CORA Cork Open Research Archive
Cartlann Taighde Oscailte Chorcaí

Title	Co-simulation of electricity distribution networks and peer to peer energy trading platforms
Authors	Hayes, Barry P.;Thakur, Subhasis;Breslin, John G.
Publication date	2019-07-24
Original Citation	Hayes, B. P., Thakur, S. and Breslin, J. G. (2019) 'Co-simulation of electricity distribution networks and peer to peer energy trading platforms', International Journal of Electrical Power and Energy Systems, 115, 105419 (10pp). doi: 10.1016/j.ijepes.2019.105419
Type of publication	Article (peer-reviewed)
Link to publisher's version	http://www.sciencedirect.com/science/article/pii/S0142061519302972 - 10.1016/j.ijepes.2019.105419https://data.mendeley.com/datasets/79shk8f79t/1
Rights	© 2019, Elsevier Ltd. All rights reserved. This manuscript version is made available under the CC BY-NC-ND 4.0 licence. - https://creativecommons.org/licenses/by-nc-nd/4.0/
Download date	2026-11-06 20:24:16
Item downloaded from	https://hdl.handle.net/10468/8347

UCC
University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

Co-simulation of Electricity Distribution Networks and Peer to Peer Energy Trading Platforms

B. P. Hayes[a,*], S. Thakur[b,c], J. G. Breslin[b,c]

[a]*Department of Electrical and Electronic Engineering, University College Cork, 60 College Rd., Cork, Ireland*
[b]*Data Science Institute, National University of Ireland Galway, IDA Business Park, Lower Dangan, Galway, Ireland*
[c]*Discipline of Electrical and Electronic Engineering, National University of Ireland Galway, University Road, Galway, Ireland*

Abstract

There has been significant recent interest in local electricity trading platforms, and particularly in the application of distributed ledger and blockchain technology for distributed, or peer-to-peer energy trading in local energy communities. Several projects worldwide have demonstrated this concept on a small scale in Low Voltage (LV) distribution networks and microgrids. However, previous work in this area has not sufficiently addressed the potential impacts of peer-to-peer energy trading and other local electricity trading mechanisms on the control, operation and planning of the electricity distribution networks. Accordingly, this paper presents a methodology for the co-simulation of power distribution networks and local peer-to-peer energy trading platforms. The distribution system simulator is interfaced with a peer-to-peer energy trading platform, which employs a blockchain-based distributed double auction trade mechanism. The presented co-simulation approach is demonstrated using a case study of typical European suburban distribution network. It is demonstrated in the paper that this approach can be used to analyse the impacts of peer-to-peer energy trading on network operational performance. The analysis presented in the paper suggests that a moderate level of peer-to-peer trading does not have significant impacts on network operational performance.

Keywords: distribution networks, co-simulation, peer-to-peer energy trading, distributed ledger technology, blockchain, microgrids, network planning

1. Introduction

A number of distributed and local electrical energy trading mechanisms have been proposed in the literature. These energy trading mechanisms are designed to enable a more decentralized operation of the power system, better utilisation of grid assets, and improved integration of distributed energy resources via local energy balancing [1, 2, 3, 4, 5]. In particular, the application of distributed ledger or "blockchain" technology for peer-to-peer energy trading in microgrids and local energy communities has received significant attention [6, 7, 8, 9, 10]. Several projects worldwide have demonstrated the concept of blockchain-enabled peer-to-peer energy trading on a small-scale in Low Voltage (LV) distribution networks and microgrids [11, 12, 13]. A systematic review of blockchain and distributed ledger technology in the power and energy sector and its associated applications, challenges and opportunities is presented in [14].

However, it is currently unclear if such electricity local trading mechanisms are suitable for wide-scale implementation and what impacts these would have on the control, operation and planning of electricity distribution systems, if implemented on a large scale.

This paper provides a framework for the co-simulation of realistic, three-phase unbalanced distribution networks and decentralised electricity trading mechanisms. There has been a significant research interest in decentralised electricity trading in the last several years; however, most work in this area to date has focused on energy trading mechanisms in microgrids, or on energy-sharing between multiple microgrids. There is a gap in the literature with regard to a methodology for analysing the possible impacts of local energy trading on utility-owned distribution network infrastructure. This paper addresses this gap by presenting a methodology and software tool for the co-simulation of electri-

*Corresponding author.
Email addresses: barry.hayes@ucc.ie (B. P. Hayes), subhasis.thakur@nuigalway.ie (S. Thakur), john.breslin@nuigalway.ie (J. G. Breslin)

city distribution networks and a blockchain-based local energy trading platform. To the authors' knowledge, this is the first paper that provides a framework for analysing the impacts of local energy trading on MV and LV distribution network operational performance, examining the potential impacts on several power quality indices, including three-phase voltage fluctuations and imbalances. This is achieved by detailed, three-phase modelling and simulation of typical European LV electricity distribution networks using the open-source electricity network simulator OpenDSS [15]. These distribution network models are integrated with the P2P energy trading platform. In this paper, a blockchain-assisted distributed double auction trading platform is used to facilitate P2P trading between individual users of the LV network. This paper develops a co-simulation framework designed to investigate the potential network impacts from various alternative trading mechanisms, including blockchain-based P2P energy trading platforms. The presented co-simulation approach is demonstrated using the IEEE European Low Voltage Test Feeder [16], which represents a typical European suburban distribution network configuration.

The paper is structured as follows: Section 2 discusses the previous work on this topic. Section 3 provides an overview of the co-simulation approach used in this paper, and describes the blockchain-based double auction approach used to simulate P2P energy trading. Section 4 describes the case study, Section 5 gives the results of the distribution network simulations, and Section 6 concludes.

