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Impact of Peer-to-Peer Trading and Flexibility on Local Energy Systems

Thesis submitted in fulfilment

of

Doctor of Philosophy

by

Desen Kırılı



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Institute for Energy Systems

School of Engineering

University of Edinburgh

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Abstract

To meet the 2050 net zero emission targets, energy systems around the globe are being revisited to achieve multi-vector decarbonisation in terms of electricity, transport, heating and cooling. As energy systems become more decentralised and digitised, local energy systems will have greater potential to self-sustain and hence, decrease reliance on fossil-fuelled central generation. While the uptake of electric vehicles, heat pumps, solar and battery systems offer a solution, the increase in electricity demand poses challenges in terms of higher peak demand, imbalance and overloading. Additionally, the current energy market structure prevents these assets in the distribution network from reaching their true techno-economic potential in flexibility services and energy trading. Peer-to-peer energy trading and community-level control algorithms achieve better matching of local demand and supply through the use of transactive energy markets, load shifting and peak shaving techniques. Existing research addresses the challenges of local energy markets and others investigate the effect of increased distributed assets on the network. However, the combined techno-economic effect requires the co-simulation of both market and network levels, coupled with simultaneous system balance, cost and carbon intensity considerations.

Using bottom-up coordination and user-centric optimisation, this project investigated the potential of network-aware peer-to-peer trading and community-level control to increase self-sufficiency and self-consumption in energy communities. The techno-economic effects of these strategies are modelled while maintaining user comfort levels and healthy operation of the network and assets. The proposed strategies are evaluated according to their economic benefit, environmental impact and network stress. A case study in Scotland was employed to demonstrate the benefits of peer-to-peer trading and community self-consumption using future projections of demand, generation and storage. Additionally, the concept of energy smart contracts, embedded in blockchains, are proposed and demonstrated to overcome the major challenges of monitoring and contracting.

The results indicate benefits for various energy systems stakeholders. Distribution system end-users benefit from lower energy costs while system operators obtain

better visibility of the local-level flexibility along with the associated technical challenges in terms of losses, imbalance and loading. From a commercial perspective, community energy companies may utilise this study to inform investment decisions regarding storage, distributed generation and transactive market solutions. Additionally, the insights about the energy smart contracts allow blockchain and relevant technology sectors to recognise the opportunities and challenges of smart contracts and distributed ledger technologies that are specific to the energy sector. On the broader scale, energy system operators, regulators and high-level decision-makers can compare the simulated impact of community-led energy transition on the net zero goals with large-scale top-down initiatives.

Lay Summary

Many countries around the globe set targets to become carbon neutral by 2050 which initiated the decarbonisation process of electricity, transport, heating and cooling systems. One approach is to digitise and decentralise the electricity systems by installing smart metering and incentivising the installation of distributed renewable generation such as rooftop solar panels. This way, local energy systems would have greater potential to self-sustain and hence, decrease reliance on fossil-fuelled central generation. While the domestic uptake of electric vehicles, heat pumps, solar and battery systems offer a solution, the increase in electricity demand poses challenges in terms of higher peak demand, imbalance and overloading. Additionally, the current energy market structure prevents these assets in the distribution network from reaching their true techno-economic potential in flexibility services and energy trading.

The notion of peer-to-peer energy sharing is a transactive local market structure that allows prosumers (i.e. consumers who can produce energy or are proactive in changing their consumption) to sell their excess generation to their neighbours. Using local energy markets and community-level control algorithms, this work achieved higher levels of community self-sufficiency and self-sufficiency.

This work investigated the potential of network-aware and carbon-aware peer-to-peer trading and community-level control to increase self-sufficiency and local consumption of locally generated renewable energy in energy communities. For this, community-level optimisation algorithms were used to minimise the overall carbon emissions and costs of the community by shifting their energy consumption to hours of renewable energy generation. The techno-economic effects of these strategies were modelled while maintaining user comfort levels and healthy operation of the network and assets. The proposed strategies were evaluated according to their economic benefit, environmental impact and network stress. A case study in Scotland was used to demonstrate the benefits of peer-to-peer trading and community self-consumption using future projections of demand, generation and storage.

The implementation of peer-to-peer energy sharing and community control methods require monitoring of local demand and generation and also a legally binding

contract between the parties involved in energy trading and flexibility services. This work proposed and demonstrated the concept of energy smart contracts, embedded in blockchains, to overcome these major challenges.

The results indicate benefits for various energy systems stakeholders. Domestic energy consumers would benefit from lower energy costs while system operators obtain better visibility of the local-level flexibility. From a commercial perspective, community energy companies may use this study to inform investment decision. Additionally, the insights about the energy smart contracts allow blockchain and relevant technology sectors to recognise the opportunities and challenges in the energy sector. On a broader scale, energy system operators (e.g. National Grid), regulators (e.g. Ofgem) and high-level decision-makers can compare the simulated impact of community-led energy transition on the net zero goals with large-scale top-down initiatives.

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Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own.

Desen Kırh
July 2022

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Nomenclature

Abbreviations

| | |
|----------------|--|
| BEIS | Department for Business, Energy & Industrial Strategy (UK) |
| C&I | Commercial and industrial |
| COP | Coefficient of performance |
| CVEI | Consumer Vehicle and Energy Integration |
| DER | Distributed energy resources |
| DFES | Distributed Future Energy Scenarios |
| DLT | Distributed ledger technologies |
| DNO | Distribution network operator |
| DSR | Demand-side response |
| DSO | Distribution system operator |
| DUoS | Distribution use of system |
| ERQ | Encourage-real-quotation |
| ESC | Energy Systems Catapult |
| ETH | Ethereum |
| EV | Electric vehicle |
| EVM | Ethereum Virtual Machine |
| FES | Future Energy Scenarios |
| GB | Great Britain |
| GDPR | General Data Protection Regulation |
| HEMS | Home energy management systems |
| HP | Heat pump |
| IoT | Internet-of-things |
| MILP | Mixed integer linear programming |
| NFT | Non-fungible token |
| NGESO | National Grid - Electricity Systems Operator |
| P2P | Peer-to-peer |
| PMU | Phasor measurement units |
| POA | Proof of authority |
| POB | Proof of benefit |
| POS | Proof of stake |

| | |
|-------------|----------------------------------|
| POW | Proof of work |
| PV | Photovoltaic solar energy system |
| RES | Renewable energy sources |
| SDR | Supply-to-demand ratio |
| SoC | State of charge |
| SoH | State of health |
| SSEN | Southern Electricity Networks |
| ToU | Time-of-use |
| V2G | Vehicle-to-grid |
| VPP | Virtual power plants |
| WPD | Western Power Distribution |
| ZUoS | Zonal Use of System |

Symbols and notations

| | |
|------------------|--|
| λ | Electricity tariff or carbon intensity (p/kWh or CO ₂ /kWh) |
| $P2P$ | Peer-to-peer electricity pricing (p/kWh) |
| $C - P2P$ | Carbon-aware P2P electricity pricing (p/kWh) |
| σ_{t,t_0} | Delay penalty (p) |
| d_t | Inflexible demand (kWh) |
| g_t | Generation (kWh) |
| τ | Operational limit (kW) |
| P | Active power (kW) |
| p | Rective power of flexible assets (kW) |
| E | Energy (kWh) |
| SoC | State of charge (%) |
| ω | Battery self-discharge ratio |
| η | Efficiency (%) |
| ρ | Supply-to-demand ratio |
| Pr | Peak-time premium (p) |
| μ | Distribution cost coefficient |
| SS | Self-sufficiency (%) |
| SC | Self-consumption (%) |
| R | thermal resistance (m ² K/W) |

Chapter 1

Introduction

1.1 Background to the research

In response to the 2050 net zero emission targets, energy systems around the globe have been undergoing major changes. In specific, electricity networks and market designs are revisited in order to accommodate the increasing amount of renewable energy sources (RES), as well as new types of loads, such as those from the electrification of heating and transportation systems. The penetration of distributed renewable energy production, in particular wind and solar generation, have advanced in recent years in response to supportive energy policies, economic incentives and changes in the sector, such as the establishment of energy communities and microgrids [19]. Through the active participation of consumers, energy communities were created in the UK and the rest of Europe which sometimes involve engagement in energy trading, investment in renewables or taking part in initiatives for energy autonomy and self-sufficiency [20]. In 2020, RES such as solar, wind, hydro and biogas contributed 43% of the annual electricity demand of Great Britain (GB) [21]. However, as shown in Figure 1.1, the carbon intensity of GB electricity consumption is still relatively high ($334\text{gCO}_{2\text{eq}}/\text{kWh}$) in comparison to other European countries such as France and Sweden where the former has a high penetration of nuclear energy production and the latter has a high share of hydropower in its generation mix [1]. Around 75% of GB's carbon emissions from electricity production are contributed by gas power plants. Therefore, maximising contribution from decentralised renewable energy generators is key to reducing the dependency on centralised generation, carbon emissions and meeting the 2050 net zero goals.

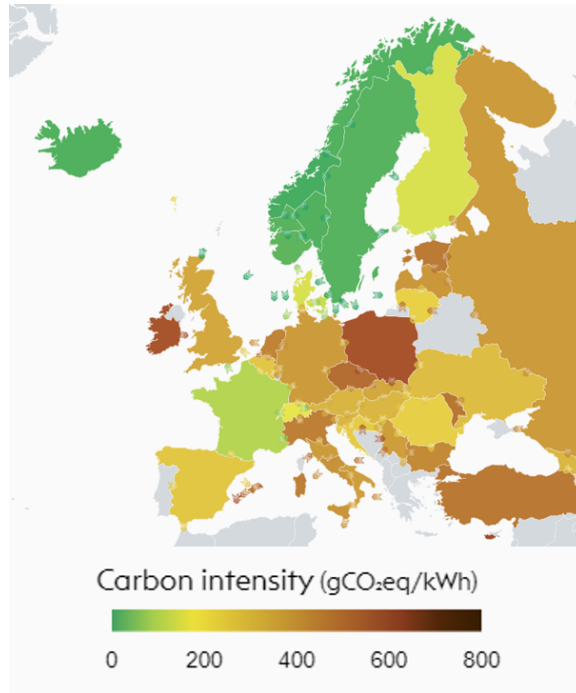


Figure 1.1: Carbon intensity of electricity consumption in Europe where red to green colour scale show highest to lowest levels. (Great Britain (in orange) has 334gCO₂eq per kWh) [1].

Despite the increasing volume of small-scale decentralised generation, their potential is often overlooked as these distributed assets are not coordinated by the system operator for balancing the grid and are too small to participate in energy or ancillary service markets. While the uptake of electric vehicles, heat pumps, solar and battery systems offer a solution, the increase in electricity demand poses challenges in terms of higher peak demand, imbalance and overloading [11, 22]. Often in literature, their participation is enabled by an aggregator or a community manager [22]. Local-level energy management and distribution methods are needed in order to leverage the flexibility present in the decentralised load, generation and storage assets. Unlocking this potential could accelerate the path to carbon neutrality, increase energy security and decrease costs as it would delay the need for infrastructural upgrades and installation of new centralised generators. In other words, coordination of local energy systems, including energy sharing and trading amongst peers, offers a bottom-up approach for tackling the energy trilemma [23].

1.2 Significance of local energy systems

Local energy systems play an important role in the path to achieving carbon neutrality as highlighted by the bottom-up decarbonisation strategy *Community Renewables*, published by the GB's electricity system operator National Grid [24]. This strategy has a focus on increasing penetrations of distributed energy resources (DERs) and flexible loads such as electric vehicles (EVs) in order to decrease the distribution system demand during hours of high consumption (e.g. the evening peak demand hours). The Association of Decentralised Energy in the UK [25] estimated that 16% of the peak electricity demand could be shaved by shifting load to off-peak periods and optimising the use of on-site generation. Through active management of flexible loads and DERs, they estimated that coordinating local energy systems could yield savings up to £600 million by 2020 and £2.3 billion by 2035.

Nevertheless, the current system operation paradigm is unable to monitor and control the large portfolio of small-scale distributed assets [12]. Additionally, the use of a centralised energy management technique is of concern as the renewable generation and load forecasts would be required for all users in the distribution system [26, 27]. To address this, decentralised energy management methods have been proposed in literature along with distributed ledger technologies such as blockchain [28, 29]. Following the recent trends of decentralisation and democratisation in many sectors, various local energy market designs have emerged which enable small distributed suppliers to compete with the conventional suppliers of energy [30, 31]. Such local energy markets enable prosumers to trade electricity with their peers through the notion of peer-to-peer (P2P) energy trading. P2P energy markets could offer the grid the flexibility needed while producing economic benefits for the domestic users of energy and contributing to the decarbonisation of energy systems.

1.3 Research problem and hypothesis

Local energy systems coupled with P2P trading and flexibility coordination offer a solution to the challenges associated with the increased penetration of DER and high-consumption low-carbon loads such as EVs. Future projections of EV and heat pump installations estimate penetrations levels as high as 45% by 2032 [32]. The uptake of these smart assets is encouraged to meet net zero goals, however, this would also

amplify the foreseen increase in system imbalance volumes and peak energy demand. Therefore, these solutions should be simulated in detail in order to evaluate their impact on the distribution network but also on the user comfort as these strategies often include load shifting.

To address these problems, this work investigates the feasibility of P2P trading and local flexibility coordination in the near future using a use-case based in Scotland. A network and comfort-aware simulation approach is implemented and the results are evaluated from various perspectives which include economic benefit, carbon emission savings, user comfort levels and grid signals.

To summarise, the hypothesis of this research is that P2P energy trading and coordinated local flexibility can provide economic benefits to the participants and also contribute to the decarbonisation of energy systems whilst maintaining a healthy operation of the network in the next decade.

1.4 Research approach

The research approach in this work has a community outlook with a focus on maximising the benefit to the local energy system users while decreasing the community carbon footprint. This research modelled energy communities using future penetrations of DER, EVs, heat pumps and storage. Following this, it compared various local energy management techniques such as cost-minimal and carbon-minimal community-level optimisation. From an energy market perspective, it implemented three different forms of community-based P2P trading methods and compared these against the optimisation scenarios.

Additionally, as the local energy systems are located on the distribution network of electricity systems, a network-aware approach was implemented in this work where the simulation of optimisation and P2P markets were coupled with a power flow analysis. Using this approach, the impact on the network was analysed to ensure a healthy operation of the system.

Following this, it should be mentioned that the control approach in this work assumed access to the users' assets which could result in a lower comfort level and quality of life for the participants. To minimize this effect, a user-aware approach was utilised where the user comfort was expressed through delay-based penalty matrices embedded in the optimisation function and the thermal comfort levels were monitored.

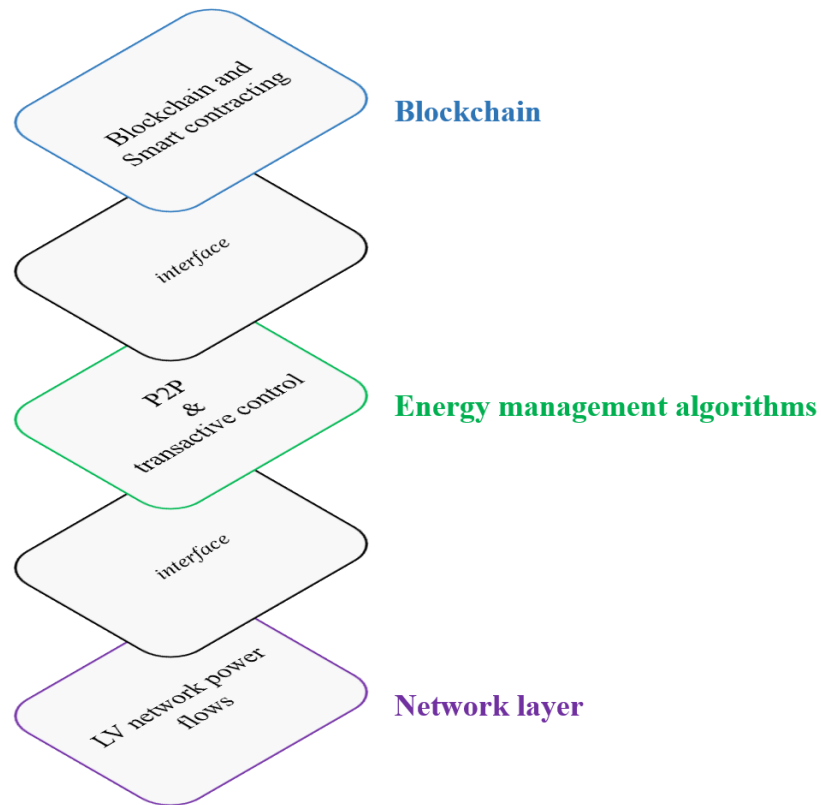


Figure 1.2: The three levels of co-simulation in this work that include blockchain, energy algorithms and grid simulations.

Various challenges, including privacy and security, were identified in relevance to the real-life adoption of community optimisation and P2P methods introduced in this work. Therefore, the research approach included an investigation of distributed ledger technologies which offer a decentralised secure method for transactions. In specific, blockchain-based smart contracts were simulated and analysed as a solution to the concerns related to the scalability of local energy management techniques.

Due to the different aspects of local energy systems researched in this work, a multi-layer simulation methodology was developed. These three layers include blockchain implementation, simulation of local energy management algorithms (including P2P markets and optimisation) and power flow analysis of the distribution network. This multi-layer simulation structure is illustrated in Figure 1.2.

1.5 Highlights of research methodology

The highlights of the research approach employed in this work include:

- A real use-case based in Scotland was used to prove the benefits of community-level optimisation and P2P trading. The results yielded better matching of local demand and generation and proved the feasibility of these methods without significant effects on network operation and user comfort levels. The simulation of this use case involved collaboration with the industry and network operator. Three neighbourhoods with up to 238 residential and 43 small commercial loads were simulated.
- A comparison of inter-neighbourhood and intra-neighbourhood trading was performed. Additionally, differing penetrations of small commercial loads (e.g. bakery, hospital, bank, etc.) in neighbourhoods led to an analysis of the impact this has on the local energy pricing.
- Participation in P2P trading was shown to defer the installation of distributed batteries. A sensitivity analysis was performed to examine the relationship between distributed storage penetration and P2P energy trading participation to evaluate the effect on the community self-sufficiency and self-consumption levels.
- A novel P2P market design was proposed for the first time in this thesis which incorporated carbon-informed pricing of electricity in local energy systems. This approach used the dynamic grid carbon intensity to evaluate the carbon savings achieved through the use of local solar generation. This new method, namely *carbon-aware P2P trading*, was shown to yield significantly lower carbon emissions while retaining most of the economic value in the community.
- The use of blockchain-based smart contracts was demonstrated as an enabling technology for the scalable implementation of smart local energy management techniques proposed in this thesis.
- In addition to the technical outputs, the most extensive systematic review of energy-related smart contracting was provided along with a detailed critical discussion on the future of energy smart contracts. The information from this

review was used to output a novel six-layer taxonomy of smart contracting in energy systems.

- Additionally, the opportunities and challenges associated with the adoption of P2P markets and community-level optimisation were discussed. The operation of P2P markets under the recent disruptive conditions, such as the COVID-19 lockdown and 2020-2021 winter gas scarcity pricing, were qualitatively analysed. Lastly, this thesis also evaluates the implications for various stakeholders in the energy systems which range from end-users to the electricity system operator.

1.6 Key findings

The key findings from this work are summarised below:

- P2P trading increases energy sharing in the community by 14%, reaching 70% self-consumption and 32% self-sufficiency levels in the simulated case study.
- The impact on the network signals such as voltage stability and power losses are negligible when P2P sharing is coupled with peak shaving implementation.
- Inter-community P2P trading yields the highest cost savings worth £210 per household annually. This is 7% more profitable than community-level cost optimisation.
- Carbon-aware P2P trading saves 35tCO₂ in a year. It achieves 7.2% carbon reduction if 4% of the cost savings is sacrificed.
- Blockchain and smart contract implementation outweigh the benefits now. By 2032, the more efficient consensus mechanism Proof-of-Stake will enable wide-scale implementation. However, the associated energy use and computational expense will decrease cost and carbon savings by 18.0 and 11.2%.

1.7 Structure

The thesis is structured into a total of seven chapters where Chapters 3, 4, 5 and 6 contribute most of the technical knowledge. The relationship between the chapters is shown in Figure 1.3 where the literature survey in Chapter 2 feeds into the technical

chapters. While Chapters 3, 4 and 5 focus on the modelling and simulation of the smart local energy systems and markets, Chapter 6 proposes the use of blockchain-based smart contracts for the implementation of peer-to-peer energy trading and distributed control to overcome the challenges of security and privacy. Lastly, Chapter 7 concludes the research and summarises the main findings from the previous chapters. The direct and wider impacts of the work are presented along with its limitations and lastly, a scope for future work is provided.

Each chapter is summarised below. Chapter 2 reviews the literature in local energy system modelling, surveying the motivation, methodologies and contributions of existing work. The challenges, limitations and opportunities associated with the design and simulation approaches are also discussed. It is divided into sections such as co-simulation and optimisation, local energy markets and smart contracting which directly relate to the next chapters.

Chapter 3 describes the bottom-up demand and generation modelling starting with assets such as electric vehicles, rooftop solar panels and batteries. It features cost-minimal community-level optimisation with considerations of user comfort and network operation. It investigates the value of local-level flexibility offered in residential demand-side response services.

Chapter 4 develops the co-simulation structure consisting of local energy markets and distribution network models. The chapter also compares different local energy market initiatives such as community and auction-based peer-to-peer trading methods. It analyses the relationship between storage and peer-to-peer trading. Additionally, it proposes a new local energy trading mechanism that is aware of the grid carbon intensity, namely *carbon-aware peer-to-peer trading*.

Chapter 5 focuses on the coordination and control of smart local energy systems. It compares different strategies and the resultant impact on user profit, carbon emissions and imbalance on the grid. In specific, it compares community-level optimisation with minimum cost and carbon objectives and three different local energy trading mechanisms which are namely intra-community, inter-community and carbon-aware peer-to-peer market methods. The implications for various stakeholders including system and network operators are also discussed in detail in this chapter. As a highlight, it features use-cases from Huntly, Aberdeenshire, Scotland.

Chapter 6 explores the implementation of the optimisation and P2P methodologies presented in the previous chapters and proposes the use of a tamper-proof

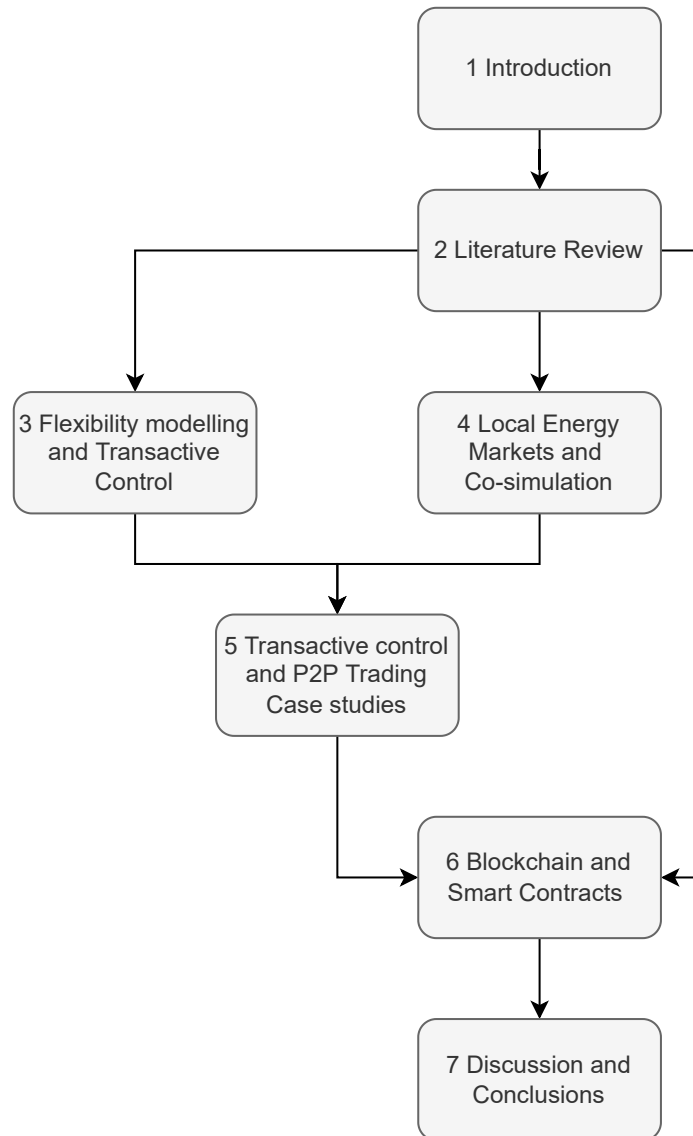


Figure 1.3: Relationship between the thesis chapters.

decentralised ledger technology in the form of blockchain-based smart contracting. It demonstrates the design and execution of smart contracts for peer-to-peer trading applications and evaluates the associated computational expense against the benefits. Using the trends in the existing work, it discusses and makes recommendations with regards to the future of smart contracting and blockchain applications in energy systems.

Lastly, Chapter 7 concludes the research and summarises the main findings from the previous chapters. The direct and wider impacts of the work are presented along with its limitations and lastly, a scope for future work is provided.

1.8 Dissemination and code outputs

During the course of this PhD project, there have been 8 publications which include 4 journals and 4 conference papers.

1. M Zerai, **D Kirli**, J Calautut, T Morstyn, A Kiprakis. “Cost-effectiveness of virtual power plants based on residential aggregators”. IET Renewable Power Generation. 2022
2. **D Kirli**, B Couraud, V Robu, M Salgado-Bravo, S Norbu, M Andoni, I Antonopoulos, M Negrete-Pincetic, D Flynn, A Kiprakis. “Smart Contracts in Energy Systems: A Systematic Review of Fundamental Approaches and Implementations”. Elsevier Renewable and Sustainable Energy Reviews (RSER). 2022.
3. **D Kirli**, J Hampp, K van Greevenbroek, R Grant, M Mahmood, M Parzen, A Kiprakis. “PyPSA meets Africa: Developing an open-source electricity network model of the African continent”. IEEE AFRICON. 2021
4. **D Kirli**, M Parzen, A Kiprakis. “Impact of the COVID-19 Lockdown on the Electricity System of Great Britain: A Study on Energy Demand, Generation, Pricing and Grid Stability”. Energies. 2021
5. R Gilmour, **D Kirli**, S Michalski, J O’Donnell. “Towards bottom-up modelling of the electricity demand of Huntly in 2030”. uSIM2020 - Building to Buildings: Urban and Community Energy Modelling. 2020

6. Y Gao, **D Kirli**, M Zeinali, S Mukherjee, A Birzhanova, J Thompson, N Pindoriya, A Kiprakis. “Development of a hardware in-the-loop co-simulation platform for smart distribution networks”. IEEE 15th International Conference on Ecological Vehicles and Renewable Energies (EVER). 2020.
7. I Antonopoulos, V Robu, B Couraud, **D Kirli**, S Norbu, A Kiprakis, D Flynn, S Elizondo-Gonzalez, S Wattam. “Artificial Intelligence and Machine Learning Approaches to Energy Demand-Side Response: A Systematic Review”. Renewable and Sustainable Energy Reviews. 2020.
8. **D Kirli**, A Kiprakis. “Techno-economic Potential of Battery Energy Storage Systems in Frequency Response and Balancing Mechanism Actions”. The Journal of Engineering. 2020.

In addition to the code and scripts produced to achieve the methodology of this thesis, the work and skills developed during this doctoral research contributed to the following repositories:

1. Zonal Use of Systems simulation platform (private repository owned by Scene Connect)
The simulation modules for asset control for reduced carbon emissions which included network, demand, and smart asset modelling. Partially published in [11].
Python (Pyomo, Scikit-learn, PVlib, etc.), MySQL, HELICS, API, GridLAB-D
2. Electricity Data Pipeline (public repository owned by Desen Kirli)
A tool for extraction, cleaning and visualisation of the GB electricity system data including system demand, frequency and wholesale electricity pricing. Published in [33].
Python and API
<https://github.com/desenk/Electricity-Data-Pipeline>
3. Energy Smart Contract (public repository owned by Desen Kirli)
Smart contract code sample designed for the purposes of distributed control and energy & flexibility trading to serve as a starting point for energy systems researchers to implement smart contracting. Published in [12].
Ganache, Solidity, Python, Matlab
<https://github.com/desenk/energy-smart-contract>

4. UKGDS2DSS (public repository owned by Centre for Sustainable Electricity and Distributed Generation)

A script for automated conversion of the UK Generic Distribution System (UKGDS) network models to the dss format for use in the distribution system simulator, OpenDSS. The output includes various typical rural and urban distribution network models which are potentially useful for other researchers.

OpenDSS and Python

<https://github.com/sedg/ukgds2dss>

Chapter 2

Literature Review

This chapter surveys the key literature in the field of local energy systems modelling. It reviews the motivation, methods and contributions of existing work. It is divided into three sections which are local energy system coordination and optimisation (Section 2.2), decentralised energy markets (Section 2.3) and smart contracting (Section 2.4). These sections provide a discussion of the research gaps which directly relate to the next chapters - as previously shown in Figure 1.3. Lastly, the chapter concludes with a summary of the identified research gaps in the literature that this thesis was set out to address. Section 2.4 of this chapter was published in [12].

2.1 Introduction

The proliferation of small-scale renewable energy generators has significantly altered the way energy is generated, distributed, and consumed [34]. The rapid increase in the number of prosumers (who are pro-active agents with generation or storage resources) provides an opportunity for a more decentralised electrical system operation [35]. Despite the increase in DER and flexible loads on the distribution network, their techno-economic potential is hindered by the current method of system operation which overlooks the flexibility offered by domestic-scale distributed assets [22]. The ongoing transition from centralised to decentralised energy provision and coordination is illustrated in Figure 2.1. This figure shows that the decentralised method involves bi-directional energy sharing between the peers (shown in green). This decentralised set-up enables the integration of consumer-centric local energy markets [36] and bottom-up flexibility provision [37]. P2P energy markets and neighbourhood-

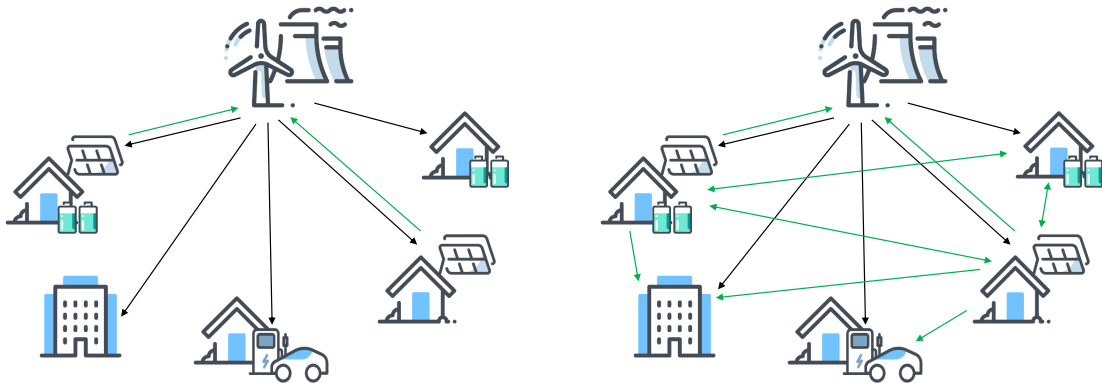


Figure 2.1: Illustration of a centralised (left) and a decentralised method of energy provision (right).

level energy coordination were shown to be capable of delivering flexibility to the grid while producing economic benefits for end-users [14, 26, 38, 39, 40].

Recognising the value of local energy systems, the European Commission proposed a novel regulatory structure for the concept of *energy communities* [41]. This legally enabled peer-to-peer energy trading where peers located in the same energy community. Through the spread of energy communities, European Commission anticipates more decentralised and market-oriented coordination of local supply and demand where the community members act in a collective manner to accelerate the net zero transition. As an added benefit, this regulatory framework is expected to increase the public acceptance of renewable energy technologies and neighbourhood coordination methods. The pro-active and autonomous nature of energy communities separates it from previous examples of coordinated microgrid response [42, 43].

It should be noted that a *peer* in this thesis refers to a residential end-user rather than a commercial/industrial user. Hence, *peer-to-peer* trading is solely used for trading between residential end-users on the distribution network. Additionally, *community* refers to the energy community consisting of peers in a neighbourhood (i.e. with geographical proximity). *Community-level* actions are performed in a coordinated manner to achieve a common goal. For instance, *community-level optimisation* harmonises the efforts in the whole neighbourhood at once rather than individually minimising costs at each node.

2.2 Coordination and optimisation in local energy systems

2.2.1 Motivation

The distributed generators and energy storage are often coordinated by an aggregator or a community manager in order to enable their participation in energy and flexibility markets [22, 44, 45, 46]. Using local energy management techniques, the existing flexibility from the decentralised load, generation and storage assets can be leveraged.

Coordination in this context refers to the control and synchronisation of smart homes and assets to reach a common objective. In particular, this concept can be used in energy communities and/or neighbourhoods in favour of the grid. Balancing services such as load shifting and peak shaving can be delivered through the residential aggregation of loads and generation [22]. When coordination is coupled with optimisation, load shifting can be employed for minimising bills [47].

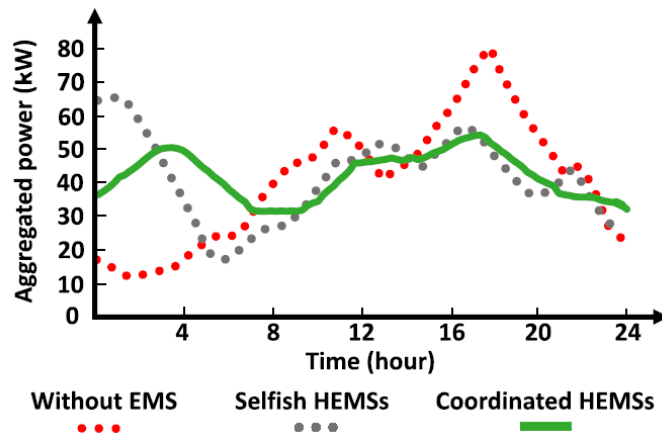


Figure 2.2: Aggregated neighbourhood demand profiles associated with the no-control, selfish HEMS and coordinated neighbourhood cases in red, grey and green respectively. The coordinated control case is shown to result in the lowest morning and evening peak demand [2].

Safdarian et al. [2] showed that high volumes of selfish household optimisation result in adverse aggregated effects such as rebound peaks in demand and unfavourable operation conditions in different parts of the distribution grid. The aggregated load profiles, shown in Figure 2.2, demonstrate that the coordinated response from home energy management systems (HEMS) (in green) provides a relatively flatter demand

curve when compared to the no-control and selfish operation cases. Additionally, it reduces the peak demand value by approximately 20%. To achieve these effects and also decrease the stress on the network, the concept of community energy coordination, in the form of coordinated HEMS optimisation, has been proposed by various researchers including [26, 45, 48].

2.2.2 Coordination methods

There are multiple methods and topologies of coordination proposed in the literature and so far, there is no consensus on the number of existing coordination topologies which range from four to seven [26, 48, 49, 50]. Therefore, the most common and relevant coordination topologies were chosen to be studied in this section. These four topologies were illustrated in Figure 2.3 which are (a) centralised, (b) distributed with a coordinator (also referred to as “coordinated”), (c) fully distributed and (d) hybrid design.

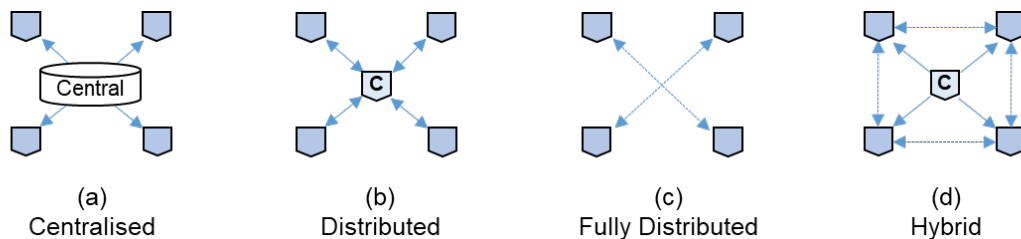


Figure 2.3: Four types of neighbourhood coordination topologies where C denotes the coordinator.

The centralised topology, shown in Figure 2.3(a), represents a solution that is most similar to the business-as-usual operation of the network. It employs a central entity such as the utility or network operator which communicates information to the end-users as shown in [51, 52]. In this topology, the end-users often communicate little to no information to the central entity. Therefore, this method has a high level of privacy. However, this also means that the network operator has no visibility regarding the load and generation forecasts of the individual users.

On the other hand, Figure 2.3(b) offers a distributed approach with a local energy coordinator similar to research in [53, 54, 55]. The coordinator role can be played by a peer, aggregator or distribution system operator. The coordinator receives information about the load and generations profiles of its local peers. Peers share this

information with the coordinator but do not communicate with each other directly. Visibility of local energy demand and supply allows the coordinator to aggregate the local flexibility for participation in balancing services. As this information is shared with the coordinator, the privacy level is lower from the end-user's perspective. Yet, it reduces the communication and computation burden in comparison to the centralised topology. In addition to flexibility provision, this topology can also facilitate community-based P2P trading. The coordinator allows the formation of energy communities as the optimisation in this topology takes place at this level. Therefore, this technique would allow coordination of the peers to meet a communal objective such as reducing the collective carbon footprint [26]. As shown in [11], this coordination method is used for bottom-up network control scenarios as well as for reducing costs and carbon emissions.

The fully decentralised method in Figure 2.3(c) allows each household to become its own decision maker as it offers higher levels of autonomy than the central and coordinated approaches - as shown in [56, 57, 58]. This method has higher levels of privacy as the information is shared with individual peers rather than the coordinator. This method allows fully decentralised implementation of local energy markets which include auction-based P2P trading. This method requires negotiations between peers and hence, iterations in order to clear the energy and flexibility markets. This method further decreases the computational and communication load as optimisation is performed at each node and communication only takes place between trading parties [48].

Lastly, Figure 2.3(d) shows a hybrid approach which is also sometimes referred to as nested coordination method [30]. This may either serve as a transition topology between options (b) and (c) or as a hybrid solution. It also allows the co-existence of auction-based local energy trades and coordinated flexibility provision.

In this thesis, the distributed coordination topology was used as the research has a community outlook where the individual effort of the peers are controlled and harmonised to achieve benefits for the users, environment and the local energy system. This is discussed in more detail in Chapter 5.

2.2.3 Optimisation methods

There are various optimisation methods presented in the current literature but in this section, only the methods used in similar coordination topology were considered.

Hence, heuristic and meta-heuristic optimisation techniques were not considered as the most prominent method in literature was convex optimisation (e.g. mixed integer linear programming) [59].

The different convex optimisation problems found in previous work can be categorised into two groups: plain mathematical optimisation methods and decomposition methods. Examples of mathematical optimisation methods include linear programming and mixed integer programming [40, 50, 60]. Decomposition in this context refers to the division of large-scale optimisation problems into multiple sub-problems. Decomposition algorithms (e.g. ALADIN and alternating direction method of multipliers (ADMM)) are often used to solve computationally intractable problems. One of the key driver for using ADMM is the consideration of multiply agents/decision-makers, whereas mixed integer linear programming (MILP) method is more efficient when working with a single decision maker [48]. To summarise, the most dominant factors for choosing an optimisation algorithm are the specific coordination topology and the computational complexity of the problem [26].

For the coordinated control of neighbourhoods, reviewing the literature revealed that (non-decomposition) mathematical optimisation algorithms were most commonly used due to their robust nature [2, 48]. In particular, MILP was found to be suitable for coordinated neighbourhoods, as shown in [60, 61]. The advantage of MILP is that it is capable of solving a simultaneous sizing and scheduling optimisation problem, where the objective is to minimise costs and/or environmental impact, and where the system to be optimised is represented by a number of nodes and various equality and inequality constraints. In [61], a smart community energy management method was used to coordinate batteries and solar systems in order to simulate “user-dominated demand-side response” and P2P trading. This study along with [60] showed that MILP can significantly decrease the computational time and complexity for such problems. Therefore, as the formulated problem was computationally achievable, MILP was chosen as the optimisation algorithm in this thesis.

Several other works used MILP for optimising local energy systems with hot water systems, residential batteries and EVs. In addition to electrical systems, MILP also has been used for multi-vector optimisation. For instance, Kauko et al. [62] used MILP to optimise thermal storage in local energy systems in Norway and Ata et al. [63] demonstrated its use for a multi-vector system which considered gas and heating systems. Meanwhile, [64] adapted the single-objective MILP formulation to include

multiple objectives using an urban network as a case study. The main shortcoming of MILP is that the optimisation model is evaluated at each time interval. This increases the computational expense in comparison to the meta-heuristic methods. On the other hand, this method achieves more accurate optimisation results.

Further details are provided in Chapters 3 and 5.

2.2.4 Modelling user comfort

Research presented in [45, 50, 65] focus on the benefits of transactive control and neglect the impact on the users. The most recent review articles, including [26, 49] highlight the research gap with respect to integrated user comfort modelling. In studies such as [11], the user set-point and the resultant indoor temperature are compared to estimate and quantify the change in user comfort due to transactive control actions. While most of the research in this area considers thermal comfort limits related to heating and cooling, there is a lack of consideration for the inconvenience caused by delaying the user-scheduled EV charging actions. Lotfi et al. [49] stated only one publication that considered and quantified this as “discomfort index” [66]. However, this study is limited to home energy management system (HEMS) optimisation rather than neighbourhood-level coordination.

2.2.5 Discussion of research gaps

This section reviewed the literature relevant to neighbourhood coordination and community-level optimisation. This subsection discusses the three major research gaps that were identified.

First, to increase the social acceptance of neighbourhood coordination, the modelling and optimisation methods have to integrate an understanding of user satisfaction rather than just evaluating it as a performance indicator. Despite the advantages of transactive control, it might incur inconvenience to the users, comprising their quality of life. Almost all of the research focused only on thermal comfort limits, however, there is also disutility caused by delaying EV charging sessions and other asset operations. Hence, there is a need to improve user-centric optimisation methods in the modelling framework of local energy systems. To address this, this work proposed a user-centric optimisation method. This method has an integrated user comfort component in the optimisation step. It takes into account the increased risk of lowering

user satisfaction when rescheduling the user-set actions to achieve minimum costs or carbon emissions.

Second, most of the literature did not consider a real case study in terms of asset penetration levels and network topology. Thus, the cost savings and network benefits require validation through the use of a pilot study. In addition to neighbourhood control, this also applies to P2P energy trading. In this thesis, penetrations of flexible loads including heat pumps, EVs and batteries along with solar PV generation were considered. A pilot study located in the north of Scotland was chosen as a use-case where the local DNO provided a dataset of asset penetration levels for the near future. This dataset in combination with the local network topology was used to simulate and validate the impacts of P2P energy trading and user-centric and network-aware optimisation in the near future.

Lastly, from the perspective of the DNO, losses, transformer usage and voltage levels are also significant indicators in addition to the energy imbalance. However, most research work seem to focus on the economic effect and peak load rather than evaluating the technical impact of community coordination on the network. In response to this, this thesis modelled the digital twin of a real LV distribution network in the north of Scotland using line data obtained from a British DNO. It analysed various grid operation indicators which include peak load, imbalance volumes, losses, transformer usage, voltage levels, etc. Presenting these technical results clarifies the technical impact of such coordination methods which increases the likelihood of their adoption.

2.3 Local energy markets and co-simulation of market and grid

2.3.1 Motivation

The current top-down energy market operation neglects the residential consumers and inhibits them from directly participating in energy trades or balancing markets due to their low consumption and generation capacities. The majority of end-users are only allowed to buy electricity from the grid and sell electricity to the grid, often using a fixed tariff. On the other hand, local energy markets are designed to be consumer-centric and aim to provide economic benefit to the participants [67]. The

term *local energy market* (LEM) refers to a small-scale economic system that coordinates consumption, generation, storage and additionally other energy vectors, such as transport and heating, in an energy community and/or microgrid. In this thesis, *P2P trading* is considered to be a subset of local energy markets which indicates that the users live in the same neighbourhood. This means that they are located on the same electricity network, often behind the same primary or secondary substation. Mengelkamp et al. [68] defined P2P energy trading as a “marketplace platform for trading locally generated (renewable) energy among residential customers within a geographically and socially close community”. Similarly, this work only considers residential users as peers when demonstrating the benefits and drawbacks of participation in LEMs.

According to [29, 69], P2P trading is vital for moving towards fairer energy systems as it offers more choice to the sellers and buyers, and increases the transparency of the energy trading process. Additionally, it complies with the three pillars of the energy revolution which are namely digitisation, democratisation and decentralisation. LEMs also aim to increase the resilience of the grid in a cost-effectively by unlocking the export potential of the distributed generation surplus. The use of P2P platforms to offer grid services, in addition to local energy trading, is illustrated in Figure 2.4. In this figure, the P2P platform coordinates energy transactions within the distribution network and additionally provides flexibility services through the coordination of users which is perceived as a federated virtual power plant by the grid operator. According to the World Energy Council [23], this would accelerate the inclusion of smaller and more diverse assets and present the consumers and producers with more freedom and control regarding their energy preferences. This method would also aid with increasing awareness about fuel poverty, highlighting the social impact of this P2P model that enables electricity to be donated and discounted [27, 70, 71].

2.3.2 Enabling technologies

The enabling technologies can be divided into two categories depending on whether they operate on a virtual or a physical layer. The physical layer enablers include smart metering and communication infrastructure. On the other hand, the virtual layer has contributors such as distributed ledger technologies and new market negotiation technologies.

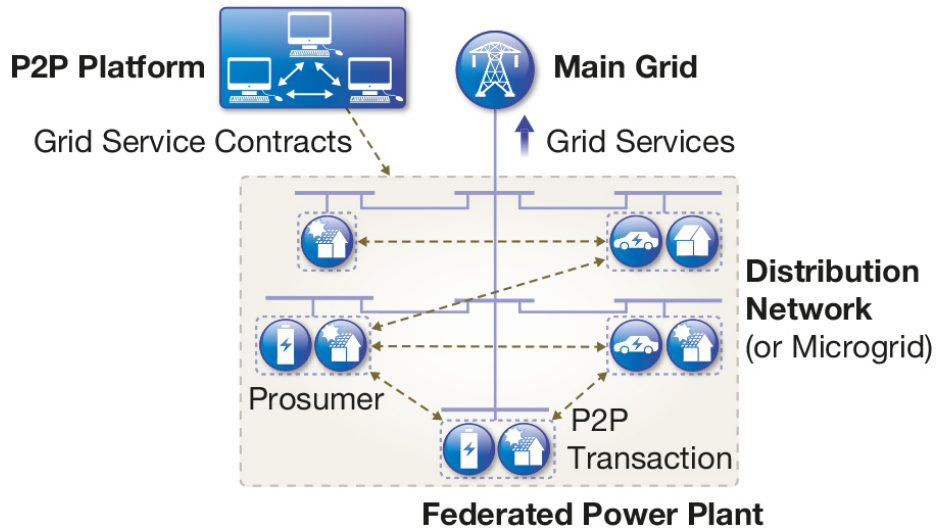


Figure 2.4: The P2P platform coordinates energy transactions within the distribution network. This platform is also capable of providing flexibility services through the coordination of user which is presented as a federated power plants [3].

In recent years, blockchain-enabled P2P trading and community-centric energy sharing applications have received an increased research interest as demonstrated by [40, 72, 73, 74]. There is also an increasing focus on the LV microgrids and local distribution networks for the application of blockchain technologies in P2P energy trading [36, 75, 76]. Nevertheless, while these technologies are mentioned in the literature, only a few studies actually implement the energy management algorithms in smart contracts or demonstrate the steps of smart contracting in a repeatable format. The more detailed review of enabling technologies, focusing on blockchains and smart contracting, is presented in Section 2.4.

2.3.3 Types of consumer-centric local energy markets

Various reviews [14, 26, 30, 67, 77, 78, 79] and research work [57, 80] primarily divided local energy markets into two categories. While Sousa et al. [30] refer to these as “full P2P” and “community-based P2P” methods, others call them “auction-based” and “distributed”. In this thesis, these two types were often referred to as “auction-based” and “community-based” LEMs.

