWHs gives 2127 devices).
- High uptake: Klugit devices are installed on 80% of existing EWHs (80% of 5317 EWHs gives 4254 devices)

Table 4.7: Energy generated and costs for São Miguel in 2020

Technology	**Energy generated in 2020 (MWh)**	**Operational cost (€/kWh)**
Thermal (CTCL)	218673.81	0.1241
Geothermal	169447.68	0.101
Wind	15028.81	0.101
Hydro	23846.95	0.101
Solar PV	21	0.1011
Biogas	700	0.0924

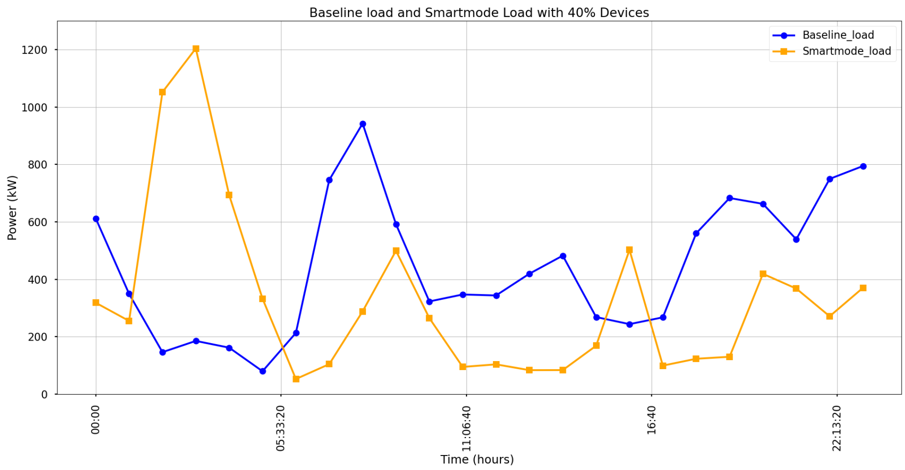

Figure 4.16: Total load compared to baseline and smart mode demand of fleet of Klugit devices.

Figure 4.16 below shows the total generation profile for São Miguel (pink curve) and a load of these EWHs operating both in smart mode (orange curve) and baseline mode (blue curve). For this analysis, the medium uptake scenario was considered. While the magnitude of the impact of the devices may be limited in this scenario, we can see an increase in the early morning load when the fleet of devices operates in smart mode. This impact is only expected to increase as the number of devices increases.

This shift in early morning load from the connected devices operating in smart mode is shown in Figure 4.17. The pink line shows the existing generator load or standard load profile with passive EWHs, in other words, the current situation. The green lines represent the load curve if the aggregated EWH were operating in the smart mode in the different uptake scenarios. There is load shifting taking place, especially with an increase in the load in the early morning when the devices are heating. Installing the devices can reduce the total energy used by 2831.98 kWh per day or 0.21% of total energy under the medium uptake scenario. This figure is solely from installing the device on existing EWH and is complementary to the other benefits mentioned earlier.

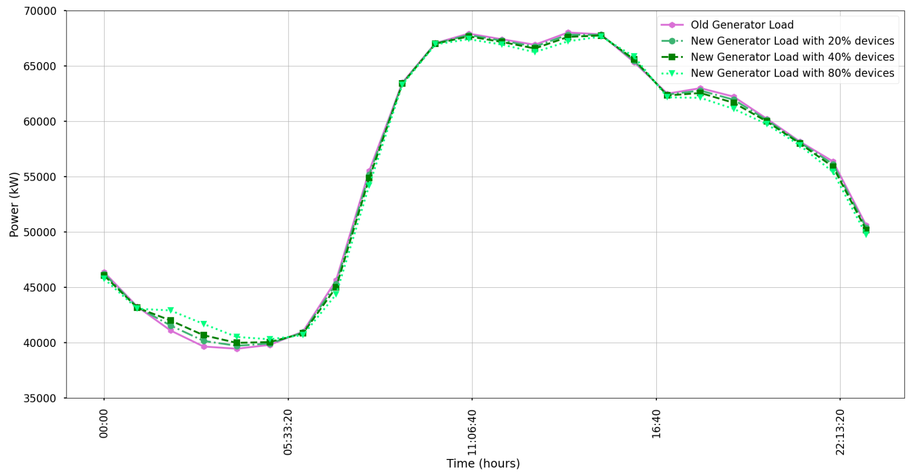

Figure 4.17: Baseline load vs smart mode load.

4.5.2.3 Avoided emissions

The reduction in energy use and associated operating costs are not the only benefit that this aggregated group of intelligent EWH may provide. Due to the high share of imported fossil fuels (both fuel oil and diesel) used by EDA to generate electricity throughout the Azores, the carbon intensity of the electricity is high with a value of 421.5 gCO_2/kWh in 2020 [193], which is well above the average for Portugal which stands at 201 gCO_2/kWh [194]. This highlights the importance of reducing emissions in the Azores islands, especially reducing the amount of fuel oil imported. Because of the high carbon intensity of fuel oil, even though the absolute amount of energy saved using intelligent EWH is less than 1% of total energy, by reducing the electricity used, especially from the CTCL plant, the group of EWH can have a significant impact on the emissions profile of São Miguel. Through the analysis of the hourly generation and demand profiles, the amount of thermal generation that can be displaced by the intelligent heating of the EWHs can be quantified.

Figure 4.18 compares the thermal generation used for residential water heating in the passive (black) and smart modes (green) in the medium uptake scenario. This leads to a reduction of 0.37% of thermal generation or 2831.98 kWh per day with a generation cost of €0.1241/kWh. Solely based on the avoided generation from the CTCL plant, assuming a unit cost of a Klugit device of €85 per unit, the costs to equip 2127 residential homes with the device will be repaid in 1.4 years, solely from not needing to use the CTCL plant to generate this extra electricity that is not needed. This is in addition to the direct benefit to the consumer of nearly €100 annually based on reducing energy consumption.

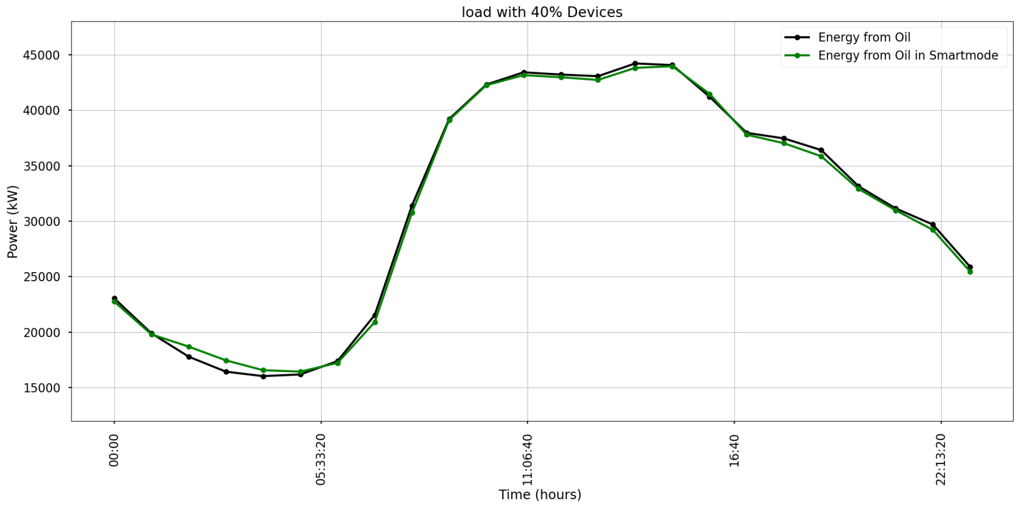

Figure 4.18: Energy from thermal generation from CTCL in the baseline and smart modes.

Displacing this thermal generation will also have positive impacts on the emissions profile of EDA. Assuming that the aggregate group of intelligent EWH can displace 2831.98 kWh per day in the medium uptake scenario and using a carbon intensity of 670.729 gCO_2 /kWh for the thermal generation, leads to a reduction of 693.31 tons CO_2 per year in the emissions from thermal generation by simply plugging in one of these devices to manage the heating load of an EWH efficiently. In total, EDA emitted 368 000 tons of CO_2 in 2020 and therefore the aggregated devices can reduce this total by 0.18% by only installing 2127 of these devices across São Miguel. This can have important implications for reducing CO_2 emissions and improving air quality.

4.5.2.4 Impact on the physical infrastructure

Another possible benefit that intelligent EWH may offer the system operator is the reduction of load placed upon the physical infrastructure, such as transformer units in low-voltage networks. These EWH and other distributed energy resources may operate as so-called non-wires alternatives concerning investing in physical infrastructure upgrades [195]. Data from a substation from the region in São Miguel where some of the devices were installed is used for the analysis. The daily transformer load profile of the substation is shown in Figure 4.19. The total transformer load is shown in pink while the baseline, passive EWH demand is shown in blue. While the lines are nearly identical there is a slight decrease in the energy used during the two peaks, at around 12:00 and again at 20:00. There is also an increase in the demand during the early hours of the morning at around 03:00. The intelligent EWH operation is shown in orange under the medium uptake scenario. The straight horizontal lines represent the mean load for the different loads over the entire day.

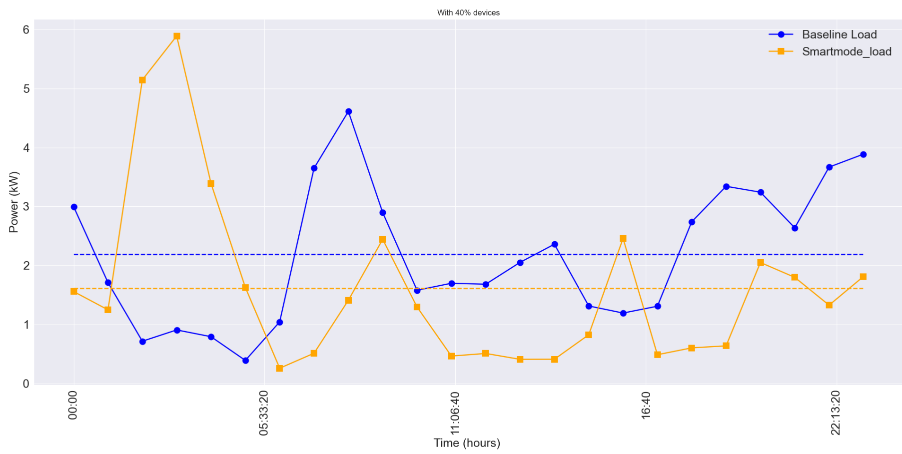

Figure 4.19: Transformer load with baseline and smart mode loads.

Figure 4.20 shows the baseline transformer load in pink (Transformer Load). The green line is created by removing the baseline EWH load and replacing it with the intelligent load from the devices. There is load shifting occurring when the smart EWHs are operational. However, there is no peak reduction occurring. The peak load is slightly increased, and the minimum load is reduced. However, the objective of this device is not currently related to minimizing the impact on the physical infrastructure.

The objective is to reduce the cost of satisfying the consumers' hot water demand. Therefore, in the future, the objective may be modified so that reducing the impact on the physical infrastructure is considered. This can be achieved by allowing the utility to control the EWH in times of high system stress. This is possible as the simple device transforms a passive EWH into a controllable distributed energy resource asset that can be used to satisfy several objectives from different agents.

4.5.2.5 Results from the customer satisfaction survey

At the end of the pilot project, consumer semi-structured interviews, surveys, and questionnaires were also carried out to qualitatively measure consumer satisfaction with the devices installed. The quantitative survey consists of 20 questions, 18 categorical questions about recommendations, application features, design, installation, and usability on a scale from 1 to 10. There is one multiple-choice question with five different prices and a section for consumer suggestions for improvement. The consumers gave the device a global average score of 7/10. The following list contains the key areas of focus in the questionnaire:

- Recommendation: how probable they would recommend the device to a family or friend.
- App features (with 8 questions): measuring the actual satisfaction with the features themselves, and seven others measuring the importance of the following list of characteristics:

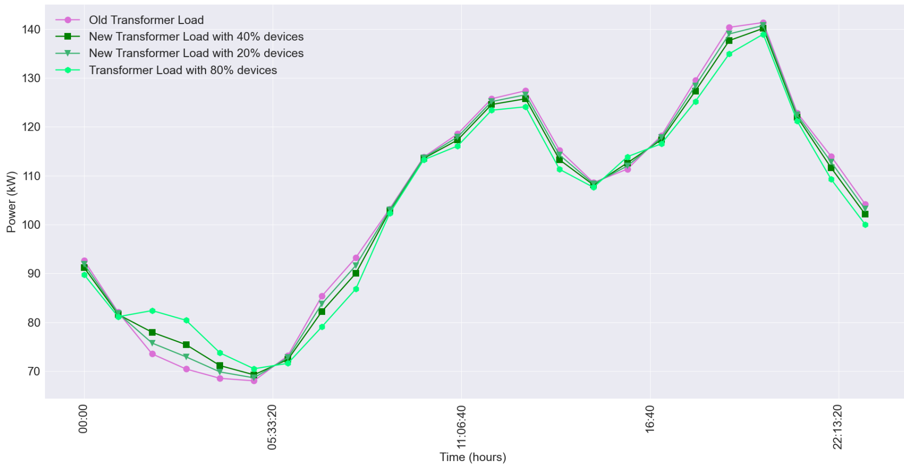

Figure 4.20: New (smart mode) and old (baseline) transformer load.

1. The priority given to the “low peak” period and avoiding the “high peak” period to heat water
2. Reduction of thermal losses from the water heater
3. Viewing savings in the app
4. Visualization of the reduction of CO_2 emissions
5. Visualization of the forecast for upcoming hot water needs
6. Request additional hot water when needed (Heat Now) in the app
7. Turn off smart mode when needed

- Design: consisting of 3 questions measuring satisfaction on the following topics:

1. Design and user experience of the mobile app
2. The appearance of the product
3. Packaging

- Installation process: assessing the level of satisfaction during the experience of the device installations.

- Usability: 3 questions measuring satisfaction, safety and trust, and feeling:

1. Satisfaction with the ease of use
2. Degree of safety and trust when using the device
3. The feeling of owning one of the devices

From a qualitative perspective, an interview script was prepared with 14 groups of small open-ended questions that had 10 participants. Each participant was asked the same group of questions individually via remote, semi-structured interviews. The interview discussed the installation process, the existence of other water heaters, the previous use of other devices to control energy consumption (timers, etc.), the difference between Klugit and those devices, lack of hot water during the test period, satisfaction, the use of the app and the 'heat now' feature, changes on the bill, feelings about savings presented on the app and overall services, and finally the probability of recommendation for the device and services.

Results from the survey indicate that the consumers' DHW demand was met during the pilot project. In the user satisfaction and recommendation category, four users gave the device a full 10/10 score while only two gave a score of under 5/10, so the median score was 8/10. Regarding the ease of installation, only two users gave a score under 7/10 and the median value was again 8/10. There was an average of 7.3/10 for ease of use of the device (median value of 8/10) and 6.1/10 for satisfaction with the functionality of the device, with a median value of 7/10. The average rating for the satisfaction of the mobile application was 7/10 with a median of 8/10. In terms of aesthetics and packaging of the product, the average score was 7.3/10 (median 8/10) and 7.6/10 (10/10) respectively. The functionalities of the device that the consumer valued as most important and would like to be included in future versions of the device are as follows (ranked from the most important to the least important).

1. Load shifting or avoiding high tariff periods
2. Reducing the contracted power by ensuring that the EWH is not operating simultaneously with other major appliances
3. The ability to disconnect the smart mode or use the 'heat now' function when necessary
4. The sustainability and design of the device and the packaging
5. The ability to visualize savings from the smart mode in the mobile application
6. Viewing the forecasted schedule for hot water demand
7. Reducing the thermal losses from the EWH
8. Reducing CO2 emissions from the energy used to heat the EWH

Notably, the consumers stated that the installation of the device was quick, easy, and simple to carry out. Several consumers were already using a programmable plug for their EWH which might have made the installation process simpler for them. Concerning the two users who were not completely satisfied with the device, the major reasons were not related to the device. In one case, there was a weak Wi-Fi signal which made communication difficult between the device and the home router. In the other case, the consumer was required to use hot water during peak periods and the device was specifically designed to avoid use during peak periods. The consumers stated that the major reason for using the mobile application was to use the 'heat now' functionality and then to view the estimated savings from the smart mode and the forecasted schedules for hot water demand.

In terms of areas identified for further improvement, the survey and questionnaire identified the following:

- Improve the device's WIFI connectivity
- Modify the system to allow for heating during high tariff periods if necessary to meet the DHW needs of the consumer
- Once enough data has been gathered, modify the device to act more like a standard programmable plug. Propose a heating schedule to the consumer and request approval of this schedule. The schedule will not be changed unless directed by the consumer. Suggestions for improvement will be sent to the user but will require their approval before being applied. This will allow the user to become more familiar with the heating patterns of the EWH. This will help users regarding the optimal periods of EWH operation, especially those users who already have a standard programmable plug as was the case in several of the users in the Azores pilot study.
- Improve the feedback given to the consumers, especially around their savings in the electricity bill. Accurate and up-to-date savings can act as positive reinforcement for consumers.
- Add an option to switch the application to Portuguese (and other languages in the future) to improve ease of use.

4.6 Chapter Conclusions

This chapter has discussed the innovative development, implementation, and validation of a device to convert a passive EWH into an intelligent, controllable distributed energy resource to enable increased prosumer participation in smart grids. The device makes use of machine learning techniques to accurately forecast DHW demand based solely on the data received from a clip-on temperature sensor.

This chapter contains the details of a case study carried out in collaboration with EDA on the island of São Miguel, Portugal. The pilot project showed that these devices function very well and are highly effective in terms of controlling the heating of water to provide benefits to both the consumers and the system operator. In terms of direct benefits to the consumer, the device reduced the energy used to heat water by an average of 1.33 kWh per day per device, or 26.43% throughout the pilot study, which is significant. This energy reduction led to an estimated average saving of 35.5% per consumer. The annual cost savings enjoyed by the consumer equate to €97.63 without affecting the thermal comfort of the consumer, which is noteworthy. This monetary benefit exceeds the unit price of the device (currently estimated at €85 per unit) and with a lifetime of 5 years, the device can bring significant financial benefits to the consumers while maintaining their comfort.

The device can also provide both direct and indirect benefits to the system operator. Using a group of these devices in a coordinated manner, similar to a Virtual Power Plant in a transactive energy system, the devices have the ability to reduce the peak load of the system, increase load during low-demand periods, and displace electricity generated by fossil fuels. Using a fleet of 2127 intelligent EWHs, it is estimated that the devices can reduce total energy used on São Miguel by 2832 kWh per day just through the efficient heating of water, with no noticeable impacts on the thermal comfort of the consumer. The energy savings from these devices in terms of avoided generation from the CTCL plant ensured that the devices had an acceptable payback period. Additionally, it is estimated that these devices can reduce the carbon emissions of EDA by 693.31 tons CO_2/year. The chapter also showed that the device was well received by the consumers, being easy to install and operate. Overall, the qualitative results showed that the device did not affect the consumer's comfort while saving the consumer a considerable amount of their monthly heating bill. The consumers enjoyed the sense of control of their EWH and their ability to visualize their estimated savings and forecasted hot water demand. This device can be harnessed by prosumers to actively engage in the energy system, especially if the distribution utility uses transactive energy signals to request demand response potential or also services.

In summary, this chapter has shown that a rather cheap and user-friendly device to intelligently control an electric water heater can bring significant benefits to both consumers and the system operator. These benefits included energy savings, peak load reduction, and reduced emissions through avoided generation. The chapter showed that modern control and forecasting methods based on machine learning can help foster a bottom-up transformation of previously passive assets owned by consumers into active DERs which can provide numerous benefits to both the owners and other system participants.

Chapter 5

Technical Impacts of Increased Prosumer Participation on Distribution Systems

In transactive energy systems, prosumers will participate according to their economic and comfort preferences as well as signals from the system operator. By engaging in the energy system, the prosumers will directly impact the technical operation of the local distribution networks. These impacts will need to be monitored and mitigated so that the distribution system can function optimally. This calls for a careful balancing of the economic and thermal comfort considerations of the prosumers while ensuring that the distribution system operates efficiently and reliably. The previous chapter briefly touched on the technical impacts that a group of prosumer-owned DERs can have on the local distribution system, but a more robust framework is needed which considers a diverse set of prosumers and focuses on the technical impacts of DER operation in distribution networks. This can be done by considering the Technical Virtual Power Plant (TVPP), which has emerged to coordinate and control the growing number of Distributed Energy Resources (DERs) within power systems using transactive energy principles. This chapter's objective is to develop a TVPP operational framework to optimize the scheduling of a diverse set of DERs operating in a day-ahead energy market, considering grid management constraints. The effects on network congestion, voltage profiles, and power losses are presented and analyzed. In addition, the thermal comfort of the consumers is considered, and the trade-offs between comfort, costs, and technical constraints are presented. The model quantifies and allocates the benefits of the DER operation to the owners in a fair and efficient manner using the Vickrey Clarke Grove mechanism. This framework is based on a stochastic mixed-integer linear programming (MILP) model, and various case studies are thoroughly examined on the IEEE 119 bus test system.

The framework shows that aggregation is an effective means to harness the full potential of prosumer participation to improve the technical operation of smart grids using transactive energy principles. Also, the results show that the operations of the TVPP improve the financial metrics and increase consumer engagement while improving numerous technical and operational metrics.

Chapter Highlights and Novel Contributions:

- A stochastic (MILP) model is developed that considers the technical constraints of the network to optimize the scheduling of a diverse set of distributed energy resources and loads within a distribution system.
- The concept of a TVPP is extended to investigate the technical impacts of aggregating diverse DERs and quantify the benefit that the TVPP can bring to the system.
- The benefits of the different types of DERs are quantified. These marginal benefits are allocated in a fair and efficient manner using the VCG mechanism from cooperative game theory.
- The impact of a TVPP on the thermal comfort of building occupants under different HVAC operational strategies is quantified. This quantification allows for an evaluation of the tradeoffs between thermal comfort, financial outcomes, and technical impacts of different operating strategies of commercial HVAC systems in the presence of DR programs.