2. Literature Review

2.1. Current State of the Art in Peer to Peer Energy Trading Platforms

P2P energy trading has been proposed as a means of efficiently coordinating large numbers of highly-distributed energy resources in power systems [17, 18]. Several authors have proposed market designs and incentive for energy trading between small-scale electricity producers and consumers in distribution networks [19, 20] and in microgrids [21].

The participation of large numbers of distributed users with flexible demands in the electricity market is a related concept, which is discussed in [5, 22, 23]. Generally, time-of-use electricity pricing has been used as a means of incentivising demand response in an efficient manner [24]. One of the issues associated with this is the possibility of reducing the load diversity factor and creating new demand peaks if all users take advantage of the same low price period [22]. Alternative electricity pricing schemes designed to mitigate against this problem and improve distribution network utilisation have been investigated in [5]. The transactive energy approach outlined in [1, 2] aims to provide a network environment for distributed energy nodes as opposed to the traditional hierarchical grid structure, and recent years have seen significant efforts towards standardisation of these techniques and ensuring wide-scale interoperability.

An approach for carrying out P2P energy trades between buyer and seller agents using an iterative double auction mechanism is proposed in [25]. This approach was implemented using blockchain algorithms in [7]. This paper investigates methods for coalition formation amongst peers and the results in [7] suggest that this approach is effective in terms of maximizing social welfare, with acceptable convergence and computational complexity. A consortium-based approach to peer-to-peer electricity trading system was proposed in [9]. This approach was demonstrated using case studies featuring electricity trading between Electric Vehicles (EVs).

Previous work has also studied the interactions among interconnected autonomous microgrids [26]. A joint energy trading and scheduling strategy for these was developed in [27]. A transactive energy trading framework for distribution system operation, dealing with both economic issues in energy trading and the technical issues is proposed in [28], where the transactive energy trading problem is solved based on Alternating Direction Method of Multipliers (ADMM). A review of game theoretic approaches as they apply to local energy trading is given in [29].

A P2P market structure based on a Multi-Bilateral Economic Dispatch (MBED) formulation is introduced in [30], allowing for multi-bilateral trading with product differentiation, for instance based on consumer preferences. The issue of prosumers' individual preferences for the source/destination of the energy they consume/produce is also explored in [31]. An industrial application of P2P energy trading, with a machine-to-machine based implementation of blockchain energy trading between chemical plants is discussed in [10]. The role of battery flexibility in local electricity markets is dealt with in [32]. A multi-agent-based simulation framework for evaluating the performance of different local energy trading mechanisms was presented in [33]. The security and privacy implications of local electricity markets are discussed in [3] and [4].

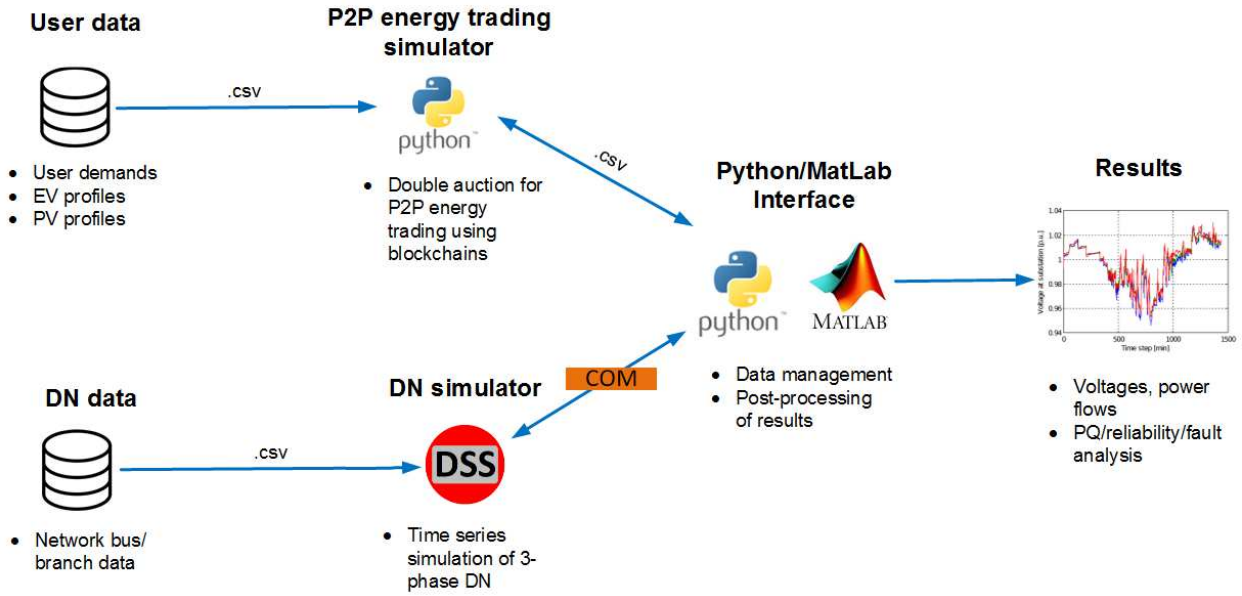


Figure 1: Overview of approach for co-simulation of electricity Distribution Network (DN) and peer-to-peer (P2P) energy trading platform.

2.2. Peer to Peer Project Trials and Demonstrations

A number of P2P energy trading trials and demonstration projects have been carried out to date (e.g. [11, 12, 13, 34]). An exhaustive list of recent projects in this area is provided in [14]. However, the scope of such projects is typically limited by regional and national electricity grid and market regulations [35]. In all cases studied, the aim has been to develop scalable P2P energy trading solutions, suitable for large-scale implementation. However, most trials in this area to date have focused on demonstrating P2P energy trading in small localised areas served under microgrid, or "private wire" arrangements in order to avoid regulatory problems.