The auction-based market utilises multiple bi-lateral contracts between the users and often involves negotiations and iterations. The price of the energy exchange is

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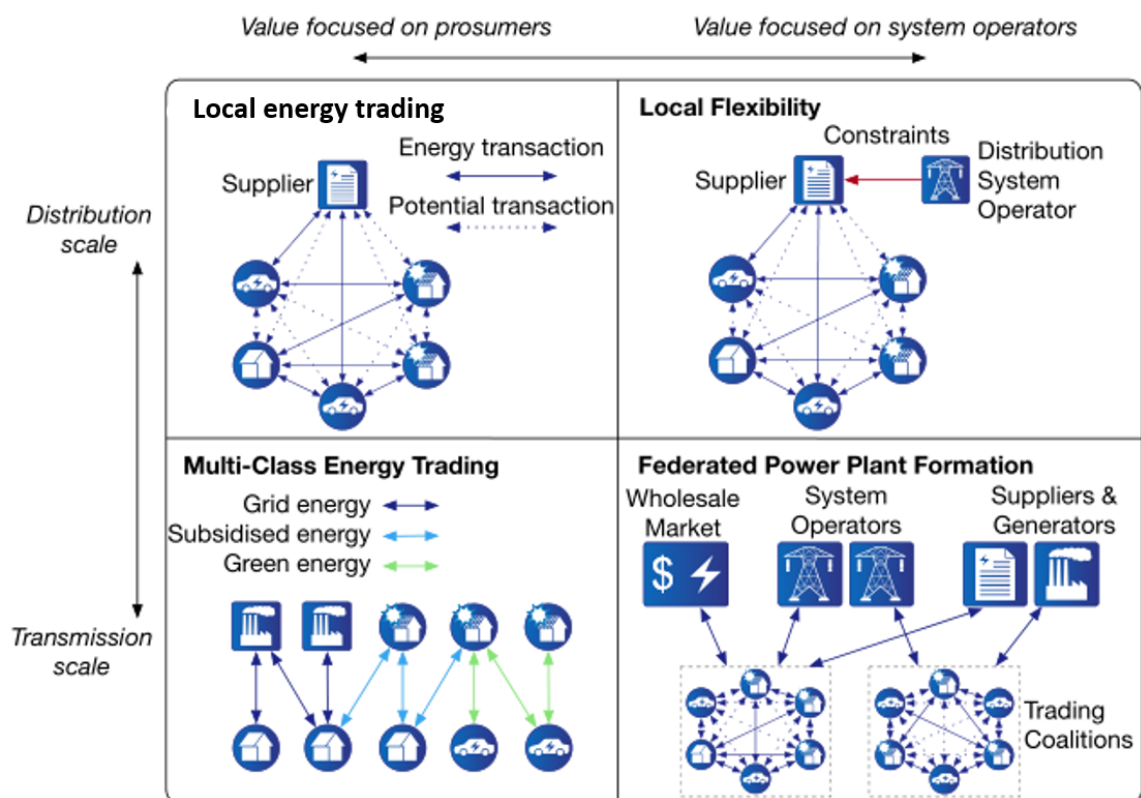


Figure 2.5: Categorisation of P2P-based energy and flexibility markets according to their targeted system (e.g. distribution or transmission) and beneficiaries (e.g. prosumers or operators) - from [4].

2.3. LOCAL ENERGY MARKETS AND CO-SIMULATION OF MARKET AND GRID

derived from the bids and offers of only the participating users. The advantage of this method is that a heterogeneous user group can be simulated as shown in [80]. Some peers can express their preference to buy energy from low-carbon DERs and others may donate energy to low-income participants. Nevertheless, this market heavily depends on communication and trust between the parties involved. Thus, it has a high computational demand and communication burden [26].

In addition, the auction-based approach might result in conflicts and market coalition formation, the community-based approach has a more naive outlook in the sense that it uses a coordinated approach. Hence, this method does not require the direct communication between peers and collectively determines the price. In [81], this method computes the community energy buy and sell prices through evaluations of the energy surplus or deficit in the local network. This approach is more suited for achieving community goals. The downside of this method is that the task of coordination is often handled by a community manager who can be a peer, aggregator, DSO or a centralised algorithm which has access to the user information [82].

Additionally, there is a hybrid approach which is a combination of the two previous approaches [30]. For instance, some studies incorporate bi-lateral trading between microgrids that have nested community-based P2P markets. In this thesis, both of the traditional approaches were simulated and compared along with inter and intra-community trading scenarios. More information is presented in Chapter 4.

The review work in [82] categorised the research work according to the product differentiation and key performance indicators (KPI). This was the only work that considered user preferences and customer satisfaction - in terms of “quality of service” and “quality of experience”. But, both KPIs were financial calculations related to the distribution of benefits amongst the peers rather than the inconvenience of implementing profiting P2P market actions via distributed control of user assets. For instance, the “quality of experience” KPI evaluated the price points of each consumer (i.e. in auction-based markets) to measure the fairness of the local energy exchanges. This means that if they all trade at the same price (similar to community-based energy markets), the fairness of the community would be the highest. Nevertheless, the KPIs presented by this work revealed that user comfort is not modelled in the majority of the P2P-related literature. Thus, this thesis applied the consumer-centric optimisation technique developed for the neighbourhood coordination simulations in

LEM simulations in order to ensure that the life quality of the users was not compromised.

In a separate set of work, Morstyn and McCulloch [4] showed that P2P energy trading platforms offer benefits to the prosumers and systems operators by providing services on distribution or transmission levels [4]. Rather than purely trading energy amongst the peers on the distribution system, these platforms can be used to provide value to the network and system operators through local flexibility and federated power plants. These approaches were categorised according to their targeted system (e.g. distribution or transmission) and beneficiaries (e.g. prosumers or operators) in Figure 2.5. This thesis focused on the distribution end of the scale as it is concerned with LV microgrids. Hence, the types of local markets reviewed in this section are limited to local energy trading and local energy flexibility.

2.3.4 Co-simulation of energy markets and grid models

This literature survey identified that there is a need for a holistic approach toward local energy systems in addition to the two dominant streams of research which focus on the either efficient and fair design of local energy markets or achieving more balanced networks via distributed control and virtual power plants. There is relatively recent work that explores the impact of P2P markets on LV distribution networks [83, 84, 85]. For instance, Hayes et al. [83] took into account physical constraints of the grid whilst allocating local supply to the households and analysed per-unit voltage drops caused by individual market actions. This work was part of an Irish project called EnerPort that has various industry partners which demonstrates the increasing interest in this field.

Studies such as [67] anticipate that local energy markets will lead to lower grid stress and enhanced operation of distribution networks in the future. Therefore, co-simulation of the market and grid is necessary to simulate the technical impact of the local energy exchanges. Previous work has shown that the use of LEM algorithms can accelerate the integration of flexible assets and also improve local network balancing due to better managed allocation of local energy resources [44, 86, 87, 88]. However, these simulations validate the impact of LEM algorithms under certain conditions and there is no comparison between different algorithms. Another perspective is that the optimal market actions decided by the market module may result in higher peak loads and higher/low voltage levels. This would threaten the adoption of local energy

markets in real life as they would increase the burden on the distribution system operator.

While most co-simulation research used the IEEE LV European case study [27, 83], others such as [89] and [82] used the 39-bus and 37-bus radial systems. Following the most prestigious publications, the IEEE LV European case study was employed in the initial chapters of this thesis (in Chapter 3). Nevertheless, the use-cases from the pilot project in Scotland used real network data to construct LV case studies to validate the impact on the network - these are presented in Chapter 5.

2.3.5 Review of research and pilot projects

In addition to the trends in research, the use of P2P technologies in the energy sector also attracted attention from the industry in the UK (Electron [90] and Emergent [91]), USA (TransActive Grid by LO3 Energy [92]), Netherlands and France. In the UK, Open Utility has a local energy transaction platform, called Piclo, where commercial users of electricity can digitally buy and sell units for the next half-hourly period [93]. As some generators, especially the community energy assets, have discounts for local users, P2P trading presented an economic benefit to the consumers. A good example is the Delabole Local Tariff which provides electricity to the users within a 2-kilometre radius at a tariff that is at least 20% cheaper than their standard rate [93].

18 different research and pilot projects, in the field of peer-to-peer trading, are summarised in Table 2.1, noting the countries they operate in and the start year of the project. The first initiative of local energy markets was launched in 2010 by the German renewable electricity and gas supplier LichtBlick [94]. While one to two projects were launched every year till 2015, seven projects started within the year 2015. Most notably in that year, TransActive Grid deployed a pilot microgrid in Brooklyn which is probably the most famous example of P2P electricity trading [95] cited by many studies [68, 96]. All of the listed projects enable the users to participate in a local energy market and trade with their neighbours. While some focus on consumer-centric market design (e.g. Energy Collective), others also consider implementation in terms of hardware and communications (e.g. P2P-SmarTest).

2.3.6 Carbon savings of local energy markets

In order to assess the carbon saving potential of local energy markets, the avoided mass of carbon dioxide emissions has to be calculated. In most cases, the local generation is supplied by solar energy which is assumed to be carbon neutral [11]. Previous work and projects mostly used a simplified conversion method to calculate carbon savings achieved by multiplying the energy savings with a constant per-unit carbon emission value [97, 98]. The assumption of a constant carbon intensity value misrepresents the varying pattern of carbon intensity throughout the day due to the periodical nature of RES. Thus, this indicates a knowledge gap in analysing the variable carbon-saving nature of local energy trading in the literature.

Studies including [80, 98] have shown up to 18% reduction of carbon emissions, assuming a constant rate of $0.55\text{kgCO}_2/\text{kWh}$ based on the assumption that the central generation is completely gas powered. However, the average carbon intensity of electricity in the UK is 0.233kg of carbon dioxide equivalent per kWh [5] which highlights the need for a more detailed analysis of the carbon saving potential of P2P energy markets. On average, the carbon emission levels are significantly decreased during the middle of the day and overnight, due to solar and wind generation. Additionally, electricity price and carbon intensity do not always have a directly proportional relationship. Hence, minimum cost scenarios do not reflect the full decarbonisation potential of P2P markets.

The assumptions of the previous work regarding constantly high grid carbon intensity do not provide correct information to the optimiser which leads to results which are inadequate for estimating the carbon savings resulting from cost-minimal load shifting. This is because, as shown in Figure 2.6, the morning surge sometimes results in the highest per-unit carbon emission value of the day. In addition to diurnal changes, there is also seasonal variation due to lower energy demand and higher solar contributions during the summer months, however, this cannot be generalised as it is volatile to the wind energy output in the winter.

Therefore, in order to assess the potential of P2P markets as a bottom-up decarbonisation tool, there is a need for an in-depth carbon avoidance study. The research work addressed this and also developed a P2P pricing mechanism that takes into account carbon dioxide emissions. The novel concept of carbon-aware P2P pricing along with the methodology of carbon intensity computations is provided in Chapter 4.

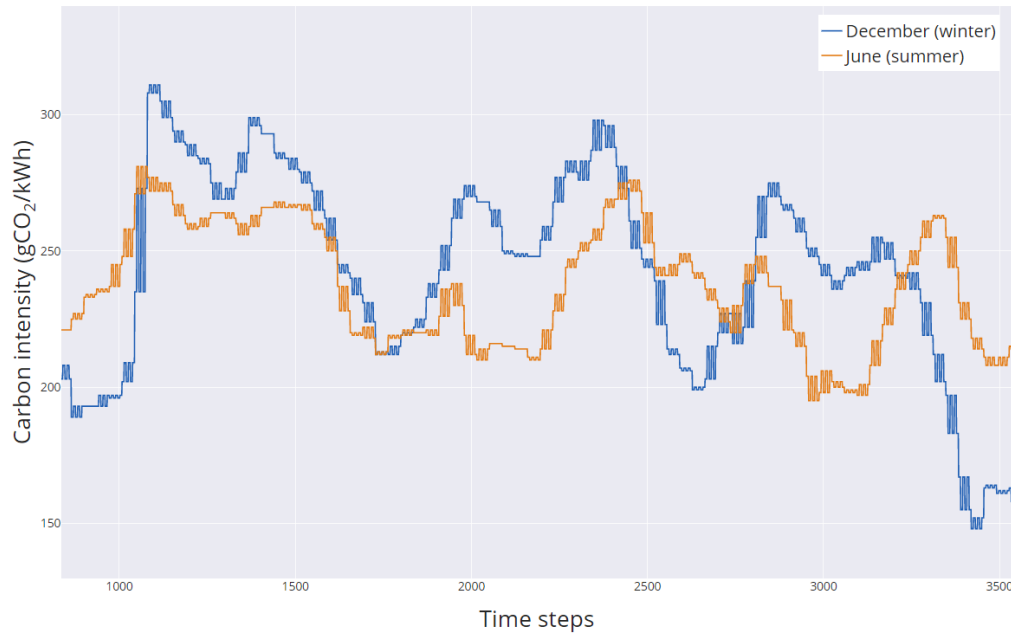


Figure 2.6: 2019 winter and summer carbon intensity of electricity imported from the grid - data from [5].

2.3.7 Discussion of research gaps

To summarise, this section reviewed the developments in the local energy market research and co-simulation methods. This part presents the identified research gaps and explains how this thesis addressed them.

First and most significantly, while most of the previous work provided detailed economic results, the considerations of carbon emissions were found to be inaccurate and rudimentary. Often, a single average value of carbon emissions was used for a whole year of simulation [97, 98]. However, carbon intensity is highly variable with seasonal and diurnal patterns (See Figure 2.6) which indicates a major research gap in this area. In response to this, this thesis evaluated the carbon emissions from all of the simulated cases using the half-hourly measurements of grid carbon intensity. This resulted in more accurate representations of carbon savings achieved by participation in P2P markets. Additionally, this thesis proposed a *carbon-aware* P2P energy trading method for the first time. This method introduced the integration of a carbon incentive in the P2P market price which rewards sharing of energy when the carbon intensity of the grid energy is high.

Second, this section examined the co-simulation of the grid and market models

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and evaluated that the current research trends either focus on the market design or network operation. Therefore, more research in the area of network and market co-simulation is required and hence, a *network-aware* P2P trading method was used in this thesis. Additionally, a very small portion of the P2P-related research took user comfort into account. Whereas, this work employed a user-centric optimisation method with integrated consideration of user satisfaction.

Third, almost all publications to date use the standard IEEE LV European network for their simulations [4, 7, 83]. A real use-case is required to study the realistic network effects of P2P energy trading in order to increase the acceptance of LEMs by the network and system operators. As previous work [4, 83] did not simulate any small commercial loads in their networks, these results do not provide an accurate representation of a real LV network in GB. Therefore, research using real use-cases should validate the findings. As mentioned previously, to address this, this thesis simulated a real part of the GB distribution network located in the north of Scotland using line data from the local network operator. Additionally, the small commercial and industrial (C&I) loads were also modelled but excluded from P2P participation (in order to avoid market distortion). Hence, this work also addressed the knowledge gap regarding the effect of small C&I loads on the P2P prices and network operation.

Lastly, [99] evaluated that decentralised storage is more beneficial than centralised for P2P applications, however, the benefits of P2P trading vary in different research works as they use different penetrations of solar PV, batteries, etc. This may create uncertainty about the actual benefit of P2P and it is more difficult for local energy companies and operators to estimate the benefit of such systems. Hence, the relationship between normalised storage penetration (using the local demand as a basis) and normalised P2P participation was presented in this work. In addition, when simulating the real use-cases, the predictions of the local network operator were used to determine the rate of EV, solar PV and storage uptake.

The details about the carbon-aware and other variations of P2P trading methods are provided in Chapter 4 and the results from the use-cases are presented in Chapter 5.

2.4 Blockchain-based smart contracting in energy systems

This section reviews the literature about the enabling technology called smart contracting which is key for the implementation of transactive markets and control. Using a database of 178 papers, it specifically focuses on the use of smart contracting in energy systems. This work has been published in [12].

2.4.1 Introduction

Smart contracting, along with distributed ledger technologies (DLTs) may offer a solution to the scalability challenges of neighbourhood coordination methods and P2P energy markets, as highlighted by the systematic review of Andoni et al. [29]. Blockchain technology or distributed ledgers represent a base layer technology that provides a secure and immutable ledger of digital transactions and value transfers in a network. Smart contracts are codified using an underlying blockchain architecture and therefore intrinsically inherit many of its desired properties, such as automation, decentralisation, immutability and security. In fact, it can be argued that *smart contracts are the aspect of blockchains that is the most relevant for the energy application layer*. While blockchain architectures are concerned with data storage, involving aspects such as cryptographic security or reaching consensus on the information to be written on the blockchain, the contractual operations and transactions to be executed on the blockchain (whether they concern money, energy or flexibility commitments) is a concern of the smart contracting layer.

Smart contracts are self-executable programs that are able to monitor and change the ledger according to user-defined rules. They can be triggered when certain conditions are met and can automatically execute and control energy trading events. They use computer hardware to process data, verify conditions, deal with negotiations and validate a contract. The records are append-only (i.e. irreversible) and transparent. Hence, the requirement for an intermediary or a system operator is eliminated. As a result, this holds the potential to automate and accelerate automated negotiations and contracting between the parties [100]. Smart contracts offer a virtual means of reaching and enforcing a credible agreement and/or transaction [101]. In turn, this can enable the development of new forms of social organisations, such as Decentralised

Social Organisations (DAOs), in the energy space, self-organising energy communities or microgrids. On the regulatory side, a report on distributed ledger technologies published by the United Kingdom government chief scientific advisor [102] identifies smart contracts as a crucial factor that can unlock the full potential of blockchain technology.

Finally, despite its significant potential, smart contracting is still a developing technology and has several open challenges associated with its implementation, such as privacy concerns, the risk of cyber-attacks (such as hacking) and the energy required for computation and blockchain deployment of the contracts. So far, smart contract applications in energy systems have been mostly focused on research, proof-of-concept and demonstration projects (such as P2P demonstration projects run in a local community or microgrid). However, as the technology scales up, security vulnerabilities and threats, implementation and communication issues, as well as financial and environmental costs of deploying smart contracts will become increasingly important to consider. This is already the case in areas where smart contracts are already deployed on a large commercial scale such as Decentralised Finance (DeFi) and non-fungible tokens (NFTs).

To conduct this analysis, a systematic search and review method was employed to evaluate how smart contracts are used in the field of energy systems. To obtain the literature of interest, the phrase “smart contract” was queried along with “energy” or “electricity”. The literature is that feature the aforementioned keywords in their title, abstract and list of keywords, using Scopus which is one of the most comprehensive indexes of peer-reviewed scientific publications, comprising of both journals and conference proceedings. After filtering for relevance, this resulted in a corpus of 178 peer-reviewed publications, on which this study is based.

2.4.2 Fundamental principles of smart contracts

This section presents the background information and fundamental principles regarding the definition of a smart contract, including an example of a generic energy smart contract.

2.4.2.1 Blockchain technology overview

Blockchain and other distributed ledger technologies are a key underpinning technology for smart contracts.

Intuitively defined, a blockchain is a chain of information blocks (usually, containing information about crypto-currency transactions or smart contract specifications), linked together through cryptographic methods. It has alternatively been described as an append-only log, or a distributed ledger of transactions [103]. Unlike a centralised database, this ledger is *distributed*, meaning no single party has control over writing information to the blockchain. In fact, a number of nodes or peers all have a copy of the whole blockchain (or the key information of the chain), and mutually agree on how the information can be written or added through a *consensus protocol*.

A key feature of blockchains is that it is *tamper-proof*: information written in previously accepted blocks cannot be changed, a property assured through cryptographic hashing. In more detail, all the transaction information contained in each block is efficiently hashed through a so-called Merkle tree in the header, while each block contains a hash of the header information of the preceding block. In practical terms, these cryptographic links created through hashing means that any unauthorised change (i.e. tamper) with the information in a previous block is immediately detectable by all nodes. Typically, in blockchain systems, if a transaction in a previously accepted (or “mined”) block needs to be changed or reversed, this can only be achieved by recording the reverse transaction in a future block, accepted by all parties.

A key issue in blockchain systems is the method of reaching consensus among the nodes on each information block to be stored, i.e. the *consensus protocol*. There are many variants of consensus protocols deployed or proposed (see [29, 103]), but the main ones are:

1. *Proof of Work (POW)*: This is the form of consensus in most open blockchain systems, supporting their own cryptocurrency, such as bitcoin [104]. In POW consensus, the node that has the right to add the next block to the chain is determined by solving a cryptographic puzzle (technically, through a so-called “zero-knowledge proof”), i.e. a puzzle that is hard to solve, but easy to verify. Adding a new block is often referred to as “mining”, and the nodes that perform this activity as miners, which are rewarded a certain amount of native cryptocurrency (or sub-unit of it) for each new block they successfully mine. In the Bitcoin system, the puzzle consists of computing a number of leading zeros, with the difficulty of the puzzle can be adjusted by increasing/decreasing

the number of zeros required to be computed. In practice, the puzzle has become exponentially harder to solve over time, currently requiring specialised hardware (called ASICs, application-specific integrated circuits), pooling computation resources into so-called “mining pools”, and especially, a large amount of energy consumption. This large energy required to undertake POW computations is, popularly, one of the most well-known and striking features of POW blockchains, as it currently exceeds the energy consumption of several countries (with Ireland, Denmark or Argentina alternatively mentioned¹). The sustainability of the high energy use has been questioned, with most mining pools being established in places with very cheap energy. While this often happens in areas with excess generation from renewables, in many cases it utilises questionable sourcing of cheap energy in some countries/regions (which are often based on coal or other fossil fuels).

2. *Proof of Stake (POS)*: This alternative consensus mechanism relies on giving more weight (and hence a greater chance to mine the next block) to nodes that have a greater “stake” in the system” (e.g. own more of the cryptocurrency). This eliminates the need for energy-consuming PoW-style mining to establish trustworthiness, and can also make generating blocks much faster. Currently, the Ethereum network is actively exploring transitioning to a PoS-type model, partially due to much lower energy costs to assure consensus.
3. *Proof-of-Authority (POA)*: This consensus mechanism can be seen as a variant of Proof-of-Stake, where the stake is the identity of the validator. POA relies on a (relatively small) number of pre-approved validator accounts or “authorities”, that have the right to validate transactions and add new blocks. Authority nodes are required to go through a pre-selection process, disclose their identity and register with a public notary database and comply with a series of rules to remain trustworthy. Since they are rewarded for doing this and receive energy in the network, they have an incentive to remain trustworthy, and avoid being compromised by attacks. POA protocols have proved especially popular in private (enterprise) blockchains, including energy applications (e.g. the Energy Web Foundation blockchain system). This is due to the high transaction rate that is achievable in POA-based systems, and much lower overheads and energy

¹Readers can consult <https://cbeci.org/> for the latest figures.

costs than, e.g. PoW systems. However, having a small number of authority nodes can be seen as going against the decentralisation principles underlying blockchains, hence this is a less suitable alternative for public, permissionless blockchains.

4. *Other protocols*: A number of other protocols have been proposed, including: proof of elapsed time, proof of activity, consensus mechanisms relying on Byzantine Fault Tolerance etc. The reader can consult Andoni et al. [29] or the NIST overview [103] for detailed discussions.

Different types of consensus protocols are appropriate for different types of blockchain systems. The main types of blockchain systems are:

1. *Permissionless blockchain systems*. This includes most of the blockchain systems supporting known cryptocurrencies, such as Bitcoin, Ethereum etc. In this type of blockchain there is no central authority granting access to the blockchain. In fact, in many cryptocurrency systems (e.g. Bitcoin), the users or holders of cryptocurrency wallets remain completely anonymous, identified only by their public key and cryptographic signature. Some wallets may be suspected of belonging to criminal activity or hacking, but until the users behind them attempt to exchange their cryptocurrency in “flat” (regular) currency, it is extremely hard to establish their real identity.
2. *Permissioned blockchains* (also known as “private” or “enterprise” blockchains). In this type of blockchain, not any party can join, there is a central authority granting access according to pre-agreed rules. Such blockchains often refer to a specific system of application (e.g. prosumers in a microgrid P2P energy trading scheme, parties trading energy given a specified protocol etc.). Permissioned blockchains can (and have) sometimes come under criticism for not following what some authors see as the “truly decentralised” ethos at the core of blockchain technology. Yet, it is worth pointing out that permissioned blockchains are still very different in implementation to centralised databases: while there is a process of verification and granting access, information is still stored and written in a decentralised fashion among nodes, on a distributed ledger.

There are advantages and disadvantages associated with each type. Permissionless blockchains are described in some sources as the only ones that are “truly” open or decentralised: it is impossible for any party to change the stored information or rules, unless they gain control of 51% of the computing power, which is unlikely in a large system like Bitcoin (although some authors have raised concerns about the increasing concentration of mining pools).

Most energy applications reported in the literature fall (implicitly or explicitly) in the “permissioned blockchain” category. This is because in energy trading, the identity of the parties trading will be generally known at least to some actors in the system (unlike cryptocurrency transactions, where wallet owners can remain completely anonymous). For example, smart meters points, where energy is imported or exported, have a physical, identifiable location on the power grid. On the flip side, however, this may also hold the promise of using forms of consensus that are quicker and much less energy-intensive than Proof-of-Work mining, which would lead to a more environmentally sustainable proposition, from an energy use perspective.

2.4.2.2 Relation between blockchains and smart contracts

Most well-known blockchain systems (e.g. Bitcoin, Ethereum) were set up around a so-called “native” cryptocurrency, and the main aim of the blockchain is to record the transaction in that crypto-currency, between users who store such currency in a digital wallet. This digital wallet is protected and accessed by users through a system of public-key (or asymmetric) cryptography, and allows transactions to be digitally signed.

In addition to cryptocurrency transactions, a blockchain can also store software code, called smart contracts, that is executed when the pre-defined conditions are met. A smart contract is embedded on the blockchain, in a similar way to a cryptocurrency transaction (which is the most common use case of blockchain). Specifically, the compiled code and specific pieces of information, such as the list of functions to be executed are sent from a wallet to the blockchain. This code and information must then be included in a block that is added to the ledger (though the consensus mechanism), at which point the smart contract code will execute to establish the initial state of the smart contract. Similar to currency transactions, cryptographic hashing secures the smart contract in a decentralised way from attempts to change or tamper with it. Once its code is stored on the blockchain, a smart contract can be

compared to a software process that will be run when specific conditions arise (e.g. a certain amount of energy consumption or production). Practically, the execution of the code embedded in a smart contract is deployed in a virtual environment that is physically hosted by all the nodes that constitute the blockchain, as if they were a single computer.

As a result, once a smart contract is deployed, it cannot be updated - if an attack occurs due to some fault or vulnerability in the contract code, it is not easy to fix, due to the decentralised nature of blockchains. This is true in open, permissionless blockchains, for example, the DAO attack on the Ethereum blockchain in June 2016 – in which the Ethereum community decided to hard fork the blockchain, resulting in a different cryptocurrency. It is possible that in a permissioned (enterprise) blockchain which most energy applications are likely to use, fixing attacks by restoring the blockchain could, arguably, be easier to do, as a central party controls the access to the system.

2.4.2.3 Definition and lifecycle of a smart contract

Smart contracts were first introduced by computer scientist Nick Szabo in 1996, with the vision of using computer code in order to automate legal contracts while using cryptography to make them secure and tamper-proof [105]. Szabo defines smart contracts as “a set of promises, specified in digital form, including protocols within which the parties perform on these promises” [106].

Another research line in the community [107] has focused on defining “smart legal contracts” (or “Ricardian contracts”), that aim to capture the defining elements of a legal agreement in a format that can be expressed and executed in software code. Many smart contracts presented in the literature do not place the same weight on the formal legal aspects as the Ricardian approach.

Their “smart” nature is related to their ability to self-enforce using a specified set of rules once the pre-defined criteria are met. When deployed on a blockchain, smart contracts can automatically reach and enforce agreements which result in a faster process and reduced costs. This is especially beneficial for recurring trust-free agreements/transactions with a low financial value such as half-hourly peer-to-peer energy trading. The core principle of a smart contract is based on the “if-then” logic which requires to program the desired outcome/action and the condition(s). For instance, the outcome of a smart contract can be an action such as the discharge of

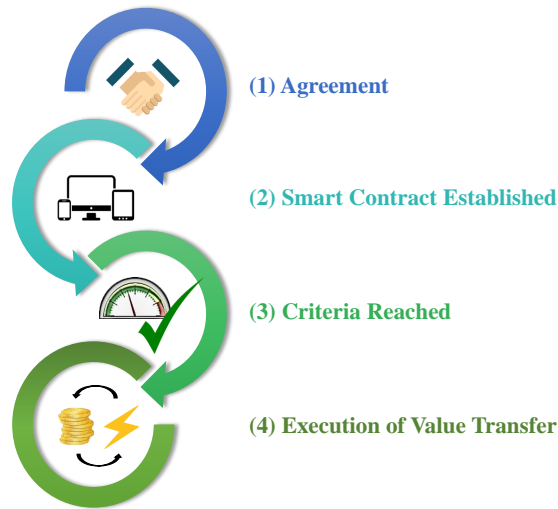


Figure 2.7: Four fundamental steps for execution of value transfer using smart contracts.

a battery whereas the condition for this action to be triggered can be the electricity export price going over a threshold value or the successful transfer of the required funds from a buyer.

Since they are secure and tamper-proof, smart contracts are used in other sectors with confidence. One example is the financial smart contract template developed by the British multinational investment bank and financial services company Barclays [108]. One of the key advantages of smart contracts over regular contracts is the cryptography techniques used. This is highly valued by utility businesses as it creates an encrypted and secure ledger of contracting actions. In addition to the recognition of this in literature, Makmur et al. [109] presents the case study of Persero, an Indonesian state-owned utility company with a reach of over 72 million customers, highlighting the role of smart contracting in billing due to its tamper-proof and secure nature.

To summarise, a smart contract is a sort of agreement between parties that is automated, enforceable and self-executing. Even though it is mostly computed digitally, some parts of the smart contract can be programmed to have human input and control. Figure 2.7 concisely depicts the lifecycle of a smart contract in four fundamental steps which are (1) agreement amongst the parties, (2) establishment of smart contract, (3) verification that the criteria are fulfilled and (4) execution of

value transfer (e.g. money and energy exchange). Step (3), namely verification of criteria reached, provides a novel advantage for the energy systems and especially local electricity markets. Indeed, smart contracts can enable automated peer-to-peer energy trading:

Smart meter data can be used to verify energy transactions and trigger the billing process of a smart contract. This would result in a fairer and faster settlement, increasing the benefit to both the consumer and producer. The main goal of smart contracts is to provide more secure transactions in comparison to the traditional contracting methods and to decrease processing and verification costs and time.

Although these characteristics make smart contracts very suitable for financial transactions using cryptocurrencies [110], the use of smart contracts energy sector is still in its development phase as there are multiple concerns related to security, privacy, scalability and billing [28, 111].

2.4.3 Application areas

In this subsection, an analysis of smart contract applications in energy systems are presented with a focus on peer-to-peer trading and transactive control in line with the previous chapters. Smart contracts are used in many applications, ranging from energy trading to the coordination of distributed assets. The type of applications of smart contracts can be categorised into two main categories: *energy and flexibility trading* on the left-hand side, and *distributed control* on the right-hand side. In this subsection, the two main themes and all the different areas of energy applications illustrated in the figure are presented.

2.4.3.1 Energy and flexibility trading

As smart contracts run on a blockchain that has been initially designed to store financial transactions, the most intuitive application of smart contracts corresponds to trading and payment between two entities. As a result, in research, smart contracts are mostly used in the context of energy or flexibility trading applications. In these applications, the main objective of the smart contract is to facilitate the matching between consumers and prosumers (providing micro-generation and/or storage), but also to propose a secured and trusted payment or settlement mechanism. Smart contracts have been used for the following specific applications:

P2P trading Smart contracts are often employed for P2P trading applications. The smart contracts first receive the bids and offers from the different stakeholders (producers, prosumers and consumers), which usually also requires a deposit from the buyers. Different approaches are then used by smart contracts to match the buyers (consumers) with the sellers (producers). Approaches range from heuristic methods to more complex approaches that include double auctions and power flow validations [112]. In terms of heuristic methods, the smart contract usually matches buyers and sellers and validates a trade as the bids come. This matching can be performed by comparing the amount of energy and the price of incoming bids and offers [110]. Once the smart contract has validated a trade, which consists of a price, an amount of energy and a time of delivery, the smart contract for P2P trading can then be used to analyse the monitoring of actual consumption and production coming from the smart metering infrastructure [113]. This analysis can then automatically trigger the settlement within the smart contract in order to distribute rewards and penalties according to the contract condition. When P2P trades do not cover all the needs of consumers or the generation from producers, smart contracts can then facilitate transactions between the peers and the grid. Troncia et al. [114] uses a smart contract-based ancillary service peer-to-peer energy exchange platform which acts as a “virtual decentralised market authority”, negating the need for the presence of a physical central operator. This is tested with 50 nodes and prove the potential application in local ancillary services. In order to minimise the computation costs of their Ethereum platform, the proposed smart contract uses a continuous double auction (CDA) model. Liu et al. [115] uses the flexibility of EVs for P2P trading using a novel Proof-of-Benefit (PoB) consensus to remove the need for an intermediary. They also achieve demand response and lower power fluctuations by providing the right incentives. Finally, smart contracts can also be used as a support for P2P trading, i.e. the trading process is not implemented in the smart contract, but a smart contract can be called to process a specific function. For example, [116] uses a smart contract to allow consumers to request energy, but also to validate eligibility, and process the financial transaction. However, the trading process that consists in matching consumers energy requests with available energy in the microgrid, is done outside the blockchain, at run time.

Peer-to-grid Although the P2P area corresponds to the vast majority of smart contracts applications reported in published research, some works also use smart contracts for P2G transactions, as it is explained by Khalid et al. [117]. Indeed, after local P2P trades have been validated by a smart contract, remaining energy needs can be traded between the consumers and the grid. In this case, the smart contract is used for billing purposes, but also to store and sign energy transactions between the prosumers and the grid [110, 118], similar to the situation in the retail market category. When Peer-to-Grid transactions are required to compensate for energy shortage or surplus, the smart contract uses the grid electricity prices at the current hour in order to determine the amount of money required for the financial transaction. The P2G also considers vehicle-to-grid (V2G) examples such as [119, 120, 121].

For example, in [119] Proof of Authority is used to validate transactions and synchronise the data which are authenticated by authorised aggregators. Moreover, the recent work of [122] studies a setting where residential batteries are aggregated through a smart contract to provide forward bids on the wholesale energy market.

Retail market Smart contracts can also be used for retail market applications, to allow consumers to choose a supplier, to sign a contract with the supplier, but also to securely store time series from the energy monitoring infrastructure and provide associated billing services [123, 124, 125, 126, 127]. This is achieved by first allowing the DSO to register every smart meter to the smart contract. Then, suppliers can broadcast their offers for energy through the smart contract, which will authenticate interested customers by using the smart meter address and by requiring a money deposit. Payment is then executed by the smart contract after the monitoring and settlement period are validated [125]. Hu et al. [128] use a trading mechanism embedded in smart contracts which uses the market prices in China as a case study. A method called encourage-real-quotation (ERQ) is employed for determining the clearing price. The proposed method allows the generator to enter their offer after the consumers bid on their required energy amount. On the other hand, Lu et al. [126] use smart contracts to create a contract between households and suppliers (once households have declared energy quantities and prices they accept to pay), to monitor the energy consumption and production of the household, and to process the settlement.

Similarly, smart contracts can be used jointly with smart meters to measure in real-time the amount of energy generated or consumed and automatically adjust demand and supply. Smart contracts can also help to implement automated activities such as defining electricity costs for a period, payment policies, times for buying and selling electricity. Indeed, by leveraging the features of smart contracts, the speed, reliability, scalability, and security of the energy markets can be improved. [129, 130].

Demand-side response In the current wholesale market settings, balance responsible parties and aggregators can contract ancillary services, in the form of flexibility from end-users to achieve equilibrium between energy supply and demand. For a demand reduction or increase, the aggregator requires the registered end-users to meet a given load profile. This process is called Demand Response (DR). Smart contracts can be used at different stages of this process. First, in the case of DR events, smart contracts can compute and store the forecasted baseline profile and the required profile for buildings that are registered to the DR event [131], or they can periodically define the available flexibility, prosumer energy profile and calculate the grid energy balance [132]. Then, similar to the use of smart contracts in P2P transactions, smart contracts can be used to set up a specific contract between interested consumers and the aggregator, in which case the smart contract specifies the acceptance of the DR request, with the required load profile [133]. Then, smart contracts can analyse the demand reduction provided by the buildings, by comparing the measured load profile with the forecasted profile. Smart contract design, from a game-theoretic perspective, has also been proposed for incentivising participation in demand-side response schemes [134, 135]. Moreover, appropriate billing and payment can also be automatically generated by a smart contract in order to reward or penalise consumers who met the targeted load profile or not respectively [136, 137].

Market design Finally, in the energy trading area, smart contracts can be used to clear a market in order to determine the prices of energy trades. Unlike the *peer-to-peer* category that corresponds to full peer-to-peer trades, in which a buyer buys energy from a specific seller, in this category, the application corresponds to hybrid peer-to-peer, as defined in [30], in which a buyer does not know which producer provides the energy procured. Hence, this category regroups applications such as double auctions [96, 117, 138, 139, 140, 141, 142, 143, 144], but also more complex market

design approaches that directly includes a validation of the trade from power flow computations, as it can be carried out using Distributed Locational Marginal Pricing (DLMP) and AC Optimal Power Flow (AC OPF) [112, 140, 145, 146]. Also, [147] uses smart contracts to implement a modified Vickrey auction. In this application, the available energy from prosumers is computed by a specific smart contract and sent to a trading smart contract. The trading smart contract also receives consumers' valid bids, and determines the winning consumer bid as the highest bid, whereas the price is the second highest price. The smart contract iterates until all bids have been satisfied or no energy is left. P2P energy trading was also proposed in [148] for electric vehicles. Indeed, [148] implements a contrary auction mechanism in which discharging electric vehicles offering the lowest price are chosen to supply a local set of charging EVs.

Unlike auctions that can efficiently be implemented within smart contracts [149], optimisations such as AC OPF are too complex algorithms to be implemented in current smart contracts languages. Indeed, as an example, Solidity language does not support complex numbers computation. However, researchers proposed different ways to use smart contracts for these applications, as an offline optimisation from which the solution is stored in a smart contract [140], or by using the alternating direction method of multipliers (ADMM) algorithm, which allows a smart contract to coordinate other nodes that process offline more complex computations as required by the optimisation problem [112, 146].

Also, hybrid peer-to-peer trading through smart contracts has been implemented in [150] by using mathematical formulas for the matching of consumers and producers and dynamic pricing. Therefore, in [150], all consumers pay electricity at the same price, which varies in time depending on the ratio and difference between the total demand and the total supply of the community.

Finally, [70] uses a smart contract design to determine the right level of subsidies for solar panel electricity production in a community. Indeed, in [70], smart contracts are used as an instrument to compute automatically the linear Bayesian-Nash equilibrium that aims to compute the right level of subsidy a government should allow to solar PV production. In this case, smart contracts are used to gather the monitoring of solar PV production, to determine the subsidy level using Cournot quantity models, to automatically contractualise the agreement between households and the

government, and finally to transfer money from the government to households that produced electricity from their solar panels.

2.4.3.2 Distributed control

EV management In the field of EV charging systems, smart contracts can be used for different purposes. First, smart contracts can implement lighter optimisation algorithms such as limited neighbourhood search with memory to balance the distribution of EV users among parking spaces while achieving fair profits distribution among the owners of EV charging places [121, 127, 151].

One of the most popular application areas of smart contracting is smart charging for EVs [152]. Smart contracts are also used for peak load shifting and shaving by leveraging the flexibility of EV loads [153]. Similar to [154, 155] which deal with smart energy communities, [156] implements an energy trading platform amongst EVs in smart campus parking lots using local controllers. In [148], a smart contract was designed to allow P2P energy trading between Vehicle-to-grid-capable electric vehicles (producers) and all EVs (consumers). Finally, [157, 158] focus their research on autonomous vehicles where they both use smart contracts for smart charging purposes.

Battery management Smart contracts are also a powerful tool that can be used to securely coordinate assets that are distributed [159]. In the case of batteries control, a smart contract can be used to store the information of distributed batteries, such as the state of charge or state of health, and automatically send control recommendations to all batteries in order to synchronise or prioritise the charge or discharge of the distributed instances, as it is shown in [159, 160]. Decentralised control of batteries has also been proposed in [122] where a smart contract facilitates the control of residential batteries to participate in wholesale markets.

Grid management The development of the Internet of Things allows grid operators to have better monitoring, understanding, and control of their network and the power systems as a whole. In this context, smart contracts can be used to securely and synchronously store data from Phasor Measurement Units when a fault happens on the grid [161]. Smart contracts can also be used to automatically coordinate actuators or take control decisions between contradictory set point requests from different

assets of the grid [80, 162]. Finally, due to the security characteristics inherent to smart contracts, they can also be used to grant access to grid data, such as market data for example in [163].

Virtual power plants The concept of Virtual Power Plants (VPP) involves the operator that monitors the production or consumption of different assets in order to better coordinate and optimise the aggregated production [122, 164, 165] or reduce curtailment [166, 167]. In this context, some authors [168] have proposed smart contracts to store and read data from distributed assets, in order to help for better synchronisation of the production.

Audit and certification of supply-chain Smart contracts can also be used to establish a transparent supply chain. Both [169, 170] take advantage of the self-executing and tamper-proof nature of smart contracts. The former, employ the chain of custody method in order to calculate and assign renewable energy and carbon credits. Ashley and Johnson [169] observed significant reductions in time and cost as smart contracts eliminate the need for external auditing. This also immediately allowed the energy producers to monetise the credits. The latter uses a similar approach. However, the focus is more on issuing guarantees of origin and green certification. Pajic et al. [171] also acknowledge the auditable quality of smart contracts in the scheduling services of EV charging.

Internet of Things Another suggested application for smart contracts in energy is IoT applications. In more detail, as Internet-of-Things concepts (IoT) become more widely used in the energy sector for smart cities and remote assets monitoring and control, there is more concern about the control and security of the data gathered by IoT devices, especially when it is managed centrally by a single system. To address this issue, “PrivySharing” provides a secure alternative with an encrypted private blockchain-based framework for smart cities [100, 172]. “PrivySharing” enables data sharing with external parties via the use of a digital token called “PrivyCoin”. As the authors show, in an IoT context, privacy is a key concern for smart contracts, as data can be transferred and shared between different parties for monitoring, bidding or other purposes. These data can include the geographical location of a prosumer, or

other personal information, that should be protected. Therefore, it is essential to provide anonymisation through encryption, hash function or other means of anonymising so that other parties do not access the data transmitted between the owner and the receiver of a communication [100, 172]. In a similar approach to “PrivySharing”, Tan et al. [173] performs privacy-preserving energy scheduling for energy services companies. Unterweger et al. [174] summarises lessons learned regarding privacy-preserving Ethereum-based smart contracts.

Smart homes and energy management systems Lately, smart contracts have also been employed for home energy management systems (HEMS) in order to coordinate flexible loads and assets such as scheduling home heating and cooling. The secure nature of smart contracts plays an important role in the coordination of home appliances in order to minimise bills or decrease the user’s carbon footprint. For Smart Home applications, smart contracts are used to coordinate assets, to automatically take control decisions (switch appliances on or off) depending on the state of some variables because they ensure the communication channel is secure [175, 176, 177, 178]. For instance, [179] proposes a “smart-home-based IoT-Blockchain” that employs three different sorts of smart contracts which allow access control, judging misbehaviour of the assets and registration of new policies to the access control. They demonstrate the application of the three contracts using Ganache, Remix, and web3.js. Rather than smart contract design, other publications focus on increasing the reliability of existing IoT services using the tamper-proof nature of the smart contracts [180]. The scale within this application may vary from a single household to an energy community. Afzal et al. [181, 182] manage the scheduling of appliances within the community to offer DR services and [136] coordinates a group of smart buildings using a network of smart contracts on the blockchain.

2.4.4 Objectives of energy smart contracts

This subsection presents the capability of smart contracts and the objectives of their use in energy. Smart contracts can be programmed to reach an agreement and verify the transfer of value between parties. It analyses the range of functions embedded in energy smart contracts in the literature. These functions can be triggered by external events or by the contract itself. The main objectives implemented in energy smart contracts were classified as functions for managing a portfolio of participants

or contracts, market clearing, storing data, optimising a problem or running complex computations. The main characteristics of each of these functions are analysed below.

2.4.4.1 User and asset management

As most of the smart contracts in the energy sector are used to facilitate energy trades, an important set of functions implemented within smart contracts focus on the management of the users and the assets. Hence, one basic function of smart contracts corresponds to the registration of the different users (prosumers, consumers, producers) [183, 184] or assets [125]. The registration allows the users or assets to define their profile (e.g. prosumer, consumer, etc.), but also to link a monitoring device to their profile [124]. This allows end-users to then authenticate themselves, using their smart meter address [117, 125]. Furthermore, the registration functions can also require a money deposit in order to validate the participation of an end-user in a smart contract. Smart contracts can also be used to grant access to data streams, as it is proposed in a function implemented in [163]. Then, the management of end-users involves functions that update the list of end-users [117], but also that record statistics related to each agent, such as the quality of the electricity provided by prosumers in [123]. Han et al. [110] proposes to store the type of producers (e.g. renewable energy generator) in order to allow buyers to access energy that follows their preference.

Similar to user management, some smart contracts implement functions for asset management, in order to sort and categorise assets, such as charging or discharging energy storage systems as proposed in [101, 119].

2.4.4.2 Contracting operations

Smart contracts can be used to set up an agreement between two entities (e.g. agents, equipment, etc.) [123]. Indeed, in smart contracts such as those described in [123], a smart contract broadcasts the list of available suppliers to every end-users, in order to help them find an adequate supplier. After the matching is completed between a producer and a consumer, the smart contract automatically sets up a signed contract between them, either for the retail market application [123] or for Demand Response events. This contract between two entities can include the amount of energy reduction/increase required, along with the time window within which the effort must be provided by the consumer [133]. Finally, billing functions have also been implemented

in smart contracts in order to automatically determine the daily or monthly bill between end-users or buildings and the energy provider [117, 136, 185]. For example, in the context of a cooperative energy community, the smart contract in [136] provides a function embedded within the smart contract to compute the bill of individuals based on the total electricity price of the community.

2.4.4.3 Management of energy bids and offers

One of the main interactions of end-users with smart contracts is the submission of energy offers. Hence, most of the smart contracts for P2P energy trading implement a function that receives and saves the bids or requirements of end-users, as it was implemented in [96, 110, 112, 147, 181, 183, 184, 186, 187, 188, 189]. Bids can include the amount of energy, the time at which the energy is needed or available, the price that is desired to buy or sell the proposed quantity of energy, and finally, also the power [188]. The bids can be specific and limited to particular assets, such as distributed batteries, as it is proposed in [189]. Finally, smart contracts are also often used to validate a bid or to determine the eligibility of an agent given his/her deposit for example [147, 184]. Once bids and offers are received, some studies implement a broadcast function that aims to communicate the received offers to the registered end-users [125, 188], or to specific trading partners [112]. Other smart contracts allow agents to get access to a ledger so they can read offers, as proposed in [188].

Therefore, smart contracts can update the bids and offers that are received and stored. A function updates the remaining quantities of energy [181, 188]. Finally, when receiving a bid or offer, the smart contract can also ensure the feasibility of the bid, by making sure the end-user has made a deposit that is high enough to afford the requested energy quantity [188], or by ensuring that the offer from a prosumer can be honoured given the remaining energy in a battery [187].

In the context of smart contracts for demand response, a smart contract can also implement a function to allow an aggregator or an end-user to automatically accept or reject a flexibility offer [133].

2.4.4.4 Monitoring

As they provide inherent security in the communication between an end-point and the blockchain, smart contracts have also been used for monitoring purposes in the energy domain. Indeed, smart contracts can be used to gather measurement data

from pre-registered monitoring assets, such as smart meters, by ensuring that the data is generated by a trusted asset. In the energy domain, smart contracts can implement functions to gather the monitoring of actual production and demand which are callable by the system operator only [118, 123, 124, 133, 136, 137, 168, 186]. These measurements can then be used in the settlement and billing processes [71]. Hence, it is necessary that prior to the measurement, the system operator registers the monitoring devices such as smart meters, as explained in subsection 2.4.4.1 and in [125]. Furthermore, system operators can also use smart contracts to synchronise monitoring systems such as Phasor Measurement Units (PMU) in order to store and facilitate access to the state of the network when a fault arises [161].

2.4.4.5 Market mechanism and market clearing

In energy trading applications, smart contracts are often used to clear a market, which consists of determining a single price for all trades by matching demand and production. In the context of smart contracts used in market mechanisms, they are initialised by a constructor function, called by the system operator, to set up the marketplace and start the state machine [96, 190].

Following this, a function is implemented that automatically determines the trading price. There are different methods to achieve this. First, it can be determined through a double auction that maximises social welfare. In this case, the function ranks the offers in ascending order and the bids in decreasing order, selecting the intersubsection point as the global clearing price [96, 110, 186]. Other methods used to determine the trading price can vary. In [117] and [181], the trading price for the whole community is the lowest price proposed by the sellers, whereas in [124] the trading price is based on a planned grid price, which is increased or decreased afterwards in the settlement phase through compensation formulas based on the quantity of energy that was produced or consumed. In [183], the price is determined as a mathematical function that depends on the total amount of energy surplus and demand, whereas [147] implements a Vickrey auction in which the buying price is the second highest price among consumers bids. A distinct approach is taken by Son et al. [190], who propose a privacy-preserving algorithm to determine the price of energy between two peers. The price is calculated as the average of the proposed prices from the seller and the buyer. This raises the concern that the market operator could take advantage of his position to be an intermediary who buys electricity at a cheaper

price than the seller and sells it at a higher price to the buyer. To resolve this issue, an encryption of the bids is proposed to maintain privacy.

Along with the computation of the trading price, smart contracts include a matching function that allocates generation to meet demand, especially in the case of P2P contracts. Meng et al. [186] and Han et al. [110] propose to first categorise the energy offers between renewable-based and non-renewable-based in order to match the buyers' preferences [110] or to give advantage to the sellers providing renewable energy [186]. Then, energy matching can be based on the output from the double auction where the bids and offers are ordered in opposite price evolution [96, 110, 186]. In [183], the matching of buyers and sellers is completed by awarding the same percentage of energy to each energy request. If there is enough energy available, all the energy requests are awarded. If not, only a percentage of each request is awarded.

In [190], the buyer with the highest price bid is matched with the seller with the lowest price offer, which is made possible by managing two arrays-based data structures. A similar principle is used in [101], where the smart contract ranks the assets (energy storage systems) by priority. Hence, the assets that require energy with the highest priority are matched with the assets that need to discharge (produce) with the highest priority. In [181], the smart contract implements immutable predefined negotiation rules in order to match buyers and sellers. After the matching of P2P buyers was completed, most smart contracts implement a balancing function that ensures that energy requirements that were not awarded met by the grid at the grid price [110, 186], as explained in 2.4.3.1. There is also work done investigating the interaction of different nodes, a margin of error and impact of competition and/or cooperation [142, 143].