Relevant Publication(s):

M. Gough, S.F. Santos, M. Lotfi, M.S. Javadi, G.J. Osório, P. Ashraf, R. Castro, J.P.S. Catalão, "Operation of a technical virtual power plant considering diverse distributed energy resources," in *IEEE Transactions on Industry Applications*. Vol. 58, No. 2, pp. 2547-2558, March-April 2022.
Q1 Journal, Impact Factor: 4.079
Published. https://doi.org/10.1109/TIA.2022.3143479

M. Gough, S.F. Santos, M.S. Javadi, J.M. Home-Ortiz, R. Castro, J.P.S. Catalão, "Stochastic Bi-level Energy Trading Model for Technical Virtual Power Plants," in *Journal of Energy Storage*.
Q1 Journal, Impact Factor: 8.907
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Chapter 5 Nomenclature

Sets

h $\in \Omega^H$	Hours
s $\in \Omega^S$	Scenarios
$\zeta \in \Omega^Z$	Markets
g $\in \Omega^G$	Generators
ev $\in \Omega^{EV}$	Electric Vehicles
l $\in \Omega^L$	Lines
n,m $\in \Omega^{N,M}$	Nodes
k $\in \Omega^K$	Loads
hvac $\in \Omega^{HVAC}$	HVAC
$\omega \in \Omega^\omega$	Normal operation states

Parameters

g_l, b_l, S_l^{max}	Conductance, susceptance and flow boundaries of each branch l (S, S, MVA)
R_l, X_l	Resistance, Reactance (Ω, Ω)
MP_l, MQ_l	Big-M parameters related to active and reactive power flows in branch l
ρ_s	Probability of scenario s
OC_g	Cost of unit energy production
λ_h^{TOU}	TOU price associated with customers (€/MWh)
λ_h^ζ	Day-ahead market price (€/MWh)
λ_h^{ev}	EV discharging cost (€/MWh)
$PD_{s,h}^n$	Demand at node n (MW)
$QD_{s,h}^n$	Reactive demand at node n (MVAr)
V_{nom}	Nominal voltage (kV)
η_{ev}^{ch}	Charging efficiency
η_{ev}^{dch}	Discharging efficiency
$E_{ev,n}^{min}, E_{ev,n}^{max}$	Energy Storage limit
μ_{ev}	Scaling factor
$P_{g,n,s,h}^{DG,min}, P_{g,n,s,h}^{DG,max}$	Power generation limits (MW)
pf_g	Power factor of DG's
pf_{ss}	Power factor of substation
$T_{k,n,s,h}^{ideal}$	Ideal temperature set-point in house k (°C).
$P_{HVAC,k,n,s,h}^{cool,max}$	Actual HVAC unit power consumption of house k in time h

$T^{dec}_{k,t,n,s,h}$	Indoor temperature decrease with respect to the user-selected set-point in house k in period h (°C).
COP_{HVAC}	Coefficient of performance of HVAC in house k.
M_k	Mass of air in household k (kg).
c_{air}	Thermal capacity of air (kJ/kg·°C.
$T^{initial}_{k,n,s,h}$	Initial indoor temperature of household k (°C).
$T^{Dead-band}_{k,n,s,h}$	Temperature dead-band set-point for the HVAC unit of house k (°C).
$T^{therm}_{k,n,s,h}$	Set-point of house k in period h (°C).

Variables

$P^{grid}_{\zeta,n,s,h}, Q^{grid}_{\zeta,n,s,h}$	Power purchased from grid (MW, MVAr)
$E_{ev,n,s,h}$	Battery energy level of EV (MWh)
$I^{ch}_{ev,n,s,h}, I^{dch}_{ev,n,s,h}$	Charging and discharging binary variables
$P^{DG}_{g,n,s,h}, Q^{DG}_{g,n,s,h}$	DG power (MW, MVAr)
$P^{market}_{\zeta,n,s,h}$	Power purchased from market (MW)
P_l, Q_l, θ_l	Active and reactive power flows and voltage angle difference of branch l (MW, MVAr, radians)
PL_l, QL_l	Active and reactive power losses of each branch l (MW, MVAr)
$x_{l,h}$	Binary variable to indicate line status
$\Delta V_{n,s,h}$	Voltage deviation magnitude (kV)
$P^{cool}_{HVAC,k,n,s,h}, Q^{cool}_{HVAC,k,n,s,h}$	Active and reactive power flows of HVAC system
T^{amb}_{t-1}	Ambient temperature in period h in house k (°C)
$T^{in}_{k,t,n,s,h}$	Indoor temperature in house k in period h (°C).
$T^{inc}_{k,t,n,s,h}$	Indoor temperature increase with respect to the set-point in house k in period h (°C).

5.1 Introduction

In the age of rapidly increasing numbers of Distributed Energy Resources (DERs), the optimal control of these devices to benefit both prosumers and the wider electricity distribution is becoming a challenge [196]. Various control strategies for the optimal scheduling of these devices exist, and among those, the introduction of a Virtual Power Plant (VPP) based on the transactive energy concept has emerged [197]. This VPP is an entity that aggregates the disparate DERs to ensure that they act as a coordinated group in energy markets and has shown promise both in academic research and real-world applications [198]. Typically, VPPs have focused on optimizing the scheduling of DERs to reach some financial or commercial objectives. These types of VPPs are called Commercial Virtual Power Plants (CVPP) and often neglect important technical considerations related to the impact of DERs on the physical distribution grid.

In order to account for these physical impacts, a Technical Virtual Power Plant (TVPP) has emerged [199]. This agent schedules the optimal output level of generators and DERs to meet commercial as well as technical considerations. An overview of such a TVPP is shown in Figure 5.1. The figure shows that the TVPP is at the center of operations and communicates directly with various other actors, including the wholesale market operator and the DER owners. Additionally, the TVPP should communicate with RES owners to forecast energy supply to prepare their flexible demand if needed. The operator of the TVPP also optimizes the dispatch of its constituent DERs in a technically and economically feasible manner. This increases the feasibility of the proposed schedule of flexible generators as well as controllable loads. This can increase the efficiency, reliability, and penetration of these DERs within a given distribution system [200].

Within a given distribution system, there may be a diverse set of traditional consumers as well as prosumers. Commercial, industrial, and residential consumers have different load profiles, differing choices of DERs, and preferences. In order to maximize the ability of this diverse set of consumers and prosumers to engage in the energy sector, optimization frameworks should incorporate various types of consumers. This will help to maximize the potential complementary effects that may be present and reduce uncertainty or variability during operation. Uncertainty may be introduced into the framework through fluctuating load profiles from the consumers or by the output from renewable energy generators, such as solar photovoltaic or wind generation [201]. To deal with this variability, energy storage systems may be used. Using electric vehicles (EVs) as this storage is intriguing as they may have predictable charging requirements, are mobile, and through smart charging the power withdrawn during charging may be modulated to increase during high renewable energy generation periods or reduce during periods of high system load. These actions may improve the resilience of the network.

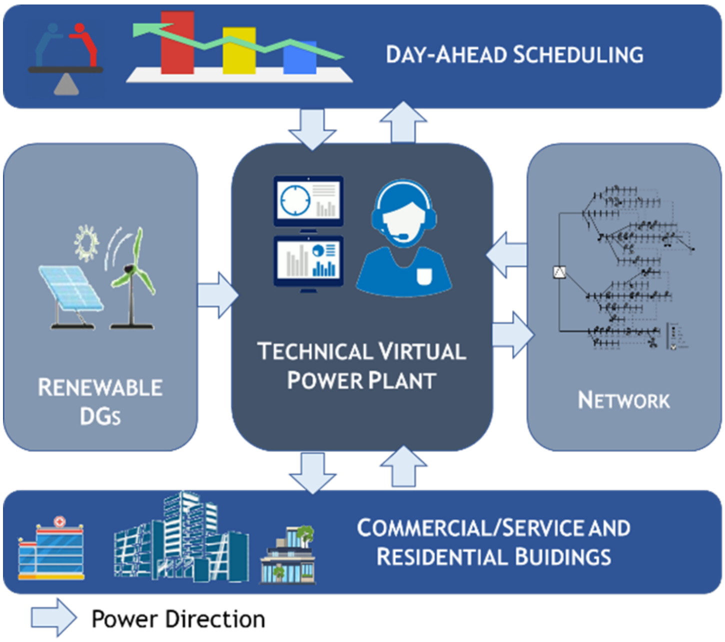

Figure 5.1: Overview of the Technical Virtual Power Plant concept

Another device class that may provide system flexibility within low voltage networks is Heating, Ventilation, and Air Conditioning (HVAC) systems. These devices may be controlled to reduce peak load or to operate in anticipation of high heating/cooling demand, such as pre-heating an office building during winter. In fact, thermal loads account for between 40% and 46% of energy consumers in commercial buildings [202]. These devices, when aggregated, can offer important sources of flexibility for low-voltage networks.

Despite the advantages that the increasing penetration of DERs can bring to power systems, there may also be some disadvantages. These may include power quality issues related to fluctuations in both voltage and frequency profiles [203]. Also, there may be issues associated with the bidirectional flow of power within the network, which may lead to congestion issues. High numbers of EVs at a particular location without smart charging may dramatically increase the load faced by the system, and the intermittent nature of renewable energy sources may also increase reserve requirements to account for rapid increases or decreases in power generation. These issues may be addressed through smart charging of EVs and by improved weather forecasting to reduce the unpredictability of renewable energy sources (RESs) generation or through the use of Demand Response (DR) programs [204].

The introduction of DERs in distribution grids can bring either financial benefits or costs to the individual owner as well as the broader range of participants in the grid. These additional benefits or costs may not be accounted for in the initial price of the DER. Thus, an ex-post allocation mechanism to account for and distribute these costs or benefits to the DER owners in a fair, efficient, and equitable manner may be needed. There are many such allocation mechanisms from coalitional game theory, including the Vickrey Clarke Grove (VGC) mechanism, which has been widely used in power systems and energy markets [205]. These mechanisms can ensure that the various impacts are allocated to the individuals who are responsible and thus increase the fairness and equitability of the TVPP. This may help to increase consumer engagement with the TVPP as consumers will be fairly rewarded for actions that benefit the grid, such as investing in DERs and enrolling in the TVPP program.

5.2 State of the Art

5.2.1 Literature review

This section presents recently published research on optimizing energy systems considering DERs from prosumers and VPPs. Many papers considering VPPs do not consider the technical constraints of the network. For example, the model presented by [206] is a combined energy scheduling and trading model for prosumers but does not consider technical constraints. This model used the principles of transactive energy, and results showed an improvement in grid operations via prosumer's participation. A further example of technical constraints not being considered is shown in the study conducted by [142]. This paper studied the participation of a CVPP in both the day-ahead and intraday energy markets. Various types of uncertainty were included in the model, and notably, a penalty function was introduced to minimize the deviation between the day-ahead and intraday dispatch schedules.

An optimization model for the aggregation of prosumers which took network constraints into account was developed by [207]. This model considered a decentralized approach to determine feasible bidding schedules between aggregators of prosumers and the distribution system operator. The objective was to minimize the aggregator's net cost of bidding in both the energy and secondary reserve markets. Uncertainty related to market price, renewable energy generation, or electric vehicles was not considered. Results show that by including network constraints in the problem, costs are slightly increased due to penalties for network violations.

Network congestion, an important technical consideration, was included in the energy management framework for prosumers proposed by [208]. The behavior of aggregated prosumers was modeled using a virtual battery model and used to schedule various small-scale resources to minimize the amount of congestion in the network. The results show a reduction in congestion as well as the preservation of consumer privacy within the model. The model relied on EVs as the primary source of flexibility and did not consider other distributed energy resources. By introducing these different forms of responsive demand or generation, the network congestion may be reduced further, especially if demand response programs are used within the model.

In contrast to the above model, the authors of [209] considered other types of DERs but not EVs in their model. The authors aimed to increase the flexibility of distribution systems. The objective was to minimize operational costs by the optimal scheduling of various DERs. While this paper considered other DERs, it did not consider network constraints.

The vast majority of VPP models neglect the technical constraints of the system. However, a model considering a TVPP was formulated by [199] to maximize the profit of the TVPP while minimizing the outage costs due to contingency occurrences. While the constraints of the distribution grid were considered, there was little analysis of the impacts of the TVPP's operation on the grid, such as congestion management, voltage profile fluctuations, and losses in the lines. Instead, the model focused on reliability indicators such as expected energy not served, system average interruption frequency/duration indices (SAIFI/ SAIDI), and expected interruption costs (EIC).

A multi-stage stochastic energy management framework for VPPs was developed in [149]. This model used a mixed-integer linear programming (MILP) approach to investigate the impacts of DR and EVs on minimizing the operating costs of a VPP. The technical constraints of the test system were not considered. A model which assessed the effects of a TVPP on both active and reactive power flows was proposed by [200]. This model accounted for uncertainty through the use of a robust capability curve and adjustable robust optimization to formulate a two-stage scheduling and optimization problem. In this paper, congestion management, voltage profile fluctuations, and line losses were not investigated.

A decentralized model for the optimal scheduling of flexible resources was developed by [210]. This model aimed to meet particular techno-social-economic objectives for the prosumers and ensure the reliability of the grid. Results show that coordinated scheduling of flexible resources reduced the system's peak load by 83% and increased prosumer costs by 28% relative to a scenario of non-coordinated scheduling. The model did not consider the effects of EVs or RESs. The impacts of the coordinated scheduling on the technical operations of the grid, such as voltage profiles, congestion, or power losses, were also not considered.

Table 5.1: Comparison with Relevant Literature

Paper	**Type of optimisation**	**Objective function**	**Types of DERs**	**Thermal comfort**	**Allocation mechanism**	**Voltage profiles**	**Congestion issues**	**Power losses**
[206]	MILP	Min Costs	PV, ESS	No	No	No	No	No
[142]	MILP	Max revenue	Wind, BESS	No	No	No	No	No
[207]	ADMM	Min Costs	EV, PV	No	No	Yes	Yes	No
[208]	Iterative LMP	Max consumer profit	EV, BESS	Yes	No	No	Yes	No
[209]	MILP	Min Costs	ESS, Wind, PV	No	No	No	No	No
[199]	MILP	Max TVPP profit	PV, EV	No	No	Yes	No	No
[149]	MILP	Max VPP profit	EV	No	No	Yes	No	No
[200]	Robust optimisation	Min Costs	None	No	No	No	No	No
[210]	MILP	Min costs	BESS	No	No	No	No	No
This chapter	MILP	Max TVPP profit	PV, Wind, EV, HVAC	Yes	Yes	Yes	Yes	Yes

From the previous paragraphs, it can be seen that there has been significant research carried out on the concept of VPPs, but limited research into their technical impacts on the distribution grid. Table 5.1 shows how this chapter investigates the effects of a TVPP in a novel manner, as the impact of a VPP on power losses, line congestion, as well as average voltage profile deviations has not been investigated to the best of the authors' knowledge. This investigation can then provide a comprehensive investigation into how prosumer participation through a TVPP can affect a distribution system. In addition, there is limited research considering the thermal comfort of consumers in a TVPP. Additionally, only a few researchers assess congestion and line losses within the system. In the existing literature, the impact of a VPP on this combination of technical constraints has not been investigated previously, to the best of the authors' knowledge. Finally, no paper surveyed quantified and allocated the benefits of DER to prosumers using fair mechanisms.

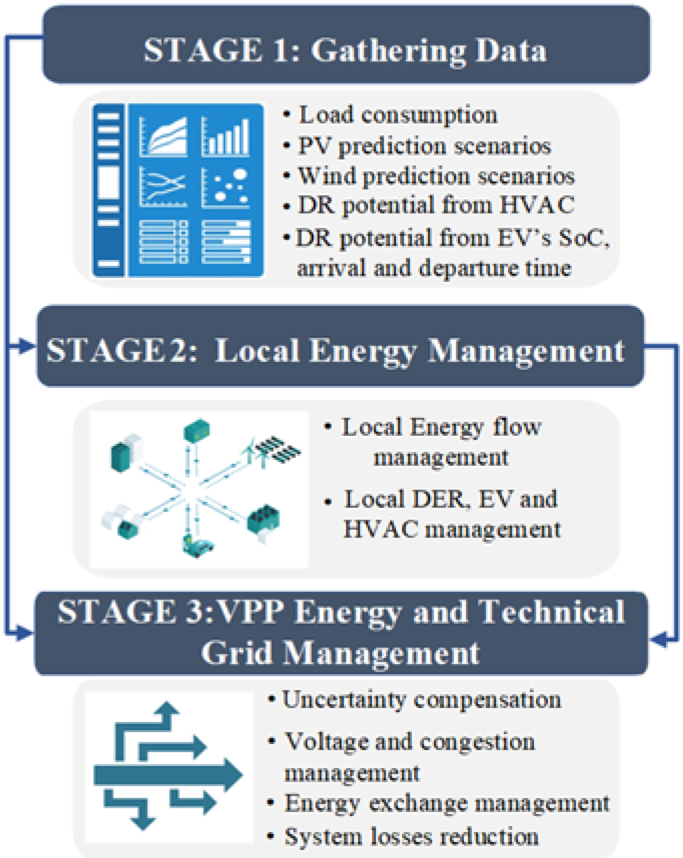

Figure 5.2: Proposed Three-stage TVPP model.

5.2.2 Chapter objectives

The objective of this chapter is to investigate the ability of a TVPP to positively impact the operation of a distribution system with a high penetration of DERs, considering both technical, economic, and thermal comfort impacts. This is done in order to increase prosumer participation in smart grids while understanding the impacts of their participation. This chapter addresses this with a three-stage model for the optimal operation of a TVPP. These stages are shown in Figure 5.2. The first stage involves collecting data and accounting for the various forms of uncertainty through the use of scenario decomposition strategies. The second stage deals with optimal energy management within the distribution system according to transactive energy principles. The final stage of the model handles the technical constraints of the system and compensates for the uncertain parameters.

5.3 Mathematical Formulation

5.3.1 TVPP energy management model

The stochastic model developed in this chapter aims to maximize the TVPP's profit from optimally scheduling various DERs. This profit is made up of two terms, revenue from power sold to commercial customers (PSC) and the cost of operating the TVPP (TVPPC) while considering the technical and economic constraints. This is shown in Equation 5.1.

$$Max : \sum (PSC - TVPPC) \tag{5.1}$$

The PSC revenue term is decomposed further in Equation 5.2. This equation represents each consumer's power consumption from daily loads, EV charging, and the usage of HVAC systems. The consumer's power consumption is subject to Time-of-Use (TOU) tariffs.

$$PSC = \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \lambda_h^{TOU} P_{k,s,h} + \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{ev\in\Omega^{EV}} \lambda_h^{TOU} P_{ev,k,s,h}^{ch} + \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{HVAC\in\Omega^{HVAC}} \lambda_h^{TOU} P_{HVAC,k,s,h}^{cool} \tag{5.2}$$

The TVPPC term is shown in Equation 5.3. These costs include payments to prosumer-owned DERs for electricity produced plus maintenance costs. There are two terms that are added to the cost and one that is subtracted. The costs of purchasing power from the market is added to the TVPPC and so is a penalty function that will be described in depth in the coming section. Finally, the revenue from the power sold by discharging consumers' EVs is subtracted from the TVPPC. The penalty 5.4 is the price paid to charge EVs or paid to activate the HVAC systems, which would not have occurred if the TVPP was not active. This penalty acts as an economic signal to encourage prosumer participation in using EVs or HVAC units. Therefore, in Equations 5.5 and 5.6, the EV's penalty term is presented to compensate for the surplus cost faced by customers. This cost can be modeled as the difference between the customer's optimal cost and resulted cost of TVPP's schedule on the charging and discharging cycles of the EVs. This surplus can be interpreted as a transactive energy-based signal paid to customers for participating in the energy scheduling of the TVPP.

$$TVPPC = \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{g\in\Omega^G} OC_g P_{g,k,s,h}^{DG} + \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{\zeta\in\zeta} \lambda_h^{\zeta} P_{\zeta,k,s,h}^{grid} - \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{ev\in\Omega^{EV}} \lambda_h^{ev} P_{HVAC,k,s,h}^{disc} + Penalty \tag{5.3}$$

$$Penalty = Penalty_{ev} + Penalty_{HVAC} \tag{5.4}$$

The EVs' optimal cost is selected as the cost of each EV introduced in the objective function as

PenaltyEV. An independent optimization problem minimizes the following cost function.

$$Penalty_{ev} = \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{ev\in\Omega^{EV}} \lambda_h^{TOU} P_{ev,k,s,h}^{ch} - \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{ev\in\Omega^{EV}} \lambda_h^{TOU} P_{ev,k,s,h}^{dch} - Cost_{ev,\omega}^{NormalOperation} \tag{5.5}$$

$$Costev^{NormalOperation} = \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{\omega\in\Omega^\omega} \sum_{ev\in\Omega^{EV}} \lambda_h^{TOU} P_{ev,k,\omega,h}^{ch} - \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{\omega\in\Omega^\omega} \sum_{ev\in\Omega^{EV}} \lambda^{EV} P_{ev,k,\omega,h}^{dch} \tag{5.6}$$

In Equations 5.7 and 5.8, the HVAC's penalty term is presented. The penalty is due to the fact that the TVPP should compensate for the additional cost faced by customers. This cost can be modeled as the difference between the customer's optimal cost and the resulting cost of TVPP's schedule on the charging and discharging cycles of the HVACs. This can be interpreted as the incentive paid to customers for participating in the energy scheduling of the TVPP. The customer's HVAC cost is calculated as the optimum cost of each HVAC introduced in the objective function as PenaltyHVAC.

$$Penalty_{HVAC} = \sum_{s\in\Omega^S} \rho_s \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{HVAC\in\Omega^{HVAC}} \lambda_h^{TOU} P_{HVAC,k,s,h}^{cool} - Cost_{HVAC,\omega}^{NormalOperation} \tag{5.7}$$

$$CostHVAC^{NormalOperation} = \sum_{h\in\Omega^H} \sum_{k\in\Omega^K} \sum_{\omega\in\Omega^\omega} \sum_{HVAC\in\Omega^{HVAC}} \lambda_h^{TOU} P_{HVAC,k,\omega,h}^{cool} \tag{5.8}$$

EVs are modeled by the expressions 5.9 to 5.14. The maximum charging and discharging rates are governed by 5.9 and 5.10 respectively while 5.11 ensures that charging or discharging cannot occur simultaneously.

$$0 \le P_{ev,k,n,s,h}^{ch} \le I_{ev,k,n,s,h}^{ch} P_{ev,k,n,s,h}^{ch,max} \tag{5.9}$$

$$0 \le P_{ev,k,n,s,h}^{dch} \le I_{ev,k,n,s,h}^{dch} P_{ev,k,n,s,h}^{dch,max} \tag{5.10}$$

$$I_{ev,k,n,s,h}^{dch} + I_{ev,k,n,s,h}^{ch} \le 1 \tag{5.11}$$

$$E_{ev,k,n,s,h} = E_{ev,k,n,s,h-1} + \eta_{ev}^{ch} P_{ev,k,n,s,h}^{ch} - \frac{P_{ev,k,n,s,h}^{ch}}{\eta_{ev}^{dch}} \tag{5.12}$$

$$E_{ev,k,n}^{min} \le E_{ev,k,n,s,h} \le E_{ev,k,n}^{max} \tag{5.13}$$

$$E_{ev,k,n,s,h_0} = \mu_{ev} E^{max}_{ev,k,n}; \qquad E_{ev,k,n,s,h_{24}} = \mu_{ev} E^{max}_{ev,k,n} \tag{5.14}$$

The state of charge (SoC) of the EV is modeled in 5.12 and relies on the SoC of the previous period plus any additional charging minus any discharging. Inequality 5.13 ensures that the storage level is always within a permissible range, and 5.14 sets the initial storage level and requires that the EV returns to this initial SoC at the end of the operational period. For simplicity, both ηev^{ch} and ηev^{ch} are set to be equal and are expressed as a percentage, depending on the node where the EVs are connected. The HVAC systems are modeled by expressions 5.15-5.26, which were obtained from [211]. The maximum and minimum temperature limits are set by 5.15 while 5.16 bounds the HVAC power use. This model utilizes a thermal resistance model which uses the cooling operation of the HVAC system and is shown in 5.17. The initial temperature is defined by 5.18. Equation 5.22 minimizes the discomfort level of the consumers. Equations 5.23 and 5.24 set the upper and lower limits of HVAC operation. The non-negativity constraints for the decision variable are shown in 5.2 and 5.26.