The anticipated benefits of P2P energy trading include better utilisation of power network assets and reduction of energy losses due to shorter transmission distances (e.g. energy is consumed closer to its source compared to current power system arrangements) [14, 36]. At the distribution network level, energy balancing can be achieved locally where sufficient distributed energy resources are available. This reduces the need for grid import and upstream network asset investment.

However, the impacts of large-scale adoption of P2P energy trading on distribution network operation and planning are very unclear. To the authors' knowledge, the co-simulation of local P2P energy trading markets and electricity distribution networks has not been investigated in detail in the literature to date.

3. Methodology

3.1. Overview of Co-simulation approach

In order for P2P energy trading to gain acceptance on a larger scale, it will be necessary for network operators to have the capability to model its impacts on the distribution networks, and the potential effects on network performance and reliability. The OpenDSS distribution network simulator is selected for this purpose since it is an open-source tool designed for modelling three-phase LV networks in detail and also since it is capable of interacting with the Python or MatLab software packages via an in-built Component Object Model (COM) interface. Python or MatLab can then be used to manage data input/output and automate electricity network simulation runs. An overview of the co-simulation approach used in this paper is provided in Figure 1.

The input data includes "User data", which comprises of the demand profiles of each user in the LV network, along with EV demand profiles and/or photovoltaic (PV) generation profiles, as appropriate. The "DN data" provides the OpenDSS simulator with the necessary information of the physical structure of the distribution network, including the network layout and the characteristics of power lines, transformers, and network control elements, such as voltage regulators. The "P2P energy trading simulator" implements the distributed double auction trading mechanism described in Section 3.2 of this paper. The "DN simulator" carries out 3-phase time series simulations of the electri-

city distribution network (DN) using OpenDSS [15]. Data is exchanged between each of these elements using comma-separated value (.csv) files. Finally, Python or MatLab may be used to manage data input/output and provide the post-processing and visualisation of the outputs from the network simulations.

MatLab is used to provide an interface between the Python energy trading simulator, OpenDSS, which is capable of quickly solving complex three-phase unbalanced networks. Initially, attempts were made to incorporate all of the relevant electrical network constraints in the same Python simulation code that implements the energy trading algorithms. However, this was found to be infeasible, due to the complexity involved in modelling unbalanced three-phase distribution networks realistically, and therefore a dedicated DN simulator was preferred. In this paper, MatLab was also used to produce the results shown in Section 5. The co-simulation approach outlined in Fig. 1 also has the advantage that the network model in OpenDSS can be replaced with a different distribution network without re-writing the Python code for energy trading. It is also possible to implement alternative local energy trading mechanisms in Python without needing to make changes in OpenDSS. The proposed co-simulation approach enables full end-to-end simulation of P2P energy trading in LV distribution networks, considering all relevant electrical network constraints (voltages, network branch loading limits, reliability and power quality requirements, and fault levels).

3.2. Overview of Peer to Peer Energy Trading Platform

Figure 2 shows the workflow of a peer in the blockchain P2P network in the blockchain energy trading simulator. It has three parallel processes. Process 1 tries to form a new block from unconfirmed transactions which can be interrupted by Process 2 if it receives a new valid block. Process 3 implements activities of each peer as they participate in energy trading. It creates transactions according to market model. For example, such transactions may represent the bid of an auction or a solution to a double auction. The simulator uses asynchronous event simulation in Python and agent based modelling.

A double auction [8, 25] is used as a trade model for P2P energy trading in this paper. In double auction, buyers (who need energy) and sellers (who have excess energy) submit their reservation price (and amount of energy to buy or sell) to an auctioneer. A buyer's reservation price is the maximum price it will pay for energy and a seller's reservation price is the minimum price at which the seller will sell its energy. The auctioneer decides on the price for energy exchange and subsets of the buyers and sellers who will trade. McAfee's mechanism [37] is used to determine the winner (who trades energy and at what price) of a double auction.

3.3. Centralised versus Decentralised Double Auction Mechanisms

There are several problems with a centralized double auction for P2P energy trade as follows:

- **Robustness:** Centralized auction is not robust as failure of the auctioneer would fail the entire trade operation.
- **Trust in the auctioneer:** The auctioneer may collude with a few peers to alter the result of the auction. Hence peers must evaluate their trust on the auctioneer.
- **Local price:** Price for energy exchange may be determined by peers who are long distance apart from other peers. The approach in [37] is used to determine winner of the double auction. According to this mechanism the price for energy trade is determined by bids of a buyer and seller pair such that (a) buyer's bid more or equal to the seller's bid and (b) there is not other buyer-seller pair who satisfies the first condition. In a large network, it may happen that such a pair of buyer-seller peers are situated at distant locations from other peers. Due to long distance from other peers they may not engage in energy trade. Hence such price should not be used for energy transfer for the entire peer network.
- **Local exchange:** Peers who are located at distant locations from each other may trade energy, which can cause energy losses due to long transmission distances.
- **Security:** It is difficult to ensure security of information shared in peer to peer energy trade. Also, such a trade platform is vulnerable to cyber attacks.

The blockchain-based distributed double auction for P2P energy trade proposed in [7] and [8] is used to mitigate these problems. The blockchain mechanism [38] allows us to securely store transaction records between two peers in a peer to peer network. Security of blockchain maintained transaction record is guaranteed by encryption and distributed consensus protocol. The blockchain mechanism eliminates the requirement of a