In the current centralised energy markets, smart contracts implement a settlement function in order to adjust the financial transaction to the actual energy transaction that occurred, as it is verified by monitors such as smart meters. The interest of using smart contracts for settlement resides in the potential reduction in the time for the settlement, as a smart contract could potentially automatise the monitoring of actual demand and production, and thus could quickly compute the balancing costs used in the classic settlement process. In smart contracts, the settlement phase also includes a redistribution of the remaining deposit money that users transferred to the smart contract.

In [186], the smart contract rewards prosumers if they meet the energy bid they submitted in the first place, and it penalises them if they produced less or more than what was agreed in the contract. In [191], the settlement includes additional grid prices fees to include the cost of balancing services. For demand response applications, the settlement function includes a verification that the realised demand reduction corresponds to the requested effort (with respect to a baseline estimation corresponding to the hourly average load over one month of data) [131, 133]. In [110], the settlement function uses the system imbalance prices from the transmission system operator in order to settle the difference between the actual and the agreed energy consumption/production, and provides rewards if the forecast used for the bids was accurate. [192] proposes an energy internet market in which electricity charges are automatically collected by the settlement function of a smart contract, and are then distributed to beneficiaries. For Electric Vehicle (EV) charging applications, settlement functions consist of updating the agreed price of the energy trade if the energy quantity overpasses what was agreed in the contract between the EV and the owner of the charging station [193]. In control applications, the settlement function can require payment from control assets when the actual operation differs from the agreed contractual setpoint [80].

[194] propose two novel settlement mechanisms embedded into smart contracts which are namely splitting and global balancing settlement. The former splits the sellers and buyers into two categories with a coefficient that denotes their contribution to the imbalance. The latter performs settlement actions for each responsible party individually. Other examples of advanced settlement methods used with smart contracts include P2P multi-settlement markets by Nakayama et al. [130] and multi-layered imbalance settlement by Danzi et al. [195].

2.4.4.6 Financial transactions

One of the most popular applications of blockchain is cryptocurrencies. Hence, most of the smart contracts used in the energy sector implement a function to process financial transactions between two entities. When smart contracts involve financial transactions between two peers or assets, it is good practice to add a payable function that requires money deposit when users or assets register or submit bids and offers to the smart contract [80, 125]. Then, the payment function can be triggered after the settlement phase in order to proceed for payment between a buyer and a seller

[101, 110, 124, 125, 184, 188, 191, 192, 193, 196]. Payment functions for energy applications are functions that are usually called by the operator only, that use the two parties account addresses (the buyer and seller, whose address must be payable) and the amount of money required from the settlement function, and that involves the pre-defined transfer function to transfer actual money from the buyer's account address to the seller's account address, as stored in the corresponding blockchain. Then, operators can call a *close* function to proceed with the transfer of remaining money from the deposit to each entity [80, 133].

2.4.4.7 Data storage

As they are based on blockchains, smart contracts can be used to store specific data that are accessible only within the smart contract. In the energy sector, smart contracts are used to store the record of energy transactions or agreed-to contractual commitments, such as the energy quantities to be traded, price, parties involved in the case of P2P transactions, the amount of power and the time of delivery [117, 140, 187, 193].

Smart contracts store the actual production and consumption [186] even though it is good practice to limit the quantity of information stored in the smart contracts. As mentioned previously, most contracts store information about buyers, sellers that submit bids and offers or assets that participate to control applications [117, 124, 125]. This is usually achieved using hash tables such as mapping in the Solidity language. That is generated when the smart contract of a marketplace is created through the construct function.

For control applications, smart contracts store information about the current asset state, such as batteries state of charge and state of health [159] or the grid state from PMU measurements when a fault occurs [161], but also achieved operating points [80]. In demand response applications, historic and baseline profiles are used in the settlement phase to assess the quality of the response which may be load increase or decrease [131, 137].

2.4.4.8 Complex computations

Although contracting languages and the associated computational cost inhibit complex computations within the implemented functions, some studies prove the feasibility of consequent calculations within the smart contracts. For example, the demand response contract in [131] computes a baseline load profile for every user, based on

the average of hourly load data over one month. For control applications, a simplified automated negotiation is implemented in [80] to allow control assets to decide on the competitive control setpoint. For P2P applications, [150] used a complex formula to determine dynamic pricing for energy transactions within a community, using tangent and exponential functions.

Lastly, optimisation can also be executed in a contract to achieve the optimal operation of power systems. AlSkaif and van Leeuwen [146] propose a contract that coordinates the AC optimal power flow (AC-OPF) computation-based on the general consensus optimisation form of the alternating direction method of multipliers (ADMM). The ADMM is used to solve a relaxed convex formulation of the AC-OPF problem by breaking it into smaller optimisation problems that can be solved locally outside the blockchain by every participating node with limited information. In this application, the smart contract is used to break the optimisation problem into smaller pieces, to keep track of participating nodes, to realise the consensus step from the ADMM algorithm and to distribute the required information to all the other nodes. Another example of optimisation in smart contracts is for battery control, presented by Baza et al. [160], where a Knapsack algorithm is implemented. This is solved in a polynomial time in order to find the charging schedules of the distributed storage units that are the most efficient in terms of energy use.

Additionally, [121] optimises the distribution of EVs among charging stations by solving a bi-objective mixed integer programming problem (MILP) by using a limited neighbourhood search algorithm with memory. [197] implements an open-source automated energy trading algorithm, written in the Solidity language, in their microgrid smart contract which was tested on an Ethereum blockchain platform.

2.4.4.9 Synchronisation and coordination

In the context of distributed control applications, smart contracts are used to coordinate and manage distributed assets. Hence, they can implement synchronisation functions such as in [159] where the smart contract synchronises different batteries from a close to real-time monitoring of their state of charge (SoC) and state of health (SoH). Then, smart contracts can act as a coordinator and aggregator for decentralised optimisation algorithms such as the ADMM algorithm for AC OPF resolution in [112, 146]. In [161], the proposed smart contract is used to retrieve the state of the grid from PMU measurements when a fault is detected by one PMU. In

this case, the communication security and trust characteristics from smart contracts are highlighted to gather measurements of the monitoring assets. Although synchronisation is difficult to be achieved due to the time required for PMU measurements to be added to the blockchain, synchronisation could be performed afterwards if measurements include a time tag. In demand response applications, smart contracts such as those proposed in [96, 181] implement control functions that securely send control signals to end users appliances in a coordinated way. As presented in [179, 180], home energy monitors such as sensors and actuators can communicate securely with each other by using the *require* method from solidity language. Finally, smart contracts can also coordinate the execution of specific tasks by local endpoints by using the *emit* method, as it is presented in [136] to execute the optimisation of batteries and controllable loads schedules at the building level. Lastly, some smart contract applications adopt a state machine model in order to manage the transition between different tasks, functions or even other smart contracts, as presented in [117, 186].

Table 2.1: Overview of P2P research and industrial projects [13, 14, 15].

| Project Name | Country of operation | Year |
|---------------------------|--|------|
| Allgau microgrid | Germany | 2017 |
| American PowerNet HQ | USA | 2018 |
| BCPG Apartment Microgrid | Thailand | 2018 |
| Brixton Energy | United Kingdom | 2019 |
| Brooklyn microgrid | United States | 2015 |
| BSES Rajdhani P2P project | India | 2019 |
| Community First Village | United States | 2015 |
| Electron | United Kingdom | 2016 |
| EMPOWER | Norway, Switzerland, Spain and Germany | 2015 |
| Enerchain | Europe | 2017 |
| Energy Collective | Denmark | 2016 |
| EnerPort | Ireland | 2018 |
| EPC Solar Group | Australia | 2019 |
| Lichtblick Swarm Energy | Germany | 2010 |
| NGRcoin | Belgium and Spain | 2013 |
| NOBEL | Germany, Spain, Greece and Sweden | 2012 |
| P2P-SmartTest | Finland, UK, Spain and Belgium | 2015 |
| P2P3M | United Kingdom and South Korea | 2016 |
| PeerEnergyCloud | Germany | 2012 |
| Piclo | United Kingdom | 2014 |
| Smart Watts | Germany | 2011 |
| SonnenCommunity | Germany | 2015 |
| TransActive Grid | United States | 2015 |
| Vandebron | Netherland | 2014 |
| Wongan-Ballidu P2P | Australia | 2019 |
| Yeloha, Mosaic | United States | 2015 |
| Micro-Grid Sandbox | United States | 2016 |

2.4.5 Review of innovative industrial and academic projects

The possibility of automatic processing in a decentralised and secure way using smart contracts has motivated the creation of a large number of projects related to power systems in different areas, such as energy markets, data storage, energy billing and CO₂ traceability. These projects use public and private blockchains with different consensus mechanisms, according to the requirements of each implementation, where the permissioned blockchains are gaining popularity due to the capacity to control access to the chain, even though - unlike open blockchains, perfect anonymity of participants is not always guaranteed. In order to show the trends in the adoption of smart contracts in the energy industry, a list of implementations and demonstrators are compiled. The following is an indicative list of projects that have created an impact in the smart contract industry and research community and presented innovations or novel implementation of smart contracts in the wider energy industry.

- *Energy web foundation (EWF)*: A non-profit organisation founded by Grid Singularity and the Rocky Mountain institute. EWF's mission is to accelerate a customer-centric electricity system view using blockchain to facilitate the deployment of decentralised apps and technologies. In 2019 the EWF launched the Energy Web Chain (EWC) [198], based on Ethereum using a public and permissioned Proof-of-Authority (PoA) consensus mechanism, promising an increase in the transaction capacity by 30x and a decrease in energy consumption in 2-3 orders of magnitude in comparison with Ethereum.
- *Grid Singularity*: A German Start-up focused on a decentralised energy exchange platform for local communities. In 2018 presents the Decentralised Autonomous Area Agent (D3A) Market Model [199], an open energy exchange engine to model, simulate and operate energy trading markets in local communities. The energy exchange can be operated by a unique DSO or multiple agents, using smart contracts to define the energy trading and matching between the customers.
- *Power Ledger*: Australian company founded in 2016, focused on peer-to-peer energy trading. Power Ledger deploys a dual-token ecosystem [76] with a PoA consensus mechanism to decrease energy consumption, limit double-spend tokens and control the access to the chain. The Power Ledger platform allows

the DSO or prosumers to manage a microgrid with a real-time energy market, traceable renewable energy certificates, manage energy peaks using ESS or choose the type and quality of the energy.

- *LO3 Energy*: founded in 2012, LO3 Energy wants to improve the community-based local generation and energy exchange. The Brooklyn Microgrid [68] was developed by LO3 Energy as a proof-of-concept peer-to-peer energy trading using existing grid infrastructure. The gained experience in the Brooklyn Microgrid helps to develop an energy exchange platform called Exergy [200] as a permissioned data platform for peer-to-peer tradings, and the Pando platform [201] that can be used by the DSO to pool local resources and establish an energy marketplace, based on bidding auctions between business and prosumers. In December 2019, LO3 Energy along with Green Mountain Power deploys a pilot energy marketplace called Vermont Green [202] as the first US authorised marketplace.
- *Prosume.io*: founded in 2016, prosume.io [203] proposes a platform based on smart contracts, IoT devices and the Prosume token with multiple applications, including peer-to-peer energy trading, smart billing, grid balancing and trading processes optimisation for electricity and gas, according to local laws in each country.
- *IBM*: In October 2016, IBM launched Hyperledger Fabric [204], an open-source, modular and permissioned blockchain focused on business. Hyperledger includes modular consensus protocols, whereas Chaincode is the equivalent of Ethereum smart contracts. In association with IBM, Energy Blockchain Lab [205] creates a decentralised carbon credit management platform in China that expect to cut between 20% - 50% the average 10-month carbon asset development cycle. Another relevant energy applications based in the Hyperledger are Car eWallet [206], Sunchain [207], and Tennet [208].
- *Share&charge*: A German foundation focused on e-mobility. Share&charge [209] promotes the Open Charging Network (OCN) as a decentralised solution for EV charging services. Different services for charging stations are included, such as Green certificates, instant payment and eRoaming contracts. These services are

provided by external companies using the OCN implementation with the Open Charge Point Protocol (OCPP).

2.4.6 Results of the systematic literature review

This section presents the results from the systematic literature review undertaken in this thesis. As shown in Figure 2.8, while the research trend for the use of smart contracting for energy applications started in 2011, it remained low key for 6 years. It is worth noting that much of this early, pre-2017 literature concerns smart legal contracts (also called Ricardian contracts), a rather different concept. Ricardian contracts are often very complex to define and crucially they are *not* implemented on a blockchain and often not even necessarily web-based. While they attracted research interest, they saw limited practical applicability. The research outputs rapidly increased after 2017, as the use of blockchain and DLT-based smart contracts were introduced and started to grow in popularity. The number of publications per year reached a pre-COVID peak in 2019 with 88 publications. This trend is likely to continue as smart contracting in energy attracts increasing interest as a means of distributed control and also aids the deployment of emerging local energy markets.

Based on the systematic review (published in [12]), 178 papers are divided into 11 key application areas which are discussed in detail in Section 2.4.3. The most prominent research area for the use of smart contracts identified are P2P energy transactions, which are the main topic of almost a quarter of the literature works reviewed. Following this, 17% of the works propose smart contract-based solutions for energy markets such as market clearing and settlement, while 14% employ smart contracts for EV management which includes smart charging and coordination.

The eleven areas are grouped into two main themes which are namely (1) *Energy and Flexibility Trading* and (2) *Distributed Control*; these are presented with blue and green shades in Figure 2.9. Around 60% of the reviewed literature works feature the theme of energy and/or flexibility trading (which includes P2P, market design, DR, retail market and peer-to-grid). On the other hand, the theme of distributed control is dealt with in 35% of the works reviewed. Nevertheless, the applications areas are more diverse including assets such as batteries, EVs, smart homes, VPPs, etc. More than half of the distributed control papers focus on the coordination and scheduling of EV charging, as they are foreseen as a critical challenge for the power systems. The remaining papers address the challenge of grid management, whether this concerns the

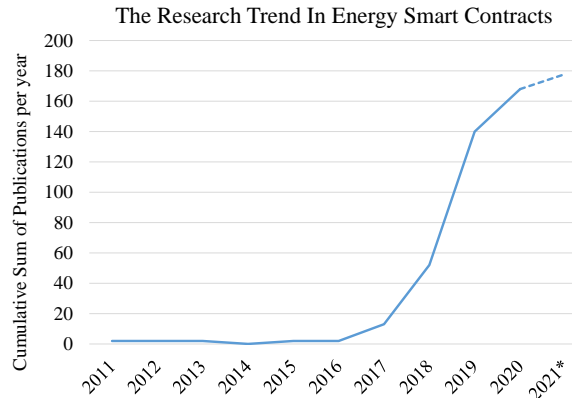


Figure 2.8: The research trend in energy smart contracts.

control of voltage control in the distribution grid or allocating control tasks amongst system operators. Another highlight is that 3% of the reviewed literature uses smart contracts for carbon audits and certification. This is anticipated to be a powerful method of carbon monitoring for meeting the net zero-emission goals.

Similarly, Figure 2.10 shows the contribution and explicit use of smart contracts functions (as presented in Section 2.4.4) by energy researchers. It is important to note that implicit use of functions (such as financial transactions for example) was not captured in this graph, that only displays functions or capabilities explicitly used and mentioned by researchers. The most used capability of smart contracts has been their ability to clear a market, either using auctions or other custom algorithms. This capability of smart contracts is tightly linked to another functionality embedded in smart contracts that is the management of bids and offers before clearing a market. This management corresponds to all the functions aiming to receive and store the bids and offers from the different buyers and sellers of energy. The high proportion of implementation of these functionalities shows that smart contracts in the energy domain have mostly been used for market applications. Then, other functionalities of smart contracts are equally represented in the literature, including the synchronisation of assets for distributed control, but also storage of energy related data, financial transactions and monitoring.

2.4. BLOCKCHAIN-BASED SMART CONTRACTING IN ENERGY SYSTEMS

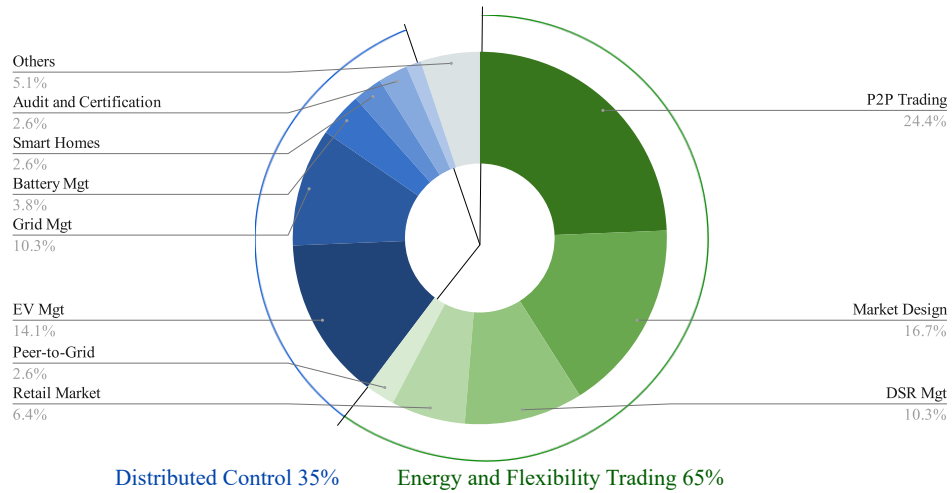


Figure 2.9: Classification of the literature in different categories of energy applications.

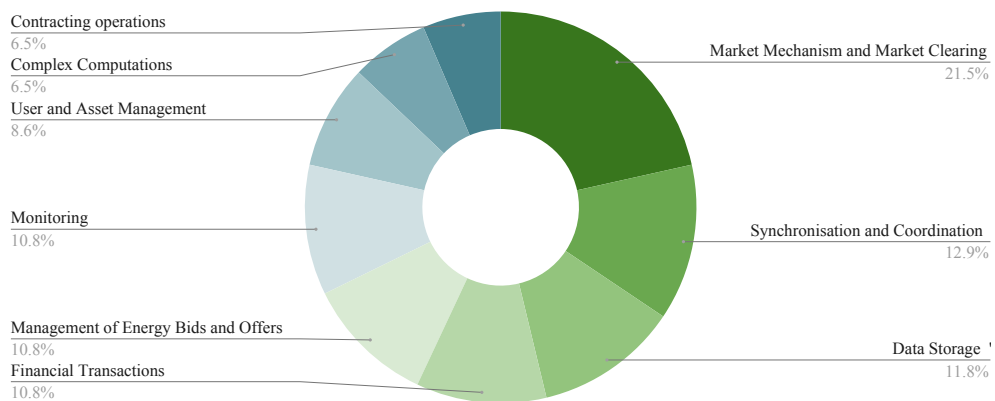


Figure 2.10: Classification of research contributions on smart contracts functions.

2.4.7 Discussion of research gaps

This section presented the findings from a systematic review of the literature concerned with smart contracting in energy systems. While a more detailed discussion of limitations along with future research directions is provided in Chapter 6, the research gaps identified are summarised here.

The most significant knowledge gaps are regarding the financial and environmental costs of executing smart contracts. While the research in energy systems proposes the use of smart contracts concentrating on its enabling aspects, there are only a few articles which evaluate the economic and/or environmental impact. The smart contract execution takes place on a blockchain and this ledger process has a very high energy consumption. If the computation takes place during peak demand hours, this might yield high costs and carbon emissions which in return might negate the benefits achieved by P2P market implementations. Therefore, this thesis designs and executes a smart contract for P2P trading applications and evaluates its environmental and economic implications against the benefits of using consumer-centric markets. Further details are provided in Chapter 6.

2.5 Key findings

This chapter provided a review of the key literature in three separate sections which relate directly to the next chapters. The identified research gaps were presented at the end of each section in detail.

First, local energy system modelling techniques were discussed in Section 2.2, focusing on the community energy coordination and optimisation techniques. Additionally, the limited consideration of user comfort and network operation in the literature was identified as a research gap.

Following this, the concept of consumer-centric energy markets was introduced and different types of P2P market mechanisms were classified in Section 2.3. In addition to the peer-reviewed literature, a survey of the pilot projects was provided to reflect the efforts related to the implementation of local energy markets. The technologies that enable the implementation of P2P markets were discussed which included smart metering and blockchain-based smart contracting. In addition, the research gaps were identified with regards to the under-explored carbon saving benefits of local energy markets.

2.5. KEY FINDINGS

Furthering the discussion on enabling technologies, Section 2.4 presented blockchain-based smart contracting. This part of the review summarised the applications and objectives of smart contracting in energy systems, using a systematic review methodology. The results from this extensive analysis revealed that P2P energy trading was the most common application area. This is inline with the existing industrial and academic projects which utilise smart contracting mostly for local energy trading. Following this, the research gaps were identified which included lack of environmental and economic cost considerations when implementing smart contracting in local energy systems.

Chapter 3

Bottom-up Modelling and Optimisation of Local Flexibility

This chapter introduces the local flexibility modelling and optimisation techniques used in this thesis for the simulations of local energy systems. Using a bottom-up approach, the flexibility offered by smart assets (including EVs and battery systems) is simulated individually rather than in an aggregated manner. Following the modelling methodology, the process of user-centric optimisation is explained which leverages the flexibility and programmable nature of the smart assets to minimise bills. The optimisation algorithm was designed such that it maximises self-consumption in the community without compromising user satisfaction. Additionally, this chapter presents a modified version of the optimisation function which allowed the implementation of distributed curtailment in order to model the participation of residential users in demand-side response (DSR).

It should be noted that this chapter describes the modelling and optimisation methodology in order to provide the background for the work and results presented in the next chapters, in specific Chapter 5 which focuses on the simulation of the use-cases.

3.1 Introduction

Currently, almost 40% of the UK's carbon emissions are contributed by households [210]. Hence, a bottom-up approach is required to tackle this issue to realise the potential of carbon and cost savings in local energy systems. The uptake of domestic-scale smart assets such as EVs and batteries, coupled with the advancements in smart

home and IoT technologies, enable the implementation of transactive control in local energy networks. This means that the passive energy consumers can now become service providers for the network and/or shift their load in order to minimise their bills. In the field of smart local energy systems, various studies [38, 211, 212] highlight the significance of bottom-up modelling and neighbourhood coordination to enable the participation of residential users in balancing services. This provides benefits for network operation and contributes towards the decarbonisation of the energy systems.

Hence, in this thesis, bottom-up modelling techniques were employed with the addition of user satisfaction considerations which are often overlooked in literature. Following this, community-level mixed integer linear programming (MILP) optimisation and peak shaving simulation methods were utilised to simulate and evaluate the value of local flexibility. The methods demonstrated in this chapter are taken further in Chapter 5 (with the addition of heat pump and thermal building models) and applied to two use-cases. While this chapter focuses more on the simulation methods, Chapter 5 provides detailed results and analysis of findings.

3.2 Bottom-up modelling methods

This section describes the different smart and flexible assets simulated. In this chapter, battery, EV and rooftop solar PV models are explained (heat pump and building models are in Section 5.2).

3.2.1 Distributed energy storage

As this thesis focuses on the distributed flexible assets, only domestic-scale batteries were simulated. For the simulation inputs, the specifications of Tesla Powerwall were used as a reference [213]. The capacity of the assets was varied between 5.0 and 13.5kWh. The roundtrip efficiency was assumed to be 90%.

The equations below outline the battery modelling methodology. Equation 3.1 shows the calculation of stored energy in the battery. This simply requires the stored energy level from the previous time step and the combined effect of the scheduled charge and/or discharge actions in this period. As shown in Equation 3.1, if no charge or discharge actions are realised, $E_{B,t}^i$ (i.e. kWh of stored energy) is equal to the energy stored in the previous time step, $E_{B,t-\Delta t}^i$ minus the amount of energy lost through idle self-discharging (denoted by ω_t). However, if the battery is charged

or discharged then the combined effect of the power import and export actions is multiplied by the corresponding charging and discharging efficiencies. The input and output power are limited by the constraints - shown in Equations 3.2 and 3.3. Lastly, to convert power values into energy usage during the time interval, they are multiplied by Δt . The efficiencies related to charging and discharging of the battery were assumed to be constant (i.e. both equal to 90%), disregarding the dependence on the charging/discharging power, temperature and battery age.

$$E_{B,t}^i = E_{B,t-\Delta t}^i \times (1 - \omega_t^i) + \left(\eta_{BC,t}^i P_{BC,t}^i - \frac{P_{BD,t}^i}{\eta_{BD,t}^i} \right) \times \Delta t \quad (3.1)$$

$$0 \leq P_{BC,t}^i \leq P_{BC,\max}^i \quad (3.2)$$

$$0 \leq P_{BD,t}^i \leq P_{BD,\max}^i \quad (3.3)$$

The state of charge (SoC) of the batteries is calculated by dividing the current level of stored energy by the battery capacity. This is shown in Equation 3.4 where the battery capacity is denoted by $E_{B,N}^i$. Additionally, as demonstrated in Equation 3.5, the SoC of the individual batteries is restricted to a range which yielded a depth of discharge of 60%. The minimum and maximum SoC levels were 20 and 80%.

$$SOC_t^i = \frac{E_{B,t}^i}{E_{B,N}^i} \times 100\% \quad (3.4)$$

$$SOC_{\min}^i \leq SOC_t^i \leq SOC_{\max}^i, \quad (3.5)$$

3.2.2 Solar energy generation from PV panels

Solar PV generation is one of the most prominent distributed generation types in the UK due to the previously available highly favourable economic incentives known as Feed-in-Tariffs [214]. This is expected to reach as high as 14% by 2032 [32]. For this study, an open-source Python-based module called Global Solar Energy Estimator (GSEE) [215, 216] was used to calculate the generation output from the PV solar panels. Using the weather data from 2019 for the use-case location in Scotland (i.e. latitude=57.4459, longitude=2.7878), timeseries of PV power flows were obtained. The peak power values ranged from 2 to 10 kWp and the overall efficiency was

assumed to be 20%. The simulated PV panels did not have a tracking feature in terms of a single or double axis. The total PV output from the community was aggregated to enable energy sharing as shown in Equation 3.6.

$$P_{PV,t} = \sum_1^N P_{PV,t}^i \quad i \in [1, 2, \dots, N] \quad (3.6)$$

3.2.3 Electric vehicle

The local DNO forecasts 45% EV penetration by 2032 in the north of Scotland [32]. The predicted increase in EV adoption poses a threat to the system in terms of potential imbalance and overloading. Hence, it is important to model the flexibility that can be offered by EVs which can be coordinated through methods of transactive control to mitigate their negative impact on the grid. A data-driven approach was used for the implementation of EVs in the simulation. For this, real data from the Energy Systems Catapult’s Consumer Vehicle and Energy Integration (CVEI) pilot study was used. Only the home charging events were taken into account as this thesis has a local network outlook. This dataset included features such as the duration between charging events, start and end SoC and charge duration.

In order to identify different EV charging patterns in the dataset, clustering was employed using the open-source Scikit-learn library on Python [217]. Studies [218, 219, 220, 221] demonstrate the use of k-means for large energy datasets with timeseries and iterate that it is the most prominent approach in literature. This is because k-means allows clustering of large datasets with multiple attributes at relatively lower computations cost. When compared to gaussian mixture models [220] and k-medoids [221] methods, performance of k-means was better in the context of distribution network load modelling and load profile characterisation due to its fast convergence and higher validity indices. Hence, k-means clustering method is adopted in this study as well.

To summarise, the k-means clustering method was chosen as it was proven to cope well with large datasets such as the one used in this section which consists of 200 users and 15,700 charging sessions. The number of clusters (i.e. k) was determined through experimentation for a range of k values between 1 and 10. For each k value, the distortion score was obtained which reflects how well the cluster centroid represents the data points in that cluster. It is computed as the total squared distance between each data point and the cluster centroid. Then, these distortion values were plotted

against the corresponding k values. Using a visual evaluation method called “the elbow method”, the point of inflection was determined [222]. This is not necessarily the point with the lowest distortion score but it is the point when the slope of the line abruptly changes creating an elbow in the plot. In this case, the k value of 2 corresponded to the point of inflection.

Therefore, using the k -means clustering method, two dominant user behaviours were identified as the shorter weekday commuter charging and the weekend charging behaviour which involves travelling longer distances and requires a longer charge period. For the clustering process, six attributes were evaluated which are shown in Figure 3.1. This figure shows the scaled outputs for the two identified groups. The red line represents the first set of charging events which are classified as the weekend charging sessions. This group had a longer time between the charges, a lower SoC at the start and hence, required higher energy from the charger and the session took longer. It should be noted that the end-of-session SoC for both groups were almost the same which was around 100%. The blue line represents the charging sessions due to everyday shorter distance driving (e.g. commuting). This group starts the session with a higher SoC and hence, it has a lower energy consumption and shorter charge duration. This group also exhibits more frequent charging events with less time between charging sessions. Using this information, EVs with different charging patterns were randomly placed on the network.

3.3 Community-level optimisation methodology

The previous section provided an overview of how the flexibility of smart assets was modelled. This section describes the optimisation methodology used to achieve maximum self-consumption and minimum costs. It should be noted that as the focus of this thesis is on community-level coordination and energy sharing, an aggregated objective function was used rather than individual objective functions per household. Additionally, the optimisation model in this work uses historical data rather than performing near real-time operational scheduling.

The community perspective of this thesis reduces the complexity of the problem as the aim is to minimise the net power import as a neighbourhood through energy sharing rather than minimising energy export individually at every node. The latter

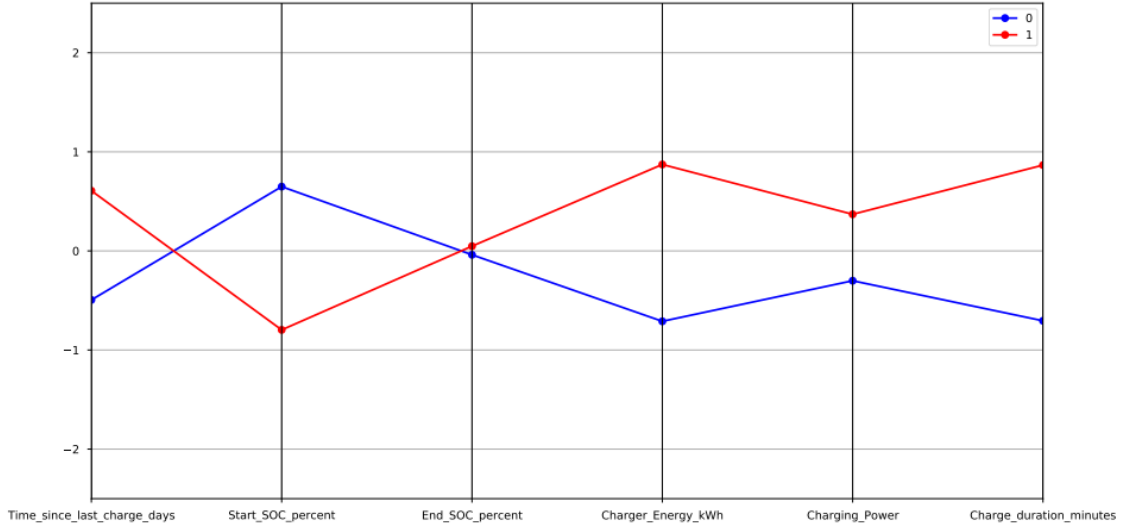


Figure 3.1: K-means clustering of EV data where two user groups were identified, shown in red and blue.

would result in a larger problem which would require a decomposition-based optimisation technique [48]. However, in this case, decomposition was not required. Hence, the mixed integer linear programming (MILP) method used by various studies in the field of neighbourhood coordination [26, 45, 65] was adopted. Another decision criterion was that the optimisation module and solver had to be open-source and free. The implementation of MILP was available through the open-source Python optimisation package, Pyomo which provides free solvers such as the COIN-OR branch and cut (CBC) [48, 223]. As the work in this thesis yielded industry collaboration, it was essential for the optimisation package to be in Python and open-source for integration with the industrial partner’s simulation platform. As the simulation workflow developed in this thesis is bottom-up, it enables the implementation of decomposition algorithms. For instance, if the future work chooses this approach, the distributed MILP optimisation by [50] can be implemented.

3.3.1 Objective function

In this thesis, optimisation was performed to simulate the community behaviour required for reaching the minimum cost and hence, achieving higher self-consumption and self-sufficiency through load shifting. Similarly, the same methodology can be

applied to minimising the carbon footprint of the communities, incurred by importing electricity from the grid during periods of high carbon intensity.

Two of the objective function inputs are electricity import and export tariffs as denoted by λ_{buy} and λ_{sell} in Equation A.4. Imported and exported power are calculated in an aggregated approach which are the variables of the cost function shown in Equation A.4.

$$\begin{aligned} \min \sum_0^T \lambda_{buy} \cdot \sigma_{n,t,t_0} \cdot P_{import} - \lambda_{sell} \cdot P_{export} \quad \forall n \in N \\ \text{where } P_{import} \in \mathbb{R}_{\geq 0} \text{ and } P_{export} \in \mathbb{R}_{\leq 0} \end{aligned} \quad (3.7)$$

Similarly for the carbon emission minimisation scenarios (presented in Chapter 5), the grid import and export tariffs were replaced by grid carbon intensity and local generation carbon intensity, respectively. The former was obtained from the National Grid's carbon intensity data portal [5] and the latter was input as 0 kgCO₂/kWh as the only type of local distributed generation simulated was solar PV.

3.3.2 User-centric optimisation

In order to quantify and incorporate the increasing level of inconvenience incurred to the user by delaying the operation of their assets, a penalty matrix σ_{t,t_0} (in A.4) was designed for each asset, n where delaying a load with respect to its scheduled start time results in an increasingly higher penalty. This is shown in Figure 3.2 which illustrates a slice of the delay-based penalty matrix taken at the 32nd time step. In this case, the EV arrives home at $t=32$ and was scheduled to start re-charging upon arrival by the user. However, as this time step corresponds to 4:30 pm, it is during the peak pricing period and therefore the charging event is delayed to off-peak hours. The penalty factor σ_{n,t,t_0} is multiplied with the cost in the objective function in Equation A.4. Hence, the optimiser did not solely minimise the financial or carbon costs as its cost function also includes some consideration of the inconvenience caused to the user to achieve some economic or environmental benefit.

For instance, delaying the EV charging to a later time in the day results in lower user utility as the asset is kept idling with a low SoC and could not be used if the user decided to unplug and use the EV before the end of the declared availability window. For example, the Economy 7 tariff offers a cheaper electricity import rate for seven hours during the night and when it was input, the EV would be scheduled during

the low cost hours. The incorporation of σ_{n,t,t_0} ensured that the charging action was rescheduled as close to the user set schedule as possible. In this case, charging the EV at the start or at the end of the low cost duration would make no difference in terms of financial costs. Nevertheless, delaying the action of charging further away from the user’s preferred start time would result in a higher penalty, denoted by σ_{n,t,t_0} where t_0 is the user set period of operation and t is the one chosen by the optimiser.

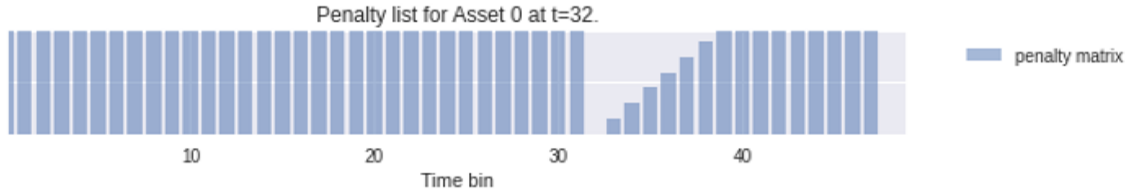


Figure 3.2: A slice of the delay-based penalty matrix for an EV that arrives home at $t=32$ and was scheduled to start re-charging upon arrival by the user.

To summarise, the significance of the delay penalty matrix is that it minimises the disutility that would be caused by the transactive control actions. Therefore, it brings a user-centric approach by integrating the user’s perspective into the purely cost or carbon minimisation algorithms. This feature differentiates the optimisation methodology in this thesis from other studies such as [45, 50, 65] which focus on the benefits of transactive control and neglect the impact on the users. The most recent review articles such as [26, 49] highlight the research gap with respect to integrated user comfort modelling. While most of the research in this area considers thermal comfort limits related to heating and cooling, there is a lack of consideration for the inconvenience caused by delaying the user-scheduled EV charging actions. Lotfi et al. [49] stated only one publication that considered and quantified this as “discomfort index” [66]. However, this study is limited to home energy management system (HEMS) optimisation rather than the neighbourhood-level coordination demonstrated in this thesis. Lastly, the consideration of user comfort is taken further Chapter 5 where the thermal comfort of users was investigated in the first case study.

3.3.3 Variables and constraints

The power imported from the grid and power exported to the grid are variables and hence, they are manipulated by the optimisation algorithm in order to minimise

3.3. COMMUNITY-LEVEL OPTIMISATION METHODOLOGY

the objective function. In most of the scenarios, the imported power is minimised by shifting the demand to the hours of solar output while adhering to a list of constraints which reflect the technical and operational limits of the assets and the network.

The power balance in the system is denoted by the relationship between power import, export and asset behaviour - as shown in Equation A.1. The term $p_{t,n}$ is the power consumption of the each asset, d_t is the inflexible load and g_t is the generation. The total sum of all terms in the equation should be equal to zero at each time step and, as shown previously in Equation A.4, the convention for power import is positive and power export and generation outputs are negative. The optimiser performs load shifting by scheduling EVs and batteries to maximise self-consumption and self-sufficiency at the neighbourhood level. In order to leverage cheap import costs (irrespective of whether that is in terms of financial or carbon costs), the optimiser employed a technology-agnostic approach by increasing or decreasing demand from different smart assets.

$$\sum_0^N p_{t,n} + d_t + g_t - P_{\text{import}, t} - P_{\text{export}, t} = 0 \quad \forall t \in [0, \dots, T] \quad (3.8)$$

This action was bounded by the flexibility range of the asset which is expressed as minimum and maximum operational bounds as shown in Equation A.2. Insights from the ZUoS pilot case showed that turning EV charging down to 0 kW of usage disabled the option of resuming charging of the vehicle. Hence, this information was reflected in the turned down capacity (i.e. τ_{\min_t}) which was limited to 1.4 kW.

$$\tau_{\min_t} \leq p_t \leq \tau_{\max_t} \quad \forall t \in T \quad (3.9)$$

The business-as-usual operation profiles were used to calculate the total energy consumption of smart assets in an arbitrary time horizon which is 24 hours in this use-case. The values for each asset were used as a reference to ensure that the demand was only shifted and not decreased which could have resulted in end-user disutility and discomfort. This equality constraint is portrayed in Equation A.3 where N is the total number of assets, t is the time step of the optimiser and t_0 is the time step fed in from the business-as-usual case.

$$\sum_0^T p_{t,n} \times \Delta t = \sum_0^T p_{t_0,n} \times \Delta t \quad \forall n \in N \quad (3.10)$$

When the optimisation algorithm was deployed on a community level, the total financial or environmental benefit for the whole community was maximised through minimisation of the aggregated electricity import costs minus the aggregated electricity export. For instance, the excess solar energy of one household may be used to charge the EV at another node in order to minimise the communal carbon footprint.

3.4 Curtailment methods for demand-side response modelling

This section is about the potential of using local flexibility for participation in residential DSR services in order to offer balancing services to the DNO and the grid through the aggregation of the flexibility offered by individual assets.

3.4.1 Participation in residential demand-side response services

Integrating network awareness into the optimisation algorithm ensures its operation within voltage limits without overloading the network. Using this approach, community coordination and optimisation result in a reduction of the costs without inducing excess imbalance on the grid.

Distribution system operators recognise the threats posed by the planned uptake of low-carbon high-consumption devices such as EVs and heat pumps. Additionally, they acknowledge the flexibility that these residential and small commercial loads can offer. Hence, the business model of DSR is now scaled from large commercial loads such as cold stores and battery farms to flexible neighbourhoods. Essentially, this shows that energy communities are seen as virtual power plants from the perspective of the system operators [26].

For instance, Western Power Distribution (WPD) operates as a DSO in different regions of the United Kingdom which are namely the Midlands, South Wales and the South West [6]. Their “Sustain-H” service is a curtailment subscription where the households are required to deliver a pre-arranged decrease in their demand. According to WPD [6], this service will be commercially available by March 2023. There are two curtailment windows of 4-hour duration which start at 8 am and 4 pm. For households to be eligible, they need to have one of the following technologies; EV

3.4. CURTAILMENT METHODS FOR DEMAND-SIDE RESPONSE MODELLING

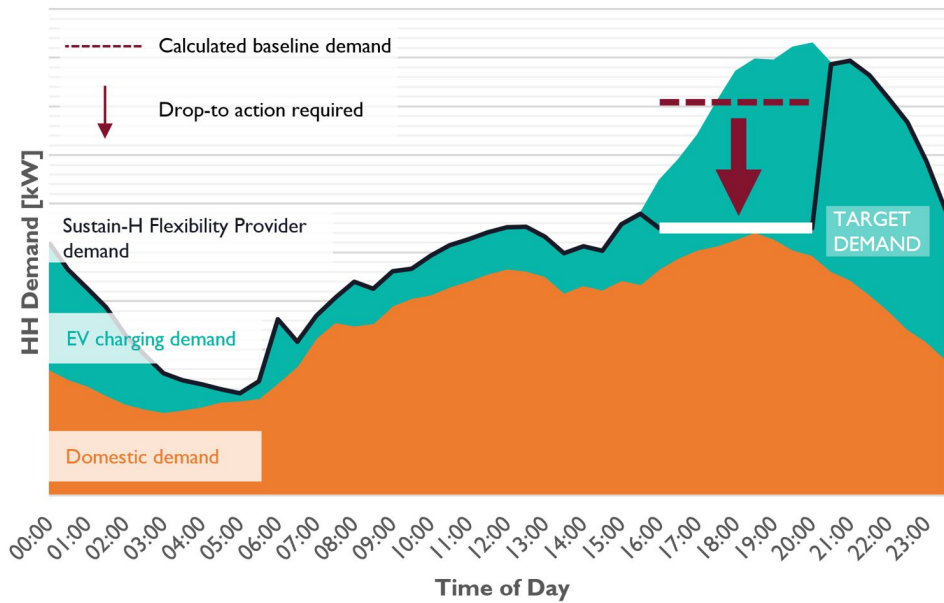


Figure 3.3: Illustration of the LV distribution network DSR service Sustain [6].

chargers, heat pumps and batteries. WPD [6] estimates a total flexibility of 1.3 GW across its operational regions by 2030.

The visualisation of this residential DSR service is shown in Figure 3.3 where the EV charging demand increases the energy demand and significantly amplifies the peak evening consumption. The plot shows the impact of the 4-hour Sustain-H service (between 4 and 8 pm) where all of the EV charging is curtailed. The compensation for this service is rewarded per kW of demand reduced and according to the congestion zones determined by the DNO. The prices are £8.00/kW, £2.50/kW and £1.00/kW for red, amber and green congestion areas, respectively.

3.4.2 Peak shaving and curtailment method

Using WPD’s residential DSR demand turn-down service as a reference and a curtailment strategy was implemented in the optimisation code. Peak shaving was performed by imposing a maximum power import limit. This limit was coded as an inequality constraint in the optimisation algorithm in order to achieve cost or carbon minimal results while participating in the residential DSR service. This is shown in Equation 3.11 where the imported power at every time step was curtailed to be less

than or equal to the variable limit, $P_{\max, t}$. During the curtailment periods (e.g. 4 to 8 pm), this limit was set to match the inflexible household demand.

$$P_{\text{import}, t} \leq P_{\max, t} \quad \forall t \in T \quad (3.11)$$

In some simulation cases, this limit was applied for the entire day rather than focusing on red-rate periods. This means that instead of just shifting the peak in time, the peak import value was reduced. This is because in some of the cases, the morning peak was observed to be higher than the evening surge or that the evening peak was just shifted to a time after 8 pm. Therefore, this constraint caps the power import level to the given limit at any time during the simulation. To achieve peak shaving results with the maximum effect, the optimisation code was modified to implement the constraint in Equation 3.11.

3.5 Network-aware optimisation approach

This section provides an overview of the network-aware optimisation modelling technique that requires interfacing of the optimisation and network modules. It also briefly presents the results from the optimisation and DSR service participation simulation. However, the discussion of the results is kept concise as the focus of this chapter is on the modelling and optimisation methodology. Instead, the results from more detailed real-life case studies are later presented in Chapter 5 along with a discussion of limitations and implications for various stakeholders.

The outputs of the neighbourhood coordination and DSR simulations include optimised operation schedules for each asset modelled in the neighbourhood, the total cost associated with net imported active power and incurred delay penalties. In order to yield these outputs and simulate the economic benefit from the DSR participation, green, amber and red congestion zones had to be determined. The battery, EV and solar PV assets were randomly distributed to the 55 nodes present in the European LV network provided by the IEEE [7] shown in Figure 3.4. A power flow analysis was performed to ensure that the network was operational with the random asset placement, on the distribution system simulator OpenDSS [224]. The maximum peak (i.e. $P_{\max, t}$) was read at the secondary substation node (shown in green in Figure 3.4). The red, amber and green zones were assigned according to the number of assets located at each feeder. The inflexible demand on the system

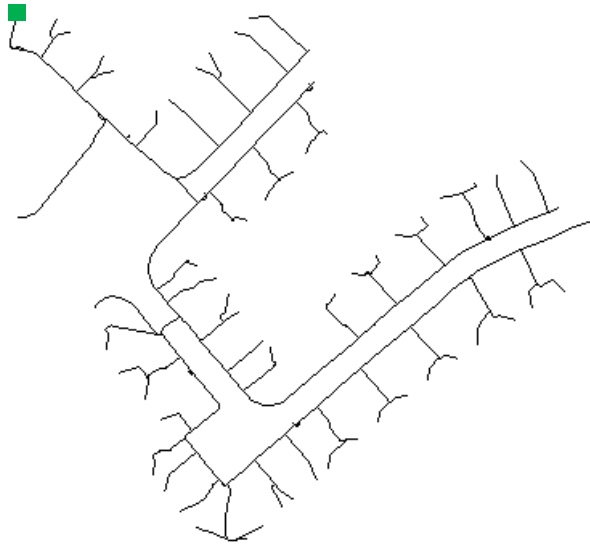


Figure 3.4: One-line diagram of the European low voltage test feeder where the substation is marked with a green square [7].

(which forms the business-as-usual scenario) was not modelled but instead real half-hourly residential consumption data from the Thames Valley Vision project [225] (in Southeast England) was fed into the nodes as consumption profiles, using the Python interface of OpenDSS [224].

The simulation revealed that the peak demand could be curtailed up to 34% of its maximum value. Therefore, it resulted in decreased power losses (2.3%) and lower stress on the network. Due to the variation in the DSR compensation, some households obtained an annual revenue of £14 and the ones in the red zone with the highest flexibility volumes were paid up to £122. In other words, the houses placed in the red congestion zone earned 8 times higher compensation per kW than others in lower congestion areas. The users who provided the highest value to the DSO had more than one asset (e.g. EV and battery) and were located in the red zone. This shows that this service may create an economic disparity between the users in the same neighbourhood. In their report, the Centre for Sustainable Energy examined social justice in the future energy systems and highlighted how certain flexibility services can contribute to the wealth gap as the users with higher flexibility volumes often have the capital to invest in EVs and home batteries while less flexible households

are often already using the bare minimum volume with no additional flexible capacity from costly smart assets [226].

To summarise, the network-aware optimisation methodology shown in this chapter creates a feedback loop which allows monitoring of the grid signals. This increases the relevance of this thesis for DNOs and aggregators and also ensures healthy operation of the system.

3.6 Key findings

This chapter demonstrated a user-centric and bottom-up approach to modelling distributed demand and generation starting from asset-level and reaching community-level simulations on the distribution network. It is important to consider user comfort when performing optimisation for minimum cost and/or carbon footprint to make sure that the life quality and utility of the users are not compromised. To achieve this, the optimisation methodology in this chapter incorporated a delay-based penalty matrix that was minimised inside the objective function.

Additionally, this chapter demonstrated the value of distribution-level flexibility to the DSO and the potential economic revenue it can bring to the participants. To achieve this, a network-aware optimisation technique was introduced which achieved interfacing between Python and OpenDSS. In the future, the need for residential DSR and hence, network-aware optimisation is expected to increase as the number of EVs and heat pumps on the distribution networks grow.

The user-centric community coordination and optimisation methods shown here are taken further in Chapter 4 through the integration of local energy markets. After that, Chapter 5 uses the same methodology to simulate network-aware curtailment and P2P trading case studies.

Chapter 4

Local Energy Markets and Co-simulation of the Grid and Market

This chapter builds on the optimisation and grid simulations by adding the layer of local energy market simulations. Briefly, it explains the motivation behind the use of local energy markets. It presents the co-simulation structure which facilitates the communication between the market and grid models. It compares community-based and auction-based P2P trading methods and proposes a novel approach to integrate carbon awareness into the local energy market design. It analyses the relationship between energy storage and P2P trading and evaluates their separate and combined effect on community self-sustainability and self-sufficiency. Additionally, it discusses the use of P2P trading during some noteworthy times of pricing affected by the COVID-19 lockdown and the winter gas scarcity. The results from the methodology presented in this chapter are shown in Chapter 5. Parts of this chapter were published in [33].

4.1 Introduction

In the business-as-usual setup with a flat tariff, there is no communication of the real-time grid stress, carbon intensity or wholesale pricing to the end-users on the distribution network. However, dynamic pricing and local energy market technologies can transfer this critical information to the end-users through pricing and other methods in order to influence their consumption patterns and the magnitude of peak

load. Therefore, using peer-to-peer trading, load shifting and peak shaving algorithms, energy communities become more self-sufficient and reduce their reliance on the central generation.