$$T^{min}_{HVAC,k} \leq T^{ideal}_{k,s,h,n} \leq T^{max}_{HVAC,k} \tag{5.15}$$

$$0 \leq P^{cool}_{HVAC,k,n,s,h} \leq P^{cool,max}_{HVAC,k,n,s,h} \tag{5.16}$$

$$\begin{aligned} T^{in}_{t,k,n,s,h} = (1 - \frac{\Delta T}{1000 * M_k c_{air} R_k}) * T^{in}_{t-1,k,n,s,h} + (\frac{\Delta T}{1000 * M_k c_{air} R_k}) T^{amb}_{t-1} - \\ (\frac{COP_{HVAC}}{0.000277 * M_k c_{air}}) P^{cool}_{HVAC,k,s,n,h} \qquad \forall k, t \geq 1 \end{aligned} \tag{5.17}$$

$$T^{in}_{t_0,k,n,s,h} = T^{initial}_{k,n,s,h} \qquad \forall k \tag{5.18}$$

$$P^{cool}_{HVAC,k,s,n,h} = u_{k,s,n,h} P^{cool,max}_{HVAC,k,s,n,h} \qquad \forall k, t (u = 0 OFF, u = 1 ON) \tag{5.19}$$

$$T^{in}_{t,k,n,s,h} \forall k, t \in argmin_{T^{in}_{t,k,n,s,h}, T^{dec}_{t,k,n,s,h}, T^{therm}_{t,k,n,s,h}} [\frac{1}{N_k} \sum_{h \in \Omega^H} \sum_{k \in \Omega^K} \sum_{s \in \Omega^s} (T^{inc}_{t,k,n,s,h} + T^{dec}_{t,k,n,s,h})] \tag{5.20}$$

subject to:

$$T^{therm}_{t,k,n,s,h} \leq T^{ideal}_{t,k,n,s,h} + T^{inc}_{t,k,n,s,h} \qquad \forall k, t \tag{5.21}$$

$$T^{therm}_{t,k,n,s,h} \leq T^{dec}_{t,k,n,s,h} - T^{ideal}_{t,k,n,s,h} \qquad \forall k, t \tag{5.22}$$

$$T^{in}_{t,k,n,s,h} \leq T^{therm}_{t,k,n,s,h} + T^{dead-band}_{t,k,n,s,h} \qquad \forall k,t \tag{5.23}$$

$$-T^{in}_{t,k,n,s,h} \leq T^{dead-band}_{t,k,n,s,h} - T^{therm}_{t,k,n,s,h} \qquad \forall k,t \tag{5.24}$$

$$-T^{dec}_{t,k,n,s,h} \leq 0 \qquad \forall k,t \tag{5.25}$$

$$-T^{inc}_{t,k,n,s,h} \leq 0 \qquad \forall k,t \tag{5.26}$$

Kirchhoff's Current law governs the flow of current into and out of a node and this constraint holds for each node in the system. This constraint is applied to the active power flow in Equation 5.27 and the reactive power flows in Equation 5.28. In these equations, $P_{l,s,h}$ and $Q_{l,s,h}$represent the active and reactive power flow in the line respectively, and $PD^{n}_{l,s,h}$ and $QD^{n}_{l,s,h}$ represent the active and reactive demand at the nodes, respectively. $PL_{l,s,h}$ and $QL_{l,s,h}$ represent the active and reactive power losses in the line, respectively.

$$\begin{aligned}\sum_{g\in\Omega^G} P^{DG}_{g,n,s,h} + \sum_{k\in\Omega^K}\sum_{ev\in\Omega^{EV}} (P^{dch}_{ev,k,n,s,h} - P^{ch}_{ev,k,n,s,h}) + P^{market}_{\zeta,s,h} + \sum_{in,l\in\Omega^L} P_{l,s,h} - \sum_{out,l\in\Omega^L} P_{l,s,h} = \\ (PD^{n}_{s,h} + PD^{cool}_{HVAC,k,n,s,h} + \sum_{in,l\in\Omega^L}\frac{1}{2}PL_{l,s,h} + \sum_{out,l\in\Omega^L}\frac{1}{2}PL_{l,s,h}; \qquad \forall\zeta\in Z\end{aligned} \tag{5.27}$$

$$\begin{aligned}\sum_{g\in\Omega^G} Q^{DG}_{g,n,s,h} + Q^{market}_{\zeta,s,h} + \sum_{in,l\in\Omega^L} Q_{l,s,h} - \sum_{out,l\in\Omega^L} Q_{l,s,h} = \\ (QD^{n}_{s,h} + QD^{cool}_{HVAC,k,n,s,h} + \sum_{in,l\in\Omega^L}\frac{1}{2}QL_{l,s,h} + \sum_{out,l\in\Omega^L}\frac{1}{2}QL_{l,s,h}; \qquad \forall\zeta\in Z\end{aligned} \tag{5.28}$$

Inequalities 5.29 and 5.30 present linearized AC power flow through each feeder, which is governed by Kirchhoff's Voltage Law. Note that $\theta_{l,s,h}$ refer to the angle difference $\theta_{n,s,h}$ and $\theta_{m,s,h}$ where n and m are bus indices corresponding to the same line l based on [170]. The big-M formulation was used, set to the maximum transfer capacity, to avoid non-linearity.

$$|P_{l,s,h} - V_{nom}(\Delta V_{n,s,h} - \Delta V_{m,s,h})g_l - V^2_{nom} b_l \theta_{l,s,h}| \leq MP_l \tag{5.29}$$

$$|Q_{l,s,h} - (-V_{nom}(\Delta V_{n,s,h} - \Delta V_{m,s,h})b_l) - V^2_{nom} g_l \theta_{l,s,h}| \leq MQ_l \tag{5.30}$$

The maximum amount of flow that can pass through a line is given by inequality 5.31. Equations 5.32 and 5.33 represent active and reactive power losses in each line l, respectively.

$$P_{l,s,h}^2 + Q_{l,s,h}^2 \leq \chi_{l,h} (S_l^{max})^2 \tag{5.31}$$

$$PL_{l,s,h} = RL_l (P_{l,s,h}^2 + Q_{l,s,h}^2)/V_{nom}^2 \tag{5.32}$$

$$QL_{l,s,h} = \chi_l (P_{l,s,h}^2 + Q_{l,s,h}^2)/V_{nom}^2 \tag{5.33}$$

The active and reactive power limits of the DGs are given by Equation 5.34 and Equation 5.35, respectively. Inequality 5.36 limits the DGs ability to inject or consume reactive power.

$$P_{g,n,s,h}^{DG,min} \leq P_{g,n,s,h}^{DG} \leq P_{g,n,s,h}^{DG,max} \tag{5.34}$$

$$Q_{g,n,s,h}^{DG,min} \leq Q_{g,n,s,h}^{DG} \leq Q_{g,n,s,h}^{DG,max} \tag{5.35}$$

$$-\tan(cos^{-1}(pf_g))P_{g,n,s,h}^{DG} \leq Q_{g,n,s,h}^{DG} \leq \tan(cos^{-1}(pf_g))P_{g,n,s,h}^{DG} \tag{5.36}$$

For stability reasons, the active and reactive power limits at the substations are given by Equation 5.37 and Equation 5.38.

$$P_{\zeta,s,h}^{market,min} \leq P_{\zeta,s,h}^{market} \leq P_{\zeta,s,h}^{market,max} \tag{5.37}$$

$$Q_{\zeta,s,h}^{market,min} \leq Q_{\zeta,s,h}^{market} \leq Q_{\zeta,s,h}^{market,max} \tag{5.38}$$

The reactive power that is withdrawn from the substation is subject to the bounds presented in inequality 5.39.

$$-\tan(cos^{-1}(pf_{ss}))P_{\zeta,s,h}^{market} \leq Q_{\zeta,s,h}^{market} \leq \tan(cos^{-1}(pf_{ss}))P_{\zeta,s,h}^{market} \tag{5.39}$$

Equation 5.40 requires that all nodes with demand at hour h are connected and have a single input flow through line l. The inequality shown in Equation 5.41 places an upper bound of 1 input flow for the terminal nodes.

$$\sum_{l\in\Omega^L} \chi_{l,h} = 1 \qquad \forall m \in \Omega^k, l \in n \tag{5.40}$$

$$\sum_{in,l\in\Omega^L} \chi_{l,h} - \sum_{out,l\in\Omega^L} \chi_{l,h} \leq 1 \qquad \forall m \notin \Omega^k, l \in n \tag{5.41}$$

5.3.2 Allocation mechanism

The Vickrey-Clark-Groves (VCG) mechanism is a commonly used mechanism within cooperative game theory [205]. This mechanism is an efficient way to ensure that the dominant strategy within a cooperative game is for the individuals to act in a truthful manner. The outcome of this mechanism is a set of truthful private valuations submitted by the agents. This mechanism allows the first-best outcome to be implemented. This mechanism ensures that prosumer i receives a monetary transfer equal to the true marginal contribution of that DER to the distribution system. Formally, the transfer t_i that agent i receives is described by Equation 5.42:

$$t_i(\tilde{v}) = \sum_{j \neq i} \tilde{v}_j(f*(\tilde{v})) - \sum_{j \neq i} \tilde{v}_j(f*(\tilde{v}_i)) \tag{5.42}$$

The VCG mechanism is used in this model to accurately quantify and allocate the benefits provided by the various types of DERs to the system in such a manner that provides a fair and efficient valuation of the DER's contribution to the TVPP.

5.4 System Layout and Case Studies Considered

This section presents the layout of the test system and the assumptions used in the model. Following this, various case studies are discussed.

5.4.1 System Layout

In this chapter, the 119-bus test system is used to perform the numerical analysis. The system has a nominal voltage of 11 kV, and demand of 22709.72 kW and 17041.068 kVAr [170]. The size and location of RESs, and also the power factor of RESs, are all taken from [170]. The type of DG units and the buses to which it is connected, as well as the points of interconnection between the EVs parking lots and HVAC systems and the network, are also shown in 5.3 and are taken from [170]. Two types of DG units are considered as illustrated: wind power and solar power. The installed capacity of these units is 1 MW in both cases. EV characteristics are taken from [171] and the initial value of the SoC is either 50% or 62.5% depending on the individual EV in the EV parking lot. The solar and wind plants are modeled using a set of scenarios to represent the power generated while accounting for uncertainty in the output. These scenarios are derived from real data and have been taken from [170]. There are three sources of uncertainty, solar generation, wind generation, and demand. Three scenarios for each parameter were developed. This resulted in 27 scenarios (three scenarios for each parameter or 3x3x3) which were reduced using k-means clustering techniques as described in [170]. In addition to the above, the following assumptions and system data are also considered:

- A time horizon of 24 hours is considered;
- In each node, a voltage deviation of ±5% is allowed;

- The reference node is the substation, with a voltage magnitude set to 1 p.u. and the angle to 0°;
- The value of the power factor of the DG units is 0.95 and the substation is 0.8, both inductive;
- EV charging and discharging efficiency are considered the same and equal to 90%;
- The operation cost of EVs during charge and discharge is 5 €/MWh;
- The EVs discharge cannot go below 40% of their total load capacity;
- The operation cost of solar DG units is 18.24 €/MWh [212];
- The operation cost of wind DG units is 13.2 €/MWh [213];
- Commercial buildings can also charge EVs at night;
- Optimization for usage during a summer period for a location in Southern Europe.

Commercial and service buildings (hospitals) are distributed throughout the network and are fed through nodes 20, 33, 43, 69, 77, 83, 108, and 112 as shown in Figure 5.3. The demand profile for each type of consumer at each node is obtained from [214].

Each one of these commercial prosumers has HVAC and EV units, with each EV park having 25 cars. EVs are to charge at the period with the lowest electricity purchase price, considering demand response. The arrival and departure times for the EVs are sourced from [215]. In this distribution network, there are different line capacities depending on the line's location. These are 500 kVA, 800 kVA, and 1200 kVA. In those lines closer to the substation, the line capacities are higher.

5.4.2 Case Studies considered

The developed work was based on four case studies. The first case uses the external grid to meet the demands of the system. This is a benchmark case to examine the various effects of the latter case studies. The second case allows for the aggregation of distributed RES systems (solar PV and wind) to meet a portion of the demand in addition to the external grid. In addition, the impacts of DR, through a TOU tariff (shown in Table 5.2), are investigated. The TOU rate is sourced from [216]. The third case study investigates the potential of EVs and commercial HVAC systems to increase the flexibility of the system. This case examines the possibility of the EVs acting as mobile energy storage systems to help support the grid's operation in cases where there is a sudden drop off in the generation from RES generators. The case study considers the power purchased from the market, the aggregation of power from the EVs, HVAC use in commercial buildings, and DR flexibility with no generation from RES units.

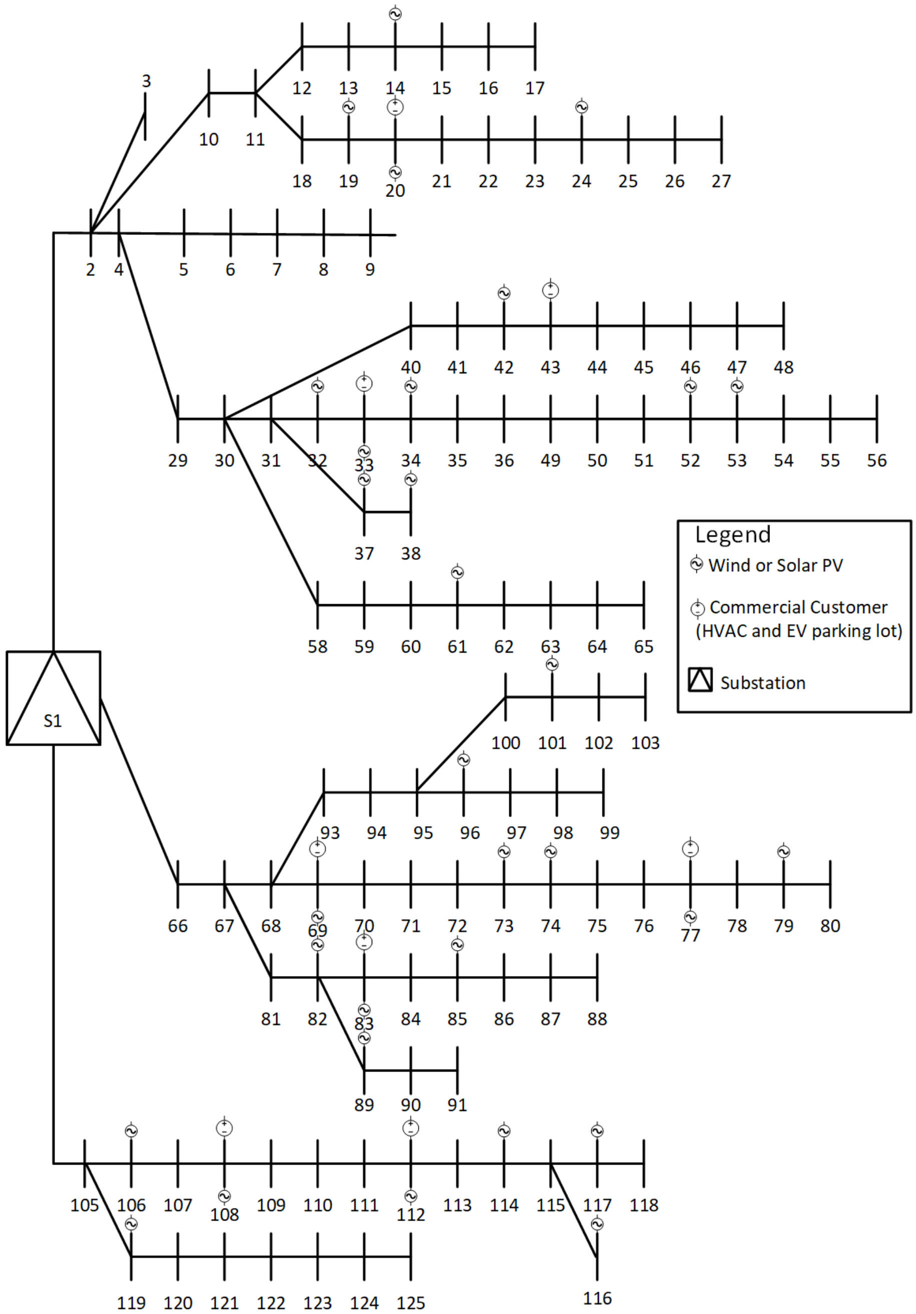

Figure 5.3: Layout of the test system used.

Table 5.2: TOU Tariffs used

Time	Tariff (€/MWh)
10:00-21:00	61.27
21:00-10:00	40.36

The fourth case study extends Case 3 by including RES generation to the EVs and HVAC systems to examine the combined impact of these technologies on the technical and economic performance of the TVPP. This case study considers the power purchased from the market, the aggregation of power from the DGs, and the aggregation of power provided by a variety of sources such as EVs through Vehicle-to-grid (V2G) interface technologies, HVAC use in commercial buildings, and DR flexibility through the ToU tariff. In this last case, the variation of the temperature range in commercial buildings is assessed.

The model is programmed in GAMS 24.0 and solved using the CPLEX 12.0 solver. The simulations are conducted on an HP Z820 workstation with two 3.1 GHz E5-2687W processors and 256 GB of RAM with an average CPU time of 1200s.

5.5 Results and Discussion

5.5.1 Impact of TVPP on Profits

The revenues from the power sold to the consumers, the operating costs of the TVPP, and the final profit of the TVPP for all case studies are shown in Table 5.3. From the table, it can be seen that as more DERs are added to the system, such as solar PV, wind, EVs, and HVAC units, the profit of the TVPP increases. This increase is mainly due to the reduction in operating costs as the revenue of the TVPP largely remains constant. This cost reduction is due to numerous factors, such as increased local generation, which is cheaper than the external grid, and the optimal scheduling of the EV charging and HVAC operation to minimize use during periods of high TOU tariffs.

Table 5.3 shows that there is a 48% reduction in the operation costs when DER is included (Case 2) in the system compared to Case 1. When EVs and HVAC units are added to the DERs (Case 4), costs are reduced by 56% relative to the base case. In terms of profits, Case 2 sees a 94% increase in profits compared to Case 1. When all DERs are included (Case 4), profits increase to €32026.23. The energy mix of Case 4 is shown in Figure 5.4. The contributions of the DERs (wind, solar, and V2G) are shown. The charging demand for EVs is also shown. It can be seen that there is a large amount of EV charging during the early hours of the morning and then a slight increase when the solar PV units are generating. There is a decrease in EV charging during the peak periods in the evening. Notably, the implementation of a TOU ensures that there is a reduction in the load during peak hours. If this DR program is not included, we may see an increase in the peak load during the evening as a result of EV charging. This will bring extra costs to the consumers and negatively impact the network.

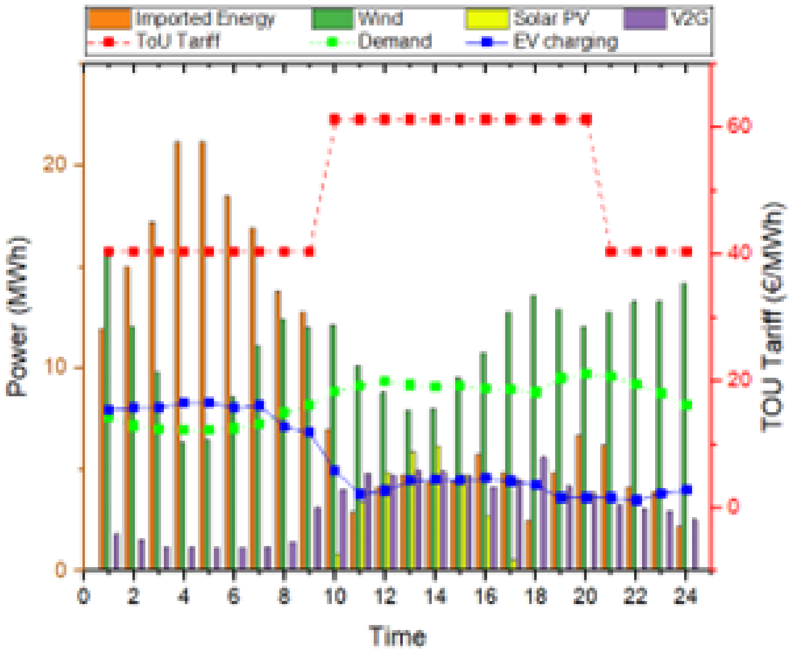

Figure 5.4: Energy mix for Case 4

5.5.2 Marginal contribution of DER assets

This section investigates the marginal contribution of each DER asset type to the overall profit of the TVPP according to the VCG mechanism. By quantifying the contribution of each DER type, appropriate compensation may be paid to the owners of the DER may be made so that the owners are incentivized to participate in the TVPP. By using the VCG mechanism, it is ensured that the DERs with the largest positive impact on the TVPP are compensated in a fair and efficient manner. This is important to understand as DER assets may include significant investment costs, and the choice of the allocation of capital to these DER assets are a significant factor in the optimal operation of a TVPP agent.

Table 5.3: Financial performance across the various case studies

	Revenue (€)	Cost (€)	Profit (€)
Case 1	44091.62	28849.79	15241.83
Case 2	44517.26	14992.79	29524.47
Case 3	44143.67	16989.28	27154.38
Case 4	44783.89	12757.65	32026.23

The marginal contribution of the DERs assets to the profit of the TVPP is shown in Table 5.4. This table shows that EVs provide the most significant impact on the TVPP operation. This is due to their ability to both absorb and provide power to the TVPP during different times. The ability of the EVs to provide proper power compensation is limited by the size of the battery. HVAC units do not offer significant technical benefits. However, they provide essential sources of thermal comfort control for commercial buildings and thus are important for the TVPP. HVAC units may also provide vital peak reduction services.

Table 5.4: Allocation of marginal DER benefits

DER type	**Contribution %**
Solar PV	36
Wind	18
Electric vehicles	39
HVAC units	7

5.5.3 Technical impact of TVPP

In this optimization model, the technical constraints of the distribution system are accounted for. These include the capacities of the lines within the system. Table 5.5 shows the instances where line loads are exceeded in Case 1 and how the subsequent cases helped reduce or eliminate instances where the line load capacities were exceeded.

In Case 1, there are 19 instances where the load exceeds the rated line capacity. In Case 2, there are three instances. Case 3 sees 15 instances, and in Case 4, the rated line capacities are not exceeded at all. In Case 3, only the EVs and HVAC units are operating. The ability of EVs to offer power compensation is limited due to their size. This is why the relatively high number of line capacities is being exceeded.