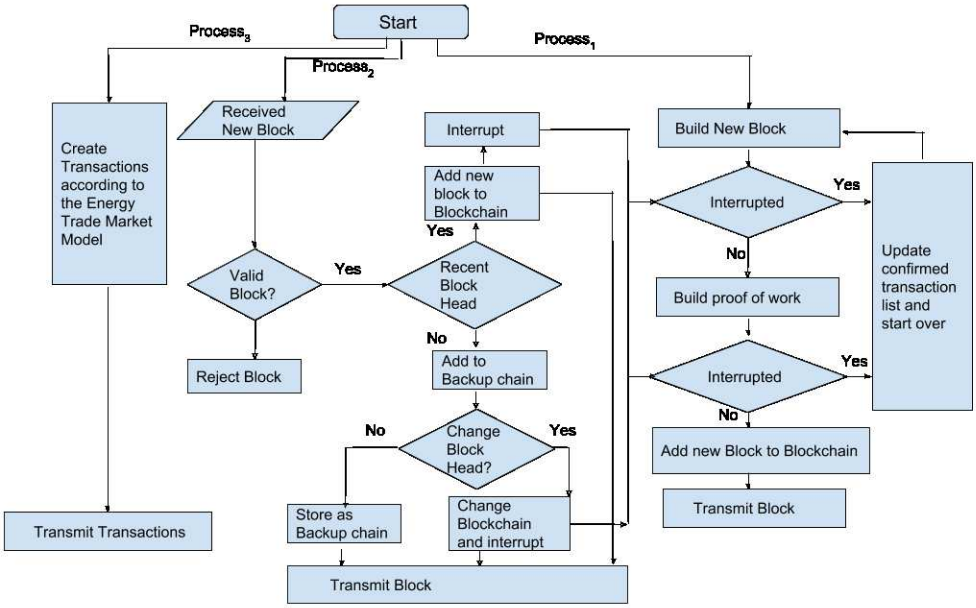


Figure 2: Overview of Python-based blockchain energy trading simulator.

trusted third party to verify a transaction between two parties. In the proposed distributed double auction, any peer may act as the auctioneer and the blockchain mechanism ensures that each peer acts lawfully while it acts as an auctioneer.

3.4. Peer to Peer Energy Trading Platform based on a Distributed Double Auction Mechanism

It is assumed in this paper that some or all of the peers are "prosumers", defined as active energy customers with flexible load and/or generation resources. These local energy resources may comprise of controllable electrical demands (e.g. EV chargers, electric heat pumps, smart appliances), on-site electricity generation, or battery storage equipment. These local resources can be controlled automatically in response to electricity price signals using home or building energy management systems. In the analysis presented in Sections 4 and 5, it is assumed that residential customer EV charging schedules can be adjusted in response to price signals.

Figure 3 shows an overview of the proposed method for P2P energy trading. It is summarised below as follows:

1. Houses equipped with local energy resources form a blockchain peer to peer network for energy trade. Houses in close proximity (w.r.t the energy distribution lines) with each other become neighbours in this peer to peer network.

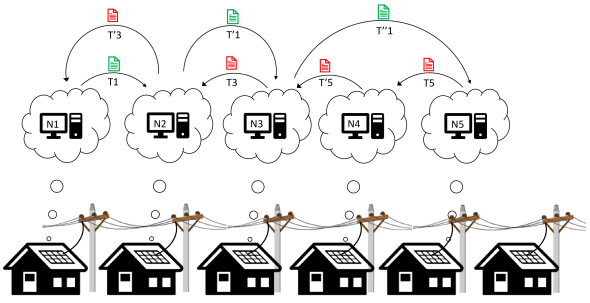


Figure 3: A peer informs other peers about its energy supply/demand requirement using transactions. Any peer can act as an auctioneer if it receives multiple supply and demand transactions from other peers. If a peer fails to solve a double auction then it forwards its unspent transactions to another peer. If it succeeds to solve the double auction then it sends appropriate tokens to the peers.

2. Energy surplus or deficiency information are encoded as blockchain transactions and a peer (a house) sends such a transaction to a neighbour to express its energy need. For example $N1$ sends the transaction $T1$ to $N2$ to express that it has energy surplus and $N3$ sends the transaction $T3$ to $N2$ to express its energy deficiency.
3. Upon receiving enough energy requirement information from its neighbours a peer executes the double auction winner determination algorithm. For example, $N2$ executes such algorithm with input transactions $T1, T3, T'5$.
4. If a peer finds winner of such an auction then it creates appropriate transactions to reflect such winner. For example, $N2$ finds that $N3$ and $N5$ should consume energy and $N1$ should sell its excess energy. It makes transactions $T'1, T''1$ and $T'3$ to reflect this result.
5. If a peer fails to determine the winner of a double auction then it will forward its unspent transactions to a neighbour. Such a neighbour may have more energy requirement information and may be able to solve the double auction. For example, $N4$ received the energy deficiency information from $N5$ as the transaction $T5$ but it could not solve the double auction. Hence $N4$ forwards such information to $N3$ as the transaction $T'5$, who solves the double auction.

Note that the outcome an auction only indicates how much energy a peer should consume or contribute. However, the actual energy consumption may be different and it will be recorded as transaction with Requirement field 0. We propose to create smart contract for payments.

Given the result of each auction, the peers can form a smart contract among them. For example if the result of the auction states that peer m_i should sell x units of energy at price y between time $[t_1, t_2]$ and m_j should buy x units of energy at price y between time $[t_1, t_2]$ then, the smart contract will involve two parties m_i and m_j, it will be funded by m_j with crypto-currency of value $x * y$.

This smart contract will be triggered by energy consumption information from m_i and m_j and such information will decide the actual payment. For example, say m_i only contributes $x_1 < x$ units of energy. Hence it will be paid $x_1 * y$ tokens and $(x - x_1) * y$ tokens will be sent back to m_j. Such a crypto-currency can be part of the blockchain infrastructure for energy trade and peers must buy these tokens with any other currency (i.e. € or $). However, the tokens used for energy trade information and auction are free as each peer is endowed with fixed number of tokens to express their future energy needs and actual energy consumption every day at a fixed time. Sidechains [39] can be used to implement this form of payment for peer to peer energy trade. For a full details of the double auction method used and its mathematical formulation, the reader is referred to [7] and [8].