The main motivation for co-simulation of market and grid in this thesis is the need for a holistic approach towards local energy systems in addition to the two dominant streams of research which focus on either efficient and fair design of local energy markets or achieving more balanced networks via distributed control and virtual power plants. There is recent work that explores the effect of local energy markets on LV distribution networks [83, 84, 85]. As detailed in Chapter 2, research in the field of local and distributed energy trading has yielded multiple methodologies that enable further advancements in distribution network decentralisation. The use of local energy trading algorithms allow for further integration of flexible assets and improved local network balancing due to better utilisation of local energy resources [44, 86, 87, 88]. Co-simulation of both market and grid layers is essential in local energy systems modelling as the most optimal market actions may lead to high or low voltage levels which increase the burden on the distribution system operator.

4.2 Market and grid co-simulation methods

In this section, the market and grid co-simulation architecture is presented which shows the transfer of information between different layers of modelling. Following this, the two most common P2P market designs are demonstrated which are namely, auction-based markets, making use of blind double auctions and community-based markets, relying on neighbourhood-level supply-to-demand ratios.

In this section, IEEE LV European case study was used which was also employed in [83, 227] for co-simulation of local energy systems. The details regarding the grid model were presented in Chapter 3.

According to Sousa et al. [30], there are two main P2P market design approaches which are “full P2P” and “community-based P2P”. Others such as [77, 80] categorise two types of P2P markets with respect to how the energy price is set where either the energy prices are set by individual sellers (pricing model similar to Airbnb and eBay) or the pricing is decided according to the demand via a local ledger (similar to Uber). The so-called full P2P market solely depends on multiple bi-lateral contracts between producers and consumers and the price of the dispatch is determined by the inputs

from the involved parties. It allows for user heterogeneity in the sense that the users can limit their choices to green DER generation and express their willingness-to-pay through bids. However, it depends on communication and trust between different parties. The other approach, namely community-based P2P, may be considered as less decentralised as certain actions such as trade management are handled at the community-level. This task is handled by a community manager who can be a peer, aggregator, DSO or a centralised algorithm which has access to the user information. There is no direct negotiation between the peers which significantly decreases the burden on computational and communication systems. Additionally, there is a hybrid approach which is a combination of the two previous approaches. For instance, there are studies that incorporate bi-lateral trading between microgrids that have nested community-based P2P markets. In this study, both of the traditional approaches are simulated and compared. However, only the coordinated approach of balancing the supply and demand of the local network is taken further via the integration of carbon awareness. Hence, the modifications of community-based P2P markets, which include carbon-aware, inter-community and intra-community variations, are used in the case study presented in Chapter 5.

4.2.1 System model

There are two main factors that deem a P2P transaction “threatening” from a network point of view which are high voltage (i.e. the system is long) or low voltage (i.e. the system is short) levels due to supply and demand imbalance, and high loadings of transformers and lines due to high import rates during cheaper periods of consumption. Co-simulation of market and grid ensure that disruptive transactions that yield such high-risk grid signals in the system are prevented. Through the use of the feedback loop shown in Figure 4.1, system stability and loading indicators are communicated to the market layer. This is a pre-requisite for clearing a transaction between the two parties if an auction-based P2P method is used. If a low voltage value occurs when simulating a community-based P2P method, the P2P price for that period is reset to match the grid price which removes the incentive to consume more of the cheaper local energy.

Figure 4.1 depicts the simulation methodology that has four core components which are listed below. It should be noted that without the carbon awareness module

(i.e. the second component), the methodology yield a co-simulation of the network and the local energy market.

1. Community-based P2P market
2. Carbon awareness
3. Optimisation
4. Network simulation

The simulation workflow starts at (1) community-based P2P market module where the aggregated consumption and generation of the community is used to evaluate the supply-to-demand ratio (SDR). The local SDR value is applied to the grid electricity import and export tariffs in order to evaluate the local pricing of electricity. If the market design is carbon-aware, then the dynamic carbon incentives are calculated which affect the computations of P2P buy and sell prices. The module of carbon-awareness is explained in detail in Section 4.3. In short, a carbon incentive is applied to the local sell prices to encourage sharing of local energy generation when the grid is producing energy with high carbon intensity.

Once the P2P buy and sell prices are computed, they are input into the optimisation module where mixed integer linear programming is performed at a community scale to minimise costs. The resultant time-series of energy import and export from different end-users are mapped onto the LV network and simulated in the network module. This module outputs power flow analysis and per-unit voltage analysis using the open-source distribution network software OpenDSS.

4.2.2 Community-based P2P

There are many ways a market can be cleared, all of which may be applied to the context of local energy systems. Hence, the scope of this study was narrowed down to one of the most popular approaches in literature which involves the use of SDR to compute P2P trading prices. P2P energy trading or sharing takes place between prosumers and consumers where energy surplus from prosumer households is shared and consumed in the community. P2P markets are usually designed to function without an intermediary or a central authority. In this study, a local energy market layer was built with enabling functions to allow trading amongst the participants

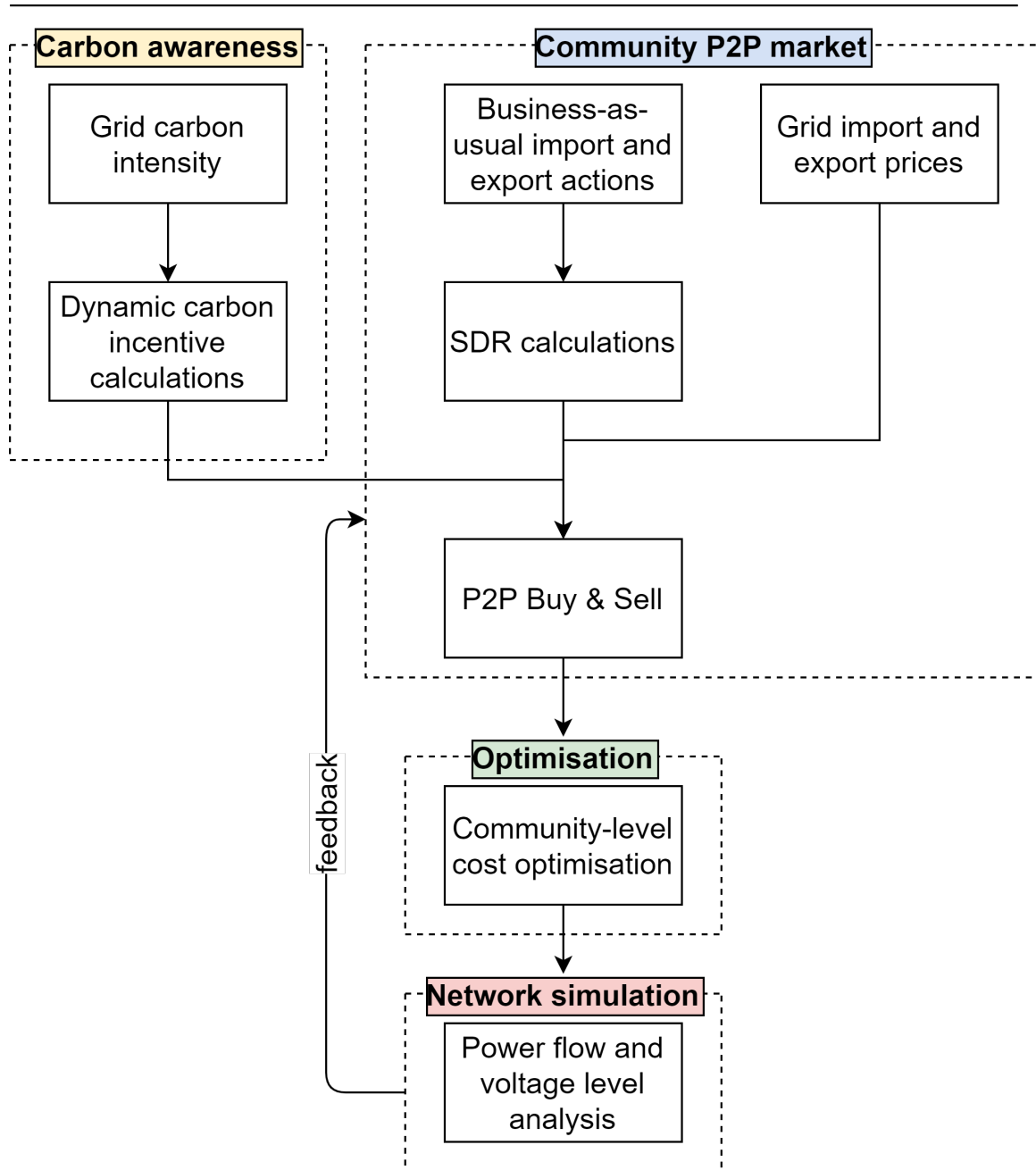


Figure 4.1: Simulation architecture for carbon-aware community P2P market.

to maximise community benefit. This method provides the option for prosumers to trade electricity with other community members who contribute to the local economy [228].

A well-known method of designing local energy markets include the calculation of SDR which is simply the local generation available in a network divided by the electricity demand [81]. As formulated by Liu et al. [229], the economic relationship between electricity price and SDR is inversely proportional. This means high SDR yields relatively low prices and vice versa. Various works in literature [81, 227, 230, 231] make use of SDR-based P2P pricing models. The same method was employed in this thesis to model community-based P2P market where the P2P price is determined in a less decentralised fashion through the use of aggregated community level data rather than individual bids and offers. As shown in Equation 4.1, SDR (i.e. ρ) was calculated as the ratio between aggregated power export and import from the households (i.e. nodes). The aggregated power export includes PV generation and any excess discharge from the battery. The inflexible household demand, EV charging, battery charging and other loads contribute to the power import. When SDR is equal to one, the local network is self-sufficient with no excess power export. If SDR is less than one, the system is short and vice versa if its value is higher than one. The P2P buy and sell prices are scaled to reflect the state of the community.

$$\rho(t) = \frac{\sum_0^N P_{export,n}}{\sum_0^N P_{import,n}} \quad (4.1)$$

Using Equation 4.2, P2P sell prices were computed where P2P sell price is a function of SDR. Similarly, P2P buy price which is a function of both SDR and P2P sell price was calculated as shown in Equation 4.3. In the following equations, $P2P_{buy}$ and $P2P_{sell}$ are the prices for users participating in P2P energy sharing in the community. λ_{buy} and λ_{sell} denote the price of energy imported from and exported to the grid. SDR is represented by ρ and the P2P pricing functions are presented for variable levels of SDR in the network.

$$P2P_{sell}(t) = f(\rho_t) = \begin{cases} \frac{\lambda_{sell,t} \cdot \lambda_{buy,t}}{(\lambda_{buy,t} - \lambda_{sell,t}) \cdot \rho_t + \lambda_{sell,t}} & 0 \leq \rho_t \leq 1 \\ \lambda_{sell,t} & \rho_t > 1 \end{cases} \quad (4.2)$$

$$P2P_{buy}(t) = f'(\rho_t) = \begin{cases} P2P_{sell,t} \cdot \rho_t + \lambda_{buy,t} \cdot (1 - \rho_t) & 0 \leq \rho_t \leq 1 \\ \lambda_{sell,t} & \rho_t > 1 \end{cases} \quad (4.3)$$

The computed P2P pricing for different scenarios was then fed into the optimiser which aims to minimise costs by increasing community-level self-sufficiency. This enabled the comparison of half-hourly dynamic pricing and various P2P tariffs. The approach assumed 100% accurate forecasting of solar output and energy demand from EVs. Figure 4.2 shows the summer and winter P2P pricing where the grid import tariff was based on 2019 prices of the dynamic Agile tariff by the energy supplier Octopus. The export price was assumed to be 5p/kWh similar to other studies in the field such as [81].

Regarding dynamic or variable pricing, this is used as a basis for P2P pricing rather than a flat tariff as the aim is to simulate the future of P2P in energy systems and numerous studies including [232] foresee a transition to this approach in the future. It is a more consumer-centric approach where the domestic consumers are billed using similar half-hourly prices to the commercial ones rather than having a fixed tariff (i.e. a volumetric calculation using a fixed p/kWh rate). There is also the commonly known time-of-use (ToU) pricing where the p/kWh rate varies for different times of the day which usually correlates to higher rates for higher demand periods. For instance, electricity prices from 4 to 7 pm would be higher to reflect the evening peak whereas from 1 am to 4 am when the system is long, the prices would be lower. Hence, this method of pricing would also result in demand shifting and is shown to result in merely shifting the peak rather than reducing the peak consumption [37, 233].

A British energy supplier called Octopus [234] readily offers their “Agile” electricity tariff which is an indexed half-hourly dynamic pricing that tracks the wholesale price of electricity (i.e. the domestic rate changes every 30 minutes instead of a fixed rate). On numerous occasions, this resulted in negative pricing (i.e. the energy supplier paid its customers to consume electricity). However, this also means that there is usually a steep price from 4 pm to 7 pm during the evening consumption surge. The following logic in Equation 4.4, is used to determine the prime-time pricing. It uses the distribution cost coefficient (μ) multiplied by the wholesale cost of electricity (λ) and Pr which is the peak-time premium (which was equal to 12p/kWh during prime time in 2019). Then it caps the price at 35p/kWh if the previous outcome is higher than this value. This is because on average the fixed tariffs were in the range of 15-20p/kWh in 2019 and it could be argued that exposing domestic consumers to extreme fluctuations in the system would be unfair.

$$\min((\mu \times \lambda + Pr), 35p/kWh) \quad (4.4)$$

Figures 4.2 and 4.3 show local P2P market prices alongside the grid tariffs. Both figures depict a summer week in the top plot and a winter week in the bottom one (where the week starts on a Monday). This is to reflect the variations between working and non-working days and also the seasonal differences that arise from the changes in demand and supply. The winter week exhibits increase in residential loads due to higher heating demand due to colder weather conditions and lower solar energy output in the northern hemisphere (i.e. higher demand, lower supply). Whereas, the summer case has the higher solar energy output due to longer hours of sunshine and higher levels of solar irradiance and lower demand (i.e. lower demand, higher supply). For these results, a neighbourhood of 65 users, with 45% EV and 14% solar PV and battery penetration, was simulated. SDR and hence, the P2P prices were calculated on a 5-minutely basis.

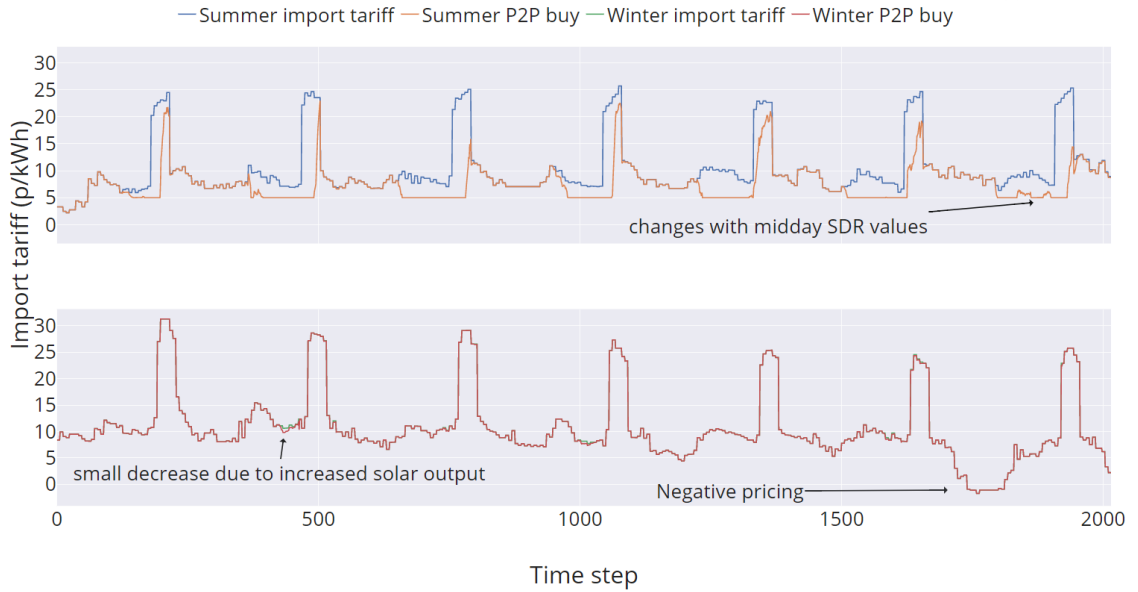


Figure 4.2: Half-hourly community-based P2P buy prices based on dynamic grid import tariff.

The top plot in Figure 4.2 shows the summer case with solar generation present during the day. There is an overall significant reduction in P2P pricing where the peak prices are lower than the import tariff in summer. As shown in the bottom plot, there

4.2. MARKET AND GRID CO-SIMULATION METHODS

is very little difference between the grid and P2P prices in winter. This is because as previously denoted by Equation 4.3, P2P buy prices are equal to the grid tariff when the SDR is zero (i.e. $P2P_{buy} = \lambda_{buy}$). Additionally, when SDR is more than 1 (i.e. a local surplus), the value of export is capped at 5p/kWh, making it more profitable to store and sell later - as illustrated by the plateaus in the summer P2P prices (shown in orange). From the consumer's perspective, shifting their consumption towards midday is incentivised as this is cheaper than the grid overnight import price in the summer. The top plot in Figure 4.2 annotates a pattern where the midday import pricing on a Sunday in the summer case (i.e. Day 7 on the top plot) follows the varying SDR values. The bottom plot shows the winter pricing and there is almost no decrease in P2P pricing except a slight decrease (i.e. 0.68p/kWh) in P2P pricing during solar generation periods. As Agile tariff was used as an input, the users participating in P2P were also able to leverage the occurrence of overnight negative pricing on Saturday night due to the surplus on the system (possibly from wind generation).

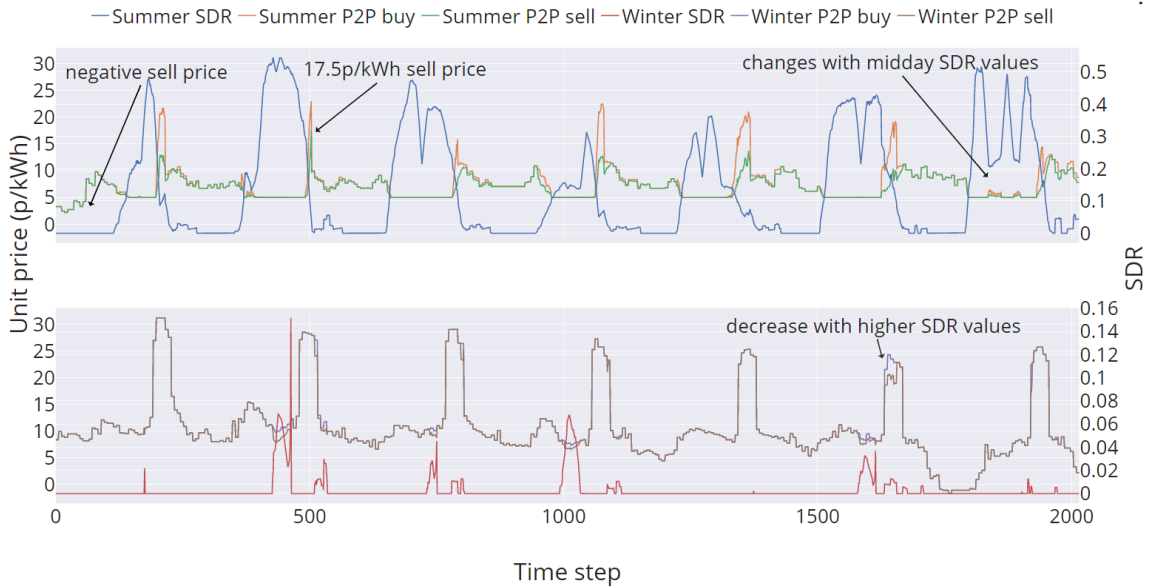


Figure 4.3: Half-hourly community-based SDR and corresponding P2P buy and sell prices in summer (top) and winter (bottom).

Similar to Figure 4.2, Figure 4.3 also shows a summer and winter case in the top and bottom plots for community-based SDR values and the corresponding P2P buy

and sell prices. The general trend for SDR was that the winter values are 30% of the summer ones. This is because of increased load due to heating and decreased contribution from solar generation. The previous figure (4.2) illustrated that P2P buy prices are lower than the grid buy prices for the summer months but closely follow grid import prices in winter. This applies to P2P buy prices as well. In this case, a grid export tariff of 5p/kWh was used. As shown in the bottom plot, lower SDR during winter months leads to highly rewarding export prices for prosumers due to scarcity of local resources. The P2P export prices follow P2P import prices which are based on the dynamic grid tariff and hence, P2P export during winter is much higher than the flat grid export rate. The annotation in the bottom plot shows a slight decrease in P2P sell pricing which is linked to positive fluctuations in SDR values. As depicted in the top plot, SDR increases with higher solar production in summer and hence, when there is more local supply, P2P sell prices are capped at the grid export price. Nevertheless, at a point of a sudden drop in SDR, the P2P sell price was more than tripled and reached a value of 17.5p/kWh (as annotated in the top plot). Another extreme in this summer week was when the sell price was negative which indicates a surplus of energy in the whole system and is reflected to local energy producers (in this market design) through the use of a dynamic grid tariff.

4.2.2.1 Relationship between energy storage and P2P market participation

A sensitivity analysis was performed to investigate the effect of storage penetration (i.e. storage-to-demand ratio) and P2P participation levels on the community self-consumption and self-sufficiency levels. Self-consumption is the ratio of loads supplied by solar generation over total solar energy output (denoted by SC in Equation 4.5). Whereas, self-sufficiency represents how much of the total load is covered by local generation. This is shown Equation 4.6 where self-sufficiency is abbreviated as SS .

$$SC = \frac{\sum_1^N E_{supplied\ locally,n}}{\sum_1^N E_{PV,n}} \quad (4.5)$$

$$SS = \frac{\sum_1^N E_{supplied\ locally,n}}{\sum_1^N E_{demand,n}} \quad (4.6)$$

Figure 4.4 (a) shows that P2P participation and storage penetration levels act as substitutes with a varying ratio at higher storage penetration levels which can be

approximated as a 4:1 ratio. This means increasing P2P participation by 4% has a similar effect on self-consumption as 1% increase in storage penetration. This shows that P2P markets accelerate the route to self-consuming communities by decreasing the magnitude of storage required. Over 90% self-consumption levels were reached when the whole community has a P2P market with only 25% storage penetration. Assuming that P2P market and implementation costs were lower than storage systems, this indicates a considerable cost saving for the community. On its own, complete P2P market participation cannot increase self-consumption beyond 50%. This is because self-consumption is mainly increased by rescheduling loads to periods of local generation output and this is limited to the flexibility of the loads. Beyond this value, there is a need for storage to capture excess energy generation in the community and discharge during periods of peak load. However, with no P2P participation, over 57% penetration results in more than 90% self-consumption. Hence, P2P participation saves the need for 35% extra storage installation and hence, it saves all the costs associated with hardware installation and maintenance.

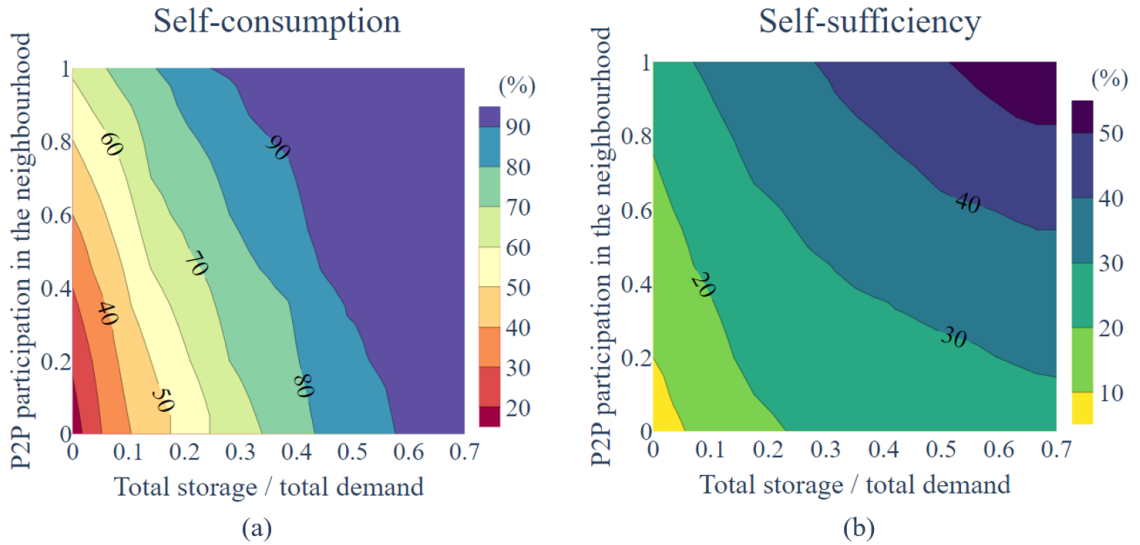


Figure 4.4: The impact of P2P participation and storage penetration levels on self-consumption (a) and self-sufficiency (b).

Another aspect to note in Figure 4.4(a) is that the gradients of the lines that separate the different levels of self-consumption are changing. The gradient becomes less steep for higher levels of storage. This indicates that bigger contributions from storage assets are required as the target self-consumption level increases for low levels

of P2P participation. For instance, as shown in the plot, when P2P is zero, an extra volume of 2% storage is required to increase self-consumption levels from 20 to 30%. Yet, the required added volume increases to 15% if the community wants to increase their levels from 80 to 90%. On the other hand, when P2P participation is 100%, the width of these zones becomes significantly smaller and similar to one another. For instance, full P2P involvement yields 62% self-consumption on its own. To reach 70, 80 and 90%, almost even increments of approximately 10% storage are required.

Without the co-existence of the P2P market and storage, the self-sufficiency value is capped below 30%. To cover more than 30% of the total load using local generation, both P2P participation and storage have to be implemented. Figure 4.4(b) illustrates the effect of these two variables on the self-sufficiency of the community. As shown, the relationship demonstrated in Figure 4.4(a) and (b) are different. From the perspective of self-consumption, P2P participation and storage may be regarded as substitutes (i.e. due to the linear relationship) where P2P participation reduces the requirement for installation of storage assets. Whereas, from a self-sufficiency perspective, they are complementary and their co-existence is desired to obtain self-sufficiency levels over 30% with a maximum of 52%. Increasing self-sufficiency means that more of the local demand is covered by the local generation. Hence, this results in lower costs for consumers and higher benefits for local producers. Full P2P participation and 53% battery penetration yields 51% self-sufficiency. Without P2P, this would be limited to 26%. Therefore, P2P participation reduced reliance on the grid by 25%. Consequently, this would reduce the stress on the grid and as the demand was covered by local renewable generation, the carbon emissions would be also reduced. Lastly, as 25% more of the demand was covered by local generators rather than commercial power plants, the revenue would be retained in the community which connotes to positive socio-economic effects.

4.2.3 Auction-based P2P

In addition to the community-based markets, another common methodology in LEM research makes use of the existing auction models and applies these to the context of local energy sharing and distribution networks. There are numerous auction methods such as [235, 236], however, double blind auctions populate most of the recent auction-based publications [83, 143, 237, 238, 239]. Three different methods, shown in [16, 240], were compared as shown in Table 4.1 where the double blind auction method outperforms the Huang Multi-Unit Double Auction method [235] in terms of percentage energy traded and welfare. The latter is a multi-unit auction that updates the demand to adjust their quantities to match the supply in case of a shortage and vice versa. Uniform pricing ensures maximum welfare, however, almost 10% of the pool remains unused. Lastly, the double blind auction method results in a 10% lower social welfare but achieves the highest level of energy shared. The advantage of the method by Huang et al. [235] is that it has a strategy-proof approach with respect to the reservation price and is shown to achieve lower levels of underreporting of the available generation by the sellers which may be used to boost the market price. As such considerations are out of the scope of this study, the trading method of Double Blind Auction [16] (based on [241]) is chosen as it results in the highest levels of energy sharing.

The following methodology was used to simulate the auction process. Each participant declares their interest to participate in the P2P auction. They submit a quantity which is the amount of energy to be imported or exported in kWh along with a reservation price (p/kWh). The reservation price is the preferred maximum buy price for the consumers and the minimum sell price for the prosumers.

At the time of this experiment, the electricity import and export tariffs were around 15 and 5p/kWh respectively, this situation creates an opportunity to form a

Table 4.1: Comparison of auctioning algorithms in terms of energy traded, welfare and other criteria using the Huang and Uniform models presented by [16].

| Method | % Shared energy | Welfare |
|--------------------------------|-----------------|---------|
| Uniform | 91.78 | 1.0 |
| Huang Multi-Unit Auction [235] | 87.43 | 0.97 |
| Double Blind Auction [16, 241] | 99.50 | 0.90 |

Table 4.2: Preferences of P2P trading participants

| | Buy, sell price | Description |
|--------------|------------------------|---|
| Preference 1 | 15, 5 | prefers cheaper electricity |
| Preference 2 | 20, 5 | willing to pay a premium for buying local |
| Preference 3 | 15, 3 | sells cheaper energy to lower income households |
| Preference 4 | 10, 5 | prioritises low-income/price-sensitive households |

local energy market where the locally generated energy is valued at a higher price by the consumers in the community, leading to a higher profit for the distributed renewable energy generation. In return, the consumers reduce both their carbon footprint and bills. From a community perspective, local energy transactions increase self-sufficiency and hence, reduce dependency on the grid supply which primarily consists of polluting sources.

In this energy market, there is also room for expressing preferences such as local consumption and green energy consumption in a similar way to the multi-class energy management work [27] in community-based markets. Additionally, local energy can be subsidised for enabling more affordable consumption by lower income households. This potentially offers a novel way to subsidise the energy usage in low-income households as buying local energy would be cheaper than importing from the grid. The different preferences of users can be expressed through pricing such as cheaper value, higher willingness to pay for local energy, discounted energy offer for low-income residents and price-sensitive users in Table 4.2.

As a result of co-simulating the auction-based P2P market and the European LV feeder grid, it was found that the aggregated active power export from the nodes increased by 14% and the reactive power import decreased by 8% as shown in Table 4.3. This is because the self-sufficiency and self-consumption levels were increased due to higher sharing of electricity in the network. However, this market design yielded 2% increase in losses and more significantly 2.2% higher voltage imbalance. Voltage imbalance in this thesis and other publications [83] is calculated according to the IEEE’s definition of phase voltage unbalance rate which is the maximum voltage deviation from the average phase voltage divided by the average phase voltage [242]. Voltage fluctuations pose a challenge in this case. With higher roof-top PV and EV penetrations to reach net-zero goals, the sudden evening spike in demand due to the decreasing solar output and connection of loads such as EV and heating is expected

Table 4.3: The effect of the auction-based market on the network in comparison to the business-as-usual case.

| Grid signals | Difference |
|----------------------------------|------------|
| Power losses | 1.90% |
| Aggregated active power export | 14.37% |
| Aggregated reactive power demand | -7.64% |
| Voltage imbalance | 2.2% |

to grow. Such sudden changes in demand and supply values cause an imbalance in the system.

4.2.4 Comparison of community-based and auction-based P2P markets

There were two types of local energy markets studied in this thesis which were based on community-level supply-to-demand ratios and individual auctions. In this subsection, these two market models are compared and the decision to take the method of community-based P2P trading forward is justified.

The auction-based market design offers individual freedom of choice and autonomy and relies on the notion of individual cost minimisation. Yet, the preferences for green energy and an option to donate energy to deprived homes may be expressed through the upper and lower limits of the user's bids and offers. On the other hand, the community-based method enables cooperation and sharing in the community towards the common goal of maximising the community's self-sufficiency rather than focusing on individual cost minimisation. The neighbourhood target can be altered to maximise savings in terms of cost and carbon.

From a technical perspective, compared to the auction-based P2P method, community P2P approach slightly increased the grid import by 2.97% and yielded negligible differences in social welfare and profits (in specific, lowered it by 2% and 1% respectively). However, the decision to choose the community-based markets was not driven by technical performance alone. A significant determining factor was the feasibility of implementing this technology by 2032 in the use-case in Scotland.

In this thesis, year 2032 was chosen as it is a critical point in the Distributed Future Energy Scenarios (DFES) [32]. This thesis decided to simulate 2032 rather than 2050 to reflect the DSO's perspective and provide local rather than national

context (see Chapter 5). This choice enabled the case studies to use local projections for renewable energy and smart asset penetrations in Aberdeenshire using Scottish and Southern Electricity Networks (SSEN)'s analysis. On a macro scale, the FES are useful as they bring a range of possible strategies based on political, techno-economic and social perspectives [243]. However, these scenarios do not reflect the potential and energy requirements of the north of Scotland observed by SSEN [32] - which is the location of the use-cases used in this project.

Therefore, the P2P market type was chosen according to how feasible its adoption would be by 2032. Community-based markets were evaluated to be the most compatible with the existing system in the next ten years [14, 30]. This is because this method yields a common pricing signal for the entire community which decreases the complexity of clearing the local market with potentially hundreds of participants which would require multiple clearing rounds and longer computational time. Additionally, the auction system poses the risk of malicious bids and the formation of coalitions which might result in unfairly high local prices that would require research into market regulation. Furthermore, information regarding participants' preferences was not available from the pilot study and hence, this would result in a less realistic simulation of 2032. Whereas, the community-based market design avoids such problems as it uses the supply-to-demand ratio data for the designated microgrid to determine the price. Sharing this information with the DNO would increase the visibility of distributed residential microgrids to the distribution system and energy system operators which increases the potential of residential DSR. This method of P2P trading can be readily used in conjunction with DSR services for the grid operators and could also contribute to more accurate and more granular forecasting of energy consumption on LV networks. This is expected to develop into a symbiotic relationship between the end-users and the system. For instance, higher accuracy in forecasting would result in a lower imbalance which could lead to lower electricity import prices and potential carbon emissions.

To summarise, after comparing the technical benefits and near-future feasibility of the two P2P market designs, the decision was made to proceed with the community-based P2P methodology as it was predicted to have higher chances of implementation by 2032 in comparison to the auction-based markets due to its community outlook (i.e. the common goal of carbon or cost savings), decreased complexity, lower computational time and avoided risks associated with auction-based market distortion.

4.3 Carbon-aware P2P trading

For the first time, this work developed a P2P mechanism that takes into account carbon dioxide emissions. This section introduces the novel concept of carbon-aware P2P pricing. As P2P trading offers an opportunity to redefine energy markets, it may be used to transmit system-level information to the end-users through the use of system-indexed variable pricing such as the Agile pricing mentioned previously. This method is used to transmit information about the carbon intensity of the grid by applying an extra incentive for sharing excess energy during high-carbon periods which acts as a penalty for consuming electricity. This workflow uses an incentive to motivate P2P agents to trade during high carbon intensity hours of the day rather than when there is excess solar generation which is often when the system-level carbon intensity is already very low.

Previous approaches merely use a conversion method to calculate carbon savings achieved by multiplying energy savings with a constant per-unit carbon emission value [97, 98]. Therefore, a gap was identified in studying the carbon-saving nature of local energy trading in literature. The method of assuming a constant value is not an accurate representation of the varying pattern of carbon intensity throughout the day due to the periodical nature of RES. Studies [97, 98] have shown 15% reduction of carbon emissions, assuming a constant rate of $0.55\text{kgCO}_2/\text{kWh}$ based on the assumption that the central generation is totally gas powered. However, the average carbon intensity of electricity in the UK is 0.233kg of carbon dioxide equivalent per kWh [5] which indicates that previous research did not realistically reflect the carbon saving potential of P2P energy markets. Additionally, on average, midday and overnight carbon levels are much lower due to solar and wind generation even though it should be noted that the relationship between electricity cost and carbon intensity is not always proportional. The assumptions regarding constantly high grid carbon intensity do not provide correct information to the optimiser which leads to results which are inadequate for estimating the carbon savings resulting from cost-minimal load shifting. This is because, as shown in Figure 4.5 and 4.6, the morning surge often results in the highest per-unit carbon emission value of the day. The methods employed in the literature demonstrate co-simulation platforms that focus on P2P market and grid simulations, whereas the study presented here introduces a novel

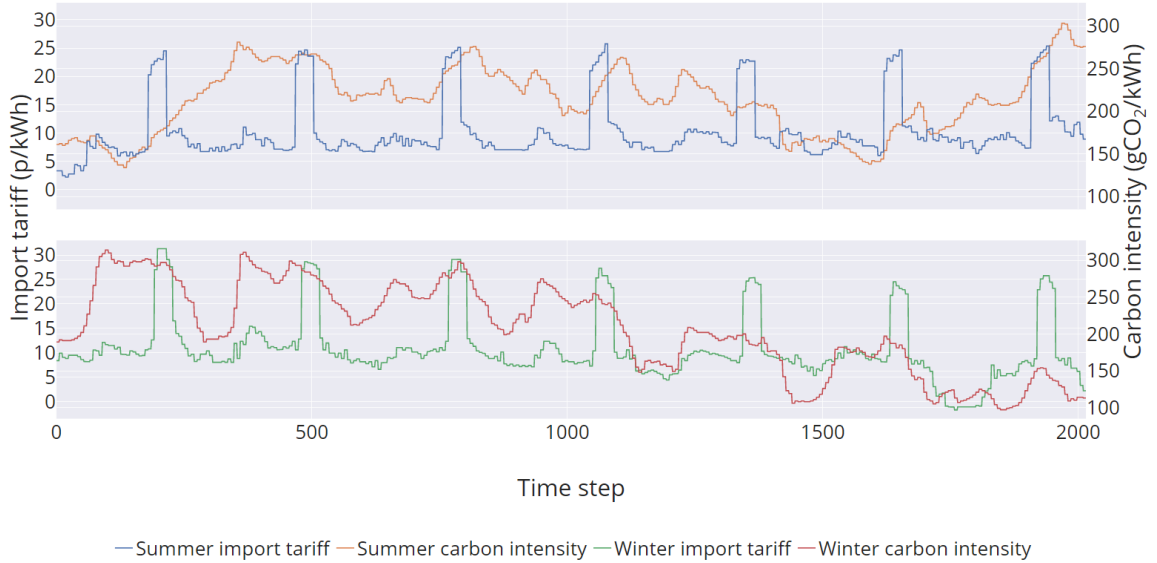


Figure 4.5: Relationship between carbon intensity and dynamic import tariff which is indexed on system buy prices.

approach by incorporating carbon awareness as one of the key layers in the simulation platform. The framework uses this information to generate carbon-aware P2P pricing which adjusts the values to take into account the grid carbon intensity at each time period. For example, if there are two periods in the simulation which have the same price, scheduling the consumption to either one of these periods would lead to the same result from the perspective of cost optimisation. Integration of carbon awareness in the simulation differentiates these periods from one another depending on the level of grid carbon intensity. This proposed carbon-aware co-simulation of network and market was previously illustrated in Figure 4.1.

To contribute to the decrease in carbon emissions on the system level the framework has to optimise pricing so that the energy is exported when the grid has the highest carbon levels. In that case, the designed carbon-based P2P pricing benefits the prosumer by increasing one's self-sufficiency during the hours of highest carbon intensity which is when the grid activates peaking plans and under normal operation conditions meets the increased peak demand by gas generation and hence increasing the overall carbon footprint of the system.

Through the use of an API, the system carbon intensity for the GB electricity

system is reached [5]. In this dataset, the carbon intensity of electricity is a measure of CO₂ emissions produced per kWh of electricity consumption. Using the analysis of Long et al. [81] as a basis, a 4p/kWh incentive for a community with 14% solar penetration is chosen. In [81], in order to ensure energy sharing is profitable for all participants, a constant economic incentive is applied which is expected to be covered by DSO for increasing self-sufficiency of the local network. This incentive creates a buffer between buy and sell prices when there is an energy surplus in the network. As the scope of this study is different and includes the relationship between local energy markets and their impact on carbon emissions, a carbon-aware P2P pricing mechanism with a dynamic incentive is designed. The carbon incentive, λ_{carbon} is a function of time that is indexed to the grid carbon footprint information from [5]. The total sum of incentives is calculated per day using the aforementioned 4p/kWh incentive as a basis. The incentive is then manipulated and scaled to reflect the temporal variations in the grid carbon intensity. In order to integrate carbon awareness the P2P sell and buy functions were revised as shown in Equation 4.7 and 4.8.

$$\text{C-P2P}_{\text{sell}}(t) = \begin{cases} \frac{(\lambda_{\text{sell},t} + \lambda_{\text{carbon},t}) \cdot \lambda_{\text{buy},t}}{(\lambda_{\text{buy},t} - \lambda_{\text{sell},t} - \lambda_{\text{carbon},t}) \cdot \rho_t + \lambda_{\text{sell},t} + \lambda_{\text{carbon},t}} & 0 \leq \rho_t \leq 1 \\ \lambda_{\text{sell},t} + \frac{\lambda_{\text{carbon},t}}{\rho_t} & \rho_t > 1 \end{cases} \quad (4.7)$$

$$\text{C-P2P}_{\text{buy}}(t) = \begin{cases} \text{C-P2P}_{\text{sell}} \cdot \rho_t + \lambda_{\text{buy},t} \cdot (1 - \rho_t) & 0 \leq \rho_t \leq 1 \\ \lambda_{\text{sell},t} + \lambda_{\text{carbon},t} & \rho_t > 1 \end{cases} \quad (4.8)$$

The carbon-aware P2P trading algorithm builds a feature of carbon-awareness into the co-simulation platform through the calculation of dynamic carbon incentive based on half-hourly grid carbon intensity values. This workflow and simulation architecture was previously presented in Figure 4.1. These carbon signals are then fed into the market layer which contribute towards the modified computation of P2P buy and sell prices which are shown as C-P2P_{sell} and C-P2P_{buy} in Equation 4.7 and 4.8. Following this, the methodology is the same as community-based markets described in Section 4.2.2 where the P2P prices are input into the optimisation and grid layers.

Figure 4.6 shows a snapshot of the 2019 carbon intensity levels in summer (i.e. yellow in the top plot) and winter (i.e. brown in the bottom plot), along with grid and P2P prices. As seen from this figure, the carbon intensity of electricity generation does not have a directly proportional relationship with grid pricing. Majority of the time, the maximum system buy prices of the day occur during the evening peak.

4.3. CARBON-AWARE P2P TRADING

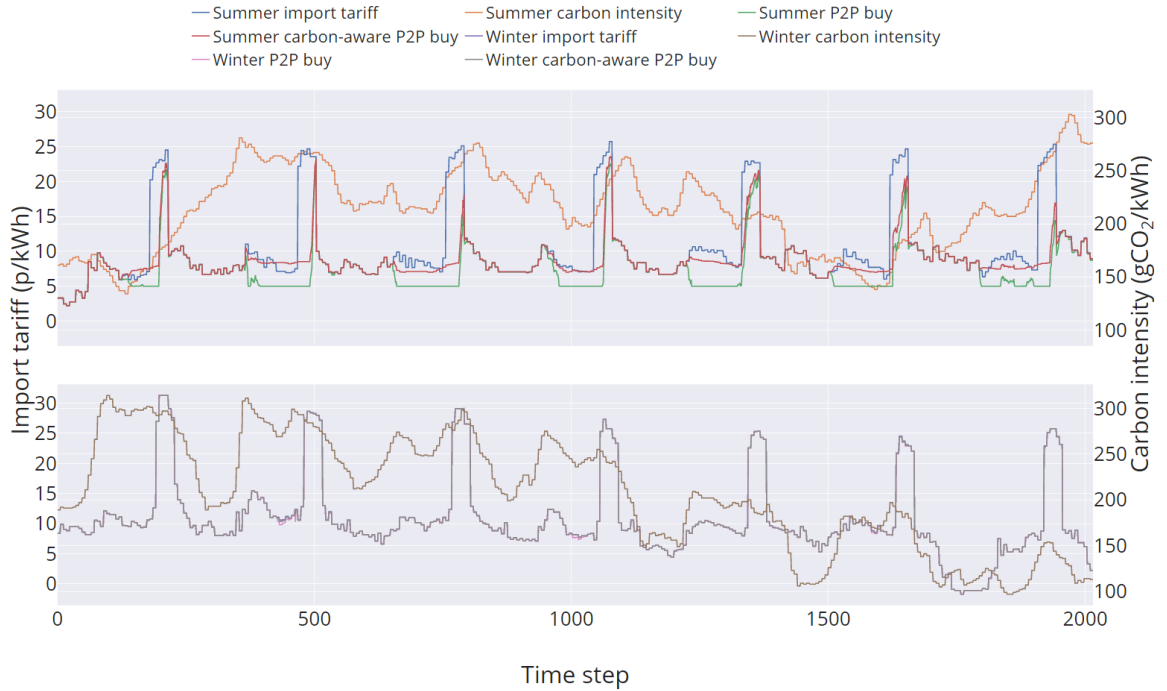


Figure 4.6: Carbon-aware P2P pricing in comparison with community P2P and grid import pricing. Summer and winter snapshots are shown in the top and bottom plots, correspondingly.

However, that is not always the case for carbon intensity as shown in both top and bottom plots in Figure 4.6 where the carbon intensity is higher during the morning surge on average. In the bottom plot of Figure 4.6, the behaviour of the designed carbon P2P pricing is presented in the winter. Both P2P and carbon P2P prices follow the grid buy tariff closely due to the low solar output and hence, the low SDR levels. The behaviour of the carbon P2P is very similar to the P2P market pricing in general. However, in the summer (shown in the top plot), carbon-aware P2P (in red) has higher buy prices than the regular P2P where the difference is equal to λ_{carbon} . This results in higher economic benefit for those who export during high grid intensity pricing and reduces the carbon footprint of the buyers.

As the goal of the optimiser is to minimise the cost of energy usage by the end-user, this hybrid approach shifts the transactions that occur during midday to this period of high carbon emissions. This approach and the carbon incentive may be sponsored by organisations of interest such as DSOs and local governments in order to encourage participation in carbon-aware P2P trading to reduce the carbon footprint of

energy communities which accelerates decarbonisation of energy systems in a bottom-up approach. The results and comparison with various community-based P2P case studies are presented in the next chapter, specifically in Section 5.3.

4.4 P2P market operation under abnormal conditions

Previous sections introduced the concepts of community and auction-based local energy markets. The electricity prices from 2019 were used in order to assess the performance of the local energy market designs under business-as-usual conditions. However, the COVID-19 lockdowns in 2020 and winter gas scarcity in late 2020 and early 2021, challenged the energy markets around the world to operate under abnormal conditions due to drastic changes in demand and supply shortages correspondingly. This section analyses these changes in demand and supply and evaluates the operation of P2P markets under these conditions.

4.4.1 Impact of COVID-19 lockdown on P2P markets

In this subsection, the possible impact of the COVID-19 lockdown on P2P markets is discussed in a qualitative manner. Analysis of the GB demand data during the March 2020 lockdown indicated that a shift to WFH would result to a net benefit for flexible stakeholders, such as consumers on variable tariffs [33].

As displayed in Figure 4.7, load duration curves show the base and peak demand by visualising the relationship between sorted demand (i.e. ranked descending) and exceedence. Whilst the base demand decreased by 10% during the lockdown, the peak and mean demand more drastically dropped by 20% and 24% respectively. The figure illustrates that the overall demand decreased as a majority of the commercial users (e.g. factories, businesses, etc.) shut down despite the increased residential consumption due to WFH. Besides the demand reduction, the lockdown also influenced the consumption pattern which results in a changed load profile shape.

In addition to affecting system prices, the impact of the lockdown was transferred to end-users on the variable Agile tariff. In Figure 4.8, an example of capping at the maximum price of 35p/kWh is shown on the 4th of March 2020 (i.e. during the pre-lockdown week). This day marked the first time a system price was over £2000/MWh since 2001. It peaked at £2242/MWh [244]. The week commencing on the 30th of

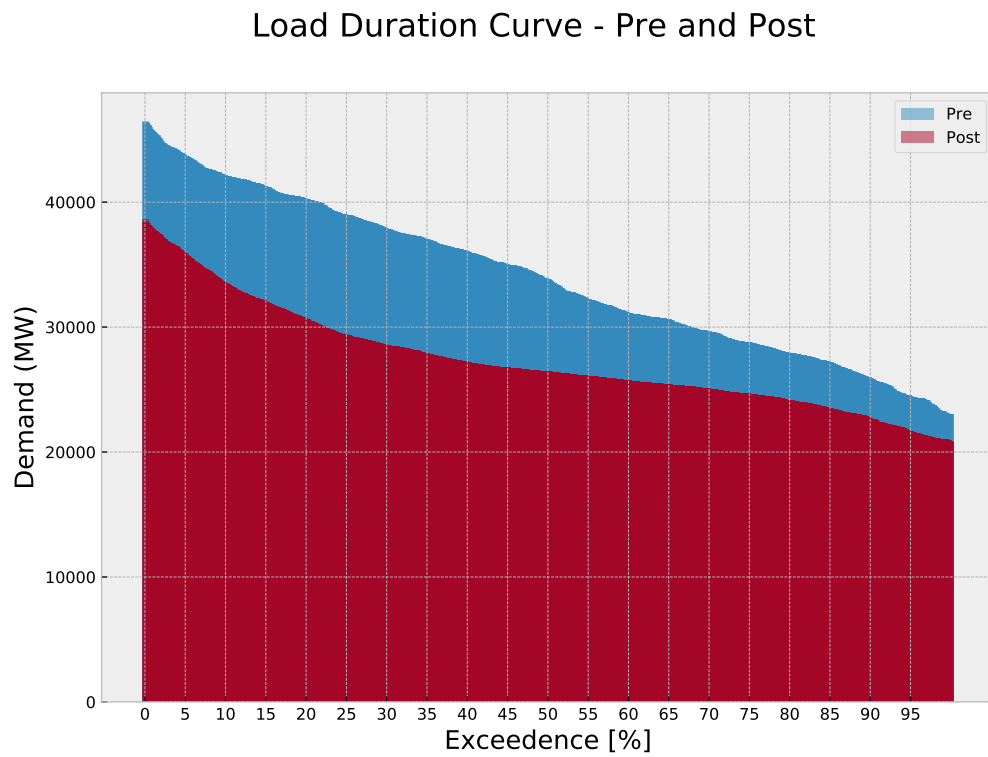


Figure 4.7: Load duration curve of system demand for pre and post-lockdown actions (w/c 02/03/20 and 23/03/20) showing the decrease in the post-action scenario with the highest decrease in peak and lowest in the base load.