Another crucial technical constraint to consider in system management is the voltage profile of the nodes within the network. The voltage profile of the buses across the study period is an important metric in terms of the reliability of the system. The voltage deviations for all nodes across the 24-hour period for Case 1 are shown in Figure 5.5. The blue areas show instances where the deviation in the nodal voltage was greater than 5%, which exceeds the limits set in the model. From Figure 5.5, it can be seen that these limits are exceeded often. In contrast to Figure

Table 5.5: Line congestion

Line	Case 1 (MVA)	Case 2 (MVA)	Case 3 (MVA)	Case 4 (MVA)
Line 1	35.03	0.00	9.42	0.00
Line 30	27.66	0.00	0.00	0.00
Line 41	30.56	0.00	0.00	0.00
Line 57	10.98	0.00	10.98	0.00
Line 62	42.12	0.45	29.79	0.00
Line 63	62.65	0.00	44.14	0.00
Line 66	53.16	0.00	53.16	0.00
Line 67	82.35	22.35	82.35	0.00
Line 68	41.09	0.00	41.09	0.00
Line 69	41.09	0.00	41.09	0.00
Line 77	9.44	0.00	0.00	0.00
Line 88	44.86	0.00	0.00	0.00
Line 99	48.94	0.00	8.47	0.00
Line 101	17.02	0.00	17.02	0.00
Line 102	57.45	0.00	57.45	0.00
Line 105	75.64	0.00	75.64	0.00
Line 106	0.63	0.63	0.63	0.00
Line 107	0.63	0.00	0.63	0.00
Line 109	44.24	0.00	25.71	0.00

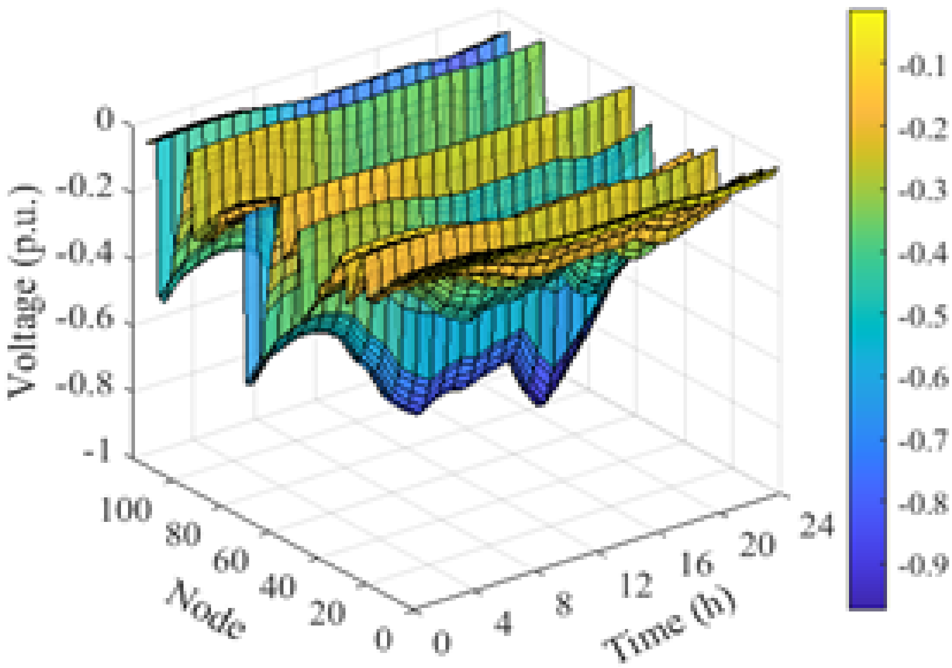

Figure 5.5: Voltage deviations for Case 1.

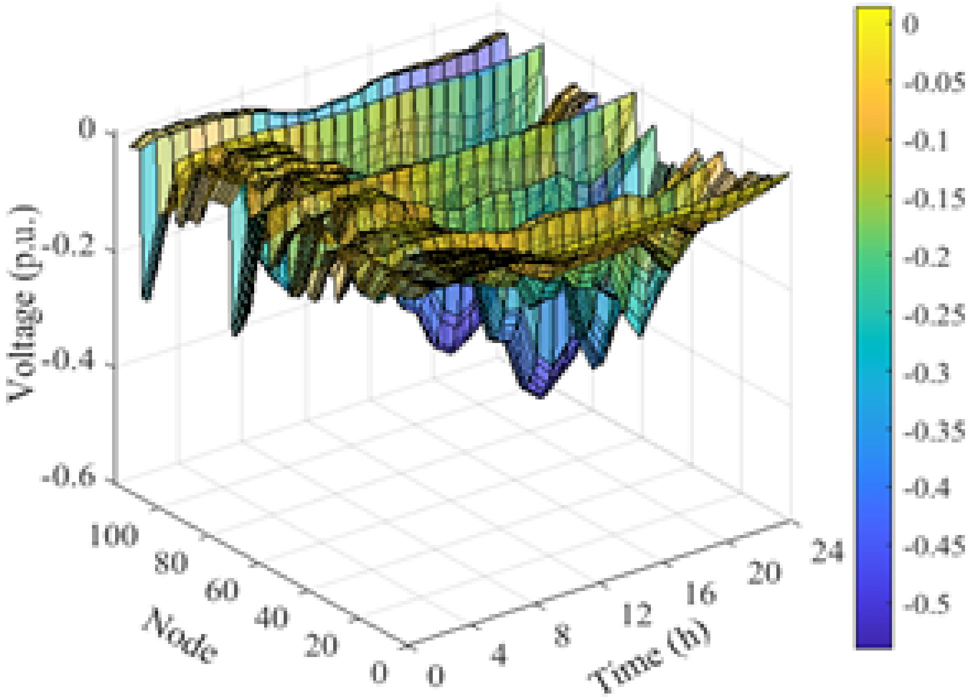

Figure 5.6: Voltage deviations for Case 4.

5.5, the results of the nodal voltage deviations seen in Case 4 are shown in Figure 5.6. In this case study, the deviations in nodal voltages have been significantly reduced and now fall within the 5% allowable deviation. The improvements to the voltage profile are due to the presence of the DG units as they generate power locally, which improves the voltage of the local nodes. The DG units also tend to be located near the end of a line which improves the voltage profile. The most significant voltage drops are seen in those nodes situated at the end nodes of the feeders, which can be seen from the grid topology. The worst performing node, Bus 79, saw a 66% reduction in voltage deviations, improving system reliability. The voltage deviations for this node for Case 1 and Case 4 are shown in Figure 5.7.

In addition to the congestion and voltage profile of the system, the power losses were also investigated for all four test cases. The losses experienced by the system across the four cases are shown in Table 5.6. There is a significant decrease in the losses in Case 2, Case 3, and Case 4. Most significantly, the reduction in losses in Case 2 and Case 4 is due to the presence of solar PV and wind generators. These local generators help to reduce the losses as they are positioned closer to the demand, and thus there are fewer losses in the distribution lines.

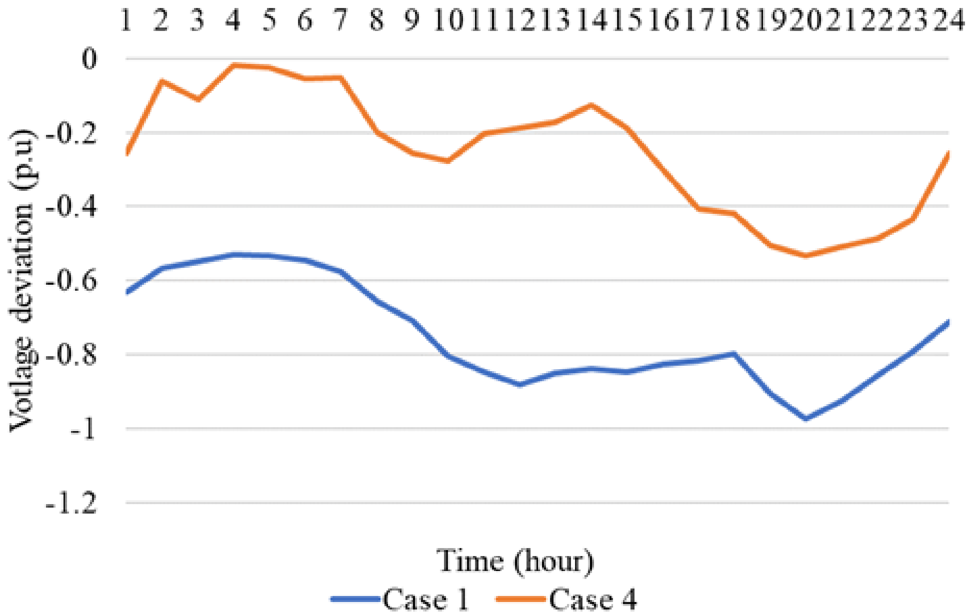

Figure 5.7: Voltage profiles for Case 1 and Case 4.

Table 5.6: System losses across the four cases

Case	Losses (MWh)
Case 1	20.25
Case 2	9.38
Case 3	14.11
Case 4	6.16

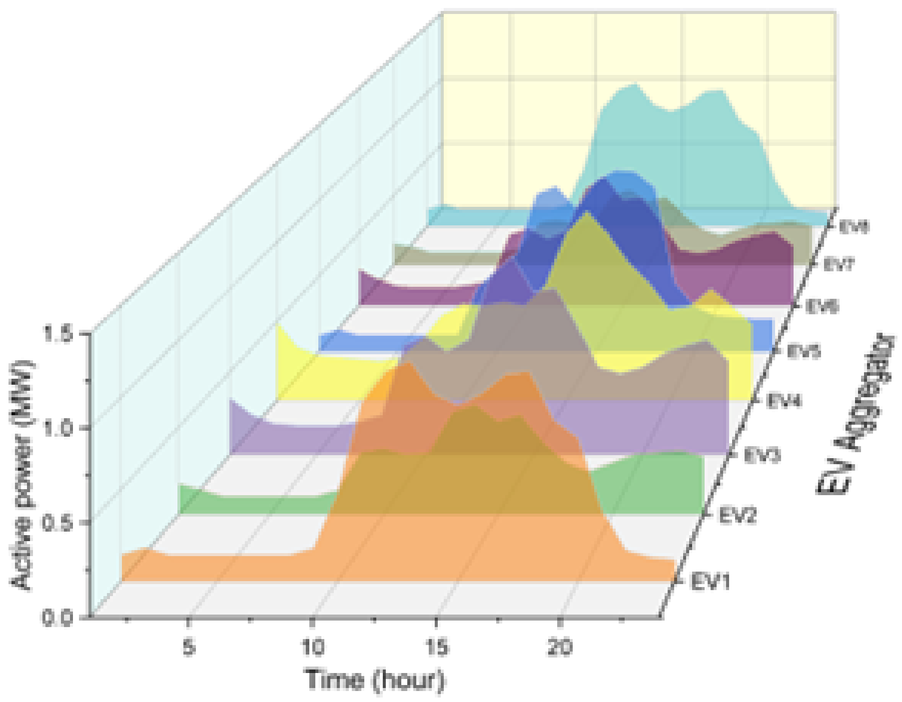

Figure 5.8: Aggregated V2G power from EVs.

5.5.4 Impact of EV aggregation

In Case 3 and Case 4, EVs and HVAC units in commercial and service buildings were included. Electric vehicles have limited ability to provide power compensation, so the EVs had a small impact on the voltage deviations.

They were able to charge and discharge according to the system demand and ToU pricing. This is shown in Figure 5.8, which shows the active power discharge from the EV aggregators. This figure only shows the active power discharge and does not show the charging of the EVs, which typically occur between 21:00 and 07:00.

The impacts of the TOU tariff are clear to see as there is significant V2G power provided by the EVs during the evening peak periods, between 19:00 and 21:00. This figure shows the ability of EVs in parking lots equipped with V2G services to contribute to meeting system load balancing requirements and their potential in DR programs. The aggregated charging demand of the various EV aggregators is shown in Figure 5.9. This figure shows that there is very little charging demand during the peak TOU period between 10:00 and 20:00. Only EV aggregator 1 has significant charging, which can be explained as this is the aggregator located at the hospital and there exists a particular minimum demand for EV charging throughout the day.

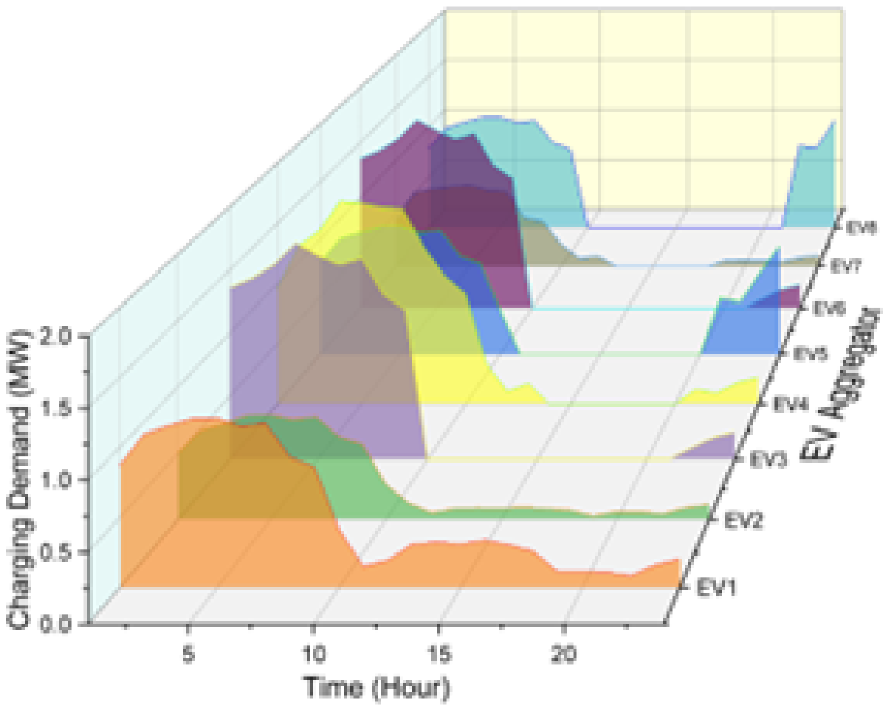

Figure 5.9: Aggregated charging demand from EVs.

5.5.5 Impacts of HVAC due to Changing Thermal Comfort

In addition to including the effects of EVs in Case 3 and Case 4, HVAC units were also included in these cases. These HVAC units were optimized to respond to the DR program (TOU tariffs) to reduce demand during high-demand periods while maintaining the thermal comfort of the consumers within the commercial buildings.

There are trade-offs between consumers' thermal comfort and the amount of flexibility that HVAC units can provide to the system. Stricter thermal comfort requirements will mean that the HVAC units must operate for more extended periods and possibly in high-demand periods, with high TOU tariffs. Three different thermal bands are considered to investigate the impacts of stricter thermal comfort bands, and the results are presented. The three thermal comfort bands are a wide range of 18° and 24°, a standard band of 19° to 23°, and a narrow band of 20° to 22°. This is shown in Figure 5.10, which compares the operation of HVAC units within the model with three different thermal comfort requirements.

In the narrow thermal operating band, the costs of operating the HVAC units increased due to the stricter operating constraints of the commercial HVAC system and the ToU tariff. Therefore, there was no HVAC operation during peak times between 19:00 and 21.00. In the narrow thermal comfort band, HVAC power demands increased by 13.11% relative to the standard thermal case.

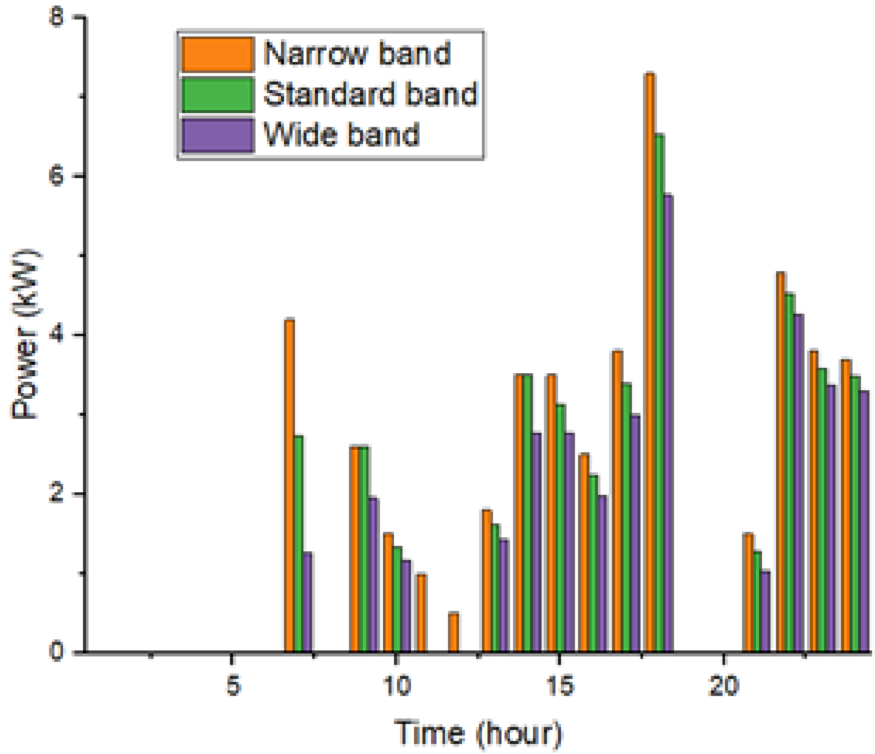

Figure 5.10: HVAC power use

Despite this increase in power demand, there were no significant technical impacts on the distribution grid. This shows that there is a trade-off between thermal comfort and operating costs but no considerable trade-off between thermal comfort and technical aspects of the distribution grid. Due to the DR program, there is a large amount of power used by the HVAC systems at 18:00 to pre-cool the buildings, which reduces the need for HVAC use during the peak periods between 20:00 and 21:00. Figure 5.10 shows the ability of HVAC units in commercial and service buildings to contribute to DR programs while maintaining thermal comfort requirements of the consumers.

5.6 Chapter Conclusions

This chapter has shown that VPPs which aggregate a diverse set of consumers can have positive technical benefits to the distribution grid. These impacts were evaluated by developing a stochastic mixed integer linear programming model for a VPP operating in a distribution system with a number of consumers. The TVPP optimized the generation of a number of prosumer DERs to maximize its profit when operating in a day-ahead energy market. Through this optimization, results have shown an increase in system flexibility, consumer participation, and RES generation while maintaining consumer thermal comfort requirements. Line losses were reduced by nearly 70% because of the model. The worst-performing node, Bus 79, saw a 66% reduction in voltage deviations. Results show that the TVPP reduces operating costs and increases the revenue from the energy sold in the system. Costs saw a maximum decrease of 56% relative to the base case. These outcomes are combined with increasing the profits of the TVPP.

The benefits of the various types of DERs have been quantified and can be allocated to the owners of the DERs. This analysis shows that EVs have the most significant marginal contribution to the profit of the TVPP, followed by solar PV systems and then wind turbines. Therefore, various types of DERs can complement each other. A diverse set of DERs operating within a TVPP provides the best outcome for the TVPP operator in terms of financial and technical outcomes. Different comfort preferences were investigated for the HVAC operation by changing the allowable limits of indoor temperature. These results showed a clear trade-off between consumer comfort and cost savings. However, there was no significant trade-off between thermal comfort and technical impacts on the system.

Overall, the results showed the numerous benefits that a TVPP can bring to a distribution grid, including increased financial performance, improved technical operations, improved energy efficiency, and enhanced environmental outcomes.

Therefore, this chapter has shown that through aggregation, prosumers can benefit distribution systems significantly. These aggregators can use transactive energy concepts and allocation mechanisms to incentivize prosumer participation and then reward these prosumers in a fair and equitable manner.

Chapter 6

Analyzing the Effects on Prosumer Privacy and Equity of Participation in Smart Grids

The previous chapters have focused on how to design frameworks to incentivize prosumer participation in smart grids. The chapters have shown that active participation in the energy system yields significant benefits, typically financial, to the consumer. These benefits accrue to the consumer through their participation in transactive energy systems. This participation typically involves sharing data using smart meters or other intelligent devices with internet connectivity. This data sharing may introduce concerns related to data privacy, and efforts should be made to address these concerns, as the right to data privacy is an essential pillar of prosumer participation in smart grids. In this chapter, an innovative Differential Privacy (DP) compliant algorithm is developed to ensure that the data from consumers' smart meters is protected. However, there may be trade-offs between protecting a prosumer's privacy and the accuracy of the data used to balance the distribution system. The effects of this novel algorithm on the distribution grid operation are thoroughly investigated, not only from a consumer's electricity bill point of view but also from a power systems point of view. This method allows for an empirical investigation into the losses, power quality issues, and extra costs that such a privacy-preserving mechanism may introduce to the system. In addition, several cost allocation mechanisms based on cooperative game theory are used to ensure that the extra costs are divided among the participants in a fair, efficient, and equitable manner.

Thus, this chapter addresses concerns related to protecting the data privacy of prosumers in a bottom-up manner that is scalable and robust. Increasing prosumer participation in smart grids may be promoted by addressing concerns relating to data privacy.

Chapter Highlights and Novel Contributions:

- Presents a Differential Privacy compliant algorithm to protect the data privacy of consumers' smart meters data, which takes into account the diverse privacy preferences of the consumers, as well as the technical and economic characteristics of the electrical system.
- Conducts a comprehensive analysis of the effects of this novel algorithm on the technical operations of a distribution grid using an AC OPF model.
- Investigates various allocation mechanisms for a fair allocation of the privacy costs to the consumers following the level of privacy chosen, according to various game-theoretic concepts.

Relevant Publication(s):

M. Gough, S.F. Santos, T. AlSkaif, M.S. Javadi, R. Castro and J.P.S. Catalão, "Preserving privacy of smart meter data in a smart grid environment," *in IEEE Transactions on Industrial Informatics*, vol. 18, no. 1, pp. 707-718, Jan. 2022
Q1 Journal, Impact Factor: 11.648
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Chapter 6 Nomenclature

Sets	
g $\in \Omega^G$	Generators
k $\in \Omega^K$	Branches
l $\in \Omega^L$	Linear loss constraints
n $\in \Omega^N$	Buses
$\lambda \in \Omega^\Lambda$	Positive variables forming the Special Order of Sets type 2
d $\in \Omega^D$	Data set
Variables	
b	Scale factor of Laplace distribution
$b_{i,j}$	Susceptance of the line
$p_{g,i}$	Active power output of node i
$q_{g,j}$	Reactive power output of node i
$p_{i,j}$	Active power transmitted in a line
$q_{i,j}$	Reactive power transmitted in a line
$p_{d,i}$	Active power demand of node i
$q_{d,i}$	Reactive power demand of node i
$p_{l,i}$	Active power loss of node i
$q_{l,i}$	Reactive power loss of node i
$R_{i,j}, X_{i,j}$	Resistance and reactance of line ij (Ω, Ω)
V_i	Voltage
θ_i	Voltage angle of node i
σ^2	Variance of Laplace distribution
ϕ	Shapley value
$\varphi_{i,t}$	Power loss at node i at time t
f	Function sensitivity
Parameters	
δ	Probability of a privacy breach occurring
M	Randomized algorithm
$\mathbb{N}^{\lvert\chi\rvert}$	Domain of algorithm
Pr	Probability of private information being released
$S_{i,j}^{max}$	Maximum power flow in line i, j
V_{nom}	Nominal voltage
$V_{nom}^{max}, V_{nom}^{min}$	Maximum and minimum voltage

6.1 Introduction

The preceding chapters of this thesis have shown that prosumer participation can bring substantial benefits to various actors within the energy system. These chapters have relied on financial incentives to drive prosumer participation. However, there are numerous other driving forces behind a prosumer deciding to participate in the energy system, including concerns about maintaining consumer data privacy. In the era of distributed energy resources in smart grids, data relating to the operation of these assets have become valuable and incredibly useful. The combination of traditional electrical networks with recent developments in modern Information and Communication Technologies (ICT), especially with the introduction of Internet of Things (IoT) connected devices, has the potential for better management and control of electrical distribution systems, which is especially true for the use of smart meters [217]. This increased communication with connected devices may improve the efficiency of operations, reduce energy losses, increase opportunities to engage in energy markets (such as demand response programs) and increase the reliability of the electric distribution system [218]. In the age of big data, these data are becoming extremely useful and valuable to system operators, and energy retailers [219].

In distribution systems, the primary source of this data is the smart meter, which can record energy use with fine granularity. The use of smart meters opens up new possibilities for the interaction between the energy retailer and the consumer. While this interaction can lead to a host of benefits for all parties, there are concerns about consumer data privacy. There exists a clear tradeoff between the utility of the data and the privacy afforded to the consumer [218].