Finally, each peer calculates its own energy requirement using weather and historical energy supply demand information. Intentional mismatch between the announced energy requirement and the actual energy consumption may affect the performance of any peer to peer energy trade. The blockchain keeps secure records of such information and any such malicious behaviour can be identified. Hence the proposed solution is a deterrent of such malicious behaviour.

3.5. A Smart Contract Implementation of the Distributed Double Auction

The distributed double auction mentioned in the previous section can be implemented as smart contracts. Figure 4 illustrates the sequence diagram of the smart contract execution of the distributed double auction.

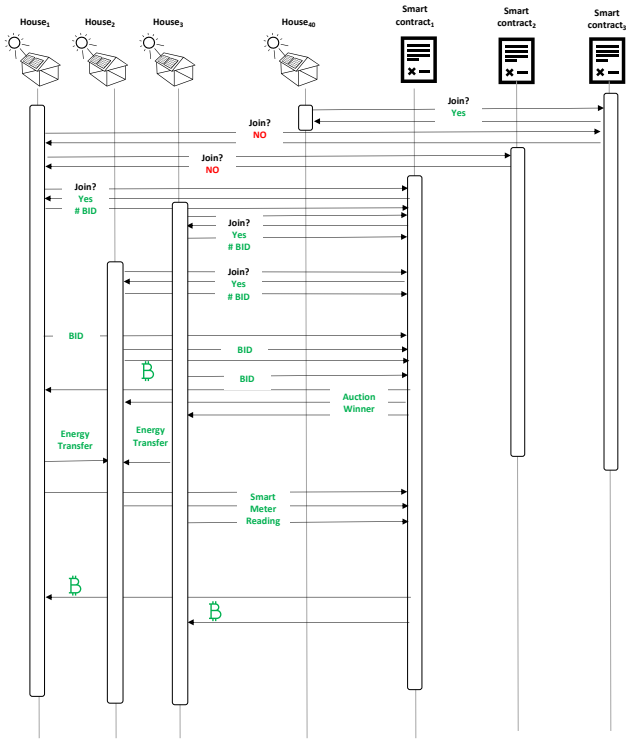


Figure 4: Sequence diagram of smart contract based execution of the distributed double auction.

The steps to implement smart contracts for the distributed double auction are as follows:

1. The following steps are executed after every fixed finite interval such as in every 5 minutes.
2. The geographical area covered under a peer to peer network is divided into n number of localities. It is assumed that peers in the same locality can trade energy. The areas may overlap, i.e., a peer may be part of multiple localities.
3. Next, n smart contracts are created in the blockchain network. In this smart contract model, we will assume that a government or regulatory authority will create these smart contracts with sufficient funding (i.e., Gas in Ethereum network) for each smart contract. It will be assumed that these smart contracts will be executed for at least the fixed time interval defined in step 1.
4. During an interval, if a house X wants to trade it will request a smart contract M_i if it can participate in the execution of the smart contract. The smart contract M will determine if X can join it. Such decision will be determined by the distance between the existing participants of M and X. For example, if X is not in the same locality as the members of M then X will not be allowed to participate in M.
5. After a peer receives approval from a smart contract for its participation it sends Hash of its bid using a Hashing algorithm (SHA256) to the smart contract.
6. After a fixed fraction of the time interval, say after 1 minute of a 5 minute interval, participation in all smart contracts will be ceased and the peers will be asked to submit actual bids and corresponding cost (both for buying and selling). The bid of each peer should match the Hash it has sent in the previous section.
7. Next, each smart contract will execute the algorithm [37] to determine the winner of the auction.
8. Each smart contract will inform the outcome of the auction to its participate and the participants should act accordingly.
9. Next, energy will be traded for the remaining of the time interval.
10. At the end of the time interval, data from smart meters of the each peer will be fed into the smart contracts to verify actual energy transfer among the participants.
11. If the smart contract can verify that participants have acted according to the solution of the auction then, the smart contract will transfer funds from it to the energy producers.

We observe the following in the above execution of the distributed double auction:

1. The synergy between the blockchain transaction settlements and electricity network operation is assumed in the above execution of smart contracts contracts. It should be noted that the blockchain simulator presented in this paper can predict the expected transaction confirmation time. The approach is designed so that the expected transaction confirmation time and the time taken for market to clear is typically less than the time step used in the distribution network simulation (5 minutes in the case study presented in this paper). This ensures synergy between the execution time of the blockchain energy trading and distribution network control centre state estimator, or distribution network simulation.
2. Market clearing: The distributed double auction described in this paper is one example of an energy trade model. It is also possible to use any other trade model, such as those described in [7]. The distributed auction model proposed in the paper is an efficient trade mode with the following properties:
   (a) Convergence: The proposed distributed auction completes in finite time, i.e., the number of times a house requests a smart contract for its participation is finite [8]. Figure 5 shows that the distributed auction completes within finite time.
   (b) Price difference: The differences among the prices of energy at the smart contracts is bounded by the maximum and the minimum allowed bid for energy. Such price difference can be even lower if the difference between the maximum and the minimum bid becomes low.

   Full details of the trade efficiency of the proposed distributed double auction are provided in [8].