4.4. P2P MARKET OPERATION UNDER ABNORMAL CONDITIONS

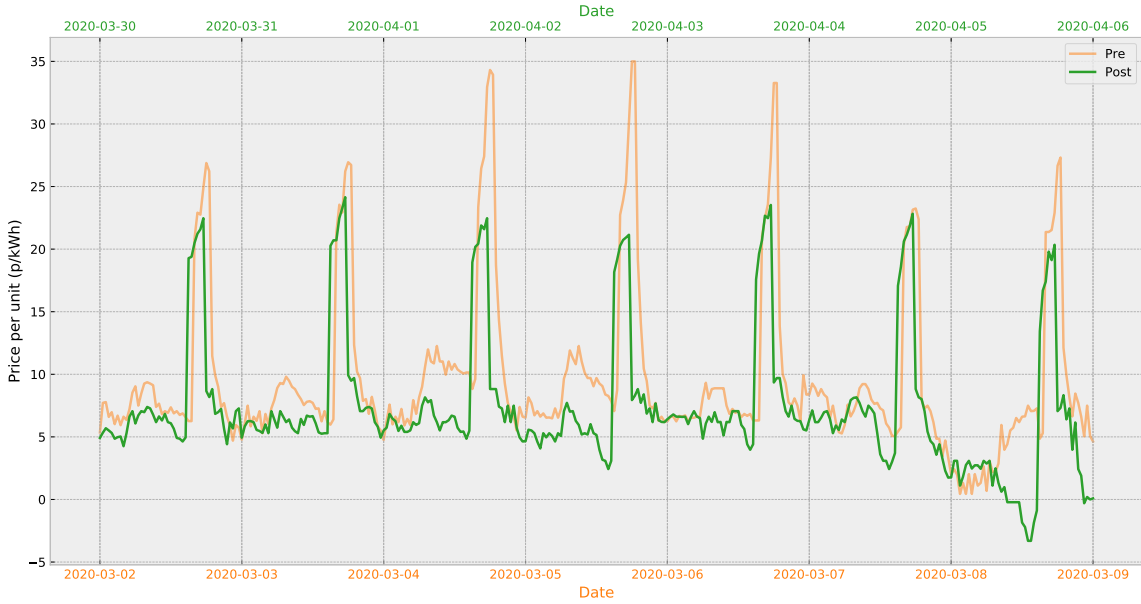


Figure 4.8: Examples of price capping (5th March 2020 on the lower orange x-axis) and negative pricing (5th April 2020 on the higher green x-axis) during pre and post-lockdown weeks respectively (using the data from [8]).

March 2020 was of interest for comparison with the other extreme, namely negative pricing, as it dropped to near -3p/kWh . The reduction in demand magnitude and changes in the profile are correlated to the changes between the pre and post-lockdown pricing profiles in Figure 4.8. Since the launch of the Agile tariff, there had been 96 occurrences of negative pricing (i.e. price $< 0\text{p/kWh}$). Almost 70% of these events (i.e. 67 out of 96) took place during the lockdowns.

In a community-based P2P market, working from home (WFH) due to the lockdown would result in a lower supply-to-demand ratio as domestic energy consumption during the lockdown had increased. Lower SDR levels indicate higher P2P buy prices for the consumers during the evening peak. Flexible assets would avoid such high-priced periods and leverage the negative pricing. For prosumers, there would be an increased opportunity to sell for higher prices during peak hours. Even though the SDR indicates local level scarcity during the lockdown, there were many instances when the system was long which resulted in negative pricing. This would result in having to pay to export electricity. On the other hand, in an auction-based P2P set-up, there would be a higher benefit for consumers assuming that sellers would offer cheaper prices than the grid import price. When compared to the grid export tariff,

4.4. P2P MARKET OPERATION UNDER ABNORMAL CONDITIONS

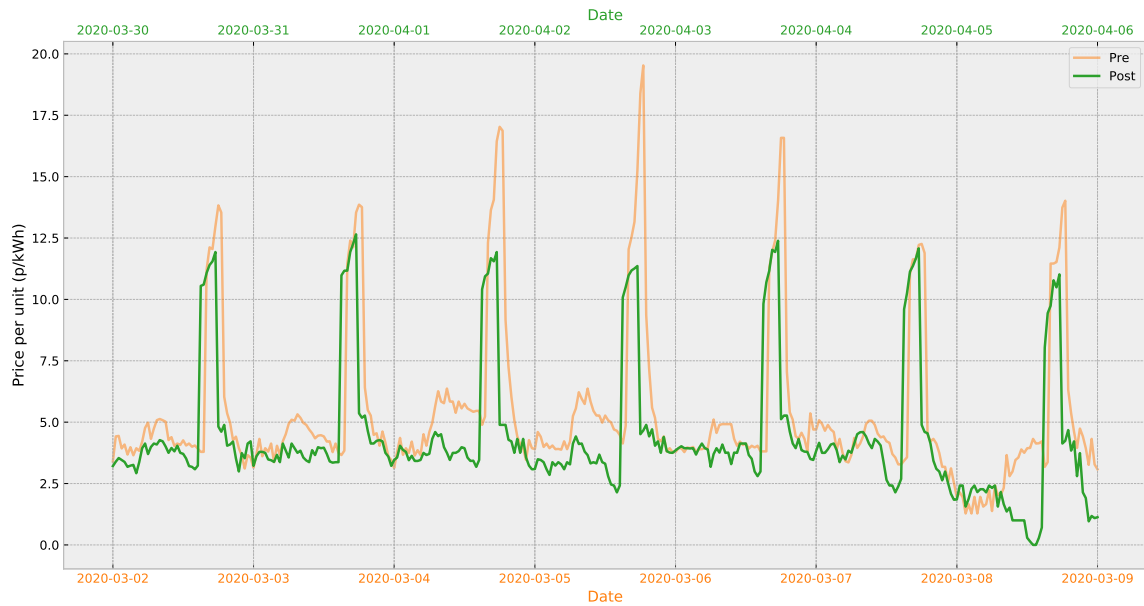


Figure 4.9: Corresponding Agile outgoing sell prices using the data from [8], that shows a high sell price reflecting the reserve scarcity (5th March 2020 on the lower orange x-axis) and a capped price of 0p/kWh (5th April 2020 on the higher green x-axis).

this would still be beneficial to the sellers, although, less than the community-based P2P trading.

Octopus also provides variable pricing for selling electricity [234]. The corresponding sell prices are plotted in Figure 4.9. The highest sell price around 19p/kWh was recorded which corresponds to the day with the highest system price since 2001. The benefit is passed on to the distributed generators. In the case of negative load pricing when the consumers were paid to use electricity on the 5th of May, there would also be negative pricing for exporting electricity (i.e. generators pay to export electricity). The pricing for generation is capped at a minimum of 0p/kWh which indicates that the energy was exported for free during that period as shown in Figure 4.9. Capping export prices at 0p/kWh could be applied to P2P markets to ensure that prosumers are not penalised for sharing energy with their community while the local SDR is low. Otherwise, this would decrease self-sufficiency of the community.

There is virtually no benefit for the distributed consumers with a fixed rate supply agreement as the average domestic household demand increased due to WFH. However, the 70 negative pricing events show that consumers with variable pricing

such as the Agile tariff are getting paid to use electricity. Such consumers can also take advantage of reserve scarcity and benefit from exporting when the grid is under stress. Regarding the commercial and industrial users, the same would apply which indicates that the users with the most flexible assets/loads would be able to take advantage of the effects of the lockdown on the pricing.

4.4.2 Impact of 2021/22 winter gas scarcity on P2P trading

The other abnormal market operation condition took place in late 2021 and early 2022. Due to a sudden increase in global gas prices in the winter caused by the scarcity during the preceding 6 months, electricity prices were increased to compensate for the wholesale price surge. The Agile import prices reflect the changes in the wholesale market till the 35p/kWh price limit was reached. As wholesale pricing is the largest contributor (40% on average), this price surge resulted in higher user bills. In decreasing order, the rest of the contributing factors are operating (i.e. billing and metering), network, policy, administration, profit margin of the energy supplier and VAT.

Figure 4.10 illustrates the daily Agile import tariff profile from 5th February 2022 where the usual morning (8:30) and evening (18:00) peaks are capped. The lower period of demand during early morning, midday and late night lead to price drops below the limit. This figure also shows that different regions in the GB are affected at different levels where North Scotland and Yorkshire have the highest and lowest prices respectively. Capping of Agile prices removes the benefit of its dynamic nature and essentially converts it into a flat tariff at 35p/kWh. If the cost optimisation algorithm used this profile as an input, it would result in a highly decreased benefit to the users.

Figure 4.11 shows the average Agile import prices in North Scotland over the last 18 months, which is used as a case study in this thesis. It shows the effect of gas supply scarcity which started in October 2021 when the 35p/kWh price cap was applied. Hence, the benefits of community-based P2P trading would have been significantly compromised. However, participants on the P2P tariff would still have access to lower prices during times of local generation surplus. Nevertheless, the participants who are on flat tariffs with fixed per kWh pricing (e.g. 18p/kWh) were affected the least by the scarcity pricing.

4.4. P2P MARKET OPERATION UNDER ABNORMAL CONDITIONS

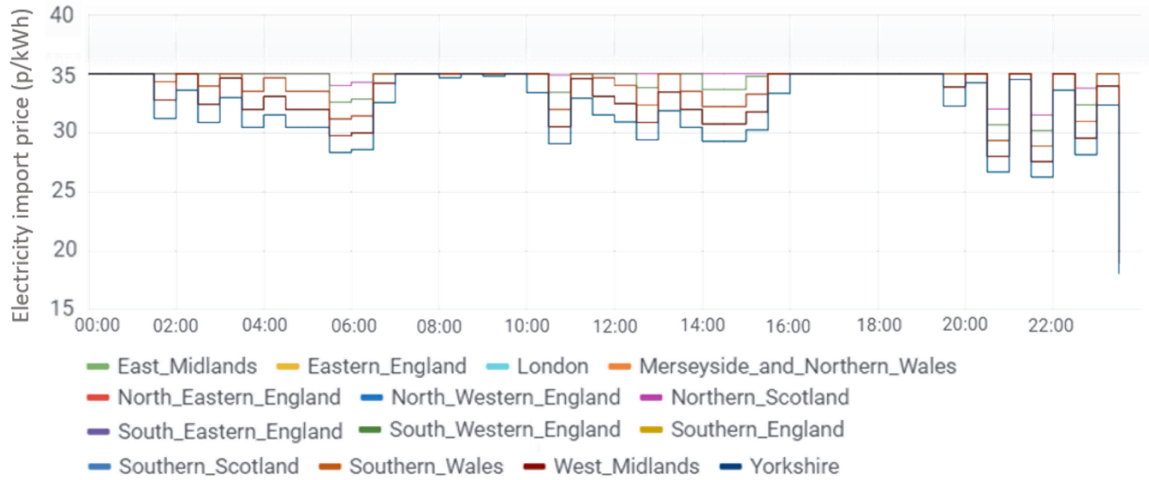


Figure 4.10: Capped Agile electricity pricing on 5th February 2022 for different regions in the Great Britain where the most expensive region is in North Scotland (pink) and the cheapest is in Yorkshire (dark blue) - data from [8].

According to Ofgem [9], the price cap is designed to protect approximately 20 million households on flat electricity import tariffs from steep increases in energy prices due to supply volatility. Figure 4.12 compares two annual energy bills based on winter 2021/22 and summer 2022 energy price caps. In this example, “typical domestic consumption values” of 2.9 MWh of electricity and 12 MWh of gas consumption were assumed. As shown, the increase in energy price caps is expected to result in an increase of approximately £700 per year. From a prosumer perspective, this means that if the grid export prices stay the same despite the increase in grid import tariff, the economic benefit of P2P trading in comparison to selling to the grid would be amplified. Hence, buying electricity locally would also result in lower bills for the consumers.

Assuming that SDR would stay the same, the effect of higher grid buy prices would not have an effect on P2P buy and sell prices during the period when SDR is equal or greater than 1 which means either the community is fully self-sufficient or there is an energy surplus. This is because the community P2P pricing mechanism where the P2P buy and sell prices are indexed on the grid sell price when the supply meets and/or exceeds demand. However, when SDR is less than 1, P2P market exporting electricity would be rewarded at the high price of 28p/kWh which is 5.6 times higher

4.5. LIMITATIONS



Figure 4.11: Average Agile import prices in North Scotland for the last 18 months which shows the effect of gas supply scarcity starting in October 2021 where the price is capped at 35p/kWh - data from [8].

than the average export tariff of 5p/kWh. The new price cap is expected to result in maximised self-consumption and higher motivation to participate in P2P trading as this would result in higher relative benefit for the generators in comparison to the previous lower price cap.

4.5 Limitations

One of the limitations of the approach was that the uncertainty of the DER was not taken into account and that the forecast of the demand and supply were assumed to be 100% accurate. To improve this, the methods used in [245] for determining the effect of uncertainty between day-ahead and actual out-turn may be applied in future research. Additionally, it should be noted that as this research is concerned with local energy systems in 2032, it assumes that all participating households have net metering.

As the pricing mechanisms for community-based markets were based on an energy supplier's tariff rather than the wholesale pricing, aspects such as network, policy, administration costs, profit margin of the energy supplier and VAT were assumed to be taken care of and included in the price. It is likely that in a future P2P market operation, the transmission network fees and other costs related to administration and policy would not be applicable. This would further decrease the costs, resulting in higher benefits for the users.

The study presented in the auction-based P2P market considered an ideal set of

4.5. LIMITATIONS

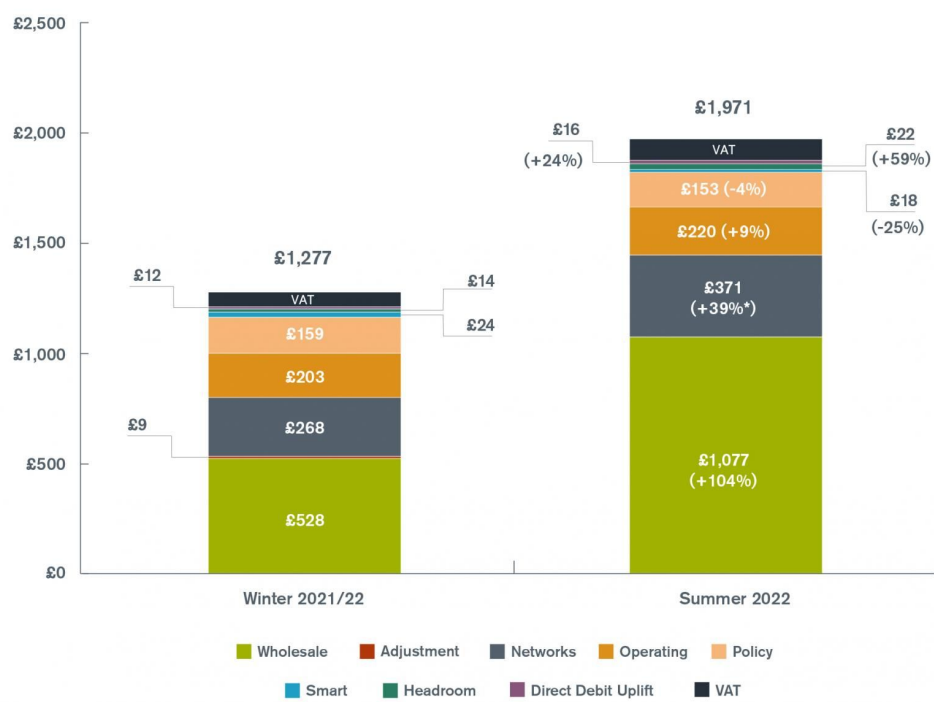


Figure 4.12: The increase in price cap announced by Ofgem and the difference in contributing factors between Winter 2021/22 and Summer 2022 [9].

users. Possible conflicts of interest between different stakeholders and/or users were not considered. The participants of the P2P community network were assumed to act in an honest manner with no intention of exploiting the system for personal gain. Therefore, misleading actions such as placing malicious bids and offers, tampering with the P2P trading within the community and other security threats were not considered in this chapter. However, these points are addressed through the use of blockchain and smart contracting technologies in Chapter 6. Additionally, due to their higher potential of adoption by 2032, only community-based energy markets were taken further in this research. Hence, the limitations caused by the auction component of the market models did not need to be addressed.

As local energy market design involves users from diverse backgrounds, ensuring inclusivity and fairness is one of the major challenges. This study did not consider the effect of low visibility or forecasting or other factors specific to certain user groups. Everyone is assumed to be equal and have access to very accurate forecasting. As it has a more systems and environmental outlook than social, aspects of inclusivity and fairness were not the focus in this study. However, Reis et al. [231] proposed a road map for community-based P2P markets to protect vulnerable consumers and the lessons from this study may be used in the future to create carbon-aware and inclusive P2P trading algorithms.

Lastly, the simulations of COVID-19 lockdown and winter gas scarcity cases were limited due to the lack of demand data available during these periods. When the data becomes available, the pricing provided in this thesis may be used to evaluate the techno-economic and environmental impacts of P2P trading during these low probability high impact events.

4.6 Discussion

This chapter presented the co-simulation methodology for network-aware local energy market simulations. Two separate P2P market modules were simulated and compared in Section 4.2.4 which concluded that community-based P2P energy markets were more suitable for the objectives of this project and more feasible for its adoption in the use-case by 2032.

When implemented in real life, the local energy markets are anticipated to yield cheaper electricity prices for all P2P agents. Additionally, as the community-based

local markets consider the supply-to-demand ratio, this results in better matching of local demand to local supply. Through the feedback loop of the network simulations, the implementation of local energy markets would have integrated local network awareness which would ensure healthy operation of the local system. P2P markets achieve lower local imbalance as the flexible demand is scheduled to match the hours of local generation surplus. This decreases the reliance on the centralised generation which is often more carbon intensive than the local supply of distributed PV generation.

The relationship between storage penetration and P2P participation was analysed in terms of their impact on self-consumption and self-sufficiency. It was found that participation in P2P markets could increase self-sufficiency by 25% which means reliance on the centralised generation would decrease by that amount. As a larger portion of the demand would be covered by the local carbon-neutral generators rather than the commercial power plants, the revenue would be kept in the community. This would result in socio-economic benefits for the community and lower carbon emissions, contributing to net zero goals. In addition, it was also found that to achieve a 90% self-consumption level, the storage penetration of the community should be 57%. Nevertheless, when the community participates in P2P trading, this value decreases to 25%. Therefore, this study showed that implementation of P2P markets in local energy systems can decrease the storage installation requirements by 32% which saves installation and maintenance costs and also avoids environmental implications of small-scale lithium-ion batteries. Additionally, avoidance of hardware on the network implies that this would help delay infrastructural upgrades. From a non-technical perspective, implementation of P2P markets is expected to increase the sense of community as it retains the economic benefits in the neighbourhood and optimises consumption and generation using a common objective whether that is cost or carbon oriented.

The benefits of P2P trading vary according to the capacity of the energy storage installed in the local system. The 2032 storage penetration in distributed networks is predicted to reach 14% according to Distributed Future Energy Scenarios (DFES) [32]. By incorporating full participation in P2P, the self-consumption of local solar production can be increased from 45% to almost 79%. Similarly, 100% P2P subscription can increase self-sufficiency values from 17% to 34% by 2032.

Recently, there were low probability but high impact events which resulted in abnormal market operation conditions which threatened the operation of local energy markets. These were due to the COVID-19 lockdown and the winter gas scarcity. The energy market prices were disrupted which affected the dynamic electricity tariffs and also community-based local energy markets as they are both volatile to system prices. The community-based market would yield lower energy prices than the Agile tariff when there is a local generation surplus. However, as the distributed demand was already high due to the lockdown and the winter heating demands, there would be less frequent instances of local surplus.

In addition to the techno-economic benefits of the P2P markets, this thesis showed that P2P market models can be designed with integrated carbon awareness in order to yield environmental benefits. A novel carbon-informed local energy market design, namely carbon-aware P2P trading, was proposed in Section 4.3 which scales the incentive provided in community-based P2P to indicate the grid carbon intensity levels. The P2P trading mechanism proposed in this work enables prosumers to shift from the conventional approach of trading with a single retail supplier to a more decentralised method of trading with other prosumers. Carbon-aware P2P trading incentivises trading during the hours of high carbon intensity grid generation. It uses an incentive to motivate P2P agents to export during the high carbon intensity hours of the day rather than when there is already a surplus of solar generation in the community (which is often when the system-level carbon intensity is already very low). This novel method introduced carbon-informed local energy trading to the field of local energy systems and showed that the use of decentralised markets could accelerate the net zero transition.

4.7 Key findings

This chapter displayed a co-simulation structure through the communication between the market and grid models. It investigated the use of community-based and auction-based P2P markets correspondingly. The relationship between community local energy markets participation and storage penetration was analysed and it was concluded that 100% uptake of P2P trading can increase self-consumption by 25%. While achieving 90% self-consumption of the local supply, P2P markets would reduce battery installations by approx. 30%, saving both economic and environmental costs

associated with residential lithium-ion batteries. Additionally, implementation of the community-based P2P trading increased the self-sufficiency levels by 25% when deployed along with distributed storage assets. It was also shown that P2P increased energy sharing by 14% in a sample European LV network whilst resulting in a negligible increase in power losses and voltage imbalance.

The contributions of this chapter included Section 4.3 which proposed a novel carbon-aware P2P trading mechanism that incorporated consideration of grid-level carbon intensity, encouraging export during high-carbon periods. Following this, there was a discussion of different P2P market designs and limitations of the methodology were evaluated. Lastly, the use of community-based P2P markets during both the 2020 COVID-19 lockdown and 2021 winter energy scarcity were discussed.

Out of the different P2P market designs that were demonstrated in this chapter, the community-based and carbon-aware markets were taken further and explored in Chapter 5 using a 2032 case study in North Scotland. More technical and quantitative results regarding grid signals, cost savings and carbon emissions are presented in the next chapter.

Chapter 5

Network Control and P2P Trading Case Studies

The previous chapters discussed the methodology of modelling local flexibility and introduced the co-simulation of transactive local energy systems. This chapter shows and evaluates the results of the flexibility coordination and energy trading strategies using the case study of Huntly, Aberdeenshire. The digital twin models and simulation platform, as published in [11], were achieved through collaboration with Scene Connect Ltd. This pilot study was used in two separate case studies which are namely “network-aware community control for load curtailment” presented in Section 5.2 and “comparison of P2P and community-level optimisation” presented in Section 5.3. The first case study explores the flexibility of the future local energy systems in terms of load shifting to achieve peak-hour avoidance (i.e. re-scheduling load away from the peak consumption hours) and peak shaving (i.e. load curtailment during the peak hours). It involves simulation of a neighbourhood energy demand in 2032 which includes heat pumps, EVs, PV generation and batteries. It assesses the carbon savings, losses and user comfort. The second case study in this chapter expands the simulation network to three nearby neighbourhoods. It compares the effect of inter-neighbourhood and intra-neighbourhood P2P trading using neighbourhood-specific supply-to-demand ratios. It also evaluates the carbon and cost outputs of the carbon-aware P2P energy sharing algorithm proposed in this thesis. Lastly, it also compares cost/carbon minimal community-level optimisation results against P2P results.

As this thesis appreciates that decarbonisation of local energy systems requires a holistic approach, the results are presented from an economic, environmental and

system perspective wherever possible. Following the presentation of the results from both of the case studies, the discussion section presents the shortcomings of the simulations and implications for different stakeholders.

5.1 Background about the use-case

The use-case employed in this chapter is the live pilot site of the Zonal Use of Systems (ZUoS) project which aims to accelerate the net zero transition through the use of community coordination to increase the consumption of low-carbon distributed energy resources. The ZUoS project enrolled various residential and non-residential distribution network users to participate in a live pilot case of community control in Huntly, Aberdeenshire. The main aim is to re-schedule the usage of EV charging points, heat pumps and renewable generation in order to optimise the use of energy at a community-scale for a lower overall carbon footprint. In addition, the pilot case records real-time building demand and DER operation data that is used for further model development and verification providing detailed insight into individual participant and community level behavioural patterns. The pilot project started in Winter 2020 with the financial support of the UK Government's Department for Business, Energy & Industrial Strategy (BEIS) to provide regulatory change recommendations and address the challenges associated with financing similar community network balancing projects.

Similar community-centric initiatives such as Northern Isles New Energy Solutions (NINES) [246] already exist in Scotland. The NINES project aims to build up a smart grid in the Shetland Islands that utilises a large-scale battery and hence helps balancing the intermittent wind energy supply providing power to domestic heaters. Despite having similar aims, the project is different from ZUoS as it focuses on storing locally generated wind energy, whereas in Huntly the focus is on employing domestic scale battery storage to absorb existing solar energy and hence maximising self-consumption. Another similar project, namely 4D Heat [247], aims to take the advantage of heating flexibility by shifting demand to times with national wind energy surplus. Similarly to ZUoS, this project focuses on neighbourhood level consumption management but does not consider the potential of the local generation. Local Energy Oxfordshire (LEO) [248] project is formed as an innovative energy trial to provide insight for the future energy strategy by launching a platform that enables

prosumers to sell energy as well as balancing services. It is designed to trade locally with the help of peer-to-peer services or execute transactions through mediated markets allowing aggregation of local resources. Regardless of similar objectives, all of the mentioned projects entail individual scheduling, optimisation and forecasting solutions that significantly vary in terms of required input signals and data.

The pilot site of ZUoS was used as a demonstrator in this thesis to apply the optimisation and P2P trading algorithms in a real world setting. The inclusion of this use-case in this thesis helped to validate the use of asset modelling and co-simulation techniques described previously (see Chapters 3 and 4). To simulate the future demand of the pilot site, a series of local datasets were used. These include the local demographics dataset, local network data obtained from the DNO, survey results about the asset preferences of the residents and area-specific predictions for increased smart asset penetrations.

The year 2032 was chosen instead of 2050 Future Energy Scenario of the National Grid Electricity System Operator because 2032 is a critical point in the Distributed Future Energy Scenarios (DFES). In line with the analysis of Scottish and Southern Electricity Networks (SSEN) that involve network simulations and investment planning processes, this thesis also used 2032 as the target year for the simulations to provide the view of the DSOs and provide local context rather than national penetration scenarios. On a macro scale, the FES are very informative as they incorporate a range of possible strategies based on political, technological, economic and social stances [243]. Nevertheless, when analysing the effect on a part of the distribution grid, these scenarios do not reflect the potential and energy needs of the north of Scotland observed by SSEN [32].

Additionally, North Scotland and in specific Aberdeenshire has the highest level of fuel poverty in the UK [249] and it was found that it also has the highest electricity regional pricing when the Agile tariff of the energy supplier Octopus [234] was analysed in this work.

With the rising energy prices and a predicted increase in the number of households with energy poverty, this area proves to be a case study of interest and importance.

5.2 Case study: Network-aware Community Control for Curtailment

This section describes the attributes of the case study that is used in this chapter. In the first subsection, it depicts the configuration and placement of smart assets in the community and modelling of domestic energy demand based on the region's demographic data and weather input. In the second part, it details the modelling methodology of heat pumps coupled with the physical building thermal models. Following this, it introduces the low voltage network topology used for power flow analysis and the network control logic alongside different scenarios that were simulated (e.g. peak-hour avoidance and network-aware peak control). Lastly, it discusses the results, with highlights of user comfort, carbon savings and per-unit voltage levels, and lists the limitations of the simulation methodology. This case study was published in [11].

5.2.1 Bottom-up demand

The use case features electrical load in the form of smart assets and household consumption profiles. Additionally, there are heat pumps coupled with thermal building models in order to monitor the effect of different control strategies on indoor temperatures.

The flexible demand from EV charging and heating loads are modelled individually and these form the majority of the household demand in 2032. For the former, the methodology of modelling is similar to the one described in the flexibility modelling section, Chapter 3. The heating loads are modelled using a heat pump and also include two thermal building models. Lastly, other smaller loads such as lighting, kitchen appliances and wet loads are simulated using a probabilistic approach.

For the simulation of EV loads, the amount of charge required, and the plug-in time vary according to a normal distribution, with the standard deviation of distance travelled per day, and plug-in times. The inputs to the deterministic home EV charger model including the aforementioned factors and also battery size, charging efficiency and so on are shown in Table 5.1. The three most dominant EV charging windows were identified using the national transportation survey as a source [17] as shown in Table 5.2. An equal presence of each group was assumed to set the availability windows of the EVs.

Table 5.1: EV charger deterministic model specifications.

| Parameter (Units) | Value |
|--|-------|
| Charging efficiency (%) | 90 |
| Battery size (kWh) | 22 |
| Maximum charge rate (kW) | 7.3 |
| Mileage efficiency (miles/kWh) | 3.8 |
| Std dev. of schedule times (s) | 300 |
| Std dev. of distance variation (miles) | 2.0 |

Table 5.2: EV default charging windows from [17].

| Arrival from work | Leave for work |
|-------------------|----------------|
| 14:25 | 05:25 |
| 17:20 | 07:30 |
| 05:27 | 20:47 |

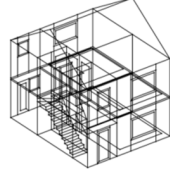
To estimate the rest of the household consumption (i.e. lighting, wet loads, etc), the occupant type of each household in this area is obtained from the local council [250] and matched with the archetypes in the Twente database [251] which outputs an estimated consumption of each household using a set of plug loads and kitchen appliances common in the UK. The resultant demand profiles are modelled such that they can reflect changes in user behaviour and external/environmental conditions.

5.2.2 Modelling thermal building response and heat pumps

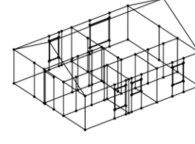
This subsection describes the methods used for simulation of thermal response from two different house archetypes and heat pumps to cover the simulated electrical heat demand.

Table 5.3: Load profiles according to the occupant type [11]

| Occupant type | % contribution |
|--------------------------------------|----------------|
| Single adult | 41% |
| Working couple | 14% |
| Working couple with dependants | 10% |
| Retired couple | 10% |
| Couple (one working) | 9% |
| Couple (one working) with dependants | 6% |
| Single adult with dependants | 6% |
| Retired single | 4% |



(a) Detached archetype



(b) Bungalow archetype

Figure 5.1: Detached and bungalow housing archetypes used for the building thermal response models.

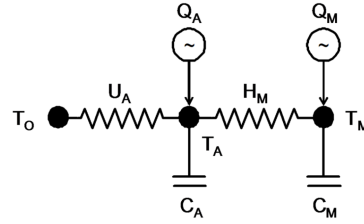


Figure 5.2: An example of the equivalent thermal model implemented using resistor and capacitors [10].

5.2.2.1 Building thermal response

The building thermal response model uses a lumped capacitance (i.e. 2R2C) which is a grey-box model for heat flow. The parameters for these models are derived from white-box building models created in the specialised heat-flow model ESP-r, by the University of Strathclyde, detailed in [252]. Two thermal building models of a bungalow and a detached house are used in scenarios where a heat pump is simulated. The geometries of the two models are shown in 5.1. The input parameters for the archetypes are summarised in 5.4. The parameters are used by GridLAB-D to create a suitable 2R2C model, represented in 5.2. The equivalent thermal parameters are derived from the input values according to equations 5.1 to 5.4 based on [10].

The total heat loss coefficient (conductance), U_A , is calculated as:

$$U_A = C_{p,air} V_{air} I_{air} + \sum_{i=1}^n \frac{A_n}{R_n} \quad (5.1)$$

where $C_{p,air}$ is the volumetric heat capacity of air; V_{air} is the interior air volume; I_{air} is the air infiltration rate; and A_n and R_n are the surface area and thermal resistance

per unit area of building surface n , respectively.

The interior mass surface conductance, H_m , is calculated as:

$$H_m = h_s \times (A_{EW} + A_{IW} + A_C) \quad (5.2)$$

where h_s is the interior surface heat transfer coefficient; A_{EW} is the external wall area; A_{IW} is the internal wall area and A_C is the ceiling area.

The total air mass, C_a is calculated as:

$$C_a = 3 \times C_{p,air} \times (V_{air}) \quad (5.3)$$

The total thermal mass, C_m , is calculated as:

$$C_m = m_f \times A_{floor} - (2 \times C_{p,air} V_{air}) \quad (5.4)$$

where A_{floor} is the floor area and m_f is the total thermal mass, per unit floor area.

5.2.2.2 Heat pumps

Heat pumps are implemented in both of the archetypes, and are programmed to operate whenever the indoor temperature goes below the temperature set-point (i.e. consumer heating schedule). The heat pump model operates at its maximum rated power when the indoor temperature is below the current set point. Each heat pump was sized suitably to maintain the set temperatures throughout the year. The detached house archetype has a heat pump size of 11 kW (electrical) and the Bungalow archetype has a heat pump size of 7 kW (electrical). Both heat pumps operate with a varying coefficient of performance (COP) depending on the differential between the outside and inside temperature, with the COP decreasing as the differential decreases [10].

5.2.3 Local network topology

Using network topology data provided by the local DNO, a distribution network power flow simulation is set up to measure the impact of the 2032 demand and different control and coordination strategies. The local network data includes voltage ratings of 400V, 11kV and 33kV. Hence, the network model covers the range from household supply points to the primary substation which serves all of the chosen region. Figure 5.3 shows the low-voltage network indicating the point of 11kV connection and also the placement of the smart assets. Existing solar PV systems were identified and

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Table 5.4: Input parameters for the building thermal model [11].

| Parameter | Detached | Bungalow |
|------------------------|----------|----------|
| Floor Area (m^2) | 106.8 | 106.9 |
| Wall Area (m^2) | 95.3 | 77.9 |
| Ceiling Height (m) | 7.5 | 4.4 |
| No. of Stories | 3 | 2 |
| R roof (m^2K/W) | 2.3 | 2.3 |
| R wall (m^2K/W) | 2.3 | 2.7 |
| R floor (m^2K/W) | 1.5 | 1.4 |
| R windows (m^2K/W) | 0.4 | 0.4 |

Table 5.5: Number of assets in the local network model

| Scenario | Solar | Battery | EV | Heat pump | Total no of nodes |
|----------|----------|----------|------------|-----------|-------------------|
| 1 | 0 | 0 | 0 | 0 | 84 |
| 2, 3, 4 | 4 (4.8%) | 4 (4.8%) | 12 (14.3%) | 7 (8.5%) | 84 |

added using satellite data. Using the responses from the project participants, a subset of users with an interest to purchase EVs, heat pumps, batteries was formed. Following the penetration level in each scenario, the assets were randomly distributed amongst this subset of participants (i.e. given that the number of assets was lower than the number of users who expressed interest).

The network model has 84 nodes in total and the total number of smart assets on the network was scaled according to the DFES 2032 Steady Progression strategy. This is summarised in Table 5.5. As shown in Figure 5.3, the blue nodes mark the households with no smart asset. The individual heat pump and EV ownerships are shown in purple and yellow respectively but where both are co-located, it is shown in orange. Battery and solar systems are marked in green and if the same node also has an EV load, it is shown in grey.

5.2.4 Control and curtailment simulations

This subsection presents network and carbon saving results from a neighbourhood in the chosen community. It compares the effects of load shifting and network-aware peak shaving control scenarios listed below.

1. Business-as-usual control (2020)

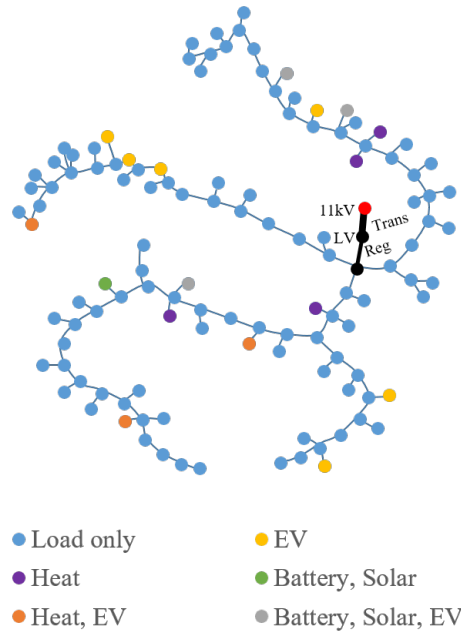


Figure 5.3: Network diagram of the LV section simulated.

2. Selfish control (2032)
3. Peak hour avoidance (i.e. load shifting) (2032)
4. Network aware control (i.e. peak shaving based on transformer loading) (2032)

Scenario 1 has a DER penetration representative of Huntly today and hence, has no DER assets connected. Scenarios 2, 3 and 4 have DER penetrations representative of Huntly in 2032. The control strategies for Scenarios 1 and 2 are the same. These are based on business-as-usual control whereby devices act to benefit the device owner, without consideration for the rest of the distribution network. In Scenarios 2, 3 and 4, the batteries connected to the network operate to maximise self-consumption, as is typical for many domestic PV battery systems in the UK.

In Scenario 2, the heat pumps follow a typical domestic demand schedule, with a morning and evening peak. The EVs start charging as soon as the vehicle is plugged in until the battery is full or the consumer unplugs it.

In Scenario 3, the heat pumps follow a typical domestic demand schedule, but with a drop in temperature of 1.7°C within DNO “red rate” periods, following the comfort-aware approach in [253]. ‘Red rate’ periods are when Distribution Use of

5.2. CASE STUDY: NETWORK-AWARE COMMUNITY CONTROL FOR CURTAILMENT

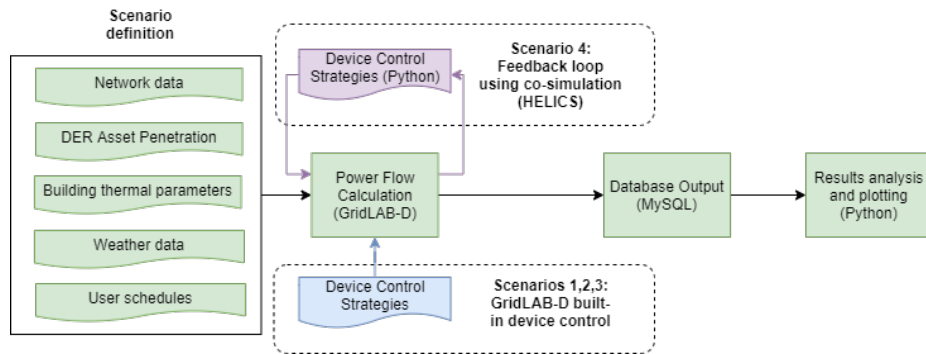


Figure 5.4: Visualisation of the simulation workflow [11].

System (DUoS) charges for half-hourly metered customers are highest and are an indication of when the distribution network is most heavily loaded. For 2020, these times are 16:30-19:30 on weekdays [254]. The EV charging behaviour is the same as in Scenario 2. However, they are forced to charge outside of DNO ‘red rate’ periods to decrease the aggregated peak load.

Scenario 4 uses a co-simulation approach and therefore this allows for the simulation to be queried and modified whilst it is running. As shown in Figure 5.4, the inputs to the simulations included the network data, DER asset penetrations, thermal parameters for the building models, weather data and user schedules of smart assets. Smart grid simulation software, GridLAB-D was used to output power flow calculations and corresponding results. In Scenarios 2 and 3, the built-in device controls were used. However, Scenario 4 required co-simulation with the external control logic implemented in Python and fed into the grid simulation through the intermediary platform HELICS. The use of this platform allowed for inspections of power flows at 30-minute intervals.

Figure 5.5 shows the control which was applied every 30-minute interval to the GridLAB-D simulation. The curtailment for both EVs and heat pumps operates to limit power for both devices. This curtailment is applied when any LV mains cable loading exceeds 90% of its maximum current rating; the limit is then removed if all LV mains cables are loaded less than 80%. If there is no limit, both devices operate as they would in Scenario 2. For the purpose of this case study, this algorithm was applied to all EVs and heat pumps. However, the platform is capable of applying a rotational neighbourhood participation scheme similar to the case study with batteries shown in [255]. Additionally, the objective of the control can be multiple as demonstrated by

5.2. CASE STUDY: NETWORK-AWARE COMMUNITY CONTROL FOR CURTAILMENT

[256] using scheduling techniques such as particle swarm optimisation. The objective criteria may include greenhouse gas emissions, voltage variation and economic benefits [257]. For the purpose of this case study, only peak-hour avoidance and peak shaving (i.e. curtailment) cases were simulated. Optimisation with carbon and cost objectives in addition to P2P energy sharing scenarios were explored and discussed in the next case study in Section 5.3.

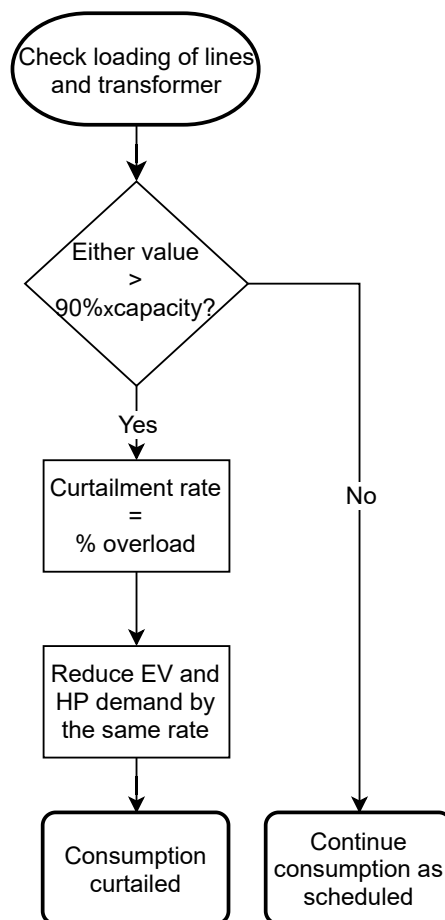


Figure 5.5: Curtailment logic for the network-aware community control, based on line and/or transformer loading. The curtailment of EV and HP loads is equal to the percentage of overloading.

5.2.5 Discussion of results

The simulation framework within this paper allowed for the direct comparison of control and DER penetration scenarios. The results below are shown for all four scenarios, and how the control of assets impacts the relative network conditions, carbon emissions, and user requirements.

5.2.5.1 Network voltages

The areas of the network with the greatest power loss were used to assess the voltage drop. The LV main line with the highest voltage drop on phase B was found to be the main-to-supply feeder 2 labelled as “F2_M2S” in the local network data. This line supplies electricity to 4 heat pumps (3 on phase B) and 3 EVs (2 on phase B). The voltage experienced by a user at the end of the LV main was assessed at the point in time when the main line phase B experienced maximum loading in Scenario 1 (i.e. 6 pm on the 22nd of November). The resulting line voltage drop is presented in Figure 5.6. Avoiding the peak hours introduced in Scenario 3 caused a significant voltage drop (to 0.9204 p.u.), resulting in a voltage below statutory limits (-6%). This was because lowering the set temperature was not enough to avoid heat pumps turning on during the peak period. The network-aware control in Scenario 4 significantly reduced the voltage drop on the 15 network nodes while the remaining two nodes have similar voltages to Scenario 2. These results showed that the control algorithm in this work would be valuable for reducing the line voltage drop.

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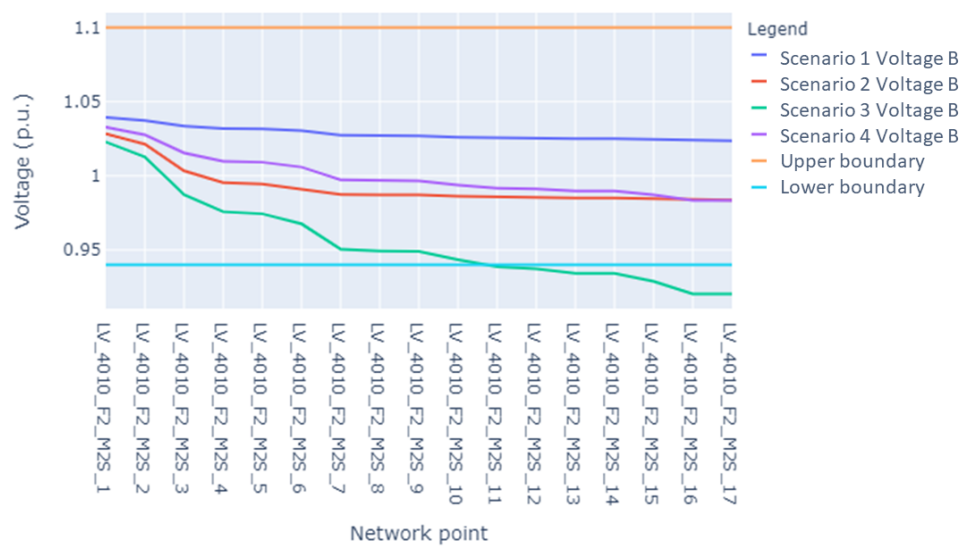


Figure 5.6: Voltage drop along a three phase LV main at the time of the highest power loss across all scenarios

5.2.5.2 Transformer loading

The future load scenarios showed a significant increase in peak time loads. The apparent power loads for all cases in the week of the year with the highest peak load for Scenario 1 were compared with the secondary substation transformer ratings. It is noted that the transformer loading in future scenarios did not exceed its rating at any simulated time step. Avoiding the ‘red rate’ periods introduced in Scenario 3 postponed the peak, but at some stages, the drop in the house temperature set-point was not enough to avoid heat pump loads at later stages of the afternoon peak hours. In case of the Scenario 4, the load was not only shifted from the ‘red rate’ periods but the high transformer loading occurring during the morning peak was also reduced compared to Scenarios 2 and 3.

5.2.5.3 Cable loading

In order to assess the effectiveness of Scenario 4 in reducing line and cable loading, the worst-case loading from Scenario 2 was compared with Scenarios 3 and 4. Current levels higher than the line ratings occurred in three of the four future load scenarios. It should be noted that the simple control introduced in Scenario 3 avoided some of the current spikes from Scenario 2, but caused new (increased) overloading at later times. A responsive approach was introduced in Scenario 4, which was able to lower the current level below the threshold every time the cables became overloaded. However, the increase in demand after the curtailment period was not released gradually and caused a rapid increase in demand. An incremental increase of the load was introduced to overcome this issue. However, there are no guidelines from the DSO about the ramp up of the demand when it comes to allowing the curtailed load to return to its normal consumption behaviour beyond the peak hours.

5.2.5.4 Comfort levels

This study employed a comfort-aware approach when implementing control for household heating needs. It adapted the analysis method in [253] as there was no forecasting of the thermal comfort available. The managed interior air temperature was compared with the user preference set points in order to express the level of comfort as shown in Equation 5.5 [253]. The temperature curtailment is limited to a maximum of 1.7°C to ensure control within the comfort bounds. The function (b_{mt}) in Equation

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5.5, quantifies the thermal comfort using a Gaussian function. Hence, the comfort level is inversely proportional to the difference between the mean preferred indoor temperature \bar{T}_{pref} and managed indoor temperature T_{mt} . The variance in preferred temperature ($\sigma^{T_{pref}}$) is also accounted for.

$$b_{mt} = \exp\left(-\frac{(T_{mt} - \bar{T}_{pref})^2}{2(\sigma^{T_{pref}})^2}\right) \quad (5.5)$$

Evaluation of the comfort levels using Equation 5.5 showed a 4% decrease in the comfort levels in Scenario 4 in comparison to Scenario 3. This was confirmed by the lower mean temperature of 16.96 °C while it is 17.15 °C in Scenario 3. Throughout the whole year of simulations, the indoor air temperature fell below the preferred temperature only 1.94% and 4.24% of the time for Scenario 3 and 4, respectively. On the other hand, Scenario 2 met the preferred temperature for every time period simulated.

Although heating in Scenario 3 was curtailed throughout the peak “red rate” periods, it was still able to come on if the indoor temperature dropped below the preferred temperature. As such, the preferred temperature was only not met, when the home was being ‘re-heated’ from a temperature dip.

Scenario 4 attempted to avoid line overloading, however, it oscillated the heat pumps off and on. This meant that the heating preferences were not always met since the heat pumps may have been curtailed during the peak demand hours (i.e. this happened 4.24% of the time) when they were required to be on at full power.

5.2.5.5 EV charging

In order to assess if the EV charging control in any of the scenarios was detrimental to the user experience, a comparison was carried out to assess the number of times in a year that the desired SoCs for the electric vehicles on the network were not met.

The simplifying assumption was that all EV users required 100% SoC for their journey to work on weekdays, and the SoC during other times was not important to them. This analysis showed that all EV charging needs were met for the entire year simulated.

Different scenarios resulted in different charging times. For example, Scenario 1 charges the EV as soon as it is plugged in (e.g. at 17:00), Scenario 3 delays the charging until after the peak times, and Scenario 4 operates with curtailed charging

5.2. CASE STUDY: NETWORK-AWARE COMMUNITY CONTROL FOR CURTAILMENT

at around 66% curtailment - indicating that the line was loaded 66% above the upper limit when all EVs were on.

User needs were met in Scenarios 3 and 4 due to the large period of time available for charging (> 12 hours in every scenario). The charging rate was set at 7.3 kW, meaning a full charge could be completed in just over 3 hours, although 7 kW chargers are increasingly common, 3 kW chargers continue to be deployed. Interrupting the less powerful chargers might result in user needs going unmet.

The results showed that under Scenario 4, EV user satisfaction was maintained, and the network overloading was reduced. The higher DER asset penetration on the network in Scenario 4 required curtailment of EV charging more frequently, resulting in reduced consumer satisfaction overall.