There are methods to protect the privacy of smart meters data in a smart grid (SG) environment, but they have their drawbacks, such as limiting the usefulness of the data or proving computationally taxing [218]. Among these privacy-preserving methods, Differential Privacy (DP) is a state-of-the-art approach to provide a mathematically provable robust privacy guarantee [220, 221]. It is an elegant method that proves the possibility of comparing results from an analysis of two data sets that contain the same information, except that the data relating to a single individual is removed in the second data set [222]. DP provides the guarantee to an individual that their probability of suffering negative impacts is not significantly increased through their choice of whether or not to be included in a data set by sharing their data [223].

6.1.1 Motivation

The work in this chapter is motivated by two research questions. Firstly, what are the costs and benefits of using DP as a data privacy-preserving technique in an SG environment, both from the viewpoint of the energy retailer as well as the consumers? Secondly, how can these costs and benefits be fairly distributed among the various agents?

Differential Privacy has proven itself to be a cutting-edge data privacy-preserving technique, which has found success in several fields, and its potential is beginning to be recognized in power systems research. At its core, DP relies on adding carefully calibrated random noise to a data set to protect the privacy of the underlying information. While adding a noise signal to a consumer's data can protect the privacy of the information, it can have adverse effects when it comes to the operation and control of the distribution system by the operator. There are also negative impacts on the electricity retailer as they need to know accurate information related to the demand [224].

The additional noise introduced by the DP algorithm will mean that the selected dispatch and power flow solutions may not be at the lowest cost as would be determined by an Optimal Power Flow (OPF) model. Thus, consumers could pay an extra amount to compensate the energy retailer for the additional costs, but this will need to be done fairly and equitably.

Moreover, consumers are not a homogenous group with a group-wide desire for a single level of privacy. There will be a diverse mix of consumers within a neighborhood, and they may have different preferences when it comes to the level of privacy given to their smart meter data [225]. In practice, this means that groups of consumers will have varying willingness-to-pay values. This will allow the utility to charge more for higher levels of privacy, which will help cover the extra costs associated with higher privacy protection in high-privacy cases. Hence, this research aims to tackle the problem of how to adequately protect the data privacy of smart meter data from a heterogeneous group of consumers while at the same time ensuring that the relevant agents, such as the distribution system operator and energy retailer, can control and operate the SG in a near-optimal manner.

The system layout used in this study is shown in Figure 6.1, where the flow of information is shown between the smart home and the energy retailer. The figure shows that the raw data from the smart meter reading will be passed through the DP algorithm at the location of the smart meter. The data is only transmitted to the energy retailer once the calibrated noise has been added. As soon as the energy retailer has received the information, supply and demand scheduling can take place, and the information is passed through the OPF model to determine the optimal power flow given the noisy demand profiles. The value of additional noise from the consumer's demand profiles is sent periodically to the energy retailer, such as once a month, to accurately determine the amount of noise in the consumer's load profile, which allows for the accurate cost allocation of the additional noise added to the consumer's smart meter.

6.1.2 State-of-the-Art

Although DP originated in computer science research, its application has spread to several other areas, such as healthcare, demographics, and the energy sector. This section will provide an overview of the current state of the art of the application of DP to the energy sector, specifically the application to the SG area. The main advantages of DP are as follows: it is simple to implement, the original data is not lost, and the level of privacy can be tuned accordingly. The disadvantages of this method include the curse of dimensionality, reduction in data utility, and the difficulty in selecting the optimal trade-off between privacy and data utility [221].

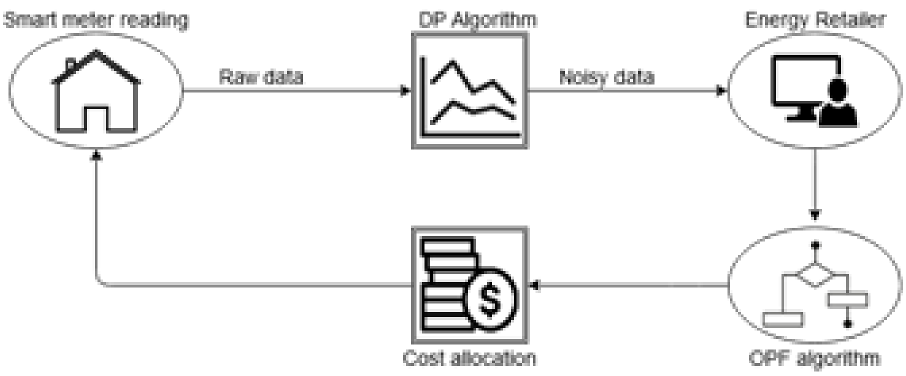

Figure 6.1: Flowchart of information through the system.

The application of DP to power systems has been studied previously in [220, 226, 227]. However, these studies have only focused on a single level of privacy for the consumers, which does not account for the diverse preferences that a group of consumers may have.

A study that accounted for heterogeneous customers was carried out by [224]. In this study, the authors developed a DP-compliant demand reporting framework that also considered economic dispatch control of various generators through simulations on a 5-bus test network. The authors did not take the technical constraints of the system into account, and they only used the Shapley value allocation mechanism to allocate the privacy costs, which had some drawbacks, especially regarding scalability [224, 228].

A real-time load monitoring algorithm that provides DP was developed in [229]. However, the authors introduced a 'peak factor' that placed an upper bound on the smart meter reading to improve the privacy guarantee further. It can be argued that this upper bound is not realistic and further undermines the energy retailer's ability to manage and maintain the grid.

A method to limit the degradation of data utility, which results from the application of DP, was presented in [230]. The authors gathered a large amount of real-world smart meter data and showed that privacy could be maintained through a low latency algorithm using an advanced metering infrastructure.

DP was combined with the privacy-preserving ability of battery energy systems in [227]. The battery aids privacy protection as, after installation, the smart meter only records the sum of the household appliances, generation, and battery storage. The charging and discharging rates can be adjusted, thus hiding the true energy use of the household. However, the authors did not investigate the effects of the individual components. Instead, they only studied the joint capability of the battery system and DP to protect the privacy of the underlying data.

Another paper that investigated the use of DP to protect data privacy related to a power system's operations was carried out by [219], where the authors proposed a DP algorithm for power line obfuscation to mask the line parameters of a given system. In assessing the impacts of DP on demand response programs, the authors of [231] evaluated the trade-off between data utility and privacy through a simple Laplace mechanism. Their extensive simulations provided robust results.

Table 6.1: Comparison with Relevant Literature

Paper	**Smart meter data used**	**Model used**	**Power system considered**	**Nodal voltages considered**	**Losses considered**	**Privacy costs considered**	**Allocation mechanism**
[219]	Yes	AC OPF	Yes	Yes	No	No	No
[220]	No	None	No	No	Yes	No	No
[226]	No	Online double auction	No	No	No	No	Yes
[227]	Yes	Multi-arm bandit	No	No	No	Yes	No
[229]	Yes	None	No	No	No	No	No
[224]	No	Economic Dispatch	Yes	No	No	Yes	No
This chapter	Yes	AC OPF	Yes	Yes	Yes	Yes	Yes

Table 6.1 summarizes the relevant literature concerning differential privacy in smart grid environments. The table shows that while some of the existing papers have studied aspects of the problem under consideration, no paper investigated the impacts of DP on smart grid operations from both system and consumers' points of view. The combination of the AC OPF model and allocation mechanisms used in this chapter are combined in a novel way to address the costs of preserving the privacy of consumers' smart meter data in a smart grid environment.

6.2 Preliminaries

This section presents the theoretical foundations and mathematical formulation of DP, OPF, and the chosen allocation mechanisms from cooperative game theory.

The individual components are related as follows: the differential privacy mechanism modifies the demand profile of the various buses within the OPF problem. Then, once the OPF is run with the modified load demand, the extra costs and benefits caused by the alteration are allocated fairly among the buses according to the level of privacy selected. This process is repeated for different levels of privacy.

6.2.1 Differential Privacy

The first part of our novel algorithm involves using DP to perturb the consumers' load profiles to guarantee the data's privacy. Within DP, the key characteristic of a differentially private system is that the result of a query from a data set should not be distinguishable from a query from a neighboring data set, which is the same except that a single individual's data has been removed from it. This can ensure that the individual should be indifferent to including their data in the database or not.

Formally, this is given by Equation 6.1, which will ensure that a randomized algorithm will behave similarly on similar input databases [222]. A randomized algorithm M with a domain $\mathbb{N}^{|\chi|}$ is (ε, δ) (the noise factor is denoted by ε) differentially private if for all $S \subset M$ and for all data sets $x, y \in N^{|\chi|}$ differing for only one individual (so that the L1 norm $\|x-y\|_1 \leq 1$) is given by:

$$Pr[M(x) \in S] \leq exp(\varepsilon)Pr[M(y) \in S] + \delta \tag{6.1}$$

This states that the probability of data exposure from data set x (which includes the relevant individual's data) must not be greater than the probability of data exposure with data set (y plus the probability of protection failure (δ). When δ is set to 0, a stricter form of differential privacy is reached (ε, 0).

The Laplacian mechanism was deemed effective for introducing the required noise to the results of a query (f) of individual data points [222]. The Laplace distribution (centered around 0) and with scale factor $b = \Delta F/\varepsilon$ has the probability distribution function shown in Equation 6.2:

$$Lap(x|b) = \frac{1}{2b} exp(-\frac{|x|}{b}) \tag{6.2}$$

The magnitude of the random noise required to achieve differential privacy is determined as a function of the largest change a single participant could have on the output of a certain query. This magnitude is termed the sensitivity of the function and is expressed as $f : D \rightarrow R^d$, the l_1 norm sensitivity of f is given by:

$$\Delta f = max_{D1,D2} \|f(D1) - f(D2)\|_1 \tag{6.3}$$

For all D_1, D_2 differing in at most one element [222], with D1 and D2 being neighboring data sets. Following on from the works in [232, 233], the sensitivity value of 1 was used for the queries used in this work. The variance of this distribution is given by $\sigma^2 = 2b^2$, and it is the symmetric version of the exponential function. This distribution can be adjusted to suit the privacy needs of each consumer, thus including the preferences of the consumer in the privacy-preserving model [229].

The DP mechanism using the Laplace distribution computes and adds the random noise drawn from the given Laplace distribution to query f. The scale of the noise will be calibrated due to the sensitivity of b. The Laplace mechanism preserves $(\varepsilon, 0)$ differential privacy and is defined by Equation 6.4:

$$M_L(x, f(\cdot), \varepsilon = f(x) + (Y_1, \ldots, Y_k) \quad (6.4)$$

Where all Y_i are independent and identically distributed random variables from the Laplace distribution defined by $Lap(\Delta f/\varepsilon)$ [222].

Equation 6.4 shows that the differentially private result of a query on the data set x is the sum of the result of the original query f plus the calibrated noise Y_i from the Laplace formulation. DP does not ensure that the data will remain private. It ensures that there exists an upper bound of the amount of privacy loss that an individual could suffer by participating in a given data set, and this upper bound is given by $exp(\varepsilon \approx (1+\varepsilon)$ when ε is small [222].

DP provides robust and provable data privacy but there are other forms of privacy that need to be protected. Chief among these is inference privacy, and there is a subtle difference between data and inference privacy. Data privacy refers to the protection of raw information from unauthorized access by an adversary, whereas inference privacy prevents the adversary from making certain unauthorized statistical inferences. Protecting data privacy is not sufficient to preserve inference privacy [234]. The level of inference privacy provided by DP has begun to receive research attention. For example, the authors in [235] show that the accuracy of inferences from DP-compliant mechanisms depends heavily on the value of ε chosen, although there is some level of inference privacy even at very low privacy levels. While protecting the inference privacy of consumers' smart meter data is undoubtedly important, the authors also believe that some level of inference from the energy retailer is crucial to operating the grid safely and reliably. There is a trade-off between data utility and privacy and through the use of this proposed algorithm, consumers and energy retailers will be able to arrive at a tradeoff that suits both parties; for example, the energy retailer may charge lower tariffs to consumers with lower privacy levels so that the energy retailers can extract more verifiable insights from the consumers' data.

The additional harm that an individual can suffer is bounded by ε in this study. Once the data has been passed through the DP algorithm, it is then passed to the OPF model.

6.2.2 Optimal power flow

An Optimal Power Flow (OPF) problem aims to determine the optimum power output levels for several generating units within a power system, which yields the least cost of operation given the physical system constraints. In this chapter, an AC OPF formulation will be used. The objective function of the AC OPF problem is to minimize the generation to meet the system demand. This is given by Equation 6.5:

$$min_{P_g,\theta} f_i(P_g, \theta) \quad (6.5)$$

Within the AC OPF problem, the active and reactive power balance equation should be met at all times. The active and reactive power in the buses of the network is given by Equations 6.6 and 6.7:

$$P_i^k = \sum_{g \in \Omega^i} P_g - (P_{d,i} + P_{i,l}) i \in N \tag{6.6}$$

$$Q_i^k = \sum_{g \in \Omega^i} Q_g - (Q_{d,i} + Q_{i,l}) i \in N \tag{6.7}$$

The power flow in any feeder must respect Kirchhoff's current law. This is considered by including linearized power flow equations. This linearization follows two assumptions. First, the voltage angle difference $\theta_{i,l}$ is normally very small in distribution networks. In trigonometric approximations, this results in $\sin \theta_{i,l} \approx 0$ and $\cos \theta_{i,l} \approx 1$. Second, the bus voltage magnitudes are expected to be close to the rated value V_{nom} in distribution systems. In this model, V_{nom} is set at 1 kV, and V_{min} and V_{max} are set at 0.9 and 1.1 per unit (pu), respectively. By using these assumptions, the complex nonlinear and nonconvex flow equations can be linearized by Equations 6.8 and 6.9.

$$|P_{i,j} - (V_{nom}(\Delta V_i - \Delta V_j) g_{i,j} - V_{nom}^2 b_{i,j} \theta_{i,j})| \leq MP_{i,j} \tag{6.8}$$

$$|Q_{i,j} - (-V_{nom}(\Delta V_i - \Delta V_j) g_{i,j} - V_{nom}^2 b_{i,j} \theta_{i,j})| \leq MQ_{i,j} \tag{6.9}$$

where $\Delta V^{min} \leq \Delta V_i \leq \Delta V^{max}$ and $\theta_{i,j}$ is defined to resemble the same line $\theta_{i,j} = \theta_i - \theta_j$.

The transfer capacity of each line should respect the maximum power flow limits, given in Equation 6.10:

$$P_{i,j}^2 + Q_{i,j}^2 \leq (S_{i,j}^{max})^2 \tag{6.10}$$

Active and reactive power losses in each feeder are given by Equation 6.11 and 6.12:

$$P_{i,j} = \frac{R_{i,j}(P_{i,j} + Q_{i,j})}{V_{nom}^2} \tag{6.11}$$

$$Q_{i,j} = \frac{X_{i,j}(P_{i,j} + Q_{i,j})}{V_{nom}^2} \tag{6.12}$$

Constraints relating to the power output of the generating units and the power flow in the lines are given in Equations 6.13 to 6.15.

$$-P_{i,j}^{max} \leq P_{i,j} \leq P_{i,j}^{max} \tag{6.13}$$

$$P_g^{min} \leq P_g \leq P_g^{max} \tag{6.14}$$

$$-\tan(cos^{-1}(pf_g) P_g \leq Q_{i,j} \leq \tan(cos^{-1}(pf_g) P_g \tag{6.15}$$

The reactive power at the substation bus should be subject to reactive power limits, under the assumption of constant power factor operation, as is shown in Equation 6.15. The quantification of the power losses within the lines is an important metric for assessing the impact of DP on the distribution system's operation. In this chapter, the power losses are linearized using the Special Order Sets of Type 2 for the losses through the branches. This approach has been validated through existing literature [236]. The losses are modelled through Equations 6.16 to 6.18:

$$|P_{l,i,j}| = \Delta P_{i,j}^{max} \sum_{l=0}^{L} l\lambda_{i,j}^{l} \tag{6.16}$$

$$\varphi_{i,j} = r_{i,j}(\Delta p_{i,j}^{max})^2 \sum_{l=0}^{L} l^2\lambda_{i,j}^{l} \tag{6.17}$$

$$\sum_{l=0}^{L} l\lambda_{i,j}^{l} = 1 \tag{6.18}$$

Through the use of the AC OPF model, the Locational Marginal Prices (LMPs) of each node at each time can be derived. These LMPs show the sum of the generator costs, the line cost costs as well as the costs imposed on the system by the demand of an extra unit load at a specific node at a specific time. Thus, the exact cost of the noise added to the node load can be quantified and thus allocated.

6.2.3 Game theory

Within the field of game theory, cooperative games (or coalitional games) are those games where coalitions of players may form due to external enforcement or the possibility of benefits from cooperation [228]. Within this chapter, the different consumers are assumed to have different preferences relating to their privacy and thus have different willingness to pay values to keep their data private. In this study, three characteristic functions from cooperative game theory are used to allocate the different costs to the different privacy classes of consumers. These include the Shapley value, the Vickrey-Clark-Groves mechanism, and the Nucleolus.

All three mechanisms have been studied in cost or benefit allocation research, including in electricity markets, but their application to differentially private local energy markets is limited. In addition to these three mechanisms, a naïve uniform pricing strategy is also applied to the problem of allocating the costs to the consumers as a benchmarking strategy. These cost allocation mechanisms will take the additional costs introduced into the system due to DP, allocating them fairly and equitably to the individual consumers following their stated privacy preferences.

6.2.3.1 Shapley Value

The first characteristic function used is the Shapley value. This technique has been widely used in electricity markets. Through the use of this mechanism, each agent is fairly allocated their marginal cost of participating in the game [237]. Shapely showed that there is a unique function that satisfies all four fairness axioms given in [238]. Simply put, the Shapley value is the average payoff that an agent (in this case, a smart meter owner) receives when entering the grand collation when the entrance order is completely random. This gives the Shapley value defined by $\phi = (\phi_i, I, \phi_n)$, where $I = 1, ..., n$ [229]:

$$\phi_i(v) = \sum_{S \in N, i \in S} \frac{(|S|-1)!(n-|S|)!}{n!}[v(S) - v(S-i)] \tag{6.19}$$

with v being the characteristic function satisfying the axioms and S is the set of all collations. The summation used in Equation 6.19 is the summation over all those coalitions S, which contain agent i. The marginal contribution to collation S by agent i is given by Equation 6.20:

$$v(S) - v(S-i) \tag{6.20}$$

In this study, each coalition will have a groupwide additional cost of privacy and the marginal contribution of each agent will be the costs that each agent introduces into the system.

6.2.3.2 Vickrey-Clark-Groves Mechanism

A widely used mechanism within cooperative games is the Vickrey-Clark-Groves (VCG) mechanism [239]. This mechanism has found prominence as an efficient way to ensure that the dominant strategy within a cooperative game is to behave truthfully, being successfully used in electricity markets in [205].

The outcome of this mechanism is to incentivize the agents to reveal their truthful private valuations (the set of agent's valuations are given by $v \cong v_1, ..., v_n$) of a certain alternative, which allows the first-best outcome to be implemented. In this study, the truthful information revealed by each consumer will be the smart meter reading after being passed through the DP masking algorithm.

This mechanism ensures that the smart meter owner i receives a monetary transfer equal to the marginal contribution of that agent to the coalition. In this case, the monetary transfer that each agent receives will be negative as it is a cost due to the additional noise added to the system. Formally, the transfer t_i that agent i receives is described by Equation 6.21:

$$t_i(\tilde{v}) = \sum_{i \neq j} \tilde{v}_j(x*(\tilde{v})) - \sum_{i \neq j} \tilde{v}_j(x*(\tilde{v}_{-i})) \tag{6.21}$$

The given VCG mechanism is efficient in the sense that the dominant strategy for the agents is to announce their true valuations regardless of the announcements of the other agents. There are some drawbacks when it comes to using the VCG mechanism, which are discussed in [228].

6.2.3.3 Nucleolus

An alternative way to examine the fairness axiom is given by the Nucleolus approach. This approach examines a fixed characteristic function and uses it to determine an imputation $x = (x_1, ..., x_n)$, which minimizes the worst inequity. This approach is in contrast with other techniques that apply the fairness axiom to a value function defined across a set of characteristic functions. In other words, the Nucleolus evaluates the degree to which each collation is dissatisfied with the proposed imputation x and then attempts to minimize the maximum dissatisfaction [240]. When applying the nucleolus approach, the excess is defined as the amount of inequity of an imputation x for collation S. The excess is represented by Equation 6.22:

$$e(\mathbf{x}, S) = v(S) - \sum_{j \in S} x_j \tag{6.22}$$

This equation measures the difference between the actual amount due to imputation x and the full potential of S. The procedure aims to solve for the maximum excess and then the procedure will need to be carried out again to solve for the next largest excess. The nucleolus has many advantageous properties, namely that the nucleolus is rational (both group and individually), satisfying the symmetry axiom as well as the dummy axiom. Computing the nucleolus is more difficult than computing the Shapley value. To solve for the nucleolus, it is necessary to find a vector $x = (x_1, ..., x_n)$ that minimizes the maximum excess $e(x, S)$ over all possible S subject to $\sum x_j = v(N)$. To minimize the maximum if a collection of linear functions is subject to a linear constraint, the problem can be converted to a linear programming problem and then solved. The process may have several iterations as the procedure solves for the maximum excess and then the procedure will need to be carried out again to solve for the next largest excess.

6.3 Method

In this section, the design of the DP algorithm is presented and the details of the case study are shown. To address the two main research questions of this thesis, the case study comprises two aspects. Firstly, the impact of DP on the technical operation of the system and its effects on an energy retailer is addressed. This is followed by an in-depth study of the cost impacts of the novel algorithm on consumers. Two different adversarial models are used in this model and the differences between the two models are discussed. The process followed in the case study is shown in Figure 6.2.