3.6. Characteristics of the Blockchain Simulator

We characterize the blockchain simulator using blockchain forks and blockchain throughput. The blockchain simulator can be used to predict the performance of a blockchain network to be built using a number of the parameters of the actual blockchain to be developed. These parameters are:

- Network Delay: This affects the performance of a blockchain network, as the time needed to disseminate transactions and blocks depends on the communication delay in the blockchain network.
- Network size: Network size can affect the performance of the blockchain, since: (a) a larger diameter

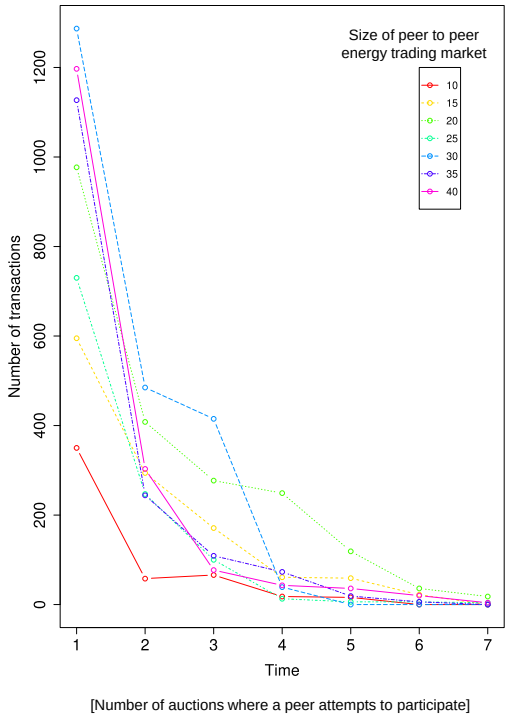


Figure 5: Convergence time of the distributed double auction [8].

of the blockchain network will require more time to disseminate blockchain data among all of its peers (b) the number of transactions to be created in the blockchain will be high for a large network.

We will use these parameters to evaluate the performance of a simulated blockchain. We will investigate the following characteristics of a blockchain:

- Blockchain Fork: A blockchain fork is a phenomenon where the blockchain splits into multiple blockchains. In a blockchain network, it may happen that more than one miner creates a new block approximately at the same time. Due to this incident, part of the blockchain network will accept a new block as the most recent block and reject another block while remainder of the network will do the opposite. Hence, the most recent block will be different for parts of the network. Blockchain forks are problematic as double-spending is possible with a forked blockchain. The principle of blockchain consensus is designed to resolve blockchain forks. For example, in a Proof of Work-based consensus, the longest branch of a forked blockchain is considered as the valid blockchain, and the blocks in shorter branches of the forked blockchain are rejected.

- Transaction confirmation time: The transaction confirmation time of a blockchain transaction can be calculated as the time it takes from creation of the blockchain to the time when the transaction is recorded into a new block. Due to the existence of forking phenomenon, confirmation time of a blockchain can include the time it takes to create a fixed number of new blocks who are child blocks of the block that contains the transaction. Transaction confirmation time indicates the throughput of a blockchain. Lower confirmation time results in higher throughput, i.e., the blockchain can successfully record a large number of transactions.

The blockchain simulator used in this paper can be applied to determine the number of expected blockchain forks from the expected network delay. Figure 6 shows how the blockchain simulator can be used to predict the number of forks. We simulate a blockchain network with 200 peers and 40 miners where the diameter of the network is 5. Figure 6 shows the number of forks as network delay is increased. It shows that the number of forks increases as network delay is increased. This result also supports the validity of the proposed blockchain simulator. As the network delay increases the probability that more than one miner will create a new block at the same time also increases. This is because, after creating a new block, a miner publishes it to the network and another miner restarts its mining process after receiving a new block. With a large network delay, the time to reach all miners will be increased and it will be less likely that a miner will restart its mining process.

Finally, it was demonstrated though simulation that the blockchain simulator can be used to predict the expected throughput of the blockchain and the expected transaction confirmation time as the network delay is increased. The first parameter that will impact the transaction confirmation time is the size of the network. It was found that the predicted transaction confirmation time decreases the number of new transactions created per second is decreased. In these simulations of blockchain we used proof of work based consensus principle in a blockchain network with 200 nodes, 40 miners and network diameter 5. In Table 1, it is shown that transaction confirmation time is increased as network delay is increased.

In this paper, a full analysis of the economic feasibility of the proposed blockchain implementation is not provided. The economic feasibility will be determined by the cost to operate the blockchain network and the cost to execute smart contracts. The pricing algorithm

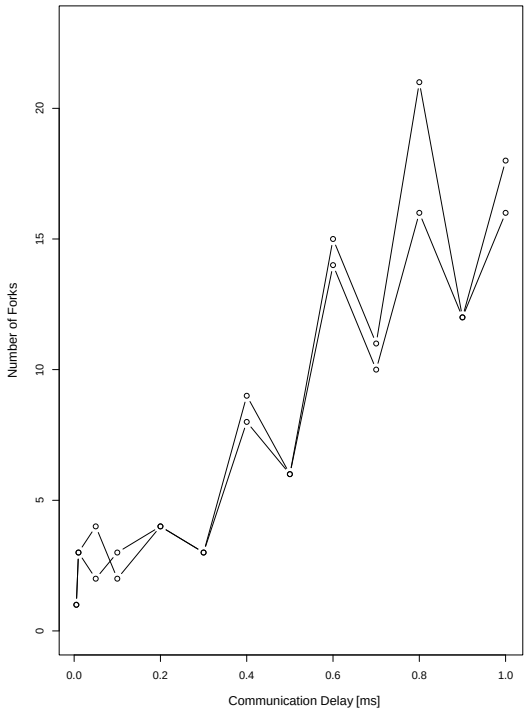


Figure 6: Number of blockchain forks as the network delay increases.

Table 1: Expected transaction confirmation time as network delay is increased.

Communication delay [ms]	**Transaction confirmation time [s]**
1	97
2	104
3	100
4	102
5	118
6	128
7	148
8	167
9	177
10	184

of smart contracts is beyond the scope of this paper. However, the blockchain simulator can predict the performance of a blockchain with respect to the proposed investment in the blockchain network (number of nodes and bandwidth). Therefore the blockchain simulator can be used to estimate the cost of operating a blockchain network for peer to peer energy trading, and can be applied in determining the economic feasibility of a blockchain-based peer to peer energy trading.