5.2.5.6 Line losses

Active power line losses for the entire LV network are presented in Figure 5.7. The highest instantaneous power loss and cumulative annual energy loss for each scenario are shown in Table 5.6. A key result is that Scenario 4 reduced the annual energy losses since the devices were intentionally operated outside of the high network loading conditions.

As shown in Table 5.6, Scenario 1 losses were significantly lower than other scenarios with the highest instantaneous value of 0.96 kW and a cumulative annual energy loss of 0.62 MWh. In Scenario 2, the power losses were significantly higher, due to the increased demand, without any network upgrade. The highest power loss was almost 10 times higher (9.57 kW) than in Scenario 1, resulting in 28.5 times higher energy losses (17.62 MWh). Although the increased load in Scenario 3 was shifted to off-peak times, the highest registered power loss increased to 10.07 kW, and the total energy loss increased to 17.9 MWh. The smart control introduced in Scenario 4 significantly increased the maximum instantaneous power loss to 11.49 kW, but the overall reduction of the LV power consumption reduced the energy losses to 15.90 MWh.

5.2.5.7 CO₂ emission savings

The difference in carbon emissions between the scenarios can be compared by using National Grid Carbon Intensity Data [258] with half hourly energy usage at the substation level. The results are shown in Table 5.6. The carbon intensity of peak

5.2. CASE STUDY: NETWORK-AWARE COMMUNITY CONTROL FOR CURTAILMENT



Figure 5.7: Active power loss on the network across all cases.

Table 5.6: Annual energy demand, carbon emissions, maximum observed line losses and total energy loss comparison between the four simulated cases.

| Cases | Annual energy demand (kWh) | Annual carbon emission (tCO ₂) | Maximum line loss (kW) | Annual energy loss (kWh) |
|-------|----------------------------|--|------------------------|--------------------------|
| 1 | 201 | 62 | 0.96 | 620 |
| 2 | 548 | 170 | 9.57 | 17620 |
| 3 | 542 | 168 | 10.07 | 17900 |
| 4 | 506 | 157 | 11.49 | 15900 |

hours (DNO “red rates”) was calculated as 326 gCO₂/kWh on average which is 7-9% higher than the rest of the day.

Scenarios 2 and 3 have approximately the same energy consumption, however, Scenario 3 reduced carbon emissions and the network losses which are both the highest at peak hours. Scenario 4 resulted in the most significant carbon savings, and minimum energy usage. As shown in Table 5.6, the roll-out of heat pumps and EVs resulted in 2.8 times higher carbon emissions when compared to the business-as-usual case. It should be noted that this evaluation assumed the generation portfolio in the future would not change. However, contributions from renewable and low-carbon sources such as solar, wind, hydro and nuclear energy are expected to increase in the future.

5.2.6 Limitations

A half-hourly data inspection and network control interval was used in order to simulate a year of operation. Inspection and control operating at a higher resolution (e.g. minutely) may be of more use to the DNO and/or the aggregator. In return, this would result in a longer run time.

The effect of a small C&I load in this neighbourhood was neglected. An increase in inflexible local loads would require higher curtailment rates from the EVs and heat pumps. Small C&I loads are taken into account in the next case study.

It is also noted that a 2R2C heat model for each house was used to convert survey parameters into building thermal response parameters. Additionally, only two types of house archetypes were used. A more sophisticated method such as 5R2C could be employed along with a larger portfolio of house archetypes to increase the modelling accuracy.

For the carbon emission analysis, it was assumed that the generation portfolio in the future would not change. However, contributions from renewable and low-carbon sources such as solar, wind, hydro and nuclear energy are expected to increase in the future. This means that the actual carbon savings in the future might be lower than the simulated values in this case study.

The study assumed that in 2032, the same type and capacity of EVs and EV chargers would be in use as there is currently no information regarding how these technologies will evolve in the future. However, it is expected that the charging times will be shorter and the battery capacities will be larger. This is expected to further

5.2. CASE STUDY: NETWORK-AWARE COMMUNITY CONTROL FOR CURTAILMENT

increase the effects shown in this study in terms of voltage drops and overloading of lines. The same assumption is extended to no local population growth, no increase in the number of dwellings in the area and no new connections to the local network. These assumptions may seem unrealistic but there is currently no information available as to how the population, dwelling density, etc. would change in the future which inhibits the simulation of such a scenario. However, the results from the four scenarios in this case study are still valid in terms of comfort levels, overloading and carbon emissions. All of these results can be scaled and the simulation scenarios can be easily adapted to reflect the mentioned considerations once the detailed projections are obtained.

The local penetration values from DFES were chosen such that they represent the Steady Progression scenario of NGENSO's FES. This scenario assumes that the rate of smart assets uptake (e.g. EVs and heat pumps) will progress in the same way in the future. However, the adoption of these technologies is expected to increase exponentially with further economic incentives and updated regulations in the future. To account for this, the next case study uses a more ambitious projection, namely Community Renewables. More details regarding this scenario are presented in the next section (Section 5.3).

5.3 Case study: Comparison of P2P and Community-level Optimisation

This section briefly introduces the case study, and the changes and improvements in the modelling methodology and input data in comparison to the previous simulations shown. It presents the Future Energy Scenarios (FES) used to simulate three neighbourhoods in Huntly, Aberdeenshire with 2032 renewable and flexible asset penetrations. Using these scenarios as a basis, the impact of P2P trading, community-level optimisation and DSO peak-shaving actions are compared and discussed in terms of economic, environmental and system stability indicators.

5.3.1 Introduction

In this section, the optimisation and LEM algorithms previously presented in Chapters 3 and 4 are used in the use-case described earlier in this chapter. However, this section differs from the previous section (Section 5.2) in that instead of focusing on a single neighbourhood, three neighbourhoods were modelled with an increased total population of 238 end-users. This allowed the comparison of intra and inter-community P2P trading and price determination. Additionally, this case study overcame the previous limitation of neglected C&I loads by modelling non-residential loads. Rather than using a single EV, PV and battery model, in this use-case a portfolio of different assets is introduced with varying specifications.

First, the scenarios used for simulating a futuristic neighbourhood are described. Second, the data inputs and methodology involved in the aforementioned improvements are described in the following subsections.

5.3.2 Future energy scenarios and asset penetrations

A number of scenarios were simulated to measure the impact of different control and coordination strategies. These strategies include asset-level configurations with optimisation of the battery systems to maximise self-consumption of solar generation by storing the excess generation during the day and discharging during high cost and/or carbon intensive periods of demand.

The DFES levels of renewable generation and flexible demand penetrations were used to analyse the effect of different coordination strategies in 2032 - similar to the

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

previous case study in Section 5.2. Table 5.7 shows the levels of penetration used. The previous case study used the Steady Progression case which assumes a constant rate of uptake using the current trends. However, this case study simulated an accelerated rate of uptake in the future using the local adaptation of the National Grid Energy System Operator’s Community Renewables scenario. In the latter case, the transition to net zero is community-led and supported by end-user behaviour change, purchases of smart grid technologies, etc. It requires a more agile adoption of flexibility and local generation which is equal to 5% faster uptake of PV and battery systems and 17% and 18% increase in penetration of EV and HPs respectively.

Table 5.7: Smart asset and solar PV penetrations following the DFES Community Renewables targets.

| Scenarios | % Asset penetration | | | |
|---------------------|---------------------|---------|-----|-----|
| | Solar | Battery | EV | HP |
| Business-as-usual | 0% | 0% | 0% | 0% |
| All other scenarios | 14% | 14% | 45% | 43% |

Table 5.8 lists the number of assets in each neighbourhood along with the total number of nodes in each sector in ascending order. The same level of asset penetration was applied to all, assuming the community renewables future energy scenario of the National Grid. Neighbourhoods 4010, 9030 and 4030 represent 27, 30 and 43% of the community with 238 simulated agents in total. This is equal to around 10% of the people who live in this district.

Below is the list of the simulation scenarios undertaken in this thesis. A brief explanation for each simulation scenario is provided which are later described in detail.

1. **Business-as-usual scenario** - models the current demand with today’s level of smart asset penetration and electricity demand.

Table 5.8: Number of assets per neighbourhood.

| Neighbourhood | Solar | Battery | EV | HP | Total no of nodes |
|---------------|-------|---------|-----|-----|-------------------|
| 4010 | 9 | 9 | 29 | 28 | 65 |
| 9030 | 10 | 10 | 32 | 31 | 72 |
| 4030 | 14 | 14 | 45 | 43 | 101 |
| Total | 33 | 33 | 106 | 102 | 238 |

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2. **No-control with increased levels of smart asset penetration** - features the increased penetrations of smart assets without any control.
3. **Optimisation for minimum cost** - applies community-level coordination to minimise cost by shifting load and re-scheduling all smart assets while respecting operational and user comfort constraints.
4. **Optimisation for minimum carbon emissions** - similar to the previous case with an objective to minimise carbon intensity of the electricity consumed in the community.
5. **(Inter-community) P2P trading** - coordinates the community energy demand and surplus using local supply-to-demand ratios at every time step - from all of the three neighbourhoods.
6. **Intra-community P2P trading** - similar to the previous case but the supply-to-demand ratios and trades occur within the individual neighbourhoods located behind the separate secondary substations.
7. **Carbon-aware P2P trading** - a new carbon-aware local energy market design with an added dynamic incentive to reward export and penalise import during high carbon intensity hours - previously described in Section 4.3.

5.3.3 EV, PV and battery models

As using a single set of EV, PV and battery specifications is not a good representation of the choices the users would have in 2032, various models of EVs, PVs and batteries were added to the asset modelling portfolio. This introduces a more diverse flexibility portfolio and corresponding savings per user. The placement of the assets involved no consideration of the socio-economic condition of the users or their willingness to invest in these specific technologies as this information was not available.

As mentioned, the previous simulations used two methods to enhance the modelling of EV home charging behaviour which were using a normal distribution to vary the arrival and departure times obtained from the national household travel surveys [17] and using a range of different distances per day which resulted in different levels of energy required to reach the preferred SoC of the users. However, the different ranges of EVs available on the market were not leveraged. In this case study, two different

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brands and four different models of EVs were used which reduces the reliance of the results on a single fixed capacity. In total, there are 106 EVs simulated which correspond to 45% penetration. The battery capacities, rated powers and travel ranges of different models are displayed in Table 5.9. Like other assets, using the responses from the project participants, a pool of users with an interest to purchase an EV was used to randomly disperse the total number of EVs across the network.

Table 5.9: Different EV models and corresponding battery capacity, rated power and maximum driving range.

| Model | Capacity (kWh) | Rated power (kW) | Range (km) |
|--------------------|----------------|------------------|------------|
| Tesla 3 long range | 70 | 11 | 448 |
| Tesla 3 standard | 57 | 11 | 378 |
| Nissan Leaf 62 | 56 | 6.6 | 336 |
| Nissan Leaf 40 | 36 | 6.6 | 230 |

Similarly, the previous simulations used a single battery type whereas as shown in Table 5.10, in this use case, a variety of battery models is used. Following the same principle as before, the batteries are co-located with nodes that have solar generation and matched according to the generation capacity. Hence, an assumption is made that users with no solar generation do not own batteries for the use of arbitrage, peak shaving and similar. While PV modelling inputs such as tilt angle, azimuth, efficiency and similar stayed the same, a range of peak kW (kWp) values (i.e. 2, 3, 4, 5, 6, 8 and 10kWp) and three different panel types (i.e. CdTe, CSi, CIS) are incorporated in the PV asset model to reflect the different PV models available in the market [215, 259].

Table 5.10: A set of battery models from different manufacturers and their rated power and capacities.

| Battery options | Rated power (kW) | Capacity (kWh) |
|-------------------------------------|------------------|-----------------------|
| Moixa standard | 3.0 | 4.8 |
| Moixa large | 6.0 | 9.6 |
| Tesla Powerwall | 5.0 | 13.5 |
| Sonnen hybrid 5.0 | 2.5 | 5.0 |
| Sonnen hybrid 7.5, 10.0, 12.5, 15.0 | 3.3 | 7.5, 10.0, 12.5, 15.0 |

5.3.4 Non-domestic load profiles

In addition to the residential demand, this case study features non-domestic loads in the local network which are shown in Table 5.11. The first branch of the network has a bike shop, church and two small size factories (baking and dairy sectors) as industrial loads. Cafe, library and newsagents are the non-domestic loads on the second branch, while the third one accommodates entertainment and hospital buildings. The available energy usage data is used for these loads where possible, however, in some cases, the information is missing and therefore a different approach was needed. The method based on the data provided by [260, 261] was developed to obtain half-hourly demand profiles and estimate non-domestic electricity consumption.

Firstly, the floor area for each site was found or approximated using satellite images if the information was not available. The floor areas were then input into the non-residential building energy usage benchmarking tool provided by CIBSE [262] to estimate the annual electricity demand. The tool is based on a naive calculator which accounts for the business type and benchmarks it against the existing energy consumption trends to provide an estimated annual electricity demand per square meter of area (kWh/m²/yr). It was assumed that natural gas is the preferred heating source for the facilities.

This modelling approach allowed the development of half-hourly demand profiles for non-domestic electricity consumption, where data was unavailable. The final step was to extrapolate the annual demand data to half-hourly intervals across the full year. As the business sectors were identified, the prevailing opening and closing times for each sector were taken into account to guide this modelling process. Ofgem [260] provided a set of the typical workday and weekend profiles for different business sectors and facilities. Using their demand profiles as a reference, the annual energy consumption data were manipulated and scaled to generate a working and non-working day consumption profile for each season and the total energy demand was divided across the year. To validate the outcomes, the data was then compared against the report by [261] which contains averaged normalised profiles for each business sector (averaged across all building types within the sector). The report includes raw empirical demand data, processed by Element Energy and DeMontfort University.

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Table 5.11: Location and type of non-residential loads in different neighbourhoods

| Neighbourhood | No of tapes | Non-residential load type | Connection type |
|---------------|-------------|---|------------------------------|
| 4030 | 39 | Bakery, bank, cafe, garages, hotel, restaurant, office, performance hall, police station, post office, pub, shops | 10 3-phase, 9 AN, 5 BN, 8 CN |
| 4010 | 3 | Church, Bowling club, Motorcycle dealer | 1 AN, 1 BN, 1 CN |
| 9030 | 1 | Hospital | 1 3-phase |

5.3.5 Network modelling

Using a data set of line coordinates, lengths, capacitance and reactance values, the low voltage networks of the three neighbourhoods were constructed as shown on the GIS map in Figure 5.8. The relevant primary and secondary substations are labelled. The networks in black, green and red correspond to Neighbourhoods 4030, 4010 and 9030 in Huntly, Aberdeenshire, Scotland.

The challenges of constructing the network model from raw SSEN line data included partially missing line data. For instance, at the bottom of the 4010 network (in green), some disconnected lines between the so-called “supply attachment points” and the main feeder were shown in Figure 5.8. To overcome this problem, an assumption was made that the node should be linked to the nearest feeder and the following methodology was followed to create the missing data. If there was any existing line data between the node and the feeder but it was broken, using the existing line properties, the length of the line was extended to complete the connection. Otherwise, using the GIS map, the shortest length of line between the node and feeder was calculated and the line properties were assumed to be the same as the most common type.

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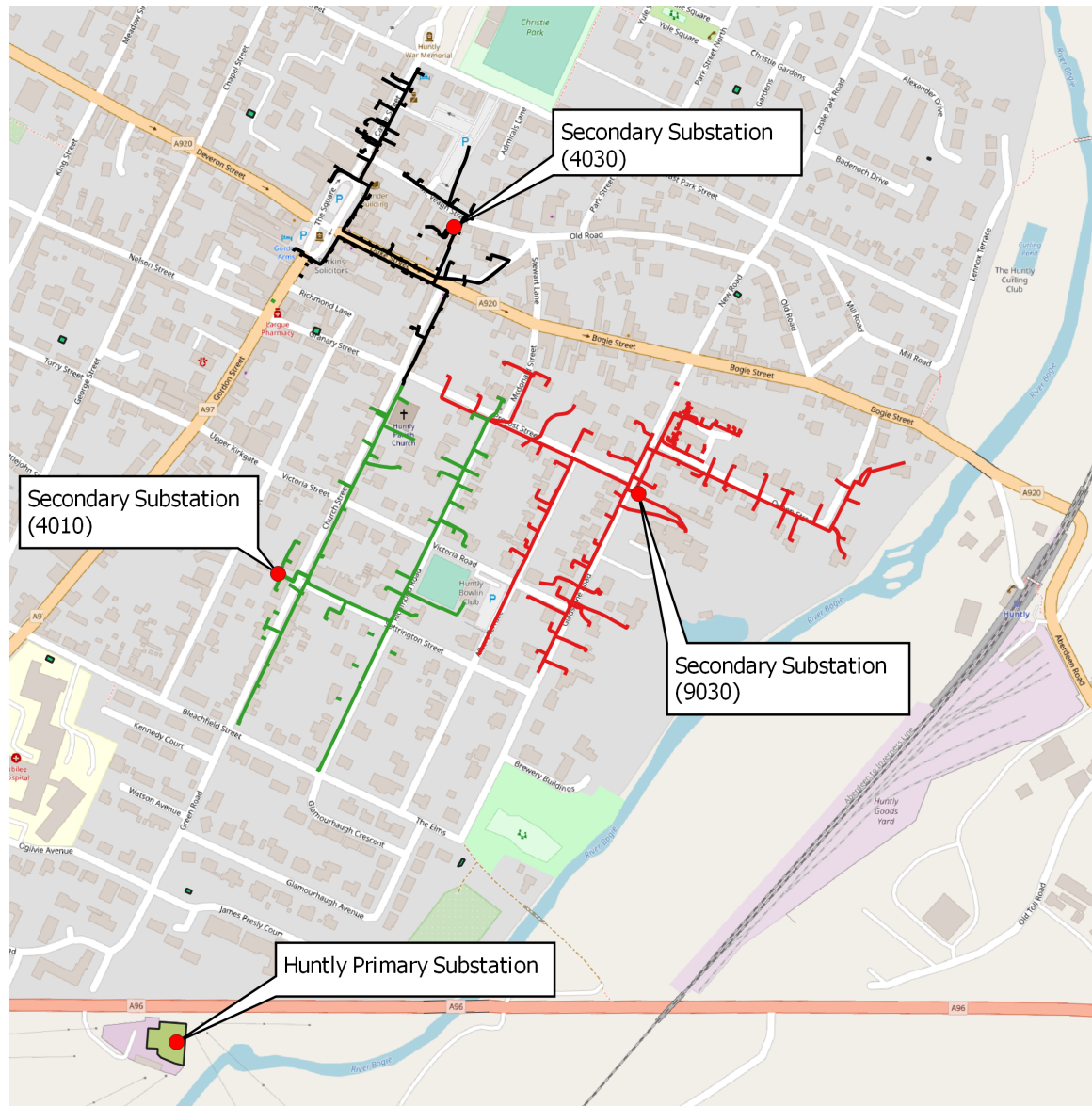


Figure 5.8: The LV network of the pilot site in Huntly, Aberdeenshire, Scotland.

5.3.6 Optimisation and peak shaving methods

The simulation workflow in this chapter followed the same market and grid co-simulation steps outlined in Chapter 4 - in specific in Figure 4.1. The optimisation and peak shaving methods employed in this chapter adapted the methodology presented in Chapter 3 and Section 5.2. Using the inputs from the digital twin models of the three neighbourhoods, optimisation was performed to simulate the community level behaviour for reaching minimum cost and hence, higher self-consumption and self-sufficiency through load shifting. Similarly, the same methodology was applied to minimising the carbon footprint of the communities, incurred by importing electricity from the grid during periods of high carbon intensity. The nature of the objective function stayed the same for both carbon and cost minimisation.

Two of the inputs of the objective function are the grid import and export tariffs. The Octopus Agile tariff was used as the grid import pricing. This dynamic half-hourly domestic tariff is indexed on Elexon system buy prices and it was previously introduced and used in Section 4.4.1. A range of export prices was used between 0 to 30p/kWh where 0p/kWh reflects no economic benefit for exporting electricity to the grid. It should be noted that often in literature 5p/kWh is used as a nominal value for the UK. Imported power and exported power are calculated in an aggregated approach which are the variables of the cost function - as previously shown in Equation A.4.

For the carbon minimal optimisation, the grid import and export tariffs were replaced by grid carbon intensity and local generation carbon intensity, respectively. The former was obtained from [5] and the latter was input as 0 gCO₂/kWh as the only type of local distributed generation simulated in this use-case was roof-top solar PV.

In order to leverage cheap import costs (irrespective of whether that is in terms of financial or carbon costs), the optimiser employed a technology-agnostic approach by increasing or decreasing demand from different smart assets. This was bounded by the flexibility range of the asset which is expressed as minimum and maximum operational bounds as shown in Equation A.2. Insights from the live pilot case showed that turning EV charging down to 0 kW of usage disabled the option of resuming charging of the vehicle. Hence, this insight was reflected in the turned down capacity (i.e. τ_{\min_t}) which was limited to 1.4 kW.

The business-as-usual asset behaviour from the digital twins was used to calculate the total energy consumption of smart assets in an arbitrary time horizon which is

24 hours in this use-case. The values for each asset were used as a reference to ensure that the demand was only shifted and not curtailed which could have resulted in end-user disutility and discomfort.

Similar to Chapter 3, the optimisation algorithm was deployed on a community scale, the total financial or environmental benefit for the whole community is maximised through minimisation of the aggregated electricity import costs minus the aggregated electricity export. For instance, the excess solar generation at one node can be used to cover the demand at another node in order to minimise the communal carbon footprint and costs. In this case study, all the heating demand is assumed to be inflexible. Hence, there are no pre-heating enabled assets.

Some optimisation and P2P strategies resulted in higher peak loads, in winter, which are later discussed in Section 5.3.8. Hence, using the constraint introduced in Equation 3.11, the peak incurred by P2P trading was shaved. This resulted in a hybrid simulation of peak shaving and P2P trading. The results drew attention to the risk of increasing the imbalance and stress on the system that could be heightened through the adoption of local energy markets and coordination techniques.

This limit was applied for the entire day rather than focusing on red rate periods. This is because in some of the cases, the morning peak was observed to be higher than the evening surge. Therefore, this constraint caps the power import level to the given limit at any time during the simulation. The business-as-usual scenario from the digital twin models was used to determine P_{max} per neighbourhood as each neighbourhood is located behind its own secondary substation as shown in Figure 5.8. Following the previous simulation approaches, the peak was also curtailed to 30% of its maximum value in some cases.

5.3.7 P2P methods

This subsection describes the method of the three different variations of local energy markets compared in this case study. These are namely the community-based P2P (see Section 4.2.2), carbon-aware P2P market (see Section 4.3) and the newly introduced intra-community P2P trading algorithm. The pricing mechanisms build on the community-based P2P trading mechanisms described in Chapter 4. In this case study, SDR was calculated based on the inputs from the business-as-usual digital twin models, using distributed solar generation and battery export as supply. Using Equation 4.2 from Chapter 4, P2P sell prices were computed where P2P sell price is

a function of SDR. Similarly, P2P buy price which is a function of both SDR and P2P sell price was calculated as shown in Equation 4.3 in Chapter 4.

Using a similar approach to Long et al. [81], an incentive was introduced to fairly reward the contributions from local energy generators. This incentive is shown as λ . Following the sensitivity analysis performed in [81], 4p/kWh was chosen for the level of DER penetration in this case study.

For the simulation of carbon-aware P2P trading, λ is a variable which is indexed to the levels of system carbon intensity as described in Section 4.3. This method was used to produce carbon-informed pricing for local energy trading. It rewards sharing of energy and penalises consumption during times of high system carbon footprint.

Having multiple neighbourhoods in this case study enabled two approaches to computing the P2P pricing. The first method is called inter-community and the second method is named intra-community. In the inter-community P2P case, three neighbourhoods were able to trade with one another and their SDR and hence P2P pricing was calculated using an aggregated approach. On the other hand, for the intra-community trading, the supply and demand were evaluated individually for each neighbourhood. Therefore, each neighbourhood trades within its own community using its own pricing based on neighbourhood-level SDR values.

The computed P2P pricing for different scenarios was then fed into the optimiser which aims to minimise costs by increasing community-level self-sufficiency. This enabled comparison of various P2P tariffs with community-level cost and carbon optimisation cases. More details about the simulations architecture were previously presented in Figure 4.1 (in Chapter 4).

5.3.8 Discussion of results

As previously mentioned, the main aim of this case study was to compare P2P energy trading and community-level optimisation in terms of economic, environmental and system level cost and benefit. For this reason, different electricity system congestion and stability indicators were analysed which included peak loads, network voltages, transformer and line losses. To assess the economic and environmental benefits, CO₂ emissions and user bills were analysed.

5.3.8.1 P2P tariffs

There are three main approaches shown here which are inter-community, intra-community and carbon-aware P2P tariffs which are outputs from the local energy market simulations.

Inter-community P2P energy trading (also referred to as simply P2P in this chapter) followed the same methodology as the community-based local energy market design in Section 4. This approach views all of the three neighbourhoods as a single pool of flexible demand and local generation. In terms of their proximity, the three neighbourhoods are located behind the same primary substation - as shown in Figure 5.8.

The carbon-aware P2P approach applies the same incentive/levy as detailed in Section 4.3. Figure 5.9 compares the summer and winter prices obtained by the carbon-aware and inter-community P2P approaches. It also displays the grid import prices which both of the pricing approaches rely on. Additionally, it shows the carbon intensity which was used to scale the carbon premium. Two days of data are plotted in Figure 5.9 where it is clearly shown that no particular correlation between grid buy prices and carbon intensity exists. The top plot shows the summer case where the carbon intensity values are relatively high (i.e. on average 150gCO₂/kWh). Both P2P and carbon-aware P2P cases yielded lower buy prices for the local participants. The summer P2P buy prices (in green) exhibit a plateau around midday when there is a surplus of local solar generation which results in SDR values higher than 1. This leads to the capping of the export prices at 5p/kWh. While this is highly beneficial for buyers as the grid value of the same generation is 2.5-7p/kWh more expensive, from the seller's view, there is no difference and hence no benefit in participating in the local energy market when compared to exporting to the grid. In order to reflect the carbon intensity of the grid supply (i.e. hence discourage import) and also reward local generators that contribute towards decreasing the emissions by supplying carbon-neutral energy, a dynamic carbon premium was applied. This brought up the export prices from the P2P's 5p/kWh to a range of 7.17 to 9.22p/kWh.

The first peak price in the summer plot is reduced by both P2P and carbon-aware P2P cases. It is 25.74, 23.58 and 22.52p per unit for the grid, carbon-aware P2P and inter-community P2P buy prices correspondingly. It should be noted that the carbon intensity is relatively high at this time which is reflected in the pricing.

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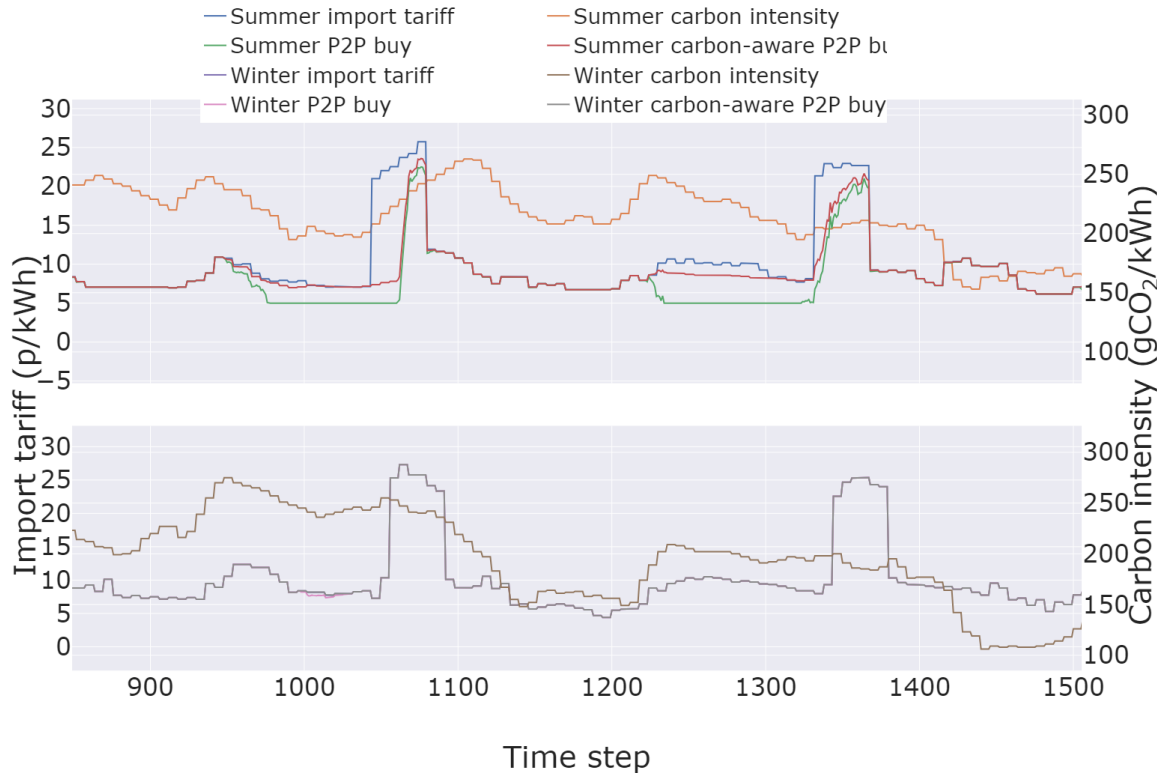


Figure 5.9: Summer and winter comparison of carbon-aware P2P and inter-community P2P trading prices, in the top and bottom plot respectively, using grid import tariff and carbon intensity levels as reference points.

On the other hand, in the bottom plot of Figure 5.9 where the winter case is shown, all three of the pricing signals are very similar. This is because SDR ranges between zero to very low values due to decreased supply and increased demand in winter.

The intra-community P2P market is a new addition in this chapter. As there are multiple neighbourhoods, the intra-community P2P approach calculates the SDR behind separate secondary substations and evaluates the local pricing according to the solar output and flexibility of the demand in that specific community. The resultant local import tariffs are shown in Figure 5.10 for a summer day. The tariff for Neighbourhood 4030 is significantly higher than the others. This is due to the large portion of small C&I loads present. A third of the nodes present in this local network have non-residential load types which increase the demand during midday (which is often

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lower in purely residential neighbourhoods). As only domestic-scale generation was in the scope of this work, any commercial-scale generation was neglected. Therefore, larger contributions from small C&I loads correlate with the increased demand on the system around midday which resulted in lower SDR values. To summarise, the supply-to-demand ratio for Neighbourhood 4030 is lower in comparison to the other neighbourhoods due to higher levels of C&I load and hence, this results in higher local energy prices in that community.

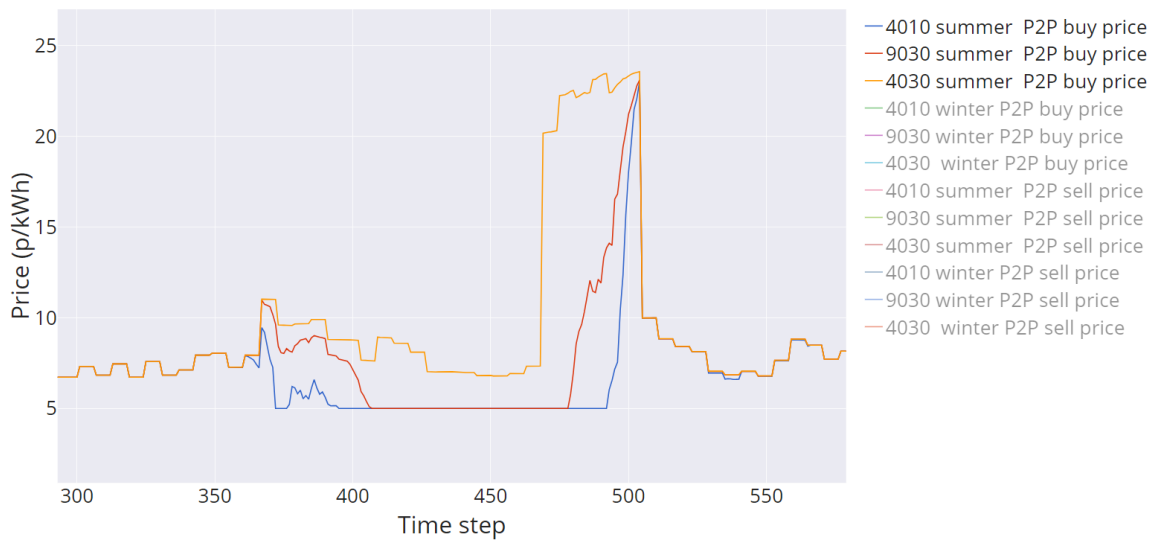


Figure 5.10: Individual local energy prices for each community where the pricing is higher for neighbourhoods with higher C&I loads.

While the previous figure discussed the differences between the different intra-neighbourhood pricing signals in summer, the next figures (i.e. Figures 5.11 and 5.12) examine the variations in pricing in winter and summer months. Following the trend previously presented, the summer months result in relatively lower prices than the grid import tariff for all three neighbourhoods. However, as the SDR is lower in the winter months, the local prices mostly match the grid buy prices. From a local energy consumer’s perspective, trading in Neighbourhood 4010 is more beneficial as during the summer, the evening peak prices are not only reduced to 23p/kWh but the duration of peak pricing is diminished to around one-fifth of the Agile tariff. Additionally, if the consumers have a flexible load, they could shift their load to periods with high SDR which resulted in the 5p/kWh plateau during the hours of solar energy output. However, in winter participation in either the 4010 or 4030 local

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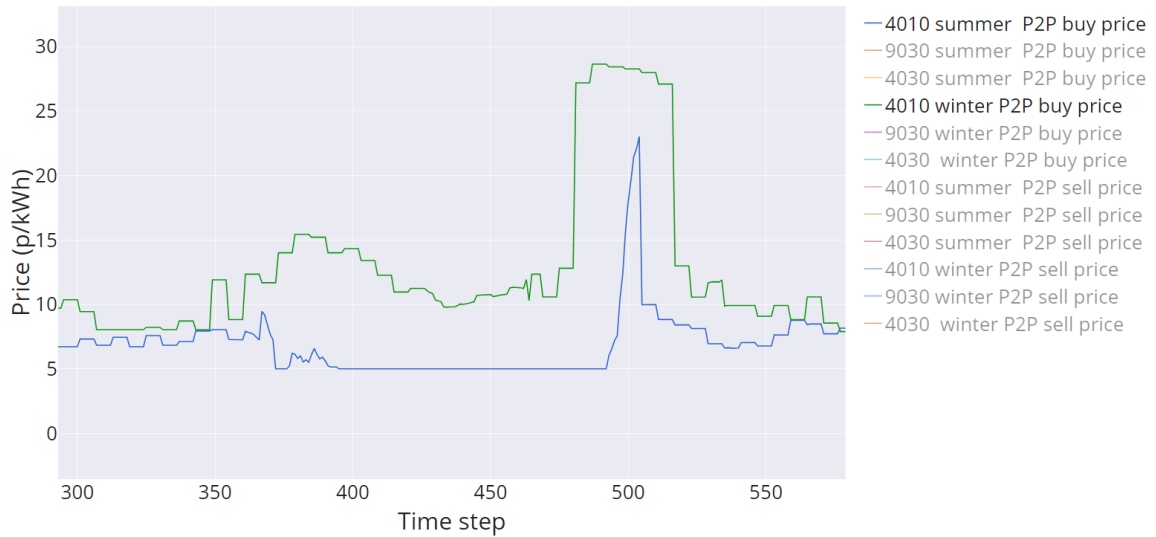


Figure 5.11: Comparison of winter and summer P2P buy pricing in Neighbourhood 4010 which is mostly residential.

energy markets makes almost no difference as they both very closely follow the grid pricing.

Overall, it was found that the consumers in Neighbourhood 4010 experienced lower prices compared to the participants in Neighbourhood 4030. This is because of the nature of the communities as 4010 is highly residential and 4030 has small C&I loads on 39 nodes. Having a highly residential neighbourhood results in higher solar penetration and lower loads which leads to a higher overall SDR average in the local market. Despite this, the 4030 residents who participate in P2P trading would still leverage the perks of dynamic energy pricing in comparison to the fixed rate tariffs. Figure 5.13 shows an example of a negative pricing event that took place in winter.

So far, the tariffs were analysed from the perspective of the consumer as the focus was on the electricity import prices. Figures 5.14 and 5.15 display the summer and winter P2P sell prices for the same neighbourhoods in order to compare the LEM participation in 4010 and 4030 from the producer's point of view. While Neighbourhood 4010 prices were more attractive for the consumers, the opposite case applies to the sellers. This is because there is a high penetration of solar energy output in this area which leads to very high SDR levels. This consequently drives down the market prices of local generation down. This is capped at 5p/kWh in this use case to ensure that the local market benefit to the seller would not be lower than exporting

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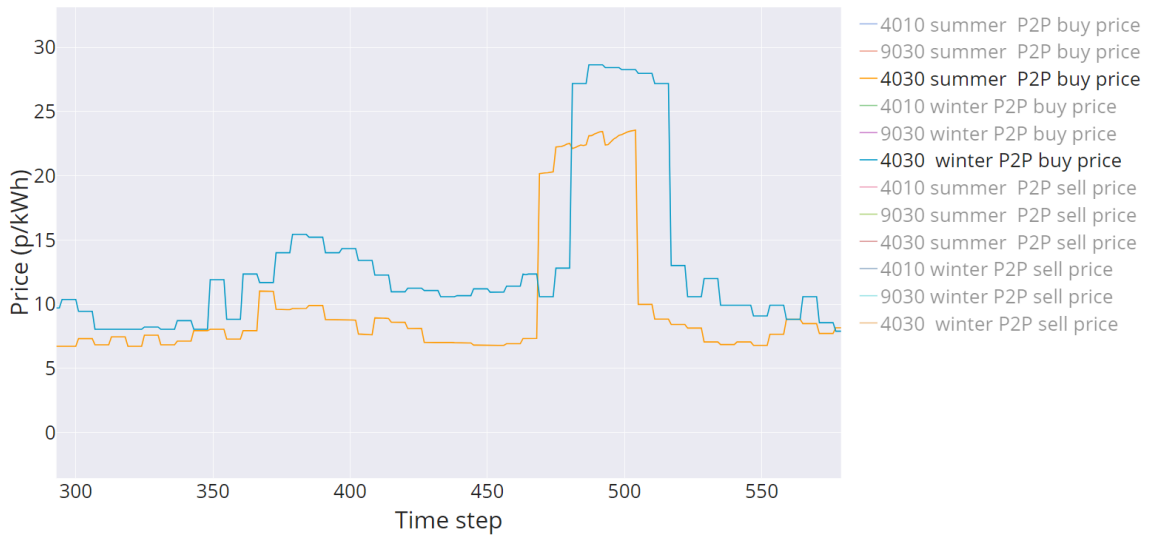


Figure 5.12: Comparison of winter and summer P2P buy pricing in Neighbourhood 4030 where a third of the nodes have non-residential loads.

energy to the grid. However, this also means that from the seller's point of view, there is hardly any difference between participating in P2P or selling energy to the grid during hours of solar output. On the other hand, if the producer is also to store the energy and sell later, they can leverage higher benefits during peak hours and overnight sell pricing when the community SDR is low. Participants with different generation methods (i.e. not solar) such as wind turbines would highly benefit from this market structure regardless of which neighbourhood they reside in. The sellers in Neighbourhood 4030 have access to more profitable sell prices that are always higher than the grid export price in this use-case. Therefore, it can be concluded from this case study that neighbourhoods with a more diverse load mix that include small C&I are more advantageous for small local producers of solar energy in the distribution networks.

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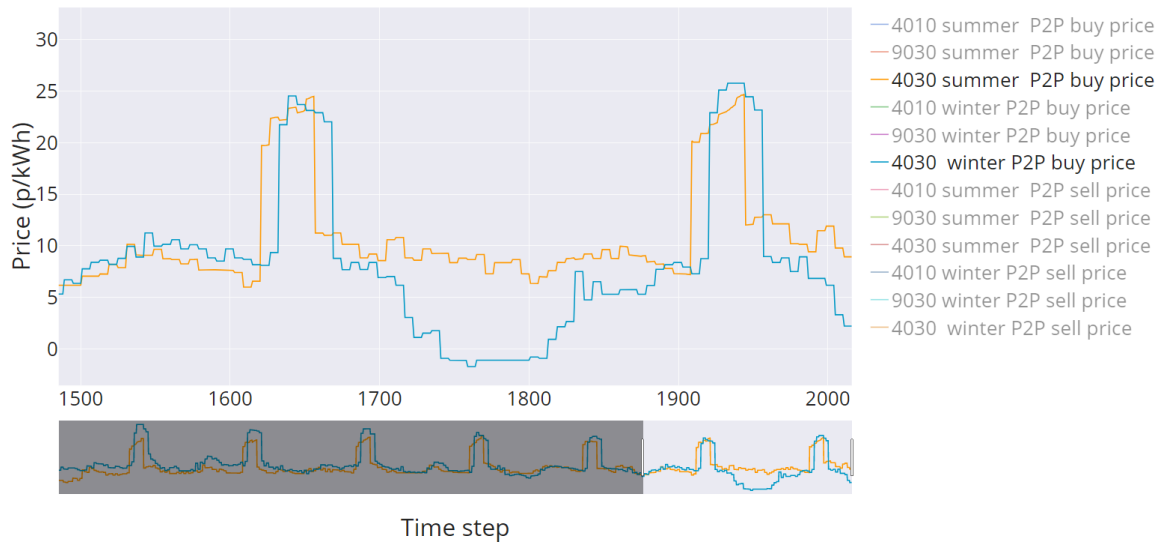


Figure 5.13: An event of negative pricing in the winter case.

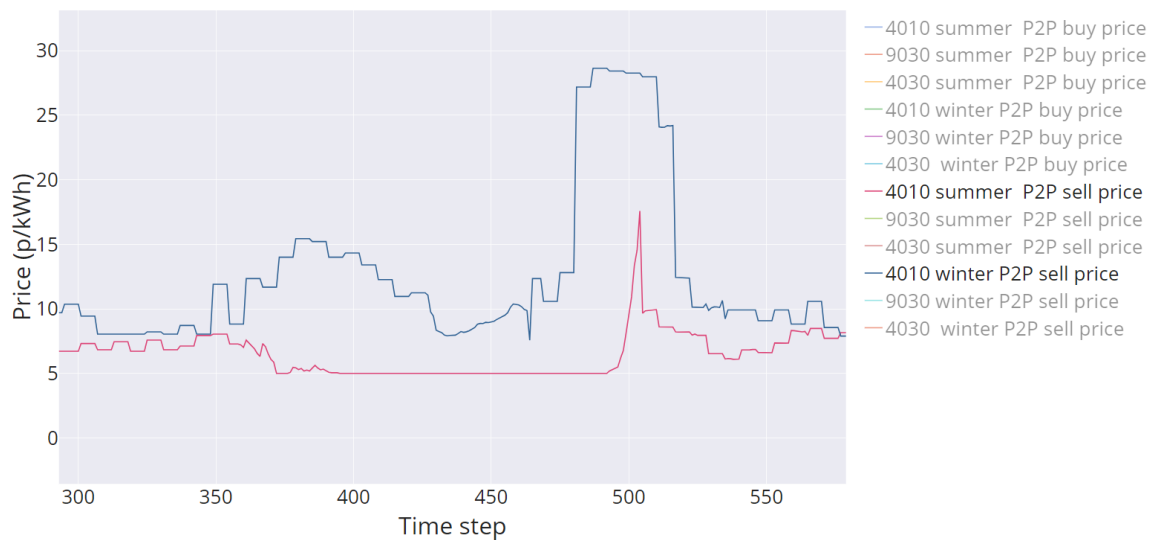


Figure 5.14: Comparison of winter and summer P2P sell pricing in Neighbourhood 4010 which is mostly residential.

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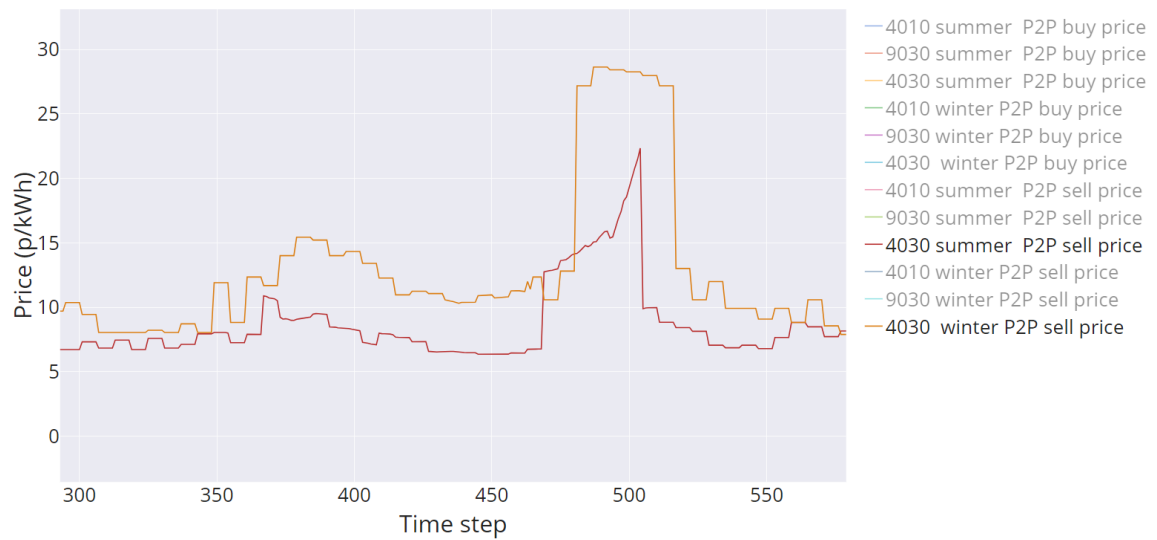


Figure 5.15: Comparison of winter and summer P2P sell pricing in Neighbourhood 4030 where a third of the nodes have non-residential loads.

5.3.8.2 Peak load and effect of peak shaving

As shown in Table 5.12, P2P and optimisation cases result in higher peak values in winter. This results in higher loading in lines and increased usage at the transformer level. Therefore, this increased peak value leads to an increase in power losses, decreasing the overall efficiency of the power flow. The higher peak values are found disruptive from the view of a distribution system operator. The case with the highest aggregated peak is the cost minimisation case where the highest peak occurred on the 6th of December at 19:25. Following this, intra P2P and P2P cases resulted in increases within the range of 0.60-0.62%. As there is a scarcity of local generation in the winter months, the local P2P prices are mostly commanded by the grid import prices. This meant that the cost signals, that reflect high system demand, did not align with the local peak demand. Therefore, the price during the local peak period was not the highest pricing of the day. This allowed the cost-focused algorithms to schedule 0.60% more loads on top of the existing peak. As a response to the increased peak in the P2P and cost minimum cases, peak shaving was applied which both resulted in an aggregated peak value of 637kW of the net power import. On the other hand, the carbon minimum and carbon-aware P2P cases led to a negligible decrease in the peak value, by only 20 to 40W. This is because during the local peak demand, the carbon intensity of the grid was relatively high which led to a small decrease in the peak power import values.

Table 5.12: Comparison of peak values for net power import during different cases against the no-control case - including P2P, cost minimisation and peak-shaving options.

| | Peak power (kW) | Difference (W) | % difference |
|----------------------------|-----------------|----------------|--------------|
| P2P | 640 | 318.56 | 0.60% |
| Carbon-aware P2P | 637 | -21.33 | -0.04% |
| P2P with peak shaving | 637 | 0.00 | 0.00% |
| Intra P2P | 641 | 325.88 | 0.61% |
| Min cost | 641 | 330.99 | 0.62% |
| Min carbon | 637 | -37.31 | -0.07% |
| Min cost with peak shaving | 637 | 0.00 | 0.00% |

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Despite causing an increase in the net power imported during the winter months, the transactive energy algorithms diminished the peak during the summer season. The percentage difference of the summer peak decrease (i.e. 1.8%) was considerably higher than the increase caused in the winter cases (i.e. 0.6%). The response from all of the algorithms was similar and approximately resulted in a 1.8% decrease of the peak value as shown in Table 5.13. This is because all of the algorithms leverage the local generation using different approaches and they all attempt to maximise self-sufficiency. For the optimisation and P2P cases that are based on a grid import tariff, the results indicated that the peak pricing (which reflects high demand on a national scale) takes place during local peak demand periods in summer. Hence, while minimising costs, the algorithm yields lower demand peaks. The difference in behaviour between the summer and winter months originates from the different seasonal usage and generation patterns. Most importantly, the lower solar generation and increased heating demand in winter vastly decrease the level of flexibility in the distributed loads.

Table 5.13: Comparison of summer peak net import values for net power import against the no-control case - including P2P, cost minimisation and peak-shaving options.

| | Peak power (kW) | Difference (W) | % difference |
|------------------|-----------------|----------------|--------------|
| P2P | 358 | -537.08 | -1.77% |
| Carbon-aware P2P | 358 | -538.97 | -1.77% |
| Intra P2P | 358 | -534.27 | -1.76% |
| Min cost | 358 | -534.27 | -1.76% |
| Min carbon | 358 | -536.03 | -1.76% |

Further experiments were carried out using the maximum import limit. The simulation case was shown to reduce the aggregated demand by up to 30% on certain days. However, as the main focus of this case study is the comparison between P2P and community-level optimisation, this analysis was not taken further. Table 5.14 shows the results from a winter day where the aggressive peak shaving method was applied. The results reflect the flexibility of each neighbourhood where the maximum peak reduction of 4.30% takes place in 4010 which is highly residential and the lowest reduction of 0.02% is experienced by 4030 where one-third of the nodes are C&I. These results confirm that the penetration of small C&I loads decreases the flexibility

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of the community which is also linked to poorer performance of Neighbourhood 4030 in terms of price reductions in the intra-community P2P market case. It should be noted that the flexibility of non-domestic loads was disregarded in this case study.