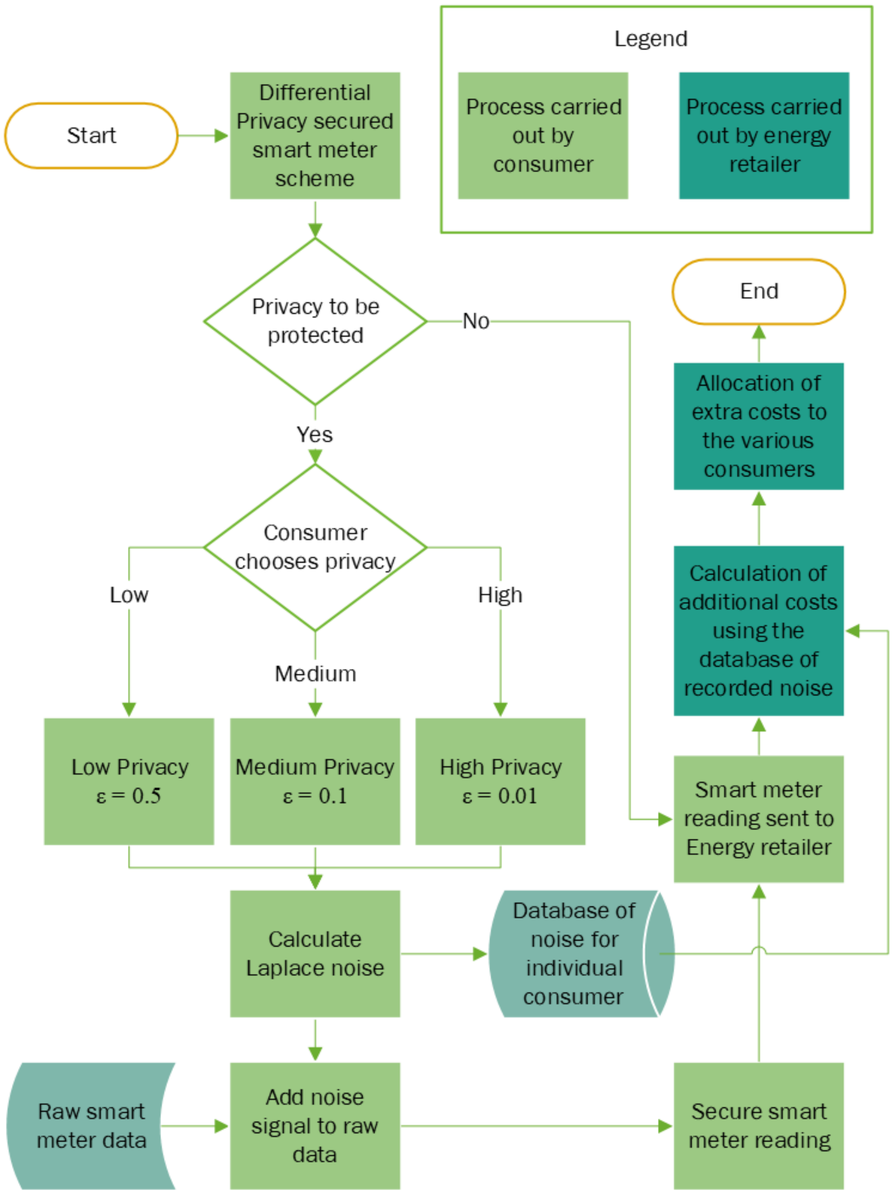

Figure 6.2: Flowchart of the developed algorithm.

Figure 6.2 shows how the choices and preferences of the consumer are taken into account. Also, the parties responsible for each of the actions are shown in the figure, which allows for easy task identification. To account for varying levels of consumer preferences for privacy, three levels of noise (and thus privacy) are used in the model (i.e., low, medium, and high). The corresponding privacy parameters are set at $\varepsilon = 0.5, 0.1, 0.01$, respectively. The lower the value of ε, the stronger the privacy guarantee [241]. Besides, a base assumption of no privacy guarantee is included. Thus, the options available to the consumer are as follows: i) no privacy, ii) low privacy ($\varepsilon = 0.5$), iii) medium privacy ($\varepsilon = 0.1$), and iv) high privacy ($\varepsilon = 0.01$). For this research, the considered consumers are divided equally into four categories to have a representative sample in each group.

Table 6.2: TOU Tariffs used in this study

Time	**00:00-15:00**	**15:00-18:00**	**18:00-24:00**
$/kWh	0.02982	0.03139	0.02982

It is shown in Figure 6.2. that the noise added to each consumer's meter reading is recorded in a database. Periodically, the sum of the additional noise can be sent to the energy retailer to assist in the accurate billing of the consumer. The model uses a modified sampling procedure of the random Laplacian noise to ensure that the impact on the aggregate group of smart meter readings is minimized while still protecting the data of the individual smart meter reading.

6.3.1 System viewpoint

To investigate the effects of the innovative DP algorithm from the energy retailer's point of view, an AC OPF model is run. Initially, the AC OPF model is run using a modified IEEE 33 bus test system [242]. Then, to make a fair comparison, the DP algorithm is applied to the load profiles of the various buses. The AC OPF is run for each privacy level. The AC OPF runs for 24 hours using a 15-minute interval.

6.3.2 Consumer viewpoint

To assess the effects of the innovative DP algorithm on the consumers in a distribution network, smart meter readings of electricity consumption for 32 consumers are used. Actual data was obtained from the Pecan Street Austin database [243], having a time resolution of 15 minutes. For each consumer, the data for 24 hours is used to simulate the additional privacy costs associated with the innovative DP algorithm. A three-stage time-of-use tariff, corresponding to actual electricity tariffs in Austin, Texas, in January 2018, is used to mimic real-world conditions. The ToU tariffs are shown in Table 6.2.

While DP provides strong data privacy guarantees, there are open research questions regarding its ability to provide inference privacy [244]. There will be some level of inference privacy offered by this proposed algorithm, certainly higher levels of inference privacy relative to a situation where the algorithm is not applied. Also, there are three characteristic theorems of DP which show that privacy loss by subsequent analysis or post-processing techniques is still bounded by the chosen privacy level.

The sequential composition theorem of DP, proven by [222], ensures that repeated iterations of a DP complaint algorithm (or even different DP complaint algorithms) over the same dataset do not lead to complete privacy loss. Instead, it ensures that each iteration of the algorithm reveals a portion of the private data, but the sum of privacy leakage across the iterations does not exceed the upper bound of the privacy leakage. This is proven by the following:

With a set of n algorithms, a mechanism $M(B)$ follows $n\varepsilon$-sequential composition if it obeys the following [222]:

$$Pr[M(B_1 = x_n] = Pr[M_1(B_1 = x_1] \cdot Pr[M_2(B_1 = x_2] \ldots Pr[M_n(B_1 = x_n]$$
$$\leq exp(n\varepsilon) \prod_{k=1}^{n} Pr[M_k(B_2; x_1, \ldots, x_{k-1} = x_k] = exp(n\varepsilon) Pr[M(B_2 = x_n] \quad (6.23)$$

with B_1 and B_2 representing two neighboring datasets.

A further strength of DP is the parallel composition theorem. This states that if a single dataset is partitioned into several disjoint subsets, DP can still provide bounds on the privacy leakage from the analysis of the disjoint datasets. This privacy leakage will then be bounded by the worst privacy leakage from the individual analyses and not on the sum of the privacy leakage [229].

This theorem, shown in Equation 6.24, may be applied in this case study to partition a dataset containing one day's or one week's worth of data into many separate smaller datasets, thus ensuring that the privacy leakage from each analysis is bounded by the worst individual privacy leak.

$$Pr[M(B_1 = x_n] = \prod_{k=1}^{n} Pr[M_k(B_2; x_1, \ldots, x_{k-1} = x_k]$$
$$\leq exp(\varepsilon) Pr[M_l(B_2; x_1, \ldots, x_L = x_L \prod_{k \neq L}^{n} Pr[M_L(B_1 =; x_1, \ldots, x_L = x_L] = exp(\varepsilon) Pr[M(B_2 = x_n] \quad (6.24)$$

DP is also immune to post-processing [220]. Inference may be thought of as a type of post-processing, and the inferences drawn by the energy retailer are challenging to verify. Post-processing is described by [220] as the fact that a data analyst, without additional knowledge of the private database, cannot use the output of a DP-compliant algorithm to increase the privacy loss of the individual. Formally it is described as:

Let $M : N^{|x|} \rightarrow R$ be a randomized algorithm that is (ε, δ) DP compliant. Let $f : R \rightarrow R'$ be an arbitrary random mapping. Then $f \cdot M : N^{|x|} \rightarrow R$ is also (ε, δ) DP compliant. For any two neighboring datasets, x, y with $\|x - y\| \leq 1$ set an event $S \subseteq R'$. Let $T = r \in R : f(r) \in S$. Then we obtain:

$$Pr[f(M(x)) \in S] = Pr[f(M(x)) \in T] \leq exp(\varepsilon) Pr[M(y) \in S] + \delta$$
$$= exp(\varepsilon) Pr[f(M(y)) \in T] + \delta \quad (6.25)$$

These characteristics of DP assist in reducing potential privacy loss through inference. The energy retailer cannot increase an individual's privacy loss by analyzing the DP algorithm's outputs. While it is not the only framework that quantifies a notion of risk for a single analysis, it is currently the only framework with quantifiable guarantees on the risk resulting from a composition of several analyses [222].

Therefore, these three theorems provide a methodology to minimize the risk of privacy loss caused by both types of adversaries in this case study.

6.4 Results

6.4.1 Impacts on system operation

Four privacy levels are analyzed to assess the impacts of different levels of privacy on the system operations: no privacy, low, medium, and high. The model is solved for each level of privacy separately. The results of the variations in cost according to the various runs and the percent variation in relation to the baseline are shown in Table 6.3. The Laplacian noise added to the load profiles makes the load profiles fluctuate significantly. However, this fluctuation is reduced significantly when considering a composite of buses or consumers. The addition of more load profiles has a smoothing effect while still protecting the privacy of the underlying data. If the fluctuation is still above acceptable limits, a smoothing function may be applied to the load profiles without affecting the privacy guarantee. This is due to the fact that DP is immune to post-processing [222].

In other studies [220], smoothing functions were applied to the load curves. For example, moving average, LOESS (locally estimated scatterplot smoothing), and LOWESS (locally weighted scatterplot smoothing) functions can be used. In this chapter, smoothing algorithms are not applied as the objective was to determine the full effects of DP on SG applications.

The results presented in this chapter represent the most extreme impacts of DP on the operations, and any smoothing functions will ease the effects. As expected, the higher level of privacy introduced a higher level of noise, which can be seen in Table 6.3. This means that, for specific periods, higher levels of noise led to higher errors that increased the complexity and uncertainty associated with the system operation. The following paragraphs will discuss the impacts on cost, system losses, nodal voltages, and LMPs.

The impacts on the system costs and losses from the OPF simulation are also shown in Table 6.3. In the baseline case without the novel algorithm applied, the daily system energy losses are calculated as 322.5 kWh, whereas in the highest privacy case, the energy losses are calculated to be 356.03 kWh, representing an increase of 9.7% across the entire 24 hours.

Table 6.3: Results of the AC OPF simulations

	Baseline	**Low**	**Medium**	**High**
Cost (\$/day)	157.58	158.65	169.95	165.81
Cost increase (%)	NA	0.27	2.95	5.61
Average (\$/hour)	6.56	6.61	7.08	6.52
Standard deviation	1.76	2.85	3.5	4.94
Energy Losses (kWh)	322.5	327.5	355.25	356
Loss increase (%)	NA	1.53	9.5	9.7
Standard deviation	0.0055	0.0073	0.00871	0.013

Following the analysis of the imposed costs, the results of the nodal voltages in the 33-bus test system show that the voltage profile is maintained between the limits of 0.9 pu and 1.1 pu with the nominal voltage being 1 kV during the period under study, even for the case of high privacy. These profiles have become slightly worse than the base case voltage profile by an average of 0.75% for the worst case but do not induce significant voltage issues within the distribution system. This is illustrated in Figure 6.3, which shows the fluctuations of the nodal voltage relative to the nominal voltage over the peak load period of 17:00 to 21:00. The noisy line roughly follows the baseline and never exceeds the voltage limits.

Finally, the LMPs of each node at each time are investigated. These LMPs show the sum of the generator costs, the line cost costs as well as the costs imposed on the system by the demand of an extra unit load at a specific node at a specific time. The noise added to the load profiles of each of the nodes shows the costs associated with balancing supply and demand with the noisy load profiles. The results of the LMP analysis are shown in Table 6.4. This table shows that the variability of the marginal price has increased with the application of the DP mechanism, while the average LMP is roughly unchanged. Both minimum and maximum values become more extreme with increasing noise, which may impact the distribution grid's operation. These are important aspects to consider and this extra variability should be allocated to the consumers fairly and equitably so as not to disadvantage the other agents in the system.

Taken together, these results show that the innovative DP algorithm proposed in this chapter does not introduce significant impacts to the system. The costs that it does impose can be quantified and allocated to ensure that the effect of this algorithm on the system operation is minimized. Also, the impact on computational time is investigated. In its simplest form, our novel algorithm simply adds a calibrated amount of noise to the load profile of the node for that specific period. These impacts on the computational time are shown in Table 6.5.

The computation time did not vary significantly across the different levels of privacy and this shows that the novel algorithm can indeed be used without any concerns arising about computational time.

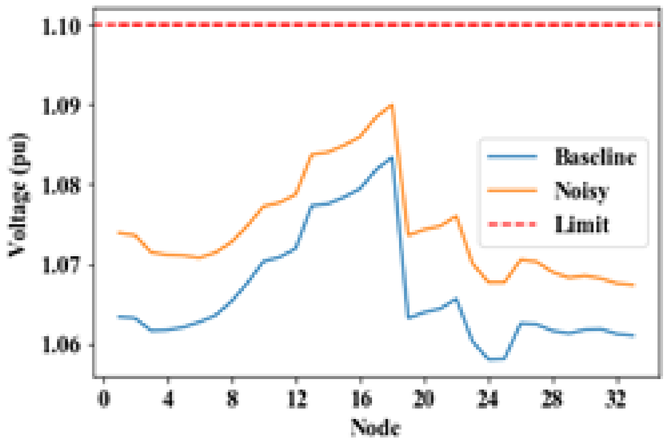

Figure 6.3: Fluctuations in the nodal voltage due to the worst-case privacy relative to the baseline voltages.

The results of this section show that an energy retailer can guarantee the protection of consumers' smart meter data with only a slight system impact. The smart meters benefits are mainly due to the granular reporting of energy consumption data and the consumers need to consent and trust that their data will be managed responsibly. Hence, the results show that our algorithm protects the privacy of the consumer without losing significant value for the aggregator of the smart meter data.

6.4.2 Impacts on Consumers

6.4.2.1 Privacy costs for the consumers

The results of the consumer impact analyses show that the innovative DP algorithm provides suitable levels of privacy with a small increase in their electricity bill. The impact of the noise applied to the consumer smart meter readings is shown in Figure 6.4.

In Figure 6.4, the noisy data (with medium privacy applied) is compared to the raw data from the smart meter of a single consumer over 24 hours. The consumer has a PV system, which explains the negative consumption readings during midday. The figure shows the masking effects of the calibrated noise while still being tightly bound around the original profile of the data. During the 24 hours, the privacy of the consumer is protected through the introduction of 2.93% of noise relative to the electricity consumed during the day.

Table 6.4: Impacts on the LMPs due to the DP algorithm

	Baseline	**Low**	**Medium**	**High**
Minimum	3.13	2.56	2.54	1.35
Average	3.92	3.85	3.9	3.97
Maximum	5.07	5.09	5.12	5.22
Standard deviation	0.81	0.97	1.00	1.35

Table 6.5: Impacts on the computational time due to the DP algorithm

	Baseline	**Low**	**Medium**	**High**
Time (s)	2.99	3.00	3.06	3.13
Percentage increase	NA	0.47	2.58	4.86

There is a correlation of 89.5% between the data sets, which shows that the masked data can still act as an efficient proxy for the raw data. The electricity bills for the different classes of consumers are provided in Table 6.6, showing the effect of a given privacy level on the consumers' bills. This table shows that our novel algorithm can protect the level of privacy of the consumer while not affecting their electricity bill significantly. The lower bills seen in the 'Low Privacy' section are lower than those of the 'No Privacy' column, but this can be expected as the noise added to the smart meter reading can be positive or negative and, in this simulation, the impact of the random noise happened to lower the electricity bill.

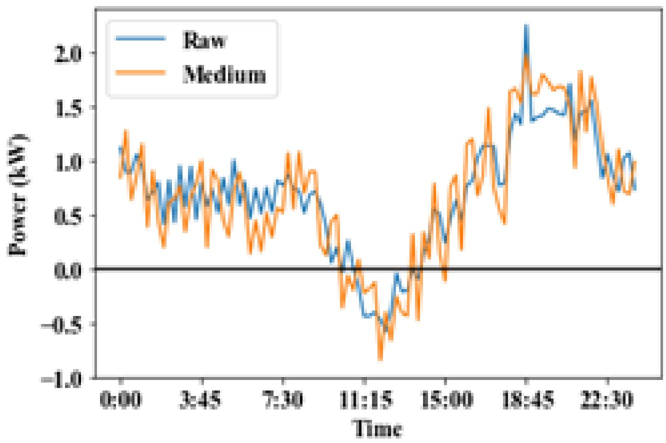

Figure 6.4: Raw data vs medium privacy for a given consumer.

This can be overcome through the periodic sending of the total amount of noise added to a smart meter reading and the energy retailer can then make the necessary adjustments to the electricity bill.

Table 6.6: Impacts of differential privacy on consumer bills

	No Privacy	**Low**	**Medium**	**High**
Monthly bill	121.97	121.33	122.54	122.94
Percentage variation	NA	0.52	0.46	0.79

Moreover, in terms of the scalability of the algorithm, Figure 6.5 demonstrates the magnitude of error per smart meter for the different numbers of consumers participating in the data set. The analysis is performed for the three categories of privacy (low, medium, and high) and the error relative to no privacy. Figure 6.5 shows that increasing the number of consumers enrolled in a DP-compliant smart meter program can reduce the average meter reading error, which can assist the energy retailer in meeting energy demand, all without affecting the level of privacy offered to the individual consumers.

Figure 6.5 shows that there is a strong trend for the relative error to decrease rapidly as new consumers are added to an existing group of consumers. However, the gradient of the reduction in the error decreases out as the numbers of participating consumers increase This trend is consistent with other literature such as [220]. In other words, the errors in each of the privacy classes follow a trend of a rapid decrease in the average error with a small number of consumers, becoming tightly bound in larger numbers. For instance, the error of the medium privacy category approaches approximately 1.36% by using the data from 200 consumers.

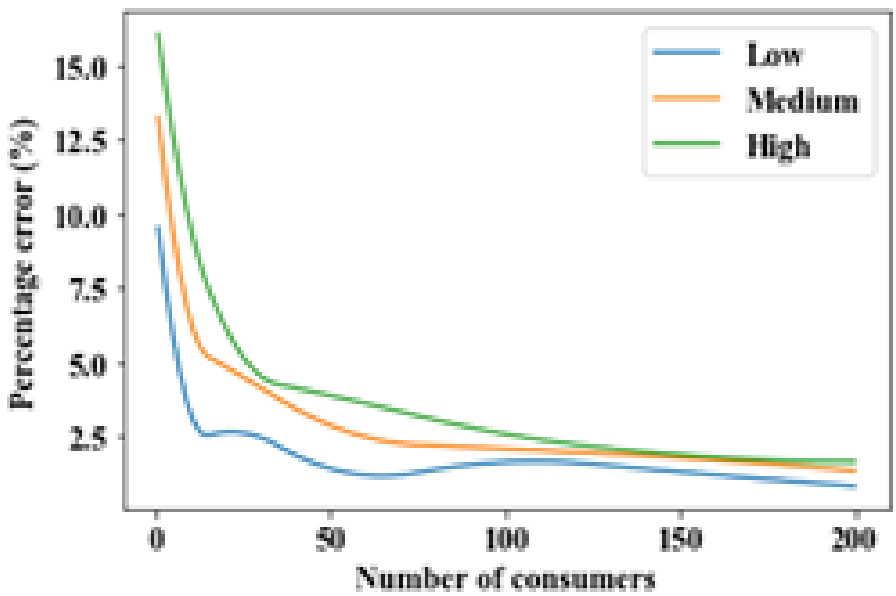

Figure 6.5: Percentage error of algorithm vs the number of consumers.

Table 6.7: Ratio of costs allocated to different consumers

	Low	**Medium**	**High**
Uniform pricing	0.33	0.33	0.33
Shapley	0.18	0.25	0.57
VCG	0.26	0.34	0.40
Nucleolus	0.14	0.27	0.59

6.4.2.2 Allocation mechanisms

In this section, the allocation of the extra costs associated with the privacy mechanism is performed. These costs should be allocated in a fair, efficient, and equitable manner. Thus, the four different existing allocation mechanisms are investigated and compared. In addition to the three cooperative game theory mechanisms previously introduced, a benchmarking strategy is also included, which corresponds to a uniform cost allocation approach where all classes of consumers equally share the extra cost burdens. The proportional distribution of the additional privacy costs amongst the different categories of consumers is shown in Table 6.7.

In this chapter, the uniform pricing approach is used as a naïve baseline of cost allocation. The additional costs are evenly distributed amongst the consumers and are shown in Table 6.7. This is a simplification of the cost allocation but serves as a benchmark for the other allocation mechanisms.

The Shapley value allocates the total surplus (in this case, the surplus is negative as the contribution of our algorithm imposes extra costs on the consumers) to the players in a unique manner, which satisfies various desirable axioms. In this study, the Shapley value allocates the extra privacy costs to the various groups of consumers as shown in Table 6.7. A lower share of the costs is allocated to the low and medium privacy groups, while the high privacy group is burdened with a higher share of the costs when compared to the naïve uniform pricing. The allocation using the Shapley value is computationally intensive as the payment rule relies on computing the Shapley values for all outcomes of the cooperative game considering all possible coalitions. The findings in this chapter are also consistent with relevant literature [228].

The results of the study according to this payment rule are shown in Table 6.7. There is a much tighter grouping of the cost allocations between the various groups of consumers when compared to the other allocation mechanisms. This shows that the marginal contribution of each group is not widely different from the others. This may be due to the impact of both positive and negative noise values added to the consumer data as this might help reduce the variability of the noisy data.

The Nucleolus payment rule relies on minimizing the maximum excess of a given imputation. In other words, this payment rule is based on reducing the maximum inequality, which a given coalition falls short of the optimum allocation. The results according to the Nucleolus payment rule are shown in Table 6.7. There is a significant variation between the high and low-privacy consumer groups, much higher than any other payment rule. This payment rule relies on the principle of whoever complains the loudest gets served first. This means that it minimizes the maximum discomfort of an agent first. This may be a useful payment mechanism in real-world privacy-preserving programs as it reduces the maximum dissatisfaction of a consumer. These dissatisfied consumers would be more likely to leave the program first.

The uniform pricing approach, nucleolus, and Shapley values are efficient allocations as they are budget balanced. As previously discussed, the VCG method is not budget balanced and requires ex-post redistribution. As discussed previously, the Nucleolus mechanism may be the best approach as it seeks to minimize the maximum dissatisfaction, thus helping to reduce the turnover of consumers within such a privacy program as the most dissatisfied consumers are more likely to leave the program.

The results of the three game-theoretic methods show that there are a variety of ways to allocate the costs to the consumers. Each of the strategies has its benefits and drawbacks when discussing the final choice of the allocation mechanism. Also, there may be other financial, social or environmental factors that impact how the costs of privacy are allocated to the consumers. Thus, the choice should be made on a case-by-case basis taking a holistic view of the community and the energy market, and relevant regulations.

6.5 Conclusions

In this chapter, an innovative DP-compliant algorithm was developed to protect the privacy of consumer smart meter data. The impacts of our novel algorithm on the operations of a distribution grid were thoroughly investigated, both from a consumer cost viewpoint and an energy retailer's viewpoint, which was an additional contribution. The losses and additional costs that the algorithm placed on the grid were investigated through the use of an AC OPF model. The use of the innovative DP algorithm increased the system costs by a maximum of 5.61%. The additional privacy costs for the different classes of consumers were allocated using a variety of mechanisms based on cooperative game theory. Out of the four mechanisms, the VCG and the Nucleolus mechanisms were proved to be the most suitable payment mechanisms. The novel algorithm presented in this chapter addressed the concerns related to accessing consumer smart meter data by guaranteeing the privacy of the smart meter data without losing significant value derived from the data set, which is crucial. Increasing the number of consumers enrolled in the program led to a reduction in the relative losses, which showed that our novel algorithm is also scalable and stable. This work showed that a computationally efficient privacy-preserving algorithm can be applied to an aggregation of smart meter data without significant impacts to either the utility or the consumers.

This chapter has developed a mechanism to allow prosumers to engage in transactive energy systems without exposing their private smart meter data to other unauthorized parties. The framework allows the consumers to choose their desired level of privacy and this additional control over their data can alleviate some of the concerns that consumers have about participating in transactive energy systems.