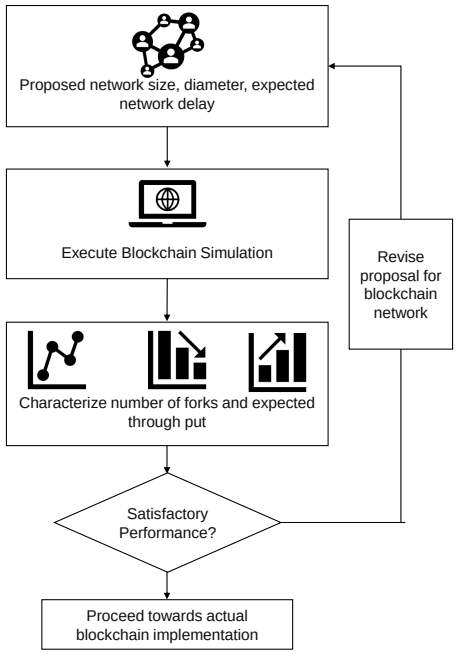


Figure 7: A workflow to determine the blockchain to be implemented.

3.7. A Method for Determining an Appropriate Blockchain

In this section, we present the workflow to determine an appropriate blockchain using our blockchain simulator. The steps (shown in Figure 7) are as follows:

- First, fix properties of a blockchain network to be built in terms of size of the network and network delay.
- These parameters are used as input to the blockchain simulator.
- Next, determine the expected number of forks and expected throughput of the network using the results from the execution of the simulation.

- If the computed performance of the simulated blockchain is not satisfactory, revise the proposed blockchain network properties, i.e., increase/decrease blockchain network size and communication bandwidth and repeat these steps again.

4. Case Study and Distribution Network Simulation Input Data

The distribution network impacts of local P2P energy trading schemes are investigated using a case study carried out on the IEEE European Low Voltage Test Feeder [16]. This test network represents a typical three-phase European LV suburban residential system, and includes residential demand data based on actual measurements from residential LV customers in a distribution network in Northern England. The distribution network layout and a sample of the demand data for each residential user connected to the network are shown in Figure 8.

The voltage at the head of the feeder (MV/LV substation) is set at a fixed value (1.0 p.u.) and there is no active voltage regulation in the LV secondary network [40]. The network consists of 905 line pairs modelled as serial impedances (consisting of resistance and reactance values) between 906 nodes. The network has a total of 55 single-phase (230 V nominal phase-to-neutral voltage) residential users, which are nearly equally distributed to three phases of the feeder (21 users on phase A, 19 users on phase B and 15 users on phase C). The network simulation calculates the following quantities at five-minute intervals: voltages at each customer connection point; active and reactive power flow in each network branch; active power losses in each network branch; number of low voltage violations (<0.9 p.u.); number of high voltage violations (>1.1 p.u.); voltage imbalance across the three phases.

In order to examine a future network scenario with a very high penetration of distributed energy resources, and to create opportunities for P2P trading, PV generation and EV charging demands were added at all 55 customer connection points in the IEEE European LV test network. Residential PV units are modelled as active power injections at each load point in the LV network. The PV production data is based on actual measurements of rooftop PV outputs at residential homes recorded by domestic smart meters in [41]. The PV units have a capacities ranging from 1.6 kW to 4 kW, use maximum power point tracking and operate at fixed unity power factor. The EV charging data used in this paper is taken from actual vehicle charging data from the same study, where each EV charger is rated at 3 kW. Table 2 lists the installed PV and EV capacity. Figures 9 and 10 show samples of the PV injections and EV charging demands taken from [41].

Table 2: Installed PV and EV units and rated capacities.

	PV panels	**EV chargers**
Rated power of each unit [kW]	1.6-4	3
Number of nodes installed	55	55
Total installed capacity [kW]	180	165

In the distribution network simulation, a five minute time step was used in order to allow analysis of the changes in network power flows and voltages over the course of one day. Two cases are analysed below:

- **Base Case**: Distribution network simulation is carried out at using the demand profiles, EV charging demands and PV generation outputs described in Figures 8-10, with no P2P energy trading.
- **P2P Case**: Distribution network simulation is carried out at using the same input data, and applying the P2P energy trading based on the double auction mechanism described in Section 3.2.

The results presented in Section 5 below provide an analysis of the impacts on the LV test network over the course of one entire day, using the demand profiles in Figure 8b, the PV generation profiles in Figure 9 and the EV charging demands in Figure 10. The co-simulation approach outlined in Figure 1 and Section 3 is used for both Base Case and P2P Case described above.

5. Distribution Network Simulation Results

Figures 11 and 12 show the active and reactive power import/export recorded at the MV/LV substation transformer in the OpenDSS network simulation. Since the case study has a very high PV penetration, there is a net export from the substation in the middle of the day, and hence kW and kvar values are negative during these time steps. It is assumed in this paper that the LV network is capable of accommodating bidirectional power flows. The largest number of P2P energy trading transactions occur between the time steps 200 and 230 (see dashed lines in Figures 11 and 12), which approximately corresponds to the hours 17:00 to 20:00 in the day. It can be seen that the P2P energy trading has a significant impact on the kW and kvar flows in each phase during these times.