Table 5.14: More aggressive peak shaving in winter which shows that highly residential neighbourhoods are more flexible than the ones with C&I loads.

| Area | Pre peak shaving (kW) | Post peak shaving (kW) | % diff |
|------|-----------------------|------------------------|--------|
| 4010 | 106.74 | 102.28 | -4.30% |
| 9030 | 129.98 | 128.59 | -1.07% |
| 4030 | 637.07 | 636.93 | -0.02% |

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

5.3.8.3 Network voltages

As shown in Figure 5.16, P2P cases resulted in lower voltage levels due to higher self-consumption. The P2P pricing reflects the level of local supply on the network which in return encouraged local consumption. On average, during high generation periods, P2P resulted in 2% lower voltage levels where the cost optimisation very slightly increased them (i.e. 0.002%). When the first level of peak shaving was applied to the cost optimisation (where the import limit was curtailed to the peak load in the no-control case), the voltage levels were reduced by 0.01%. With the maximum peak shaving, this resulted in a higher decrease of 0.02%. This is shown in Figure 5.17 in yellow, peak shaving of the cost optimisation case results in the lowest voltage levels of the non-P2P cases.

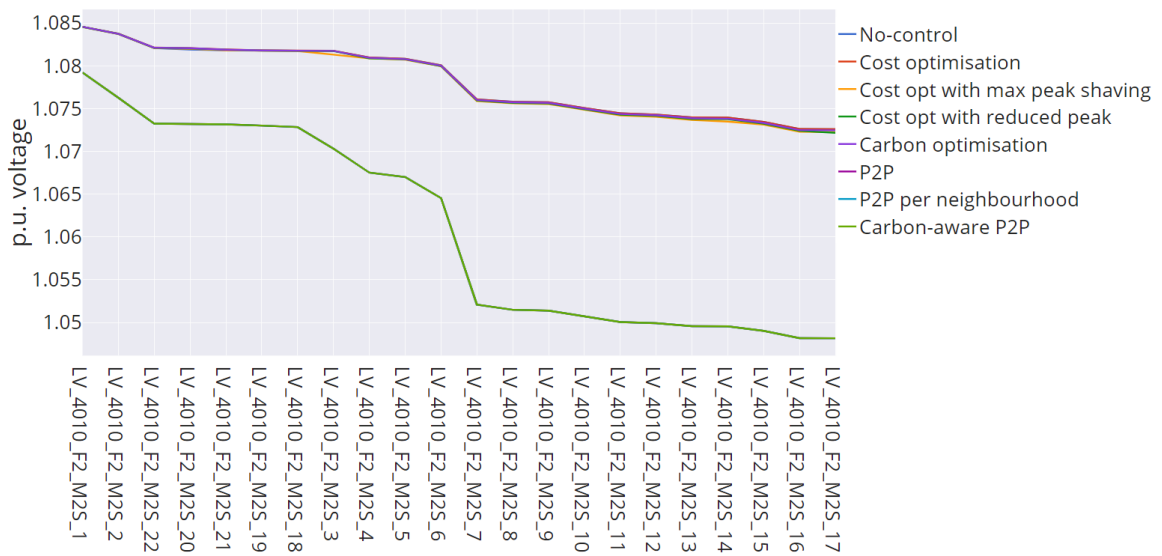


Figure 5.16: Comparison of per-unit network voltages on a high solar output on a summer day where P2P algorithms decrease the p.u. voltages by shifting demand to periods of generation.

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

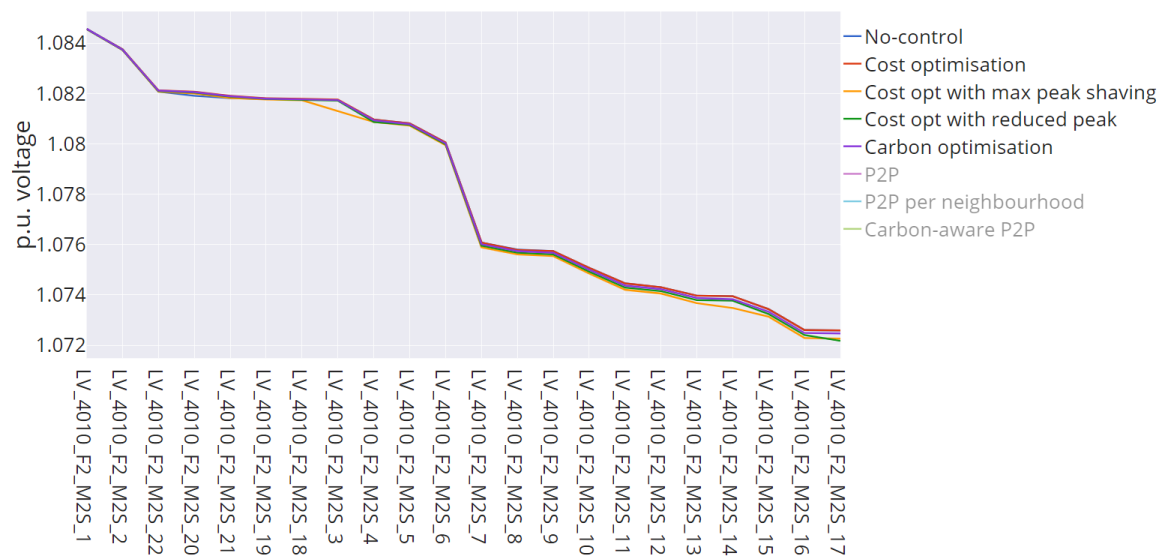


Figure 5.17: Network voltage levels of Feeder 2 during a high solar output period where implementation of peak limit (in yellow) results in slightly lower p.u. voltage levels.

5.3.8.4 Transformer loading

The transformer loadings were checked to ensure that the implementation of local energy markets or network control algorithms did not result in operations that exceed 90% of the rated capacity. It should be noted that this limit was never reached in any of the simulations across the three secondary substations. On average, all of the P2P and optimisation cases yielded 8.53A of usage. The maximum values shown in Table 5.15 were all achieved in winter as energy demand is much higher (i.e. 1.7 times on average) due to heating loads.

While the no-control case had the lowest maximum current, P2P and minimum cost cases only increased it by 0.02 and 0.03A correspondingly. This value reduced to the no-control loading when peak shaving was applied to the cost optimisation case. It should also be noted that the P2P case lowered the maximum loading on the transformer in the summer by 0.03A along with the peak-controlled minimum cost case. On the other hand, a 0.08A increase in loading was imposed by the pure cost minimisation case.

Table 5.15: Transformer current loadings for P2P and cost minimisation cases from the secondary substation transformer “P8AU_11kV_BUS”.

| Cases | Maximum loading (A) | Maximum loading in summer (A) |
|----------------------------|---------------------|-------------------------------|
| No-control | 24.87 | 17.03 |
| P2P | 24.89 | 17.00 |
| Min cost | 24.90 | 17.11 |
| Min cost with peak shaving | 24.87 | 17.00 |

5.3.8.5 EV charging

In the previous case study, one way to assess user satisfaction was to check if the EV left the home charger with the demanded SoC. Due to the delay penalty and the equal energy consumption constraint in the optimisation algorithm, the SoC requirements were always met in this case study. This is because curtailment is not allowed in the designed optimisation algorithm. Instead, the loads can be shifted to different periods in the day with an increasing penalty for delaying the actions later than the scheduled start point. Charging of the EV is ramped up and down within the provided flexibility volumes.

5.3.8.6 Battery usage

The battery behaviour and hence, the number of cycles vary according to the seasonal differences (i.e. higher solar energy output in the summer and vice versa) and the control strategy deployed. Compared to the no-control case, all cases completed a higher number of cycles annually. On average, the simulated cases used 0.5 to 2 more cycles per week during summer months than winter ones. This is due to the higher solar generation output during summer. The simulated P2P and optimisation cases have similar battery usages where they all resulted in approximately 90 extra cycles in a year. This obviously would lead to further degradation of the domestic battery which might positively or negatively affect the return on investment and the levelised cost of storage. However, this is outside the scope of this work.

5.3.8.7 Comfort levels

In this case study, the comfort levels were integrated as constraints in the optimisation algorithm using the penalty matrix for delaying the user scheduled actions. As this use case has 238 residential and 43 small C&I nodes, further evaluations of comfort were discarded.

5.3.8.8 Losses

Annual energy losses were calculated for all of the simulated cases. When compared to the benchmark no-control case, most of the cases achieved a negligible increase of 0.12% in total energy losses. The only exception was the inter-community P2P trading case which resulted in 0.24% higher energy losses annually - which might be due to the increased energy sharing between the communities. This is because most of the literature such as [27, 83] and the case studies in the previous chapters assumed higher penetrations of EVs, solar energy and storage whereas 14% solar and battery and 45% EV penetration was assumed in this case study. These percentage values were obtained from the DNO's DFES projections for the specific region in North Scotland [32]. When analysing the losses in winter, it was found that the P2P cases yielded slightly lower energy losses in comparison to the minimum cost and carbon optimisation cases in winter. This might be because the P2P algorithms take into account the local supply-to-demand ratio whereas the minimum cost and carbon algorithms discard this value completely. For all cases, the maximum line losses took

Table 5.16: Annual carbon savings in percentage.

| Cases | Annual carbon savings (%) |
|---------------------|---------------------------|
| No-control | 0.00 |
| Inter-community P2P | 6.52 |
| Carbon-aware P2P | 7.24 |
| Intra-community P2P | 6.70 |
| Minimum cost | 6.56 |
| Minimum carbon | 7.31 |

place during the winter when the net active power import was the highest in that specific case. The maximum line loss values were around 9kW. All simulated cases except the minimum carbon and carbon-aware P2P trading resulted in a 1.54% increase in the maximum line losses value when compared with the no-control case. However, minimum carbon and carbon-aware case led to 0.25% and no increase respectively.

5.3.8.9 CO₂ emissions

Even though carbon emission reduction was only the objective of the carbon minimum and carbon-aware P2P cases, all cases achieved a minimum of 6% annual carbon savings when compared against the benchmark no-control case in 2032. The detailed contributions of each case are shown in Table 5.16. The main highlight was that the novel concept of carbon-aware P2P trading introduced in this thesis was able to achieve almost the same level of carbon saving as the carbon minimal optimisation case - which is equal to 35 tonnes of carbon dioxide in a year. This validated the choice of 4p/kWh carbon premium as anything less would have resulted in smaller savings and more would have led to over penalisation of the users. The difference between the savings of carbon minimum and carbon-aware P2P case was 0.07%. However, it should be noted that the local energy market structure in the carbon-aware P2P case leads to higher economic benefits - which is discussed in the next section.

5.3.8.10 Cost savings

The majority of the optimisation and P2P algorithms have either cost or carbon focus except the carbon-aware P2P trading which brings together both of these perspectives. Hence, the cost and carbon savings of each case are presented in Figure 5.18 using percentages.

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

The cost and carbon optimisation choices showed that optimising for carbon jeopardises the cost savings and vice versa. This is because the current electricity prices do not reflect the carbon intensity of electricity consumption. While the cost optimisation achieved 9.2% cost savings, this was lowered to 8.7% with the peak import limit. The carbon minimisation case resulted in the lowest saving of 8.1% whilst having the highest carbon avoidance.

All of the local market simulations (including carbon-aware P2P) resulted in higher cost savings than the optimisation cases. This is because the electricity pricing was adjusted using the local supply-to-demand values. The inter-community P2P case yielded the highest savings (i.e. 15.8%) with and without the peak import limit. On average, each household that participated in inter-community P2P saved £207.37 during the simulation year.

Moreover, the intra-community approach yielded slightly lower savings (i.e. by 1.5%) as the average P2P prices were higher for this approach. The carbon-aware P2P case output the lowest savings out of the three local energy market approaches. Its savings were 4.4% lower than the inter-community P2P case.

The carbon-aware P2P sacrificed 0.07% of the annual carbon emission savings made by the carbon minimal case and in return, through its local energy market mechanism saved 3.3% more costs annually. When compared with the benchmark inter-community P2P energy trading case, carbon-aware P2P trading only achieves around 72% of the savings possible (for a P2P mechanism) which is equal to a total loss of £15,000 annually and on average £63.03 per household per year. This is still 2.7% higher than the cost minimal optimisation that does not implement any local energy markets.

In order to express the carbon savings in monetary terms, the social cost per tonne of carbon dioxide was used. The social cost of carbon measures the economic effect of every tonne of carbon dioxide released which contributes to global climate change [263, 264]. This measure takes into account the economic loss experienced by businesses and families due to the effects of climate change such as adverse weather events and rising sea levels. [263] estimated the social cost of carbon as US\$200 per tonne. Hence, the use of carbon-aware P2P trading would result in £5.7k savings. Another approach to express the carbon savings in monetary terms is to evaluate the avoided cost of carbon capture and storage. Using the per-unit carbon capture storage costs from [265], the use of this local energy market design would save a further £2.6k.

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

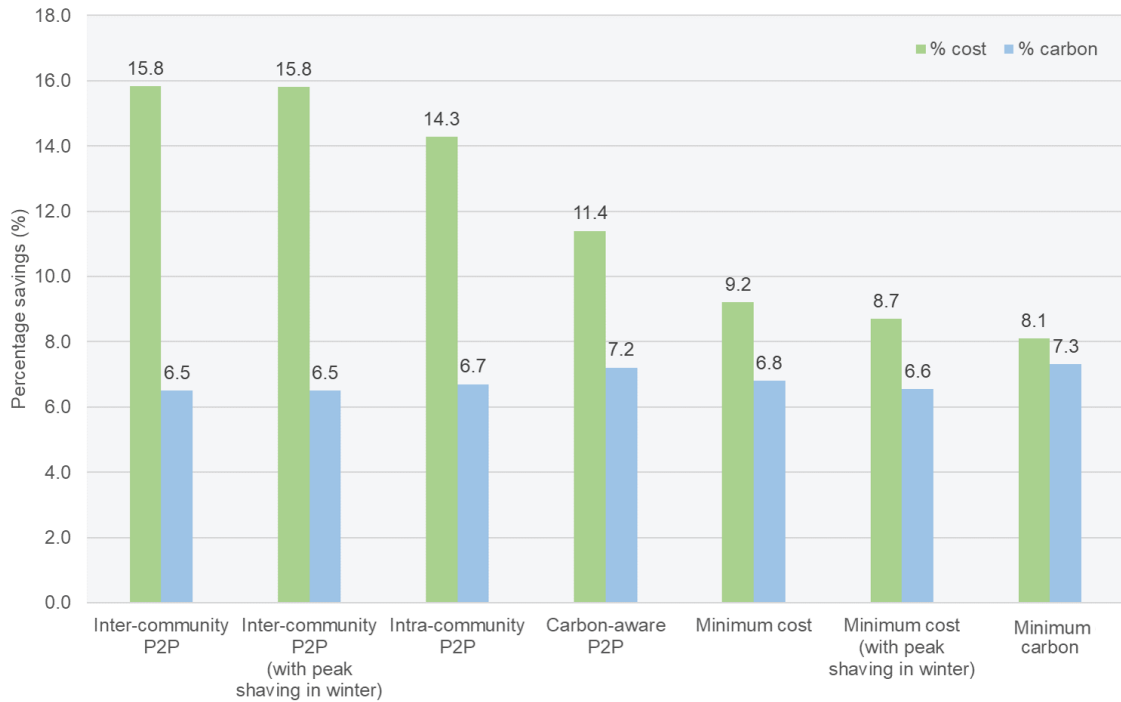


Figure 5.18: Percentage cost and carbon savings for all types of local energy market and network control methodologies.

This results in a total of £8.3k worth of carbon savings. This is still lower than the £15k sacrificed but this method provides both economic and environmental benefits as opposed to a single one.

5.3.8.11 Net power import from the grid

The annual energy consumption from 238 residential and 43 small C&I nodes added up to 30.42 GWh of energy, with contributions from 4030, 9030 and 4010 as 82.17%, 11.10% and 6.74% correspondingly. The power factors and annual reactive power demand follow the same trend - as shown in Table 5.17. As mentioned previously, the optimisation was performed such that the total energy demand of the use case stayed constant in a day.

As the key objective of implementing smart local energy systems is reducing the reliance on the centralised carbon-intensive generation, it is important to analyse the net active and reactive power import of local energy management strategies, namely P2P energy sharing and community-level cost/carbon minimisation. This also

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

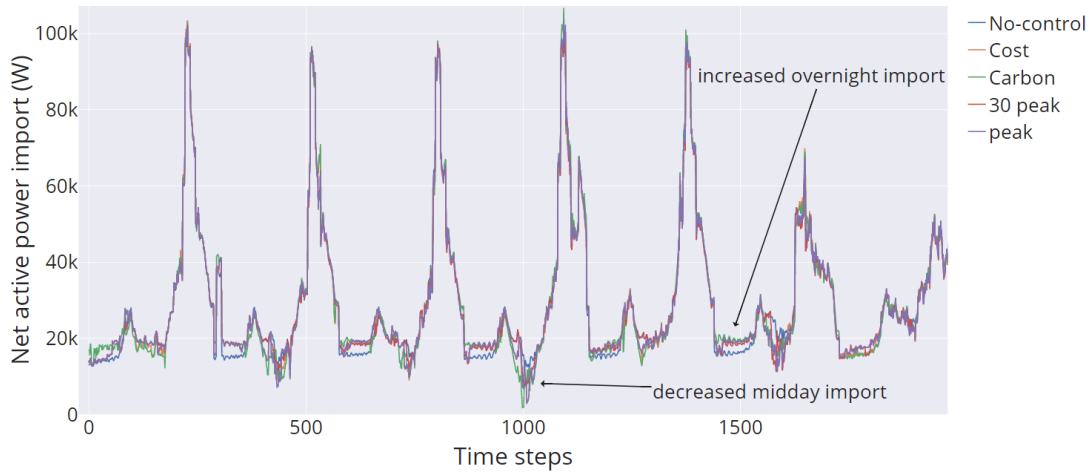


Figure 5.19: Net active power import for cost and carbon optimisation cases compared against the benchmark no-control case.

indicates the self-sufficiency and self-consumption rates of the local energy system.

The aggregated net active power import profiles for the community are shown in Figure 5.19. The highest import takes place during the evening peaks and the cost and carbon optimisation scenarios result in a decreased midday active power import. This is because more of the surplus solar energy is consumed locally and the evening flexible load is shifted to relatively cheaper periods of consumption overnight. Thus, as annotated in Figure 5.19, the overnight import is increased. The P2P cases exhibit similar net power import profiles to the optimisation cases with slight differences. The imported power during the midday is further decreased as the local energy prices are very low due to solar energy surplus. This indicates that more of the flexible load is scheduled to match the hours of solar generation. Hence, a small increase in overnight import was observed in most cases.

The self-consumption levels for the P2P cases were 71% with an increase of 6.5% from the no-control case. This is because local energy markets enabled energy sharing amongst peers and communities. Consequently, the self-sufficiency levels increased to 32%. This indicates that the communities in North Scotland can cover up to a third of their loads locally by 2032, reducing their reliance on the grid and hence, central generation with higher carbon intensity. However, to reach net zero by 2050, self-sufficiency of communities is required to be higher. One shortcoming of this case study was that only solar DER were simulated and hence, all the local generation was

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

Table 5.17: Annual active and reactive power consumption per neighbourhood and their contributions to the total.

| Neighbourhood | Active power (MW) | % contr. | Reactive power (MVar) | % contr. | p.f. |
|---------------|-------------------|----------|-----------------------|----------|-------|
| 4010 | 2047.50 | 6.74% | -269.10 | 31.08% | 0.991 |
| 4030 | 24977.42 | 82.17% | -285.22 | 32.94% | 1.000 |
| 9030 | 3372.72 | 11.10% | -311.48 | 35.98% | 0.995 |

output at the same time. If the local energy supply is diversified (e.g. wind turbine), the self-sufficiency rate should increase.

The aggregated net active power import profiles for the community are shown in Figure 5.19. The highest import takes place during the evening peaks and the cost and carbon optimisation scenarios result in a decreased midday active power import. This is because more of the surplus solar energy is consumed locally and the evening flexible load is shifted to relatively cheaper periods of consumption overnight. Thus, as annotated in Figure 5.19, the overnight import is increased. The P2P cases exhibit similar net power import profiles to the optimisation cases with slight differences. The imported power during the midday is further decreased as the local energy prices are very low due to solar energy surplus. This indicates that more of the flexible load is scheduled to match the hours of solar generation. Hence, a slight increase in overnight import was observed in most cases.

5.3.9 Limitations

This subsection lists the limitations of the second case study presented in this chapter.

This use case simulated the future demand in three neighbourhoods in North Scotland assuming that there would be no population growth and no increase in the number of dwellings. A more accurate approach was not viable as there is currently no detailed data available that provides population and dwelling density projections for this local area. Nevertheless, this does not invalidate the simulation method or the results as these can be updated as the projections become available.

The case study only simulated solar PV and no other local energy generation. The winter savings in terms of cost and carbon may have significantly improved if wind generation was taken into account. As solar energy is only available during

5.3. CASE STUDY: COMPARISON OF P2P AND COMMUNITY-LEVEL OPTIMISATION

hours of daylight in a day. A more diverse local energy mix with the inclusion of wind energy would have also increased the community self-sufficiency. Wind energy would be expected to yield great economic benefits in P2P markets in winter when the generation output from solar is considerably lower.

Due to the availability of data, only 3 neighbourhoods were simulated. Simulation of a larger area with more neighbourhoods is expected to yield better results in terms of a higher volume of flexibility and more efficient local energy markets. On the other hand, the use of local energy markets and bottom-up control approaches may become too inefficient for larger areas of applications where aggregated top-down actions are more commonly used.

While the heating was provided by heat pumps in the previous case study, this one made the simplifying assumption that the heating loads were not programmable for all of the three neighbourhoods. This simplifying assumption was applied in this case study due to unavailability of data and also the large size of the simulation network with 238 residential and 49 non-residential nodes.

Participation in P2P and optimisation strategies was assumed to be undertaken by all of the community peers. In a real life setting, achieving 100% participation would be challenging due to issues related social acceptance. But, this case study makes this assumption in order to portray the contribution of these P2P and optimisation scenarios towards decarbonisation of the energy systems and calculate the resultant cost savings. A sensitivity analysis using varying levels of peer-to-peer participation and storage penetration was previously presented in Subsection 4.2.2.

Degradation of the distributed assets such as battery and EV was not in the scope. However, the batteries were used 20% more frequently than in the no-control case which would result in quicker degradation but also possibly faster return on investments.

Sousa et al. [30] presented a hybrid P2P design that leads to inter-community trading using a premium to incentivise usage of local generation even if cheaper options are available elsewhere. This is a hybrid model which sits between the intra and inter-community approaches presented in this study. The simulation of the novel carbon-aware P2P market design was prioritised over the simulation of this hybrid design in this case study. Future work could expand on this work through simulation of this hybrid market structure.

Additionally, the issues around fairness and distribution of benefits were left out of the scope of this work. However, it is important to ensure that the new designs of local energy markets are fair as it is one of the objectives of the Scottish Government to deliver a just net zero transition [266].

Lastly, this approach assumed 100% accurate forecasting of solar output and energy demand from EVs. However, forecast errors are expected to result in discrepancies between scheduled and actual demand and generation. This was neglected in this work. Nevertheless, as observed in literature, various post-action settlement logics [126, 130, 194] can be applied to resolve the resultant discrepancies in the P2P transactions and end-user bills. More information about this is in Chapter 6 which reviews different methods of settlement strategies in P2P markets and their deployment on blockchain-based smart contracts.

5.4 Discussion

This chapter featured two case studies which were about bottom-up network-aware control and peer-to-peer trading in local energy networks. The detailed and technical discussions of the results from the case studies were provided in their dedicated sections, namely Sections 5.2 and 5.3. The discussion in this section highlights the key findings from these use-cases and provides high-level interpretations of the results. The effects on different stakeholders, which range from the end-users to the energy system operator, are evaluated. Lastly, the future implications of the simulated strategies (e.g. carbon-aware P2P trading) are evaluated and discussed in terms of net zero goals and the barriers and opportunities for their adoption in real life.

The location for both of the case studies was Huntly, Aberdeenshire in Scotland. The use of this site in this thesis was made available by the ZUoS project of Scene Ltd. In this case, Scotland provided a special case study as it has ambitions to achieve the net zero emissions goal by 2045 and become a pioneer in the field of energy system decarbonisation [11]. In addition, Aberdeenshire, North Scotland has both the UK's highest level of fuel poverty and the highest regional electricity prices [234, 249] which increases the impact of the thesis outputs in terms of social and economic benefits. However, it should be noted that the peer-to-peer trading, optimisation and network control algorithms presented in this thesis were designed in such a way that they can be applied to different networks and locations.

Using the network and demographic data from this use-case, the first case study constructed a futuristic neighbourhood with EVs, heat pumps and solar systems with storage, using DFES to represent 2032. It showed that network-aware control led to the lowest carbon emissions, energy losses and obtained acceptable voltage levels while decreasing user comfort by less than 5%.

The second case study focused on the community-level optimisation and P2P trading comparison. P2P market designs yielded 7% higher economic benefit than the cost optimisation algorithm. The simulations also showed that the carbon and cost objectives were sometimes mutually exclusive (e.g. cost optimisation jeopardised carbon savings and vice versa). However, the proposed method of carbon-aware P2P sharing achieved a trade-off with 11% cost and 7% carbon savings. Additionally, this study found that larger pools of flexibility (i.e. inter-community trading) achieved higher savings than the separate neighbourhood only trading within themselves (i.e. intra-community trading).

It should be noted that one of the recommendations from this thesis is to diversify the local energy supply. This is because as only solar was considered the P2P trading and optimisation methods revealed much higher benefits during summer days and sunlight hours. On the other hand, due to the scarcity of local generation, the advantages of adopting these technologies were not justifiable in winter. Additionally, they caused small increases in peak loads and hence higher losses. To overcome this, peak shaving was applied which demonstrated the co-existence of P2P trading, optimisation and DSR services in one simulation.

The next subsections detail the implication on various stakeholders, accelerators and barriers and the last one provides an outlook on future energy systems.

5.4.1 Implications on stakeholders

When evaluating the impact of local energy solutions, it is important to ensure that the interests of the end-users are considered to enable a bottom-up and user-centric decarbonisation approach. The end users were expected to care the most about the energy bills and the effect of any kind of implemented control methods on their comfort levels. The simulation work in this thesis assumed full access to the users' generators, storages and flexible loads. To ensure that the comfort levels were not compromised, a delay-based penalty matrix was used in the optimisation process of all P2P and community-level cost/carbon minimisation studies. Additionally, in the

second case study only load shifting rather than curtailment was modelled to ensure the satisfaction of the participant. The comfort of the users was modelled and evaluated in more detail in the first case study (which included network-aware curtailment) where actual indoor temperatures and SoC of EVs were compared against user preferences. The first case study showed at the expense of reducing user comfort (4% of the time), that the overloading of the transformer and lines were prevented which resulted in lower annual demand, carbon emissions and losses. However, a suitable method should be found to compensate the users for decreasing their comfort levels. From the end-user's point of view, participation in P2P energy trading (as simulated in the second case study) proves to bring the highest economic benefit of around £170 on average per household per year. Out of the three different local energy market designs, inter-community trading resulted in the highest savings (i.e. 18% lower bills with an average of £210 of savings per household) as it has the largest pool of flexibility and generation. While inter-community P2P trading would be preferred by the consumers, intra-neighbourhood trading yields higher selling prices which would be more attractive to local energy producers. This is because neighbourhoods with higher penetration of small C&I loads experienced more inflexible demand and hence, the generation output was more highly rewarded. The end-users with environmental awareness may choose to subscribe to the carbon-aware P2P market and sacrifice 4% of their cost savings (i.e. £63 per year) in order to reduce their carbon footprint by 7.2% (i.e. 150kg of carbon emissions per year).

Another type of stakeholder in the local energy systems is the distribution network or system operator (i.e. the current DNO and the future DSO). Stakeholders of this type prioritise healthy operation of the local grid, network control and aggregated flexibility of the community over user cost and system carbon savings. In the case of the network operator, the increased visibility of the network and, demand and generation of the users would help to avoid congestion and stress in network operation. In the first case study, it was shown that network-aware community flexibility offers voltage balancing attributes. This is shown to be a better approach than the more commonly known peak-hour or red-rate avoidance strategy as it results in lower energy losses and better maintained voltages. As shown in the second case study, some local energy sharing scenarios may increase the peak import which results in higher losses and lower voltage levels. To tackle this, a maximum power import limit was implemented in this thesis which can be a future requirement from the DNO in real

life in order to minimise the network disruption and avoid overloading of lines and transformers in the future due to increased electrification of transportation and heating. To summarise, the implementation of P2P markets and bottom-up coordination offers an opportunity for more granular and responsive network control with higher visibility of local generation and smart assets.

In addition to the operator, the role of the aggregator is also expected to become more prominent in future local energy systems. Local energy system technologies presented in this thesis create a new opportunity for the aggregators to expand their portfolio to small distributed generation, storage and controllable loads. This could result in higher profits at the expense of more complex coordination, assuming that the aggregated residential flexibility would be more competitive than the larger commercial balancing mechanism units such as a grid-scale battery. As mentioned previously, the peak shaving algorithm provided a demonstration which could be used in a similar way to the Western Power Distribution's curtailment service during peak hours [6].

As a result of higher self-consumption and self-sufficiency, the centralised generators and energy suppliers are expected to earn less. However, as only renewable and specifically solar PV generation was considered, the local energy system simulated is still highly reliant on the grid import. If the generation portfolio in the future would be more diverse and coupled with higher generation and storage capacity, then this might cause a significant reduction in the earnings for the centralised supply as instead of the commercial large generators, the economic benefit would go to local small-scale generators.

From the National Grid's perspective, higher self-consumption means lower mid-day solar export and higher self-sufficiency indicates better matching of local demand and local supply. Hence, the resultant evening demand would be lower and the overall imbalance volume would decrease. This would improve the system operation conditions and also reduce the frequency of balancing action deployment which would eventually result in lower balancing costs and hence, decreased system cost of electricity. Additionally, aggregated participation of residential resources in the balancing market would increase the volume of flexibility which may drive down the cost of balancing actions.

Even though they are not directly associated with local energy systems, local governments, decision makers and bodies like Ofgem, NGENSO and the UK and Scottish

Governments are also stakeholders. From their point of view, the most important aspects include the carbon emission savings of the bottom-up flexibility coordination. It is important to note that due to the seasonal nature of solar generation, most of the benefits from the strategies presented in this chapter show little economic or environmental benefit during the winter months. Therefore a recommendation from this study would be to diversify the local energy supplies. The case studies in this chapter also show an increase in the self-sufficiency levels of the local communities. However, this was inhibited as the sole energy supply considered in this thesis was solar PV generation. Nevertheless, through peer-to-peer trading and community level optimisation methods, the carbon-saving potential of local energy networks was demonstrated and highlighted. The demonstrated concept of user-centric bottom-up modelling increased sharing of local energy which would benefit the stakeholders in terms of accelerating the transition to net zero while bringing local benefits to the participants which indirectly contributes to other social and economic issues such as fuel poverty.

5.4.2 Accelerators and barriers

While the simulation results of local energy markets and community level optimisation prove to be very beneficial to all stakeholders, they are still not fully adopted by the industry except for the few pilot studies such as the Huntly pilot of the ZUoS project by Scene Connect Ltd. In recent years, there also have been some positive advancements relevant to the real-life adoption of local energy markets. These include smart metering, smart homes control infrastructures, economic incentives for the uptake of EVs and heat pumps and lastly increased awareness about environmental issues which affect users' energy choices. Additionally, due to the previous economic incentives (e.g. Feed-in-Tariff), there is already a considerable amount of distributed solar PV present in the UK and other European countries [267].

The barriers of real life implementation include concerns regarding security, privacy, data collection and storage. As the control and coordination methods presented in this thesis require granular monitoring of different smart assets such as EVs and heat pumps, this poses a significant threat to the adoption of the developed methodology. However, distributed ledger technologies, including but not limited to blockchains, enable tamper-proof, encrypted and decentralised storage of data. Especially the smart contracting aspect of blockchains is highly relevant to the field of

local energy systems and markets as they offer a solution to the problems related to the centralised collection and storage of residential household energy use data.

5.4.3 Outlook on future energy systems

According to the Committee on Climate Change [210], 40% of the UK's carbon emissions stem from households. They propose a range of solutions including renewable DERs and more efficient devices to reduce the per-household annual carbon footprint from 1.7t in 2014 to 0.041t in 2030 [268]. In the first case study, it was found that the carbon footprint of the simulated households would reach 2.05tCO₂ by 2032 if no action was taken. This emphasises the need for a local energy market mechanism that takes into account the carbon emissions of electricity use such as the carbon-aware P2P market design proposed in this thesis. On average, each household saved 150kgCO₂ annually using the carbon-aware P2P trading mechanism - assuming that the carbon intensity of the grid generation would not improve. The simulations showed the potential of saving a total of 35tCO₂ in a year from the three neighbourhoods in North Scotland. This indicates the significant impact of this carbon-saving local energy market design towards meeting the net zero goals.

Using the proposed carbon-aware mechanism, the transition to net zero in 2050 can be accelerated in a bottom-up manner where the carbon saving potential of the distributed renewable generation and residential demand flexibility in 28 million households would be utilised. The main advantage of this approach is that it brings system-level holistic value in addition to local economic benefit.

5.5 Key findings

This chapter presented the results of the network-aware flexibility coordination and P2P energy trading strategies using the case study of Huntly, Aberdeenshire. It described the digital twin models and the simulation platform used for the co-simulation of the 2032 use-case with increased DER penetrations.

The first case study simulated network control and evaluated the advantages of network-aware bottom-up control when compared to the fixed peak-hour avoidance approach. It featured a neighbourhood with EVs, heat pumps and solar systems with storage. It also took into account the thermal response of buildings and user comfort. To summarise, it showed that network-aware control resulted in the lowest carbon

emissions, energy losses and obtained voltage levels within the required bounds - at the expense of decreasing the user comfort by 4%.

The second case study focused on the community-level optimisation and P2P trading comparison. The results were presented with environmental, economic and system outlooks. Overall, P2P market designs resulted in approximately 7% higher economic benefit than the cost optimisation scenario. The simulations also showed that the carbon and cost objectives were not always compatible (i.e. cost optimisation decreased carbon savings and vice versa). However, the proposed method of carbon-informed P2P trading offered a solution to this by yielding 11% cost and 7% carbon savings. This case study also took small C&I loads into account and showed that higher penetrations led to lower savings. Additionally, it compared the single versus multi-neighbourhood markets and output that larger pools of flexibility (i.e. inter-community trading) result in higher savings than having an individual pool per neighbourhood (i.e. intra-community trading).

To summarise, this chapter concluded that the adoption of P2P markets and/or network-aware control brings economic benefit to the end-users and reduces carbon emissions, contributing to the net zero transition. From the DNO's perspective, it creates opportunities for better visibility of the network and flexibility provision to decrease transformer and line loadings and regulate network voltages. From a high-level holistic perspective, this chapter demonstrated the feasibility of both carbon and cost savings through the use of carbon-aware local energy markets. The adoption of this method would provide 4% lower cost savings but also achieves the highest carbon savings which adds value and functionality to the concept of local energy markets as instruments of decarbonisation.

Lastly, this chapter identified the challenges for the implementation of P2P markets and community-level optimisation (including monitoring, data storage and privacy) which are addressed by the next chapter through the proposed use of blockchain-based smart contracts (see Chapter 6).

Chapter 6

Use of Blockchain and Smart Contracts in Local Energy Systems

This chapter proposes the use of blockchain-based smart contracting as a potential solution to the barriers associated with the real-life adoption of P2P markets and community-level optimisation. Some of these challenges were introduced previously in Chapter 5 and include distributed asset monitoring, synchronisation, financial transactions, data storage and cybersecurity. This chapter also presents the key characteristics of this technology and its energy systems application areas. Synthesising the information from the literature review in Chapter 2, a novel six-layer taxonomy of energy smart contracting is proposed in Section 6.3. Following this, the methodology for smart contracting is explained and demonstrated using a case study of P2P smart contracting. This chapter also evaluates the computational, economic and environmental costs associated with the computation of smart contracting. It also explores the opportunities and threats associated with energy smart contracting focusing on the themes of scalability and security which are key for wider adoption in Section 6.8. Lastly, it provides recommendations for future research.

The majority of the material in this chapter was published by Kirli et al. [12]. Additionally, the source code of the work presented in this chapter was made available on a public repository (along with a tutorial) in [269].

6.1 Introduction

As shown in previous chapters, the predicted increase in new types of decentralised load such as EVs and heat pumps could offer the flexibility required by the grid,

in terms of load shifting, peak shaving and other demand-side response services. Nevertheless, the problem is that the current system operation paradigm is not able to coordinate and leverage the vast amount of small-scale decentralised assets on the distribution network.

Smart contracting, along with distributed ledger technologies (DLTs) offer a potential solution to these challenges, as highlighted by the systematic review of Andoni et al. [29]. Blockchain and other DLTs provide a secure and immutable ledger of digital transactions and value transfers in a network. Smart contracts have an underlying blockchain architecture and hence, they inherit many of the favourable properties, such as decentralisation, automation, immutability and security. While blockchain architectures are concerned with cryptographic security and data storage on the blockchain, the smart contracting layer deals with the contractual operations and transactions to be executed on the blockchain, in terms of P2P trades and flexibility commitments. Therefore, smart contracts are the most relevant aspect of blockchain technologies to the local energy systems.

Smart contracts are used in many applications in local energy systems, ranging from energy trading to the coordination of distributed assets - as shown in Figure 6.1. The type of applications of smart contracts can be categorised into two main categories: *energy and flexibility trading* on the left-hand side, and *distributed control* on the right-hand side. 65% of the 178 peer-reviewed papers analysed in [12] had energy and flexibility trading applications. Whereas, 35% of the literature used smart contracting for distributed control applications. Overall, P2P trading was the most common use-case for energy smart contracting where almost one in four papers used smart contracting coupled with P2P markets. On the other hand, DSR services covered 10.3% of the total.

In recent years, blockchain-enabled P2P trading and community-centric energy sharing applications have received an increased research interest as demonstrated by [40, 72, 73, 74]. There is also an increasing focus on the LV microgrids and local distribution networks for the application of blockchain technologies in P2P energy trading [36, 75, 76]. Nevertheless, while these technologies are mentioned in the literature, only a few studies actually implement the energy management algorithms in smart contracts or demonstrate the steps of smart contracting in a repeatable format. This chapter addresses both of these issues by detailing the methodology of programming and execution of smart contracts and demonstration of P2P case study.

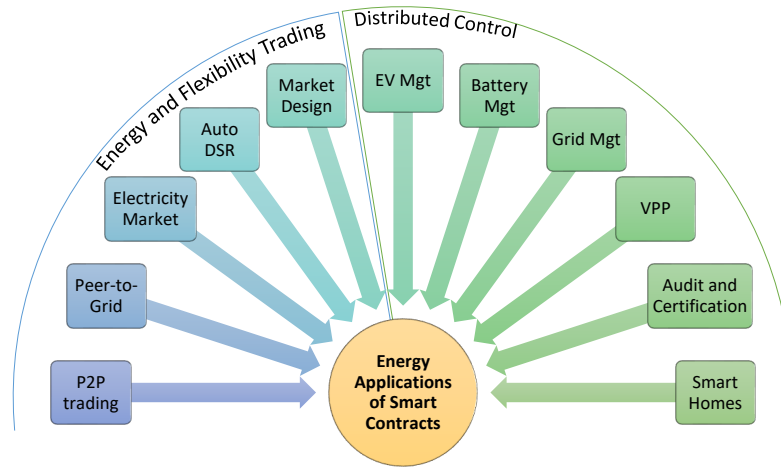


Figure 6.1: Application of smart contracts in the energy sector. Each application is discussed in one of the two main application categories identified which are (1) energy and flexibility trading and (2) distributed control [12].

Additionally, there is a gap in the literature when it comes to evaluating the impact of smart contracting on energy, in terms of computational power, energy use, costs and carbon emissions. This chapter in the thesis evaluates these aspects against the savings achieved through the deployment of local energy markets (using the results from Chapter 5).

6.2 Key characteristics of smart contracts

Smart contracts have many key characteristics that make them an enabling technology for local energy markets and transactive control. These include self-verification, security, speed and so on. However, there are also other aspects of smart contracts such as their computational expense and the fact that coding a smart contract involves reliance on specific programming languages (i.e. not including Python, Julia, MatLab which are the most commonly used languages in energy research). The key characteristics of smart contracts are summarised below and further discussed later in Section 6.8 in this chapter. The main characteristics of smart contracts are the following:

1. *Self-enforcement and automation:* Smart contracts are made of code that takes

6.2. KEY CHARACTERISTICS OF SMART CONTRACTS

decisions based on specific inputs. This code is executed automatically in a virtual environment that is shared among the nodes of the blockchain when specified conditions arise. Therefore, smart contracts are self-enforced and will execute the dedicated code automatically.

2. *Tamper-proof nature:* Smart contracts are software components that are stored on a blockchain. Therefore, they inherit distributed ledger properties, among which the tamper-proof characteristics. Indeed, being stored on a blockchain makes the smart contract code immutable and unalterable, as this would require changing the whole blockchain. A smart contract cannot be changed by any other node of the blockchain. Therefore, it is ensured that the smart contract code is original and corresponds to its designer's code.
3. *Transparency and accessibility:* Being part of a blockchain, the smart contract is transparent and accessible to all the members of a blockchain. Therefore, in the case of permissionless ledgers, everyone can have access to the content of a smart contract, whereas it might be restricted to some users in the case of permissioned blockchain.
4. *Security:* Given the high level of cryptography and the characteristics of blockchain (e.g. tamper-proof), smart contracts inherit a high level of security, as their content cannot be changed by anyone, and their execution is automatic.
5. *Speed and reliability:* This is a key aspect of smart contracts as they run in a virtual environment shared among the blockchain nodes, their code is compiled at the moment this virtual environment is triggered when the specified condition is met. This ensures a fast response that is maintained as long as there are nodes in the blockchain. Furthermore, this ensures high reliability in the execution, as the code execution does not depend on a single server as would be the case in a centralised architecture scheme.
6. *Self-verification:* Although formal verification is still an ongoing research field, most smart contract languages and blockchains verify the code embedded in a smart contract, in order to ensure the viability of the contract. For example, the self-verification steps to deploy a smart contract on a blockchain can include interaction with an EV or any other smart device.

6.3 A novel taxonomy of energy smart contracting

After a systematic review of smart contracting in energy systems (as shown in the publication by Kirli et al. [12]), a novel 6-layer structure of energy smart contracting is hereby proposed in this section. Synthesising the information published in a variety of areas that range from settlement mechanisms to cybersecurity, a multi-layer architecture was designed to describe and illustrate the flow of information that starts with the input from agents. As shown in Figure 6.2, from user input to the response of the physical assets, smart contract processes involve six different layers that the information travels through. The identified six layers are namely:

1. Input layer with information from agents, devices and the grid,
2. Energy algorithms layer such as consensus and control,
3. Native smart contracting functions layer that takes care of the user registration, financial and gas transactions,
4. Blockchain layer with verification, encryption, etc.,
5. Computation layer including processes and different threads run by the virtual environment
6. Communication layer that involves physical transfer of the information between nodes.

Layer 1 requires data from an agent, device and/or the grid. Some of the examples include bids and offer from agents engaged in P2P trading, availability signal from a smart charging EV and voltage levels from the grid to trigger an automated demand-side action. On the second layer, this information is passed to the energy management algorithms which are designed by energy researchers. In the literature, this layer usually is novel and involves optimisation techniques. For instance, this may be an advanced efficient settlement algorithm to resolve the mismatch between contracted and delivered energy. Any sophisticated form of decision-making such as control algorithms, negotiations, etc. would be performed on this layer. Such computations can be deployed off the smart contract or “off-chain” to avoid unnecessary

computational costs. The third layer involves programming of the contract which is often in a standalone smart contract language (e.g. Solidity). There are many examples where Layer 2 and Layer 3 are coded in different languages. Hence, they are expressed as separate layers. Registration of agents and devices, any form of financial transaction, etc. take place on this layer, as well as the calculation of gas usage. The output is a digital contract composed of code (and prose). Layer 4 involves the integration of the smart contract on a block in the blockchain. This brings the aspects of verification and encryption. A popular example is the Proof of Work used for Bitcoin. Implementation and computation take place on Layer 5 which involves interaction with virtual machines such as the Ethereum Virtual Machine (EVM). Lastly, the information is transferred via communication protocols. This may involve machine-to-machine (M2M) communication via wired and/or wireless means. For instance, as a result, the smart contract could trigger the smart meter to send information to a software.

6.4 Methods for smart contracting

The previous sections provided an overview of the applications and capabilities of smart contracting in energy systems. This section showcases the methodology.

6.4.1 Programming of smart contracts

As previously stated, a smart contract is a software that executes in a virtual environment distributed among the nodes of a blockchain. This software is often written in a particular language that has certain characteristics. All languages (e.g. Solidity or Vyper) are not identical and do not allow the same computation. As an example, for deployment in a blockchain, the type or size of code is restricted in order to limit the computational expense. Also, some languages used for smart contracts development are close to Turing Completeness, whereas others are not. In more detail, Turing completeness (named after Alan Turing, a pioneer in the field of modern computer science) is defined as the ability of a language to compute any Turing-computable function, i.e. to execute any recursive function, as *while*, *if* or *for* loops, among others. This property is problematic in smart contracts, as a Turing-complete language could run a *while* loop forever, depending on the memory usage, and thus overload the corresponding blockchain. To overcome this possibility, most smart contracts

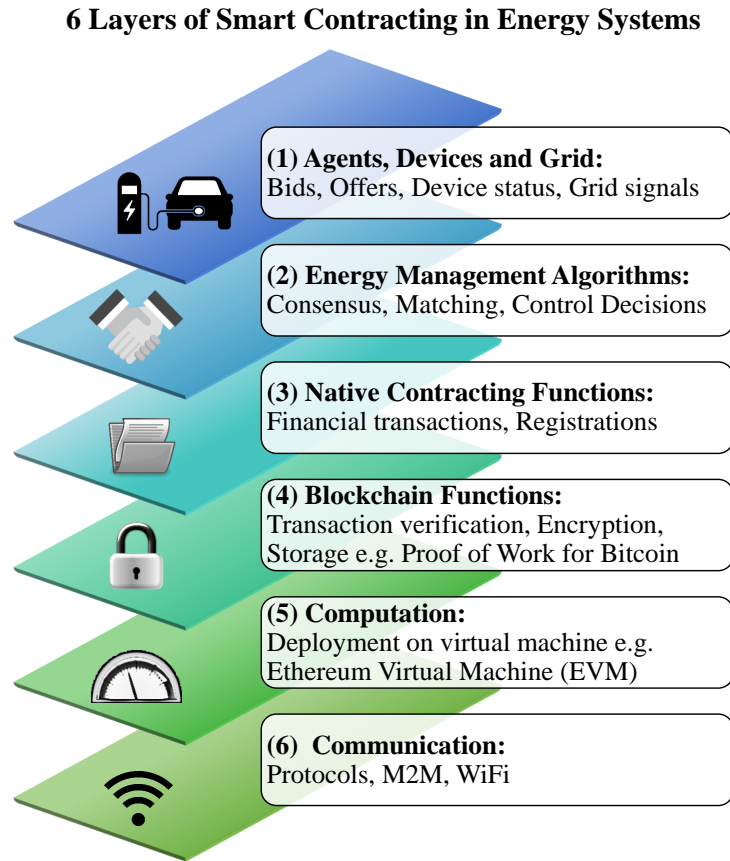


Figure 6.2: The 6-layer structure of smart contracting for energy applications.

languages are not Turing-complete (TC). However, Solidity language along with the Ethereum Virtual Machine (EVM) can be defined as a pseudo-Turing complete system, where Solidity can be considered as a deterministic TC language [270] but the gas cost limits artificially the EVM computational power, where the defined budget determines the maximum computational power and operations available for the smart contract. This prevents a smart contract from running indefinitely on the Ethereum blockchain, although Solidity language does not impose such a limit. Therefore, the flexibility of TC languages can be their biggest threat in smart contract applications due to security issues as highlighted by the *DAO attack* [271] and halting problems [272]. This showed that a TC language could affect the expected contract solution, duplicate the amounts of money spent or create fraudulent withdrawal of funds from

a contract. Unlike Solidity language, non-TC languages such as Vyper [273] reduce possible attacks and facilitate the estimation of the required computational power per contract. The use of non-TC languages is discussed in [272] through the evaluation of computational requirements from 53,757 smart contracts, where only 6.9% of them require a TC programming language to be implemented. Finally, it is essential for a smart contracting language to be deterministic so that the execution of a contract is the same in every node. This ensures consistency between the network nodes.

6.4.2 Execution of smart contracts

This section focuses on the software tools that are the most widely used to implement smart contracts in energy-related research projects. One of the most popular implementations of smart contracts consists of setting up a local private distributed ledger such as an Ethereum based blockchain, using tools as Ganache, that create a blockchain with ten accounts already configured, with 100 ethers each. Then, running a smart contract on this blockchain requires uploading it to the Ethereum Virtual Machine through one account. Therefore, the steps to set up, and deploy a smart contract are the following:

1. Configuration of a local blockchain with nodes (virtual machines) and accounts, using Ganache
2. Develop a smart contract in a given language (e.g. Solidity or Vyper)
3. Compile the Smart contract code using the language compiler
4. Deploy the compiled code (byte code) in the blockchain using either Python or Javascript Web3 libraries
5. Interact with the contract (and the blockchain) through Python or Javascript commands that are sent to the address of the smart contract via a node of the local blockchain.