Chapter 7

Dynamic Planning of Smart Grids for Increased Prosumer Participation

The preceding chapters have developed several frameworks for increased prosumer participation in smart grid systems from both a top-down (Chapter 3) and bottom-up (Chapter 4) perspective. A common theme throughout these frameworks is their focus on the short-term or operational phase of transactive energy systems. This chapter completes the thesis as it offers a long-term framework for planning infrastructure investments in smart grids considering increased prosumer participation through increased deployment of Distributed Energy Resources (DERs) as non-wires alternatives. These resources can be deployed in a manner that is either complementary to or in competition with the traditional network as the DERs can provide numerous important services to grid operators and utilities. The key to harnessing the full potential of these DERs to work with traditional network investments (such as line upgrades, and installation of network switches) is to accurately quantify the value that these different resources can offer to the system and thus estimate the trade-offs which occur when the investment decision is taken to use a certain technology.

In this chapter, this is done using an interactive planning model based on the Dynamic Monitoring and Decision Systems framework which helps to align physical, information, and economic incentives across many stakeholders within the electric energy system. Results show that the planning framework can accurately value the locational impact of different technologies in reducing congestion and increasing the number of customers served.

By utilizing this dynamic planning framework, the impacts of DERs can be accurately calculated. This can help incentivize the uptake of DERs in the areas of the distribution system which need them the most and fairly reward those prosumers who choose to participate using their DERs.

Chapter Highlights and Novel Contributions:

- Develops a novel decision-making framework for distribution systems considering long-term capacity upgrades using a dynamic peak load pricing approach.
- The framework introduces competition into distribution systems for both energy delivery and infrastructure upgrades, allowing traditional network investments to compete with prosumer-owned distributed energy resources while guaranteeing the optimal operation of the system.
- The preferences of the consumers are internalized and included in cost functions used to optimize the planning framework. This gives the prosumers the ability to decide whether to engage in the energy system.
- This chapter applies Peak-load Pricing to distribution system planning to accurately value DERs. This ensures that the DERs and other potential distribution system upgrades are priced according to their long-run marginal costs.
- In addition the distributed decision-making framework used within the DyMonDS framework reduces computational complexity and allows each individual agent within the system to make their own decisions regarding capacity investment or participation in possible energy markets.

Relevant Publication(s):

M. Ilic, **M. Gough**, "Interactive Planning and Operations using Peak Load Pricing in Distribution Systems," in *CIGRE Grid of the Future Symposium 2022*
Published: https://arxiv.org/abs/2212.02145

Chapter 7 Nomenclature

Sets

g $\in \Omega^G$	Generators
$t_{inv} \in \Omega^{T_{inv}}$	Investment Time
$t_{RT} \in \Omega^{T_{RT}}$	Operational time
l $\in \Omega^L$	Lines
n $\in \Omega^N$	Nodes
z $\in \Omega^Z$	Loads

Variables

$\lambda(\hat{g})$	Price of electricity from DER g
$\lambda(\hat{s})$	Fee paid to Aggregator/Utility for infrastructure upgrade
$\lambda_z(t)$	Price of electricity for load z at time t
$C_{g,t}$	Unit cost of generation from DER g at time t
K_t	Size of network upgrade for Aggregator/DSO determined by DSO
$p_{g,t}$	Power generated by DER g at time t
p_{dn}	Power demanded at time t
$U_z(L_z(t))$	Utility derived from load z at time t
T_{tl}	Power transferred over line l at time t

Parameters

k_t	Unit cost of capacity upgrade at time t
K_l	Transfer capacity of line l
L_z^{max}	Maximum load for consumer z
$P_{g,t}^{min}, P_{g,t}^{max}$	Min and Max power output of asset g at time t

7.1 Introduction

7.1.1 Background and Motivation

Distributed energy resources (DERs) have the potential to play a key role in future energy systems. The proliferation of these devices, which can be owned and operated by individual consumers, has primarily been driven by rapidly declining costs. While each DER can have a small impact on the broader grid, the ability to coordinate fleets of DERs means that these fleets can have significant potential to meet various objectives of system operators or consumers and play an important role in future energy systems [245]. The increasing digitization of the energy system allows increasing levels of communication between and control of various devices to serve different needs. This increased communications capability is coupled with increasing embedded computational capacity within the DERs to further the ability to coordinate and control large numbers of prosumer-owned DERs [246]. This increased coordination and control can be achieved using Transactive Energy principles as discussed in Chapter 2.

The impacts of DERs depend on the type, the number of assets controlled, and the location of the DER in relation to the broader distribution system. Additionally, these impacts can vary temporally. These fluctuations in potential impact (and thus changes in value) mean that incorporating DERs into operational and planning models for DS is highly challenging. The owners and operators may also have different objectives and preferences for installing the DERs. This variety imposes additional uncertainty and is difficult to capture using existing centralized planning methodologies. DERs can provide numerous benefits to the power system, including delivering both energy and capacity generation value, ancillary services such as reserves, frequency regulation, and ramping support, and finally, can also provide benefits related to the delivery of electricity, such as acting as Non-Wires Alternatives (NWAs) and voltage support [247].

There is a growing host of research showing how DERs can be used as alternatives to traditional distribution system investments [195]. In these situations, DERs are referred to as NWAs. DERs can provide increased planning flexibility as they typically have shorter installation times, smaller investments, and can be modular. This helps reduce the risk of implementing distribution network upgrades to meet expected load growth in the future and then that load growth not materializing. Furthermore, by developing planning strategies that explicitly consider prosumer-owned DERs, these assets can be better integrated into future energy systems.

Agents who can coordinate and control large numbers of DERs to participate in energy markets as a single actor are poised to play a significant role in future distribution systems [248]. In a future distribution system that has many DERs actively participating, the means to aggregate a diverse set of DERs to operate as a single entity, for example a Virtual Power Pool or a Technical Virtual Power Pool, as has been shown in Chapter 5 in energy markets will be essential. Having several aggregators bidding into the energy markets can increase competition as long as they are large enough to bid efficiently but not large enough to exercise market power [249]. The falling costs of DERs are reducing the barrier to entry for DER ownership, but entry into energy markets is still prohibitively high for individual DERs owners. This is a barrier to increased prosumer participation, as was identified in Chapter 2. Aggregators can help reduce this barrier to entry by grouping many small DERs, allowing them to bid into energy markets as a single entity.

In future distribution systems, competition for energy services may exist as consumers with different preferences will be able to choose the type and level of their energy service contracts. In such a world, ensuring a technology-neutral manner of valuing assets capable of providing these energy services would be crucial to the long-term efficiency and sustainability of energy services at the distribution level. There has been an increase in the research around the introduction of competition into distribution systems, not in terms of installing duplicate sets of lines and traditional infrastructure investments, but in terms of delivering energy services to consumers. This can be done by using a diverse set of DERs to provide energy services to consumers as well as system services to system operators [250]. This introduces interesting questions about open access, ownership rights, and how to ensure fair competition within distribution systems [249]. Within a newly competitive distribution system, DER aggregators will have a major role in managing and bundling together diverse assets to provide a robust portfolio capable of providing reliable energy services to maximize social welfare [251].

7.1.2 Context

Existing pricing strategies have relied on marginal pricing from classical economic theory, which, under certain assumptions, leads to efficient outcomes measured through social welfare maximization. This chapter proposes that this approach fails to accurately value DERs, assets with high investment costs and low operation and maintenance costs, which can provide alternative benefits compared to traditional investments. In the case of DERs (typically renewable energy generators or battery energy storage systems), the marginal costs are low and are below the average cost. When applied in these circumstances, marginal cost pricing results in deficits that must be recovered. These are typically recovered through various taxes or uplift payments [252]. Furthermore, increasing DER deployment is expected to improve both the short-term and long-term price elasticity of demand [249]. This further supports the introduction of competition for energy services in the distribution system.

This chapter provides a novel decision-making framework for distribution systems considering both short-term operations and long-term capacity upgrades using a dynamic peak load pricing approach. This initial model introduces competition into distribution systems for both energy delivery and infrastructure upgrades. Consumers' preferences are internalized and included in the cost functions that they provide to the Distribution System Operator (DSO). These contributions allow the model to measure the trade-offs between different classes of network upgrades. This chapter applies Peak Load Pricing to distribution system planning to value DERs and DR accurately. This ensures that the DERs and other potential distribution system upgrades are priced according to their long-run marginal costs (LRMC). The chapter argues that due to the relatively low capital costs of DERs (which are expected to decrease further) combined with their modular nature, the problem of the lumpiness of investment is greatly minimized. In addition, the distributed decision-making framework used within the Dynamic Monitoring and Decision Systems (DyMonDS) framework reduces computational complexity and allows each agent within the system to make their own decisions regarding capacity investment or participation in possible energy markets.

Peak-load Pricing (PLP) was developed in the mid-twentieth century by Boiteux (1949) and Steiner (1957) [253]. The model was extensively developed by Michael Crew and Paul Kleindofer, with important contributions by Hung-po Chao [254]. PLP is a pricing strategy for a time-dependent quantity of a non-storable commodity and is based on the theory of long-run marginal costs (LRMC) [255]. As the demand varies with time, there is a need to invest in sufficient capacity to meet the peak demand, but this capacity is not typically used at non-peak times. Existing work has extended PLP to consider multiple technologies available to meet the demand as well as both supply and demand uncertainty [253]. PLP has been applied to electricity transmission planning by [255] and centralized distribution expansion planning [256]. Importantly in PLP, the budget balance constraint is considered directly, and so PLP deals with the tradeoff between capacity utilization and consumer welfare. In addition, distributed generation, which is based on renewable energy technologies such as solar PV and wind, has most of the costs being capital costs, with only a small fraction of the costs being related to operations or maintenance. PLP explicitly considers the capital costs, therefore removing any distortions or requirements for uplift payments that may be required in other pricing strategies [252].

The DyMonDS framework has been developed over many years for various applications in the electric power system [246]. This framework has been proven as a computationally efficient and robust distributed decision-making framework for the electric power sector.

Fundamentally, DyMonDS is a multi-layered cyber-physical representation of an electric power system. In the lower layers, agents are responsible for their decision-making regarding their objectives, bidding strategies, capacity expansion plans, and risk preferences. These decisions are internalized by the agents and the output of their decision-making process is a set of bid curves that are communicated to the upper layers, which in turn optimize the system in a distributed manner. A key aspect of DyMonDS is that the individual agents compute internal bid curves for production and elastic demand. This allows consumers or generators to internalize constraints and preferences into their cost functions. This strategy can help to differentiate groups of consumers or producers. DyMonDS is formulated in a model predictive control manner that optimizes a certain period and then moves forward to optimize the next period. The outcome of the DyMonDS process is a set of physically implementable bids, and the system aligns both technical and economic signals [246].

The model proposed in this paper is based upon research that had its origins in [255]. In that paper, the basic theoretical foundation for PLP applied to upgrades in transmission network infrastructure was developed. The model was used to evaluate the trade-offs between network expansion and investments in generation in an open-access regulatory setting. The significant contribution of this work was to evaluate the marginal cost of transmission investment relative to its economic value in providing affordable electricity to the consumer.

Building upon [255], the work carried out in [257] sought to extend the problem to include both short-term operation and long-term investment planning in transmission networks. The authors determined the optimal investment level of Flexible Alternating Current Transmission System (FACTS) devices to ensure sufficient operations of the transmission system using a dynamic real options-based model considering long-term uncertainty.

The effects of demand-side resources on the optimal investments in transmission planning were evaluated by [258]. An essential contribution of this work was the inclusion of new technologies, load growth, reliability constraints, fuel prices, and environmental constraints. The model sought to address the inefficiencies caused by having separate energy and capacity markets, as existing models did not consider the cumulative inefficiencies or capital costs of the two markets.

Finally, the proposed model uses PLP to extend the work carried out in [259], which introduced the transactive energy concept and offered different reliability levels depending on consumers' willingness to pay. The authors highlighted the need for incremental network infrastructure investment and the necessary investment signals for both short-term and long-term risk management, which have been included in this current chapter by considering modular DER investments and investment signals using PLP. This chapter introduces an application of Peak Load Pricing to the DyMonDS framework to allow for competition among agents for distribution network upgrades (both traditional upgrades as well as emerging non-wires alternatives).

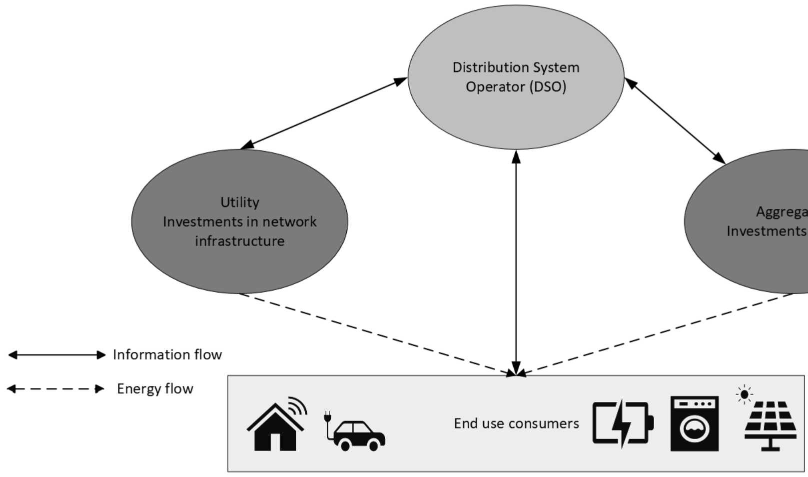

Figure 7.1: Structure of model

7.2 Dynamic Peak Load Pricing

This chapter proposes a dynamic application of peak load pricing to distribution system operations and expansion planning. This is done to allow a diverse set of assets to bid into competitive markets to provide energy to consumers fairly and efficiently based on their long-run marginal cost. As such, the model is developed as a hierarchical decision-making framework with the different agents located at different levels within the model, and it is shown in Figure 7.1. The framework aims to quantify the trade-offs between traditional investments and DERs according to PLP to account for the LRMC of the assets.

At the heart of the proposed model is the DSO. The DSO will act as a central clearing agent for both demand and supply bids submitted by consumer-owned DERs. The DSO will send out forecasts for both short- and long-term demand. The aggregators and utility submit both short-term and long-term bids to the DSO. The short-term bids are to meet the energy demand of the consumers, while the long-term bids are for investment in network upgrades. The DSO has no financial incentives in this model but purely acts to settle the price and quantity of energy traded. The DSO also does not own any infrastructure. The DSO liaises with several aggregators and a single utility. These agents coordinate with the DSO at the upper level as well as consumers at the lower level. The agents in the middle layer are responsible for aggregating the demand of several small consumers from the lower level and then submitting bid curves to the DSO to meet the demand of the consumers. Aggregators may own DERs within the system, and in this case, they also submit generation curves to the DSO to be eligible for dispatch. The aggregators may make investments in DERs depending on the long-term price signals provided by the DSO. The existing utility is also responsible for submitting bid curves to the DSO to meet the demand of its consumers. The utility may make investments in network infrastructure, such as reinforcing lines or investing in switching devices. The utility may not invest in DERs in this proposed model.

Both aggregators and the utility will develop internal bid curves. In the case of aggregators with DERs, the offer curves will also be developed internally, which will include internal considerations of any constraints (generation, ramping) of the DERs. Following this framework, the only information that is exchanged between the DSO and the suppliers (both utility and aggregators) is the demand forecasts, and the information sent from the suppliers to the DSO are sets of supply curves. Once the DSO has received both the short-term and long-term bid curves, it performs a dispatch using the simple convex bids provided by the DERs [246]. This reduces the amount of information that needs to be sent at each time step, thus increasing the computational efficiency of the model as well as increasing the privacy of consumers' data.

The DERs will receive the forecasts of the load and the price from the DSO. The DERs will then run their optimization to develop a supply curve according to their internal characteristics and decide whether to bid into the market for this period. The DERs may perturb their bid amount by a fixed amount to generate supply curves which are then sent to the DSO for clearing. Having the DERs individually generate these supply curves reduces the computational complexity of the model while also acting as a risk management measure. The DSO does not need to know detailed information from the suppliers, such as ramp rates or minimum up/down times.

There are three components of the revenue for the Aggregators and Utilities. The first component is the revenues from selling electricity to consumers. The second component is the utility of satisfying the elastic load of the consumers presented in a financial sense. The final component is related to the revenues for undertaking infrastructure upgrades (in the case of the aggregators, this is investing in DER capacity, while in the case of the utility, infrastructure upgrades are investments in switches), and these components are shown in Equation 7.1. In this initial proposal, only the aggregator can invest in new DER capacity, and only the Utility can invest in new switches. In future models, this division may shift so that either the aggregator or the utility can invest in different types of infrastructure upgrades.

$$Max \sum_{g,t_{RT},z}^{G,T_{RT},Z} [P_{g,t_{RT}}(\lambda(\hat{g}) - C_{g,t_{RT}}) + (U_z(L_z(t_{RT})) - \lambda_z(t_{RT})(L_z(t_{RT})))] + \sum_{t_{INV}}^{T_{INV}} [K_{t_{INV}}(\lambda(\hat{s}) - \kappa_{t_{INV}})] \quad (7.1)$$

In the first component of the revenue, the aggregator and utility attempt to maximize the revenue from the energy sold to customers minus the cost of producing that energy. A financial representation of the utility derived by the consumers for meeting their elastic load is shown in the second component of Equation 7.1. The third component is related to the outcomes of the long-term bids for infrastructure upgrades that the utility and aggregators submit to the DSO. The various aggregators will compete directly with the utility to be awarded these network investments. The fees awarded by the DSO contain a per unit price of capacity expansion determined by the DSO, but the investment in DER expansion is determined by the aggregator, and this is shown in Equation 7.1.

The utility competes with the aggregators to provide network upgrades. The utility, along with the aggregators, submits long-term investment bids to the DSO who then allocates the investment capacity based on least cost planning while meeting the energy demand of the consumers. The investment bids submitted by the aggregator and utility are based on peak-load pricing to recover both capital and operating costs of network upgrades. The aggregator and utility also receive a unit revenue, shown as $\lambda(s)$, for each unit of investment undertaken from the DSO. This investment has a unit cost of k_t in Equation 7.1, for investing in new infrastructure upgrades. This determines the optimal location and capacity of these investments for a given period based on their long-term bids. A load of a consumer at a certain instance is bounded between 0 and the maximum load of that consumer.

$$0 \leq L_z \leq L_z^{max} \tag{7.2}$$

Subject to the following ramping and generation limits:

$$P_{t_{RT}}^{max}(G) = h_i(P_{t_{RT}-1}^{max}(G)) \tag{7.3}$$

$$P_{t_{RT}}^{min}(G) = g_i(P_{t_{RT}-1}^{min}(G)) \tag{7.4}$$

$$P_{g,t_{RT}}^{min} \leq P_{g,t_{RT}} \leq P_{g,t_{RT}}^{max} \tag{7.5}$$

The DSO aims to maximize social welfare over the long term. The DSO acts as a market clearing agent for the bids from the utility and the aggregators. The DSO also clears the bids for long-term system upgrades from the utility in terms of increased switches or the aggregators in terms of increased DER investment. Considering this framework, the power flows in the network under consideration are modeled using the DC power flow equations. These define the power flow in line *i,j* as:

$$T^t = HP^t \qquad \forall(t) \tag{7.6}$$

with $\mathbf{H}$ representing the $nl * n$ transfer admittance matrix. The system's power balance is represented by:

$$\sum_{g}^{G} P_{g,t_{RT}} - \sum_{z}^{Z}\sum_{n}^{N} L_{z,n} = 0 \qquad \forall(t) \tag{7.7}$$

Following the work done by [255], this proposed model assumes a constant admittance matrix H and, in doing so, considers no direct relationship between line capacity and line reactance. In this formulation, a network infrastructure upgrade of capacity $K_{i,j}$ has a unit cost of $k_{i,j}$. The upgrades are strictly positive, i.e.:

$$0 \leq K_{t_{INV}} \qquad \forall(t) \tag{7.8}$$

The demand at a node for a given time, P_{d_n} is the sum of the loads from all consumers located at that node and given by Eq. 7.9.

$$P_{d_n} = \sum_{z}^{L} z_{i,j} \tag{7.9}$$

The power transferred over a given line i, j is represented by $T_{i,j}$ and is subject to the following constraints: Eq. 7.10 states that the power transferred over all lines at a given time is equal to the total generation at that same instant. While Eq. 7.11 states that the power transferred is equal to the demand of the system.

$$\sum_{i,j} T_{i,j} = P_{g_{i,j}} \qquad \forall(t) \tag{7.10}$$

$$\sum_{i,j} T_{i,j} = P_{d_n} \qquad \forall(t) \tag{7.11}$$

Eq. 7.12 places an upper limit on the power transferred in a given line.

$$T_{i,j} \leq K_{i,j} \qquad \forall(t) \tag{7.12}$$

The model assumes non-negative generation output from the generators, non-negative load from the nodes, and positive line capacity.

Following the above equations, the problem is solved by forming the Lagrangian L as shown below:

$$\begin{aligned}\mathscr{L}(P_{g,t_{RT}}, P_{d,t_{RT}}, T_{t_{RT}}, K_l) = \Omega(P_{g,t_{RT}}, P_{d,t_{RT}}, T_{t_{RT}}, K_l) + \sum_{n,t}^{N,t_{RT}} \gamma_{l,t_{RT}}(P_{g,t_{RT}} - \sum_{n,t}^{N,t_{RT}} T_{l,t_{RT}}) \\ + \sum_{n,t}^{N,t_{RT}} \lambda_{l,t_{RT}}(\sum_{n,t}^{N,t_{RT}} - P_{d,t_{RT}}) + \sum_{l,t}^{n_l,T} \mu_{l,t}(K_l - \sum_{i}^{N} T_{l,t_{RT}}) + \sum_{l,t}^{n_l} \alpha_{l,t_{RT}} P_{g,t_{RT}} + \sum_{l,t}^{n_l} \beta_{l,t_{RT}} P_{d,t_{RT}} \\ + \sum_{l,t}^{n_l} \tau_{l,t_{RT}} T_{l,t_{RT}} + \sum_{l,t}^{l} \zeta_{l,t_{RT}} K_{n,t_{RT}}\end{aligned} \tag{7.13}$$

This problem has been validated in [255] with optimality conditions resulting from the Karush–Kuhn–Tucker conditions. Assuming the power injection constraint shown in Equation 7.5 and null Lagrange multipliers α_g and β_g, the following equations are obtained:

$$P_{d_n} = \sum_{i,j} T_{i,j} \qquad \forall(t) \tag{7.14}$$

$$\mu_{l,t} \geq 0 \quad and \quad \mu_{l,t}(K_l - \sum_{i \in n}(T_{i,j}P_{g,t_{RT}})) = 0 \qquad \forall l,t \tag{7.15}$$

$$\nu_{l,t} \geq 0 \quad and \quad \nu_{l,t}(\sum_{i}^{n}(T_{i,j}P_{g,t_{RT}} + K_l)) = 0 \qquad \forall l,t \tag{7.16}$$

$$\lambda_t = \rho_{g,t_{RT}} + (\sum_{i}^{n} T_{i,j}(\mu_{g,t} - \nu_{g,t})) \qquad \forall l,t \tag{7.17}$$

$$\kappa_t \geq \sum_{t}^{T}(\mu_{g,t} + \nu_{g,t}) \quad and \quad K_l[\sum_{t}^{T}(\mu_{g,t} + \nu_{g,t}) - \kappa_{t_{INV}}] = 0 \qquad \forall l,t \tag{7.18}$$

The shadow prices of network expansion are represented by $\mu_{l,t}$ and $\nu_{l,t}$. Work done in [255] shows that while Equation (7.18) has the same form of Short Run Marginal Cost-based power flow indices, the shadow prices, $\mu_{l,t}$ and $\nu_{l,t}$, represent capacity costs as opposed to congestion costs. This PLP formulation allocates the network expansion in an optimal manner so that there is an exact balance between the costs of these expansions and the added social welfare that these expansions contribute [255].