In terms of the development and deployment of smart contracts or distributed applications (Dapp), existing research mainly used one of the three distributed ledger technologies that are: Ethereum (most used DLT that is mainly permissionless), Hyperledger (permissioned DLT) and IOTA (more scalable DLT as it does not require

mining process to store data). For Ethereum DLT, the following implementation tools are available:

- Truffle suite, which is a development framework for the development and deployment of Ethereum based applications. It includes many other tools listed below to create, compile, test, deploy and interact with smart contracts.
- Ganache, as mentioned above, is a tool that allows users to create a local Ethereum DLT with sample accounts in which a smart contract can be deployed.
- Remix IDE (Integrated Development Environment) is a popular browser-based IDE for Javascript-based smart contracts.
- Embark is an alternative framework for development, build, test and deployment of smart contracts with modular plugins. It is also compatible with Ganache for simulated blockchain.
- Go Ethereum, or Get is a command-line interface (CLI) client that allows smart contract developers to interact with a blockchain and thus to deploy smart contracts. It is the Golang implementation of Ethereum protocol but other implementations exist in C++ and Python. Parity is an alternative to such interaction software, which is written in Rust.
- Metamask is a browser extension that can be used to manage Ethereum wallets and the deployment of Distributed Applications.

Similarly, hyperledger has associated tools that can ease the development and deployment of smart contracts as Hyperledger Cello which is an application that is used to manage, supervise and deploy multiple blockchains and associated smart contracts.

6.5 Case study: P2P smart contracting

A workflow of energy smart contracting is shown in Figure 6.3, using auction-based P2P energy trading as an example. The auction-based P2P trading was chosen as the case study because the auction-related native functions of smart contracting address the issues of synchronisation, data storage and clearing which are some of the key

barriers associated with the implementation of this local energy market design. These issues were also a part of the decision in Chapter 4 which evaluated that the feasibility of implementing community-based methods by 2032 would be higher than auction-based methods.

The flowchart of P2P energy smart contracting shown in Figure 6.3, starts with the initialisation of the contract which prompts the command to read the capacity and price offered by the generators. It is assumed that the forecast, estimation and price selection are performed on the prosumer's side. In this example, the kWh magnitude of the offer is communicated to the buyers (consumers) and the bidding procedure starts for the available excess generation in the community. There is a variety of possible techniques for clearing the price as previously discussed in Chapter 4. The most commonly used one is the Double Auction which ranks the bids and offers in ascending and descending order respectively and evaluates an equilibrium price that is the midpoint between the buy and sell prices. The next step is to assess the physical feasibility of the allocations by inspecting the grid power flows through power simulations. Then, the smart contract is updated with the outcome and the energy transaction is verified using the smart meter recording of the generator. Once verified, the total units and duration of generation are checked and any scaling and penalties are applied if necessary. Following this, the payment to the generators is authorised and the transaction is stored. This means that it is now irreversible. This methodology is adaptable for different uses such as distributed control actions issued by the DSO. Following the previous simulation cases, DSO-issued demand reduction actions, the fair distribution of the benefits is automated using smart meter data to identify each participant's contribution to the overall demand reduction. Additionally, as shown in Figure 6.3, scaling or penalty functions are applied according to the metering data.

Algorithm 1 shows a brief pseudocode of a simplified smart contract for P2P energy balance update and transfer of funds. Separate data structures are created for consumers and prosumers as the information required from these agents is different. While the prosumer declares its hexadecimal identifier (i.e. address), *EnergyOffer* in kWh and e-wallet details, the consumer needs to input its address, *EnergyRequest* in kWh, the per-unit bid price and also their e-wallet details. The matched pairs for P2P trading would be input in the *LocalEnergyTransfer* which compares the requested and offered energy. If there is excess energy, the energy balances are updated

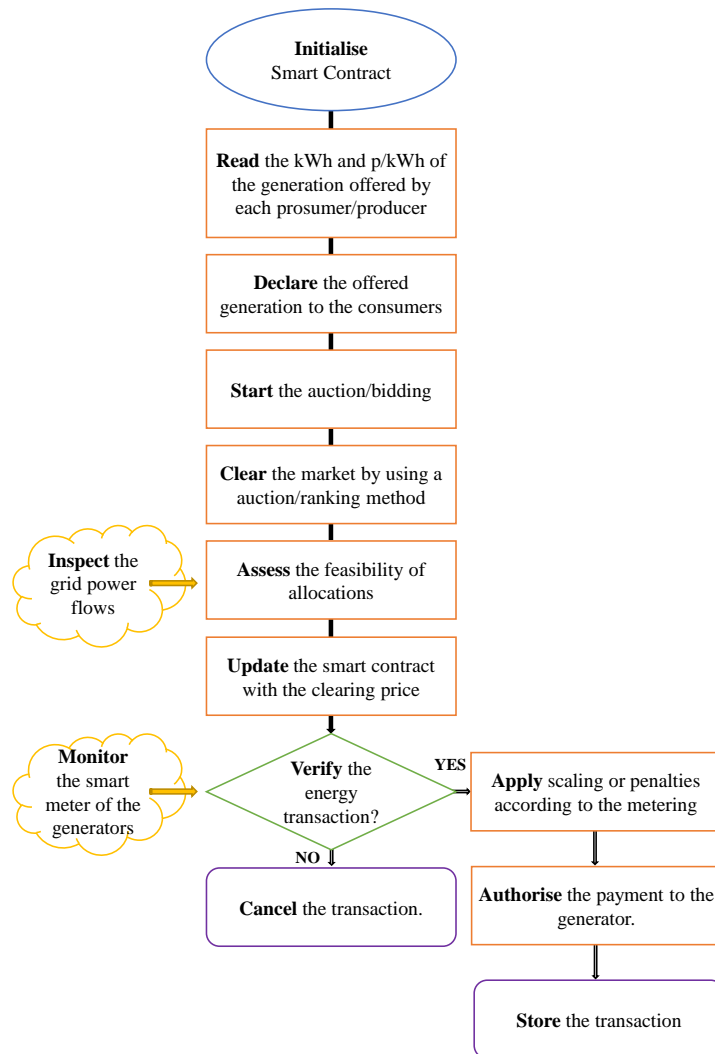


Figure 6.3: Smart contracting algorithm for P2P energy trading.

accordingly and the total price is set as the product of the per-unit bid price and the energy requested by the consumer. On the other hand, if there is not enough local energy offered, the price is equal to the per-unit price multiplied by the energy offered by the prosumer.

Lastly, Figure 6.4 describes the interfacing between the DLT (i.e. blockchain) layer and the energy management algorithm which include P2P and transactive control methods presented in previous chapters. A Python library called Web3 is used to facilitate the exchange of information between these two layers. The outcomes of the

Algorithm 1: Pseudocode for a P2P energy exchange balance update and transfer

```
initialisation
create P2Pbalance{
  define prosumer(address, EnergyOffer, Wallet)
  define consumer(address, EnergyRequest, BidPrice, Wallet)
  function LocalEnergyTransfer(prosumer, consumer){
  if prosumer.EnergyOffer > consumer.EnergyRequest then
    BalanceLocalEnergy = (consumer.BidPrice*consumer.EnergyRequest)
    prosumer.EnergyOffer -= consumer.EnergyRequest
    consumer.EnergyRequest = 0
  else
    BalanceLocalEnergy = (consumer.BidPrice*prosumer.EnergyOffer)
    consumer.EnergyRequest -= prosumer.EnergyOffer
    prosumer.EnergyOffer = 0
  end
  prosumer.Wallet += BalanceLocalEnergy
  consumer.Wallet -= BalanceLocalEnergy
}}
```

algorithms such as pricing and energy volumes are transferred to the DLT layer where the smart contract actions take place. Additionally, there is also a transfer of data and information between the network layer and the other two layers which are DLT and energy algorithms. The algorithm layer requires information from the grid layer to ensure the feasibility of the planned actions whereas the DLT layer uses device and net household metering data from the network layer in order to verify the contracted actions. The implementation of this process was published on Github [269] as an open-source repository. Solidity was used as the smart contracting language and the code was deployed on a virtual Ethereum DLT.

6.6 Ethereum gas costs, economic impact and carbon emissions

In literature, there is little consideration of cost and carbon footprint of DLT technologies and, in specific, the usage of gas in EVM. However, accurate estimates are needed as they offset the economic and environmental benefits of the P2P trading and community-level optimisation strategies previously presented in Chapter 5. This

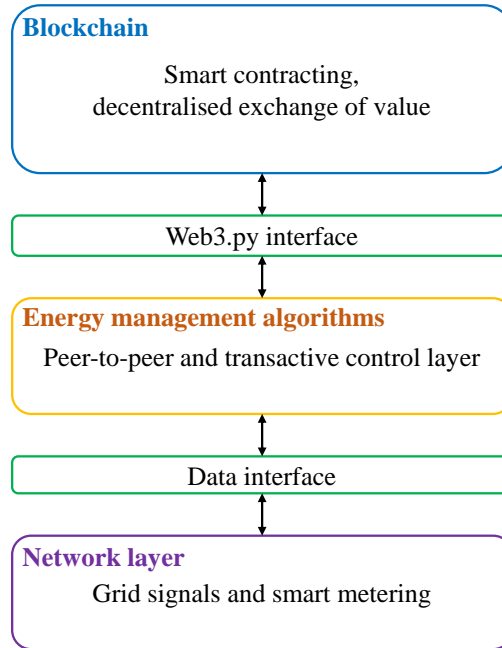


Figure 6.4: An illustration of how different layers of simulations interface with each other.

is identified as a gap in the simulation approaches of smart contracts for local energy systems. Therefore, this section introduces and evaluates the computational, economic and environmental costs.

In this chapter, smart contracts were executed in a virtual environment shared among the blockchain nodes and each node dedicates a part of its computational power to the smart contract execution process. The execution cost was assumed to be covered by the smart contract owner (i.e. the node that deploys the smart contract on the blockchain). To track the associated monetary costs, Ethereum Gas, a measurement unit for executing operations in the virtual environment was used. A single transaction between the users combines a number of elementary operations, such as addition, multiplication, etc, each of which has a set gas cost. Therefore, the final cost equates to the total sum of all operations carried out to complete a transaction.

Wood et al. [270] presented a table with the gas requirements per operation. The amount of gas increases as the complexity of operations in a smart contract increases. For example, an Ethereum (ETH) transaction to another agent costs 21,000 gas, whereas the deployment of a new contract costs at least 32,000 gas to create an

6.6. ETHEREUM GAS COSTS, ECONOMIC IMPACT AND CARBON EMISSIONS

account. The current cost for bytecode execution is 200 gas, and 68 gas per byte used to start a transaction. Also, the contract's first execution embeds an additional cost. The total deployment cost of a smart contract can be higher than 200,000 gas, with an execution cost near to 50,000, as presented in [274], where 3 types of contracts were evaluated.

In public networks, the gas cost is determined by the demand and supply, where a limited number of miners can offer their computational power to a large number of agents, generating gas price fluctuations between 10 Gwei (i.e. nanoether, 10^{-9} ETH) to 100 Gwei in a year and peaks over 400 Gwei in high congestion events, according to ETH Gas Station data [275]. The unit of wei is the smallest (i.e. non-divisible) denomination of ether (ETH) which is the cryptocurrency coin used on the Ethereum network where 1 wei is equal to 10^{-18} ETH.

In private networks, costs are usually neglected as the blockchain nodes do not need a specific financial incentive to take part in the virtual environment. To calculate the required gas for a transaction or a contract deployment the function `web3.eth.estimateGas` is used as a testnet before the deployment of the contract [276]. In order to reduce the future transaction cost of smart contracts, different gas-wasteful patterns were identified in [277] and [278], where the use of *for* and *while* loops, non 256-bit and unnecessary public variables in the code increase the contract deployment and execution cost. These practices are avoided in the smart contract design methodology shown here.

A gas limit was set to restrict the amount of gas spent on a transaction and it reflects the user's willingness to proceed with computationally expensive transactions. The gas limit may vary and is used to express different preferences in the network with regard to high and low cost computations. In this study, a local blockchain emulator, namely Ganache, was employed and computational gas units are assumed to have a set price of 20 Gwei, neglecting the volatility in gas pricing and variation in computational supply availability.

Figure 6.5 compares the smart contract execution costs against the number of participants taking part in P2P trading. As the number of users increases, the computational costs per participant, expressed as gas units, decrease and reach a plateau with values of 158k gas and lower for 80 and more participants. The shown costing (blue) is for the initial round of the trading system and includes computational expensive smart contract deployment costs. The deployment and matching functions are

6.6. ETHEREUM GAS COSTS, ECONOMIC IMPACT AND CARBON EMISSIONS

computed only once whereas other functions such as register and transfer are multiplied by the number of participants. Therefore, it is more cost-effective to have larger pools of P2P trading participants in order to achieve lower gas costs per transaction per user. In the case the same smart contract is executed again in the successive trading rounds (orange), the costs are 140,000 units of gas which was shown to be lower for 80 and more participants.

The costs and carbon footprint of running a smart contract vary depending on the smart contract architecture (e.g. the number of functions, operations and loops involved), type of blockchain (public, private or permissioned), local electricity prices and carbon intensity of the grid (assuming there is no on-site low-carbon generation). There is no established consensus whether blockchain and other DLT technologies offer lower [279, 280] or higher [18, 281, 282] transaction costs in comparison to the existing transaction methods. As an example, Ethereum and VISA transactions comparison in terms of energy consumption by [18] is presented in Table 6.1 where one Ethereum transaction was shown to consume 1.6 times more energy than 100,000 VISA transactions.

On the other hand, the Ethereum network transition is migrating from Proof-of-Work (PoW) to Proof-of-Stake (PoS) protocol in order to increase the security of the network and curb computational expense. This change of protocols for transaction verification is approximated to result in a 99.95% reduction of Ethereum energy

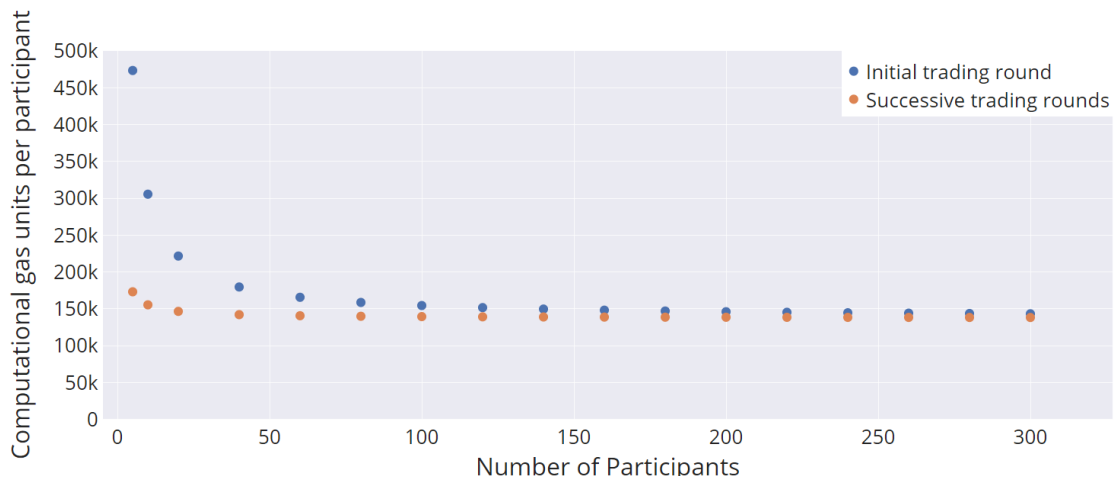


Figure 6.5: Smart contract execution costs in gas units for varying number of participants. The execution costs (per participant) decrease as the number of participants increases.

6.6. ETHEREUM GAS COSTS, ECONOMIC IMPACT AND CARBON EMISSIONS

Table 6.1: Energy consumption of Ethereum and VISA transactions [18].

| Transaction type | Energy consumption in kWh |
|---------------------------|---------------------------|
| 1 Ethereum transaction | 238.22 |
| 100,000 VISA transactions | 148.63 |

consumption [280]. This would reduce the energy consumption of one Ethereum transaction to 120Wh which is roughly equivalent to 80 VISA transactions. Further discussion on the computational expense of smart contracts and a critique of the current approaches is provided in Section 6.8.1.3. The section also summarises the current advancements in the literature and provides insights for future work.

In this case study, the energy consumption along with the corresponding electricity costs and carbon footprint of smart contract execution was estimated using the information provided by Ethereum [280] and other smart contracting sources [12, 122]. A single computational unit of gas was estimated to cost $\pounds 5.20 \times 10^{-6}$ and requires approximately 0.4Wh to compute. Following the results presented in Figure 6.5, this translated to $\pounds 0.71$ and 5.74kWh of electricity per participant for 238 users. Therefore, this would result in a carbon footprint of 1.34kgCO₂ for each transaction in this system.

If a single energy transaction was executed each day, the annual cost for a 238-user network would be $\pounds 61.7k$ ($\pounds 259.15$ per participant). Considering that the annual cost savings for the case study used in Section 5.3 (with the same no of participants) were around $\pounds 210$ per household, the benefits of P2P savings are outweighed in this example. However, this should be treated with caution as the simulated case only focused on the year 2032. With the predicted increases in flexibility volumes and local energy production, P2P markets (if incentivised and regulated appropriately) would become more profitable in future years. These costs could potentially be reduced if smart contracts were executed using permissioned blockchains [283]. Also, blockchain technology is moving towards a more efficient Proof-of-Stake verification approach which would reduce annual transaction costs to $\pounds 36.67$ ($\pounds 0.15$ per participant). Similar trends were present when the transaction costs were evaluated in terms of carbon footprint. The associated annual CO₂ emissions using PoW were estimated to be 167 tonnes of CO₂ (0.7 tonnes of CO₂ per participant) in comparison to 0.15 tonnes of CO₂ savings per household which were achieved by the novel carbon-aware P2P - as shown in Section 5.3. Whereas, using PoS as a consensus mechanism was estimated

to emit 0.35kgCO₂. Assuming half-hourly transactions, use of PoS could achieve 89% and 82% of the simulated P2P carbon and cost savings.

6.7 Limitations

One of the shortcomings of the methodology presented in Section 6.4 was that the matching and optimisation algorithms were executed outside of the smart contract (i.e. “off-chain”). In the case presented here, this method was chosen to increase computational efficiency and speed of transactions. However, it resulted in a less decentralised DLT system. The algorithms were located and executed on a single local machine and therefore, this makes the process more susceptible to malicious attacks which may cause economic loss and also loss of trust in the DLT system. Another assumption was that the gas limit was assumed to be the same for all participants. However, different gas limits may be implemented to capture the amount each user is willing to pay per transaction. If a community with more socio-economic information is simulated, these gas limits could reflect the price sensitivity of the users. This case may show that the users with higher gas limits would be able to participate in more complex transactions which may involve computationally expensive AI functions such as accurate forecasting. As a result, higher gas limits may prove to be an advantage for securing a more profitable position in the marketplace. Additionally, the users may choose to add a “tip” to their gas limit which prioritises their transactions over the others waiting in the queue. These were left outside of the scope of this study.

Energy smart contracting functions developed for the specific use of local energy markets were shown to result in lower gas consumption [150]. In this study only native solidity functions were employed, future research should leverage novel smart contracting functions published in the latest research articles such as the P2P matching functions developed by [150]. However, one shortcoming of the new and lower gas consumption methods is that they are not easy to replicate and apply in other research projects due to the lack of documentation and restricted access to code repositories.

Further discussion regarding volatility of cryptocurrencies and their effect on energy smart contracting and so on are addressed in Section 6.8.1.3 and the remaining parts of Section 6.8.

6.8 Discussion

The previous sections analysed the use of smart contracts in energy systems in terms of variety of applications and embedded functions. A methodology for implementing smart contracts for peer-to-peer trading applications was also presented along with the results in terms of gas and energy consumption of this implementation method. Based on the previous sections, in this section the key challenges and opportunities are discussed.

6.8.1 Scalability of energy smart contracts: opportunities and threats

First, this subsection discusses the opportunities and threats associated with scaling up the use of smart contracts for energy applications. It presents the key issues observed from analysing the literature and suggests solutions that incorporate a novel outlook on energy systems. It also highlights the main advantages of smart contracts such as automation, and reduction in time and cost of market operations.

6.8.1.1 Cyber-security and privacy

One of the major challenges in applying smart contracts in any sector revolves around cybersecurity, confidentiality and privacy which involve identity theft and data leakage. For what concerns cybersecurity aspects, the challenges are associated with the fact that some smart contracts decisions can be operational decisions controlling electrical grid assets, which can become a threat to the energy system. To address this issue, encryption with private keys and the addition of a hash ensure that the data received was generated by a trusted entity. The append-only and distributed nature of smart contracts provides an advantage [137, 169] when used with cryptography and hash functions to protect the data [284, 285]. Furthermore, the risk of denial of service of the blockchain that could happen from a smart contract running infinite loops with heavy computation tasks is limited by strategies such as gas limitation. To illustrate this cybersecurity aspect, [286] provides a study on “cyber-resilient” systems whereas [287, 288] show the robustness of smart contract-enabled control of battery systems against cyber-attacks.

Smart contracts are tamper-proof and immutable, in the sense, their code is self-executing and cannot be stopped by any single party, once the contract is deployed

and written on the blockchain. While often viewed as a strength, their immutability could be a weakness for smart contracts, as the contract code defines each interaction, where errors or bugs can generate unexpected results and consequences if it has not been thoroughly tested and validated [289]. The relevance of immutability in smart contracts is best exemplified by the infamous “DAO attack” [271, 290]. A malfunction allowed the withdrawal of an amount of ethers much higher than the original deposit. The losses associated with the malicious transactions were estimated to be over US\$ 150 million [291]. The permanent nature of the blockchain forced the attackers to hard fork in order to erase the malicious transactions. This sparked a new set of coding regulations and best practices to work with the deterministic nature of smart contracts which elevated the security measures [292, 293].

Despite these concerns around cybersecurity, smart contracts are also seen as a solution to increase the reliability of the whole energy chain by removing the single points of failure such as central control by a unique server or the reliance on a trusted third party (TTP). A single point of failure can pose a threat to the scalability of energy systems as it is bounded by the capacity and capability of the TTP. Secure private blockchains offer a reliable solution to this problem, as it was shown in Chapter 2 (in specific part 2.4.3.2) by works such as [294] and [105] where smart contracts were shown to be helpful for grid operations. Similarly for market applications, the work from [295] allows the users and producers to negotiate energy directly through smart contracts, without any TTP.

Finally, the ability to authenticate bids and offers is also essential, as fake bids/offers may be sent to sabotage the system using smart contracts, such as a P2P microgrid. For instance, bids and offers can be secured using private keys based encryption, whereas transactions can be authenticated by authorised aggregators [119].

6.8.1.2 Implementation and communication risks in smart contracts

Although the majority of the papers reviewed in Chapter 2 only describe projects at a proof-of-concept stage, some researchers deployed energy smart contracts on operational blockchains. These are especially Ethereum based, and rely mostly on a private blockchain. Moreover, some works present the use of single-board computers, such as Raspberry Pis to emulate a physical private blockchain with nodes physically hosted in a laboratory, which allows further experiments to be carried out [296, 297]. Goranovic et al. [296] creates a comprehensive testbed using a stacked formation of

Raspberry Pis for testing communications characteristics during smart contracts execution on hyperledger. Notholt and Coil-Mayor [297] dedicated one Raspberry Pi per agent and used these Raspberry Pis as light nodes of an Ethereum blockchain. Such testbeds could be used to assess the impacts of simulated network latency or communication errors. This is expected to become more significant for smart contracts used in market applications, especially when the settlement periods decrease in length from 30 minutes to shorter periods, such as 5 minutes. Indeed, in such a development, the impact of latency and bandwidth would increase.

Communication and synchronisation issues can play a significant role, especially in real-world smart contracts that have a “live” deployment. For example, a smart contract whose self-executing code states it must be closed once the clearing price in a certain market (called an “oracle”) drops below a certain level. It is possible that in an illiquid market prices are highly volatile, experiencing a lot of fluctuations, even within an hour or number of minutes, hence the price may drop below a critical level for a few minutes, but then be restored some minutes later. Hence, there is a risk the contract would be closed (or not closed) depending on how frequently the price is updated in a particular smart contract implementation or device. Such “oracle risks” would need to be taken into account in future implementations in energy systems. For example, spot prices in energy markets are known to be highly volatile, especially in those markets that use locational marginal pricing [298]. If the spot prices are used as “oracles” for deciding to execute or liquidate a smart contract, then the contract design must account explicitly for this volatility.

6.8.1.3 Computational expense of smart contracts

As more assets take an active role in the energy systems, their associated computational expense would increase. The benefit of automation should outweigh the cost of computation and the associated problems such as latency.

Although most of the papers reviewed did not address the subject of the cost (in gas units) of running smart contracts, this cost would not be a negligible factor, especially when smart contracts are deployed for electricity market applications [299].

Therefore, a method is proposed to predict the approximate performance and data requirements of contract execution for Ethereum-based smart contracts [300]. This would be a valuable addition to smart contract design and a good metric for

comparison of the performance of smart contracts proposed in energy related research papers.

Most smart contracts require a certain amount of data from sensors and smart meters. The deployment of smart contracts on the blockchain would be limited by the bandwidth and computational power required to transfer and process the necessary data. Fog computing (also known as edge computing), offers a solution to this problem, by the processing of data at a local level, before transferring the results to cloud-based servers [301, 302, 303]. This would result in reduced bandwidth and cloud-based storage requirements. Gai et al. [304] present an example of a permissioned blockchain system that uses fog or edge computing for a smart grid application.

For energy market operations, market clearing computations in smart contracts can be made more efficient by allowing the sharing of more information with the participants which reduces the number of unknowns and the level of discrepancy between bids and offers. For instance, the encourage-real-quotation (ERQ) rule [128] allows the producers to make an offer after the consumers place bids. This decreases the difference between bids and offers and speeds up the clearing process.

Another key concern is the volatility in price in registering and running a smart contract on a blockchain. In more detail, many current and proposed energy smart contracts are currently deployed on the Ethereum blockchain, where the cost is expressed in subunits of ether called gas. However, the price of gas can be highly volatile between subsequent weeks and even days, hence the moment of registering/deploying a smart contract needs to be chosen very carefully, to minimise both financial and environmental costs.

Finally, it should be noted that the cost for a smart contract running is not only financial. Smart contracts also have an environmental cost, since running a smart contract and associated DLTs require considerable electricity consumption. Hence, the environmental impact of smart contracts depends heavily on the source of electricity generation. As the number of energy transactions is expected to increase due to innovations such as peer-to-peer trading, in order to scale up, the existing blockchain consensus protocols used to deploy and run smart contracts need to be re-designed to minimise their energy consumption. The Ethereum Foundation aims to transition to a Proof-of-Stake (PoS) protocol (from the current energy-consuming Proof-of-Work) which could provide a significant step in this regard, if/when it happens.

6.8.1.4 Novel market mechanisms

It is demonstrated that the settlement processes are faster due to the embedded monitoring and verification functions of smart contracts [305]. As the number of peer-to-peer energy trades increases, the market regulation mechanisms need to be adapted, especially to ensure a continuous balance between production and consumption, such that the frequency and voltage are maintained within acceptable limits. Therefore, novel settlement mechanisms dealing with a contribution to imbalance on an individual, group and global level could be designed to address the increase of agents participating actively in energy trading. The novel settlement mechanisms could include imbalance contribution coefficients as proposed in [194], could be specific to a particular type of energy traded, such as solar energy trading settlement [191] or lead to the emergence of multi-layer and multi-settlement markets [130, 195].

Another concern regarding smart contracts in energy trading is fairness and the formation of oligopolies. Intuitively defined, an oligopoly represents the domination of the market by a small number of large producers. Deval and Norta [306] describe an improvement of the Proof-of-Stake with lifecycle governance of smart contracts that decreases the risk of oligopoly formation. Some research work also considered the issue of fairness of market mechanisms in smart contract design which was out of the scope of this thesis. For example, Danzi et al. [307] use proportional-fairness control in a simulated microgrid where all assets contribute to the overall action equally. Finally, market designs should also consider exceptions such as system failures (e.g. fault at a line) that could inhibit the actions prescribed by the smart contract.

6.8.1.5 Software requirements

Most researchers in energy modelling are not familiar with using smart contracting languages, such as the popular smart contract programming language Solidity. The fact that most smart contract design and modelling takes place on Solidity, rather than in the languages used by the energy systems modelling community, inhibits the research in energy smart contracts. For instance, unlike Python, Simulink does not have the right communication protocol to directly interact with the Ethereum node. There is ongoing work which develops a solution to this issue and presents an example smart contract in Simulink [308]. Both this thesis¹ and other work [297] demonstrate

¹See the energy smart contracting code and tutorial outputs in the public Github repository [269]

smart contracting using a combination of MatLab, Python and Solidity – with Python used to facilitate communication between the other two platforms. Indeed, Python3 is a suitable solution to ensure interoperability between the research application code in which agents are modelled (usually written in Python or MatLab), and smart contract code, implemented in languages such as Solidity. Finally, Solidity’s limitations such as the lack of some data types or mathematical functions are an obstacle to the implementation of smart contracts for energy use cases. For example, the fact that Solidity does not allow exponentiation for real numbers makes it unsuitable for power flow computations.

Another trend observed in recent years, due to the increasing complexity of smart contract code, has been to employ specialised companies to verify and certify the code against errors and specially security issues, such as potential backdoor attacks. This is important as, once deployed, the smart contract code is self-executing and harder to correct in a decentralised environment.

6.8.2 Legal issues related to smart contracts design

For energy applications, the contract design depends on the applicability of the law and the local legal framework which requires them to be adapted or interpreted, introducing new requirements to the programming of the contract. For peer-to-peer trading, the definition of the interaction between the participants as a Business-to-Consumer or Consumer-to-Consumer can change depending on how the contract was coded. For instance, if a prosumer is considered to be a business, they would need to contribute to grid balancing in Germany (according to the German Energy Industry Act) [309] and add a withdrawal policy according to the consumer rights law in the EU [310]. According to the EU Renewable Energy Directive [311], a “renewables self-consumer” consumes local energy that is generated behind the meter. This invokes barriers against energy trading within communities. Similarly, the Dutch law requires a supplier certification for selling energy to the grid [312].

To summarise, how an entity is considered in each market defines how the smart contract needs to operate and the local laws need to comply accordingly. On the other hand, new definitions and regulations are required to make smart contracts compatible with new energy markets or services.

Advances in the energy trading process such as the use of automated bids and offers may generate market distortions. Especially, it is argued that the use of smart

contracts in wholesale electricity markets will give rise to a need to review the EU's financial market regulations [313]:

- Regulation on Wholesale Energy Market Integrity and Transparency (REMIT) - prohibits insider trading and market manipulation and requires extensive reporting obligations.
- Markets in Financial Instruments (MiFiD II) - introduces authorisation requirements for investment services. Regarding peer-to-peer energy trading, MiFiD II discusses the use of a virtual currency.
- European Market Infrastructure Regulation (EMIR) - aims to increase transparency in Over-the-Counter derivative markets, mitigate credit risk and reduce systemic risk [314], where trading companies must report their contracts to Trade Repositories (TR), which at their turn report to the authorities [315].

Enerchain [316] is an energy trading blockchain for peer-to-peer transactions, specially designed in order to try to resolve these issues. It includes tools that ensure trades are compliant with REMIT.

Some efforts are being made in different countries to include and enable the use of smart contracts in energy markets. In Germany, the project BEST (Blockchain-based decentralised energy market design and management structures) aims to develop an open-source electricity market bidding system, supported by the German Federal Ministry for Economic Affairs and Energy [317]. One of the research topics in BEST is about the requirement for such a legal energy framework and how it complies with existing frameworks. The "Blockchain strategy of the Federal Government" [318] currently stimulates innovation, testing and application of blockchain technologies in the German industry.

For services that imply data storage issues, the General Data Protection Regulation (GDPR) [319] in Articles 17 and 21 introduce the capacity to delete personal and sensitive data from databases. GDPR introduced 3 principles that are relevant to smart contracts in energy [320]:

1. The first principle is that it considers the existence of a legal person who can fulfil its requirements. The basis of blockchain and smart contracts is decentralisation and operation without third parties, but the GDPR requires the presence of an administrator or manager who can manage sensitive information.

2. The second principle is the assumption that data can be erased or modified to comply with legal requirements. However, the immutability of blockchain does not allow tampering or editing. One way could be to allow data access on a restricted basis and the transactions could be reversed by fabricating the reverse transactions in subsequent blocks of the ledger.
3. Lastly, the GDPR assumes that data can be processed to be kept a minimum number of copies of data. The blockchain stores the data in each node connected using the append-only methods, which is against the data minimisation principle included in the GDPR.

These three principles affect the operation and decentralisation of smart contracts. Hence, it is necessary to research how the GDPR requirements can be fulfilled as most of the energy data stored may be considered sensitive. One proposal is to introduce a third party such as cloud storage systems (e.g. Interplanetary File System and StorJ or local resource servers) [321] or a data manager. The latter could include functions in the contract to limit internal data access after a time interval, introducing hashing and encrypting techniques to anonymise the stored data [322].

6.8.3 Outlook on future research for smart contracts for energy systems

In this subsection, the knowledge gaps identified from the above analysis and Chapter 2 are presented along with an outlook on future of energy smart contracts.

An open area requiring further research and attention in smart contracts is cybersecurity. Smart contracts are, by definition, self-executing and tamper-proof once agreed and deployed on a blockchain - in the sense that it is hard for a single party to stop or change their execution. While this is a clear advantage that has the potential to enable true decentralisation, this also involves considerable security risks and vulnerability to potential attacks, if the smart contract code is not properly checked before deployment. The so-called re-entrancy attacks (such as the well-known DAO attack whose only solution was a “hard fork” in the Ethereum blockchain, splitting it into 2 crypto-currencies - see Section 2.4.2.2 for details) is one example. Moreover, it is also possible for the smart contract developer to build an intentional “backdoor” in the smart contract code, of which the party accepting the contract is not fully aware, and which is impossible to change once the contract is deployed on a blockchain. Such

a backdoor could, for example, specify that the other party will automatically pay the contract maker a commission on each future sale, or could even enable one of the parties to withdraw valuable digital assets or cryptocurrencies to their own digital wallet, executing a so-called “rug pull”. As the use of smart contracts in energy systems has, so far, been mostly geared to research and demonstration projects, this has not been a significant issue in energy systems yet. But, as smart contracts gain wider adoption in commercial energy projects, the security and verifiability of smart contract code is an aspect that needs to be considered. A possible solution is to employ companies and authorities that verify and certify smart contract code before deployment, as is the current practice when deploying smart contracts in decentralised finance (DeFi) applications.

Another key challenge that smart contracts in energy face are scalability and questions of energy use. So far, most smart contract projects in the energy sector have been relatively small scale, and/or implemented on a private blockchain (as opposed to, e.g. deployment on the public Ethereum blockchain, which requires considerable gas payments). However, as smart contracts in energy scale up and applications become more commercial in nature, the constraints and costs of real implementation (both financial and environmental) need to be considered carefully and mitigated. Currently, the most popular platform for implementing smart contracts, Ethereum (though the Solidity language, also used in the illustrative example for this thesis) charges a cost in a sub-unit of Ethereum called gas. Yet, the cost of gas can be substantial - especially for a complex contract, and moreover, the value of gas is often highly volatile. Besides the financial aspect, there is an environmental impact to consider, in the energy that is consumed just to run the Proof-of-Work protocol underlying Ethereum. The transition of Ethereum towards a Proof-of-Stake protocol (if/when it happens) should reduce this idle energy consumption very considerably, but still this requires consideration of what computations should be deployed/run on a public blockchain.

Thirdly, smart contracts are not particularly “smart” themselves, in terms of having embedded Artificial Intelligence or machine learning capabilities. This is both due to the computational cost of executing complex code on a distributed public blockchain, but also because smart contract programming languages are often restricted, due to computational and security reasons (for example Solidity/Ethereum limits recursive calls and exponentiation operations, and some other smart languages

are even more restricted). This is clearly a direction where further research and development effort will be needed, as has been achieved in other domains where smart contracts are applied, such as decentralised finance. One potential solution is to have smart contracts as part of larger frameworks where AI-enabled devices perform learning and decentralised control (for example of available generation, or demand-side flexibility [323]), and make transparent, verifiable commitments to other parties in the system using smart contracts.

Finally, more research is needed from the energy and power systems community to develop smart contracts with capabilities to enable intelligent management of power networks. Smart contracts that integrate uncertain generation/loads and perform, e.g. ADMM computations have already been proposed, but augmented by AI-capabilities, smart contracts could play a key role in achieving more decentralised, flexible and “self-healing” energy networks of the future.

6.9 Key findings

This chapter added practical value to this thesis as it investigated the implementation of the P2P trading, optimisation and network control algorithms previously proposed in Chapters 3, 4 and 5. In specific, it analysed and demonstrated the use of smart contracting in local energy systems which is a part of the distributed ledger technologies such as blockchain. The methods used included native smart contracting functions such as registration and billing but also algorithms specific to the local energy market applications. The latter included verification of energy import and export via smart metering and automatic settlement. This case study also evaluated the costs and benefits of energy smart contracting using a P2P case study which is often overlooked in literature. It revealed that the economic and carbon savings achieved by P2P trading were outweighed by the costs of executing smart contracts due to their high computational costs. Therefore, while smart contracting was shown to be a valuable enabling technology for local energy system applications, their current use was shown to hinder the benefits of P2P trading. Nevertheless, as more computationally efficient mechanisms become available in the future (such as PoS), implementing energy smart contracts on a large scale is expected to become more feasible. For instance, the use of PoS would not outweigh the benefits but still decrease the cost and carbon savings

by 18.0 and 11.2% respectively. This would in return enhance the scalability of P2P and flexibility market transactions.

In addition to the methodology and case study sections, this chapter also contributed a novel six-layer taxonomy which describes the journey of smart contracting that starts with an input from the agents and devices and ends with the information transfer in the physical layer. An extensive discussion on the opportunities and threats associated with the legal implementation and scalability of energy smart contracts was also provided in order to address the knowledge gap identified in the literature survey provided in Chapter 2 (which was published in [12]). Lastly, an outlook on the future of energy smart contracts was presented, highlighting the knowledge gaps and open research questions for future research.

Chapter 7

Discussion and Conclusions

Research work presented in this thesis investigated the impact of P2P energy markets and community-level flexibility on local energy systems, in terms of grid signals, costs and carbon emissions. The following sections summarise the key findings, outputs of thesis chapters and limitations of the research approach. Additionally, this chapter makes recommendations regarding the adoption of local energy systems and their role in a future decarbonised energy systems.

7.1 Thesis statement validation

This research work titled “Impact of Peer-to-Peer Trading and Flexibility on Local Energy Systems” investigated whether P2P energy trading and coordinated flexibility could provide economic benefit to the participants and also help decarbonise the energy systems whilst maintaining a healthy operation of the network. Through the 2032 simulation results shown in Chapters 4 and 5 and the use of case studies in Scotland, this thesis statement was validated.

7.2 Summary of key findings and recommendations

In order to increase the validity of the research outputs, this thesis used a pilot study based in Scotland to demonstrate the application of community-level optimisation to minimise local carbon footprint and costs. Intra and inter-neighbourhood P2P trading algorithms were also implemented in this case study to compare the future impact of local energy management techniques, using 2032 projections of EVs, solar

energy and battery systems, etc. The inter-community P2P case yielded the highest savings (i.e. 15.8%) which was around £210 per household annually.

Additionally, this work proposed and demonstrated the novel concept of carbon-aware community-based P2P trading which increased local energy sharing by 6.5% while decreasing carbon emissions by 35 tCO₂ in one year (2019) when compared with the benchmark business-as-usual case. The end-users subscribed to the carbon-aware P2P market sacrificed 4% of their cost savings (i.e. £53 per year) in order to reduce their carbon footprint by 7.2% (i.e. 150kg of carbon emissions per year).

This work also evaluated the community-level self-consumption and self-sufficiency indicators with varying storage and P2P participation penetrations. While storage and P2P markets were shown to be substitutes for lower levels of self-consumption and self-sufficiency, this relationship became complementary for higher targets. For instance, without local energy market participation, 90% of the solar generation could be consumed locally which would in return decrease reliance on the central generation. However, this required a high level of storage penetration around 60%. Participation in P2P markets was shown to decrease this to 25% and defer the installation of distributed batteries.

The real life implementation of such control and market mechanisms is often hindered by the challenges of monitoring and coordination. This thesis put forward the concept of energy smart contracts, embedded on blockchains, as a solution to these challenges. However, through the deployment of energy smart contracts, it was observed that the computational cost and carbon footprint of this implementation could outweigh the benefits gained from local energy trading and flexibility coordination. Nevertheless, this technology is identified as a key enabler for the adoption of smart local energy systems in the near future. By 2032, the more efficient consensus mechanisms such as Proof-of-Stake or Proof-of-Authority are expected to enable wide-scale use. The implementation of energy smart contracting using PoS was estimated to decrease the cost and carbon savings only by 18.0 and 11.2%.

7.3 Contributions of the thesis chapters

Chapter 1 introduced the topic of the local energy markets and flexibility discussed in this thesis, provided some background and highlighted the significance of local en-

ergy systems. Additionally, the main outcomes, research approach and dissemination outputs were presented.

Chapter 2 reviewed the literature in local energy system modelling, surveying the motivation, methodologies and contributions of existing work. The limitations of previous work were discussed which included inadequate consideration of the effect of local energy markets on the power grid and a lack of research in the areas of the carbon-saving nature of local energy markets.

Chapter 3 detailed the approach used in bottom-up demand and generation modelling. It provided models of electric vehicles, solar panels and batteries. It featured a cost-minimal home energy management optimisation with considerations of user comfort and various pricing strategies. It demonstrated the value of decentralised flexibility through participation in residential demand-side response, in specific, peak shaving during hours of high demand. Overall, this chapter provided the modelling and optimisation methodology for the results later shown in Chapter 5.

Chapter 4 presented the co-simulation platform used to model both the electricity market and network. It discussed different methods of P2P trading and analysed the relationship between storage and P2P trading and their combined effect on self-sufficiency and self-consumption. It also concluded that establishing LEMs could reduce the investment in storage technologies and proposed a novel form called carbon-aware P2P trading which provides incentives to consume energy during hours of low carbon intensity and export energy during times of carbon intense grid generation. To summarise, this chapter provided a new perspective on local energy market design through the introduction of carbon incentive and also discussed the operation of P2P markets under abnormal conditions, such as COVID-19 lockdown and 2021/22 winter gas scarcity pricing.

Chapter 5 built on the methodologies presented in Chapters 3 and 4. It introduced various case studies from Scotland and presented simulation results in terms of network signals, carbon emissions and costs. It compared community-level cost and carbon minimal optimisation scenarios with three forms of P2P trading which are namely intra-community, inter-community and carbon-aware. Moreover, peak import limits were imposed in order to shave the peak demand and reduce the stress on the network. Using the digital twin of a part of the Scottish distribution network, this chapter evaluated the effect of community-level optimisation and P2P trading on the grid signals. The case studies included small commercial loads in addition to

domestic nodes. Eventually, this chapter demonstrated that community-level flexibility coordination and P2P trading offer economic and environmental benefits whilst maintaining a healthy operation of the network.

Chapter 6 explored the use of smart contracting as a potential solution to the major challenges of privacy, monitoring and contracting associated with local energy and flexibility markets. Smart contracting between various agents engaged in P2P energy trading was simulated and demonstrated. Further analysis of the results revealed that the benefits of P2P trading were outweighed due to the high prices and carbon intensity levels of electricity used for block-chain embedded smart contracting. However, this technology is still promising as more efficient computation methods are developed (e.g. adoption of Proof of Stake), its relevancy in local energy systems is expected to increase. Furthermore, this chapter discussed the future applications of smart contracting in energy systems and analysed issues related to scalability, cyber-security, privacy and legal perspectives.

7.4 Implications of the research

The results from this thesis provided insights into how the local energy systems are expected to evolve by 2032 and emphasised the significance of leveraging local flexibility. This work demonstrated the feasibility of implementing community-level transactive control and markets within healthy operation bounds of the network. This is expected to increase confidence in local energy markets and bottom-up flexibility coordination.

During the course of this doctoral research work, six months were spent at the community energy company Scene Connect Ltd. This secondment has significantly increased the industry relevance and applicability of this work. In fact, some of the algorithms and models developed and presented in this thesis were utilised in the pilot study of the case study presented in Chapter 5.

The results of this research work indicate benefits for numerous energy systems stakeholders. For instance, through the community-based P2P energy markets, the distribution system end-users are expected to benefit from lower electricity import costs and higher export prices. Implementing the required smart metering and monitoring systems would provide the system operators with a better visibility of the local-level flexibility along with the associated technical challenges in terms of losses, imbalance and loading. From a commercial perspective, community energy companies

such as Scene Connect may utilise this study to inform investment decisions regarding storage, distributed generation and transactive market solutions. Furthermore, the insights about the energy smart contracts would allow blockchain and relevant technology sectors to recognise the opportunities and challenges of smart contracts and distributed ledger technologies that are specific to the energy sector. On a high-level outlook, Energy System Operators such as the National Grid ESO, regulators such as Ofgem and other high-level central decision and policy-makers can compare the simulated impact of community-led energy transition on the net zero goals with large-scale top-down initiatives.

There are also further implications associated with the dissemination of this work which is expected to continue inspiring future work within the research community. An extensive list was provided in Section 1.8.

7.5 Limitations of the research and future work

This section provides an overview of the limitations associated with this thesis and makes recommendations for future work. However, it should be noted that the limitations regarding the modelling and simulation methodologies were discussed separately in each chapter.

While simulating distributed energy resources, this thesis only took small-scale solar PV into account. However, it is recommended that future work considers community-owned wind turbines as this could represent a different type of energy community which can be found in Scotland and elsewhere in Europe. Addition of wind generation is anticipated to increase the benefit of local energy markets which was hindered by the seasonal pattern of solar generation. Similarly, various types of small-scale lithium-ion domestic batteries were simulated in this work. Nevertheless, the simulation of a community-owned central battery was neglected which can be addressed by future work.

In addition, the work in this thesis assumed full access to the users' assets and ability to control them without any interruptions or overriding. However, potential outages and downtime for maintenance are expected to slightly decrease the calculated benefits. Additionally, in real life the users may override the control actions (e.g. turning on a curtailed asset). The uncertainty associated with this kind of user behaviour might decrease the value of P2P trading local flexibility to the DSO. When

simulating participation in P2P markets, some simplifying assumptions were made such as high levels of social acceptance and homogeneity in energy preferences. A more in-depth market model can be built that takes into account different types of users and their preferences. Hence, future work can contribute to the knowledge by studying the social science aspects of local energy systems such as social acceptance of P2P trading and distributed control, and uncertainty associated with user behaviour.

Lastly, the methods introduced in this thesis value flexibility of consumption and generation and hence, they reward the households with the highest flexibility volumes. However, often flexibility is provided by smart assets which are low-carbon but also, costly and energy intensive. Hence, rewarding flexibility can contribute to the wealth gap as the users with higher flexibility volumes often have the economic resources required to purchase EVs, heat pumps and storage. Meanwhile, less flexible households would be already using the bare minimum volume with no additional flexible capacity from costly smart assets [226]. Future research is encouraged to explore the social justice aspect of local energy markets and community-level coordination.

7.6 Final remark

In conclusion, the research work validated the thesis statement and proved that local energy systems are able to offer flexibility and value in terms of both cost and carbon savings in the near future (2032) through the use of case studies. It introduced the concept of carbon-aware local energy systems as an instrument of bottom-up decarbonisation. It successfully demonstrated the use of distributed ledger technologies and smart contracting for local energy systems and provided recommendations for their future development.

This thesis showed that through decentralisation, digitisation and the use of consumer-centric energy markets, local energy systems can offer economic benefit to the participants and flexibility to the system. Additionally, it demonstrated that peer-to-peer energy trading and community-level energy management strategies can significantly contribute to the decarbonisation of energy systems.

Appendix A

Formulation of optimisation model

Input parameters

| | |
|---|----------------------------------|
| Electricity pricing or carbon intensity timeseries for import | λ_{buy} |
| Electricity pricing or carbon intensity timeseries for export | λ_{sell} |
| Value from delay-based penalty matrix | σ_{t,t_0} |
| Aggregated inflexible load | d_t |
| Aggregated generation | g_t |
| Operational range of each flexible asset (e.g. EV) | $[\tau_{\min_t}, \tau_{\max_t}]$ |
| No-control operation pattern for each flexible asset | $p_{t_0,n}$ |

Decision variables

| | |
|---|-----------|
| Optimised power timeseries of the each flexible asset | $p_{t,n}$ |
|---|-----------|

Constraints

Power balance in the system:

$$\sum_0^N p_{t,n} + d_t + g_t - P_{\text{import}, t} - P_{\text{export}, t} = 0 \quad \forall t \in [0, \dots, T] \quad (\text{A.1})$$

Operational constraints for flexible asset operation:

$$\tau_{\min_t} \leq p_t \leq \tau_{\max_t} \quad \forall t \in T \quad (\text{A.2})$$

Equality constraint for energy consumption of flexible assets:

$$\sum_0^T p_{t,n} \times \Delta t = \sum_0^T p_{t_0,n} \times \Delta t \quad \forall n \in N \quad (\text{A.3})$$

Objective function

$$\min \sum_0^T \lambda_{\text{buy}} \cdot \sigma_{n,t,t_0} \cdot P_{\text{import}} - \lambda_{\text{sell}} \cdot P_{\text{export}} \quad \forall n \in N \quad (\text{A.4})$$

where $P_{\text{import}} \in \mathbb{R}_{\geq 0}$ and $P_{\text{export}} \in \mathbb{R}_{\leq 0}$

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