The DSO uses this formulation to systematically clear the generation and load bids from the aggregators and the utility. The DSO follows a sequential process to compute both the long and short-term energy prices and communicates these prices to the Aggregators and the utility. By transmitting these prices, the DSO indicates which, if any, network upgrades are required to meet the reported demand. The process includes the following steps:

1. The aggregators and utility submit their bid and demand curves to the DSO.

2. The DSO uses information regarding the technical constraints of the network plus the bid functions from the aggregator and utility to find the generation and price that maximizes social welfare. The decision variables at this stage are the price and generation needed to meet the demand in the given time window. Within Step 2, the optimal solutions for capacity and price may not be found in the first iteration. If this is the case, new price points can be sent from the DSO to the aggregator and utility, allowing them to update their bid curves.

3. Once a solution to the iterative process in Step 2 is found, the DSO publishes the capacity and prices to the aggregators and utility. The process begins again for the next step in the time horizon.

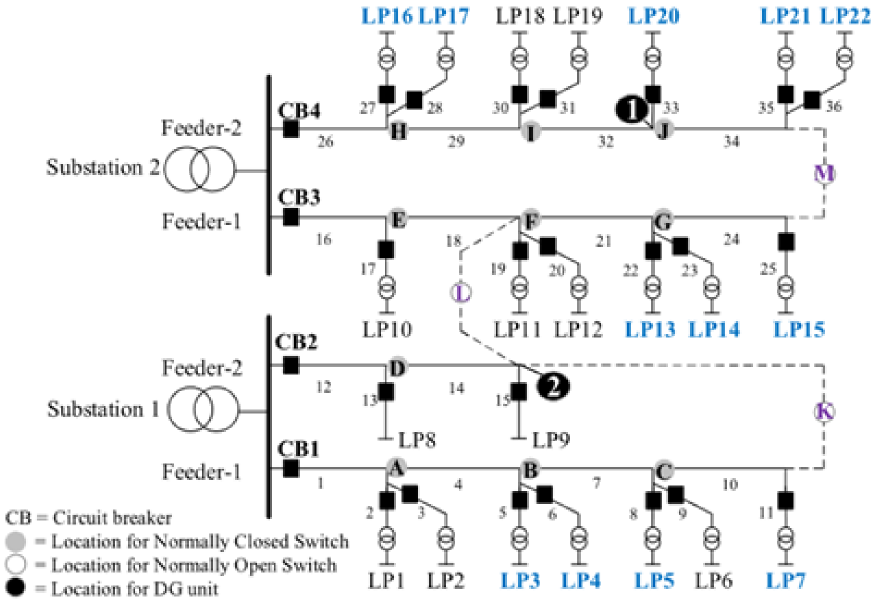

Figure 7.2: Test system used

The model introduced in the previous section was applied to a test system to quantify the extent to which DERs can compete with traditional utilities in providing energy services to consumers. The test system was the modified Roy Billington Test system as used in [259] and is shown in Figure 7.2. Within the test systems, several candidate locations for the switches (both normally open (NOS) and normally closed (NCS)) and DERs were selected. The locations for the switches are shown in locations A-M and the locations for the DERs are locations 1 and 2 of Figure 7.2. At these points, the installed capacity of the DERs can vary. The consumers are aggregated at the various nodes. Consumers have different loads and value these loads differently by submitting differing demand curves. The costs of the network investments are taken from [259] and are shown in Table 7.1. A discount rate of 7% was used.

Table 7.1: Costs of network investments

Type of investment	Capital costs	Operating costs
NOS	$85 000	$200/ year
NCS	$20 000	$200/ year
DERs	$340/kW	$17/kW/ year

7.3 Results

The results of the case study show the final value of investments in either network switches or increases in DG capacity. The results of the investments in network switches are shown in Table 7.2. The table shows the clear benefit of installing new switches as the price decreases and the number of consumers served increases until the optimal number of switches is installed, which in this case is nine.

The model highlights the most beneficial locations to install the switches. The additional number of customers served per additional switch and the impact of this on the final price is shown in Figure 7.3.

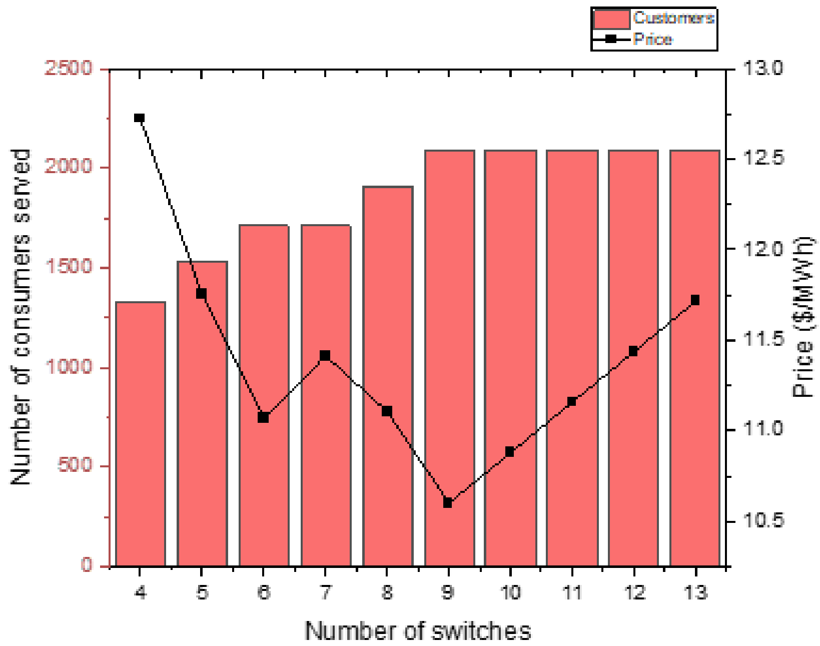

Figure 7.3: Number of customers served

Table 7.2: Results for network switches

Number of switches	Number of clients served	Price ($/MWh)	Location of switches
4	1330	12.7235	ABKM
5	1530	11.7541	ABCKM
6	1710	11.0689	ABCHKM
7	1710	11.4156	ABCDHKM
8	1910	11.1073	ABCFGKLM
9	2090	10.6023	ABCFGHKLM
10	2090	10.8809	ABCDFGHKLM
11	2090	11.1596	ABCDEFGHKLM
12	2090	11.4383	ABCDEFGHIKLM
13	2090	11.717	ABCDEFGHIJKLM

Finally, the impact of increased DG investment on the price is shown in Figure 7.4. There is a decline in the price until a capacity of 1.2 MW is reached and then above this the price begins to increase as the excess capital costs of the capacity of DG needs to be accounted for. The number of consumers served remains the same as the DG acts as supplemental generation for the existing network.

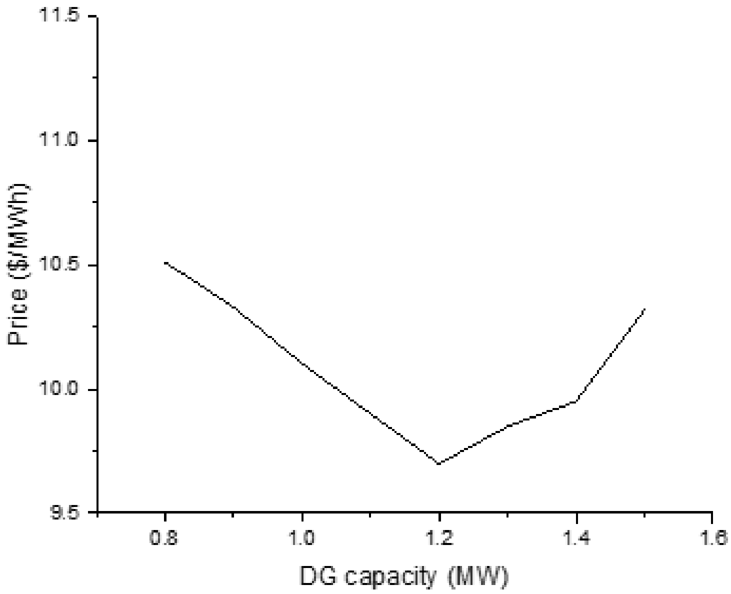

Figure 7.4: Investments in DER capacity

7.4 Conclusions

This chapter presented an interactive operations and planning model for distribution systems using a modified version of the Peak Load Pricing method. The model was implemented within the DyMonDS framework to provide a robust and distributed decision-making process for optimal investments in either network switches or consumer-owned distributed generation. Results show that the model provided the optimal investments for both technologies. Using this framework, the trade-offs between each technology can be easily and accurately calculated, allowing for a transparent process of identifying investments in network expansion while operating the system in an optimal manner. This can be used to further increase investment in DERs in optimal locations thus promoting prosumer participation in smart grid systems.

This chapter has shown that developing new planning models, as well as operational models, can also boost prosumer participation in energy systems. Forward-thinking planning models and regulations can act as means for the medium to long-term increase in prosumer-owned DERs. These planning models should work together with operational models which rely on new technologies and business models to drive the increase in prosumer participation in the short term. The combination of these models can lead to sustainable prosumer participation, sustainable in both the technologies used as well as the long-term beneficial engagements that can become the norm in decentralized, democratized, digitized and decarbonized energy systems.

Chapter 8

Conclusions

This chapter will use the research presented in the previous chapters to answer the various research questions. To begin, the primary research question is addressed and following this, each of the secondary research questions is addressed. Finally, an overview of the thesis is provided with some ideas for future extension of the work contained in the thesis.

8.1 Main Conclusions

8.1.1 Primary Research Question

Can smart grids be designed and operated in a manner to increase the active participation of prosumers and fairly account for the impacts of this participation?

There are numerous interlinked aspects that influence the level of prosumer participation in the energy system. This thesis has explored several of these aspects relating to economic, technical, thermal comfort, regulatory, and data privacy concerns. From each of these areas, increased prosumer participation will affect the smart grid in different ways and with different impacts.

This thesis has provided several frameworks to quantify and allocate the costs of these impacts to the responsible party. These cross-cutting frameworks allow the smart grid to better manage the various impacts that increased prosumer participation will bring. Each of the chapters has a specific focus on the impacts of increased prosumer participation. Therefore the answer to the primary research question emerges as a distillation of the outcomes of each of the chapters contained in this thesis.

Therefore, the answer to the primary research question is: *Relating to the first part of this research question, which is concerned with the design and operation of smart grids to increase the active participation of prosumers, the answer is yes, smart grid systems can be designed and operated in a manner to account for local conditions, consumer preferences, regulatory regimes and the availability of distributed energy resources, thus increasing prosumer participation. Regarding the second part of the research question which is related to the fair allocation of the impacts of increased prosumer participation, the thesis has shown that it is possible to design and operate smart grid systems to fairly allocate the impacts of increased prosumer participation.*

8.1.2 Secondary Research Questions

1) How has the paradigm of prosumer participation emerged and what are the key trends in this shift?

In Chapter 2, an investigation into the existing research on the participation of prosumers in smart grids, chiefly through the provision of flexibility services, was carried out. This was done through a scientometric analysis of over 1000 peer-reviewed articles which showed how the current paradigm emerged and identified key trends enabling this transition.

Through this analysis, it was shown that the research around prosumer participation in smart grids is proliferating. Additionally, the deployment of distributed energy resources owned by prosumers is increasing rapidly through a confluence of several factors, including cost reductions, enabling legislation, technology improvements, and business model innovation.

Additionally, Chapter 3 showed how enabling legislation could impact prosumers' interaction with the existing electricity grid in Portugal. The wider push for enabling and forward-thinking legislation, especially at a European Union level, is key to achieving a rapid yet sustainable uptake of distributed energy resources owned by prosumers.

Additionally, an interesting tension was identified in the research. There is a tension between prosumer participation-driven bottom-up or individual actions and a top-down transition that is driven by national or supra-national (in the case of the European Union) regulations or policies. The full potential for a rapid increase in prosumer participation can only occur when these forces work together.

Throughout this thesis, the following key trends revolving around prosumer participation emerged:

1. Aggregation of consumers is an important tool to maximize the impact of prosumer participation,
2. Increasing numbers of smart devices and Internet of Things connected devices can play a leading role in simplifying and automating prosumer participation,
3. Existing markets to reward prosumers for providing flexibility services or other ways of participating may need to be adjusted to provide accurate, transparent, and fair incentives to prosumers for their participation,

4. Economic rewards are not the only motivating factor for prosumers when choosing to participate in the smart grid. Additional considerations such as privacy of data or thermal comfort are important and should be considered,

5. As prosumers are a heterogeneous group with diverse preferences, abilities to participate, and desired outcomes, local context is key when developing a mechanism to increase their participation. There is no one-size-fits-all approach and considerable stakeholder engagement sessions should be held to identify the key issues of the prosumers or community.

Therefore, the answer to this research question is: *there are numerous interlinking factors affecting the increased participation of prosumers in smart grids. These include technical, economic, regulatory, and consumer behavior aspects, which act as enablers to the era of increased prosumer participation. Importantly, there are tensions and trade-offs between various objectives of the different agents within the energy system, and these need to be analyzed and balanced to reap the full potential of a prosumer-driven energy transition.*

2) What is the role of new information and communications technologies and novel business models in increasing prosumer participation in smart grids?

The energy system is undoubtedly experiencing a profound transition providing fertile ground for numerous new technologies and business models to take root. An important point raised in Chapter 2 was that with a significant increase in the number and type of devices interacting in the energy system, communication between these devices would be crucial to the success of any transactive energy system.

Chapter 3 showed how new technologies from the information and communication realm may ease the burden of increased prosumer participation. This technology, blockchain-based smart contracts, can easily record energy trading among prosumers and automatically send communication signals when certain conditions are met.

Further evidence of the potential for new technologies and business models was shown in Chapter 4 and Chapter 5. Chapter 4 showed that new business models might be created to actively manage intelligent distributed energy resources such as electric water heaters. Chapter 5 showed that a business model of aggregating prosumers into technical virtual power plants could be financially viable and provide benefits to numerous parties.

Therefore, the answer to this research question is: *Novel information and communication technologies and business models will play a crucial role in increasing prosumer participation in future smart grids. These technologies will be key in the digitization of the energy system which increases the type and number of services that can be offered to prosumers as well as the services that prosumers can offer the wider grid.*

3) How can automation and data-driven control methods allow prosumers to participate in smart grids in a simplified manner while still accounting for their individual preferences?

Automation and data-driven control methods are expected to play a significant role in our future societies and the energy system is no exception to this. Chapter 2 discussed how these advancements, along with the Internet-of-Things has ushered in the paradigm of active prosumer participation in the energy system. Chapter 4 showed how data-driven methods can be used to transform previously passive electric water heaters into active grid assets which bring benefits to the consumers as well as to the system operator. Automation was explored in Chapter 3 where blockchain-based smart contracts were used to automate the recording of energy trading among virtual power plants.

Therefore, the answer to this research question is: *Both automation and data-driven control methods can act as enablers for increased prosumer participation. This is done on two fronts. Firstly, they can simplify the actions that the prosumer needs to take and also account for the preferences of the prosumer, thus making it more likely that the prosumer would choose to engage. Additionally, these advancements also open up new avenues for grid managers or third-party service providers to provide incentives to harness the power of distributed energy resources through artificial intelligence. This can convert previously passive grid assets into active energy resources and more easily provide services to the smart grid when needed.*

4) How best to protect consumer data privacy in transactive energy systems to ensure these systems' stable operation?

Throughout the thesis, a recurring barrier to increased prosumer participation was the concern about prosumers' energy data privacy. This was highlighted in Chapters 2 and 4, while Chapter 6 was dedicated to addressing this issue. Consumers have the right to protect the privacy of their data, especially the data generated from their smart meters. However, these data provide valuable information to other agents in the energy system so there is a trade-off between preserving privacy and data utility. Chapter 6 recognized this tradeoff and designed a framework to robustly protect the privacy of smart meter data while showing that preserving the privacy did not lead to significant technical impacts on the distribution grid.

Therefore, the answer to this research question presented in this thesis is the following: *Differential privacy was shown to robustly protect the privacy of smart meter data in such a manner that respects the preferences of the consumer. Additionally, the impacts on the operation of the distribution system due to differential privacy were not material and can be allocated in a fair and transparent manner, thus ensuring the stable and sustainable operation of the smart grid.*

5) Can peer-to-peer energy trading be used to increase prosumer participation while ensuring the efficient technical operation of the distribution system?

A major differentiation between consumers and prosumers is that prosumers may produce or store a significant amount of energy either for their own use or sell it to other agents. Thus peer-to-peer energy trading is a key enabler of increased prosumer participation in smart grids. However, there are concerns about the technical impacts of this trading on the existing distribution grid. The research in Chapter 3 and 5 showed that this trading could occur with a positive impact on the distribution grid. Chapter 3 achieves this by using blockchain-based smart contracts and energy trading among virtual power plants. Chapter 5 allows for peer-to-peer energy trading while accounting for the distribution system's technical constraints and the consumers' thermal comfort considerations.

The research in the thesis showed that while national regulations governing peer-to-peer energy trading are emerging, there are concerns about the impact of regulation on peer-to-peer energy trading.

Therefore, the thesis provides the following answer to this research question: *Peer-to-peer energy trading can act as an effective tool to increase the participation of prosumers within a smart grid. There are essential aspects to consider, such as multi-level trading through aggregation and incorporating the consumer's technical, economic, and other considerations. Importantly, existing regulation may act as an enabler or barrier to peer-to-peer energy trading, depending on the local context.*

6) Do current planning models, typically using marginal cost pricing, allow for competition between prosumer-owned DERs and traditional grid investments in a transparent and fair manner?

Price signals that adequately reflect the total cost of deploying distributed energy resources are essential to incentivize sustained, long-term participation of prosumers within smart grid systems. This was shown in Chapter 2 of the thesis as well as in the novel energy regulations in certain countries within the European Union that are trying to ensure that prosumers are adequately compensated for the services that they provide to the electricity system.

It was shown that current pricing signals, which typically rely on marginal cost pricing, lead to sub-optimal outcomes when dealing with technologies with zero or low-marginal costs. In these circumstances marginal cost pricing results in the need for uplift payment as full cost recovery is not ensured as was shown in Chapter 7. Alternative pricing regimes can ensure cost recovery for technologies with zero-marginal costs. One such pricing strategy, peak load pricing, eas used to introduce competition between traditional grid investments and prosumer-owned distributed energy resources.

Therefore, the answer to this research question is: *In the era of increased deployment of zero-marginal cost distributed energy resources, planning models which rely on peak-load pricing effectively introduce competition between traditional grid investments and prosumer-owned distributed energy resources. This is done by using a price signal that does not rely on uplift payments and fairly accounts for the full range of benefits from both traditional investments and distributed energy resources.*

8.2 Overview and Future work

The research included in this thesis has developed several overlapping frameworks to increase the participation of prosumers within smart grid systems. Additionally, several of these frameworks analyzed the impact of this increased participation and allocated these impacts to the relevant party in an equitable manner. These frameworks ranged from top-down to bottom-up models and encompassed operations and planning considerations. This was done to account for the heterogeneous preferences, access to technologies, and local conditions which have been identified as barriers to developing a single model to increase consumer participation. Each of these frameworks contains avenues for future research.

The emergence of the prosumer paradigm and the factors enabling this transition were identified in the scientometric analysis carried out in Chapter 2. This chapter provided the context for the research and identified key areas of research that the remaining chapters of this thesis focused on. Future work may try to identify whether improvements in technology or innovative energy regulations helped drive the increase in prosumer participation.

Using this context, Chapter 3 then examined the impact of new technologies and business models for increased prosumer participation in smart grids. This chapter showed how automation through blockchain-based smart contracts can play a major role in enabling active prosumer participation. These contracts enabled peer-to-peer energy trading. Importantly this chapter showed that forward-looking energy regulations could act as enablers for increased prosumer participation, which aligns with Chapter 2. Multi-agent modelling of prosumer participation in smart grids may provide some interesting extensions of this work.

Chapter 4 then showed how novel control techniques can enable a bottom-up increase in active participation by prosumers. This was done through the intelligent control of residential electric water heaters. This evidence came from a pilot project in an island community showing the wide applicability of the frameworks developed in this thesis. The chapter highlighted the benefits that accrue to various parties because of increased prosumer participation. This result shows that it is crucial to identify as many impacts as possible that arise from increased prosumer participation and fully account for them. Future work may entail altering the objectives of the device to provide services to the distribution system operator such as demand response potential.

These impacts can include technical, economic, and thermal comfort concerns for the consumer. These impacts were modeled in Chapter 4, which developed a top-down model for aggregating many prosumers. This was done by extending the Technical Virtual Power Plant concept and including allocation mechanisms in the framework. This chapter showed the power of aggregation to harness the full potential of prosumers to impact the smart grid positively. This chapter could be extended by considering additional layers to the model and including planning aspects to the TVPP.

This potential of increased prosumer participation can only be realized if the prosumers choose to engage. One of the major barriers to their engagement, as identified in Chapter 2, is a concern over their data privacy. Chapter 6 addressed this concern by developing a privacy-preserving framework for consumers' smart meter data. This framework provided a mathematically provable level of privacy in accordance with the consumer's privacy preferences. Additionally, the framework accounts for the negative impacts on the operation of the grid and allocates these impacts to the consumers in a fair manner. This chapter addressed a critical enabler of increased prosumer participation through the development of secure and transparent method of handling prosumer data. Incorporating this framework into a smart meter and testing in a laboratory would provide further insights into the potential of differential privacy in smart grid environments.

The previous chapters focused on the immediate impacts of prosumer participation in the operation of smart grids. These impacts can also be felt in the long-term or investment cycles, as was shown in Chapter 7. In this chapter, a dynamic planning framework was developed to incentivize competition between traditional grid investments and investments in prosumer-owned distributed energy resources. The main conclusion from this chapter is that transparent mechanisms to evaluate the trade-offs between various smart grid technologies competitively are essential for long-term, sustained participation by prosumers. Importantly, additional technologies and objectives should be included into this model to provide a more comprehensive understanding of dynamic peak load pricing.

As the work in this thesis covers various fields, there are numerous areas for future work, and these include:

- The frameworks developed in this thesis have largely been solved through centralized optimization. An area of future research would be converting these frameworks into decentralized ones. This may have benefits such as improved computational performance and enhanced data privacy aspects.
- The impact on the smart grid by intelligent devices was demonstrated throughout this thesis. Extensions of these frameworks to real world settings in pilot projects or coordinating with Home Energy Management Systems showcasing interoperability is an important area of future work to examine further the real-world impacts of increased prosumer participation. In addition, local contexts and preferences matter greatly, and these factors should be considered in future pilot projects.

- The interplay between technical advancement and regulatory regimes is an important area for future research. Technology diffusion patterns within neighborhoods are a complex area of research and one where regulation plays a significant part. Methods to identify regulatory regimes that promote beneficial prosumer participation is an area that requires further attention.

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