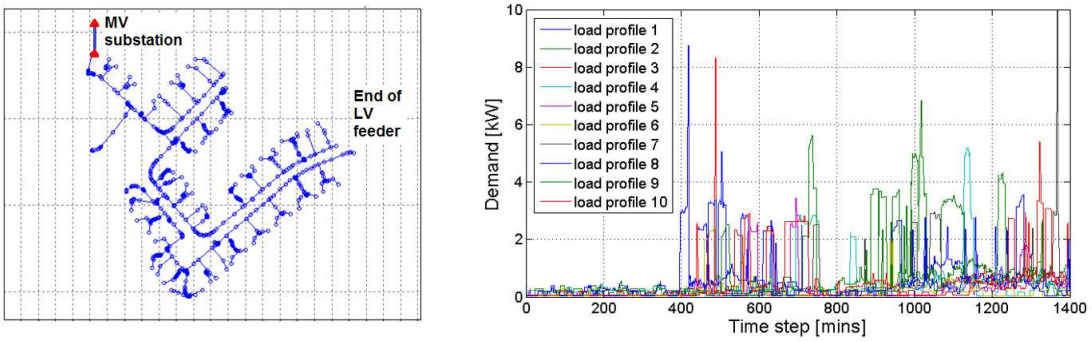


Figure 8: Distribution network test case: (a) Layout of IEEE LV test system; (b) Sample of the load profiles for 10 individual users.

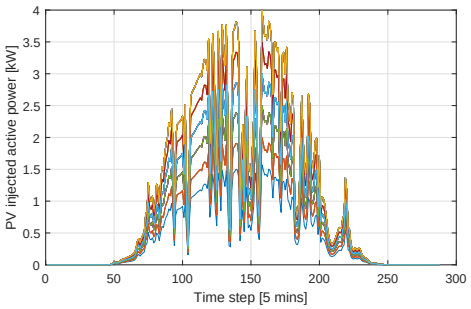


Figure 9: Samples of input data: PV active power injections.

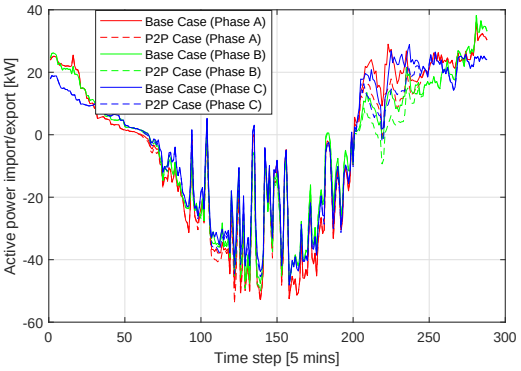


Figure 11: Active power (kW) import and export per phase at the MV/LV over the course of one day.

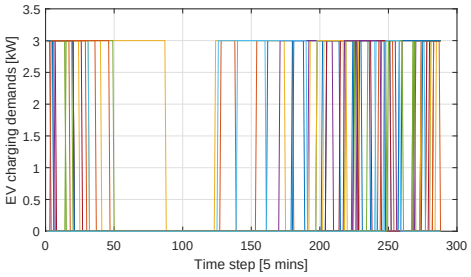


Figure 10: Samples of input data: EV charging demands.

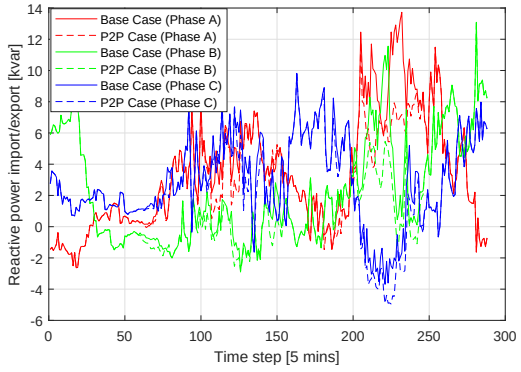


Figure 12: Reactive power (kvar) import and export per phase at the MV/LV over the course of one day.

A summary of the results from the DN simulations is given in Table 3. These results show that the net energy exported from the test DN is increased by approximately 19 kWh over the course of the day in the P2P case. The reactive power imported into the test DN is reduced by more than 6 kvarh. No significant change is observed in the maximum instantaneous kVA power demand (which occurs in the late evening and is driven by EV charging load), or in the network active power losses over the 24 hour period test as a result of the P2P energy trading.

The impact of P2P energy trading on DN voltages can also be measured using a voltage unbalance metric, which describes the differences between the magnitudes of the voltages in each phase of the three-phase LV distribution system. In this paper, the IEEE definition of voltage unbalance is applied. This is defined in [42] as the Phase Voltage Unbalance Rate (PVUR), the maximum voltage deviation from the average phase voltage as a percentage of the average phase voltage. PVUR is slightly reduced in the P2P Case (8.665%) as compared to the Base Case (8.866%), Table 3.

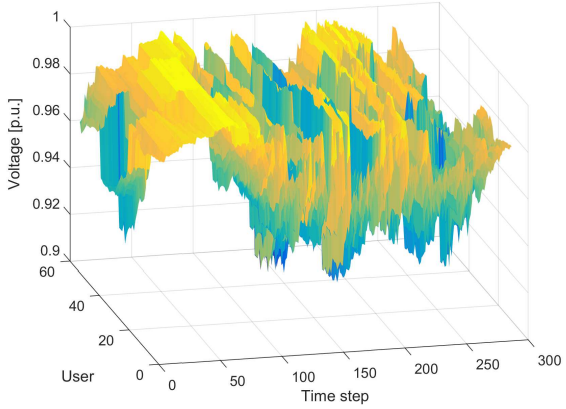


Figure 13: Base case voltage profiles for all DN users at each five-minute time step in simulation.

Figures 13 and 14 illustrate the voltage profiles for all 55 users connected to the network for the Base Case and P2P Case respectively. In order to simplify the voltage analysis and to enable direct comparison between the voltages in each case, a fixed voltage of 1.0 per unit was assumed at the MV side of the MV/LV substation transformer.

These results demonstrate that the proposed co-simulation approach allows us to analyse the impact of DN voltages of P2P trading. The user voltage profiles in the Base Case and P2P Case are similar during time steps where there are few P2P transactions. Figure 15 illustrates the differences between the Base Case and P2P voltage profiles, expressed as percentage values.. The most significant changes in voltage again occur during the time steps from 200 to 230 in Figures 13-15 (in the late afternoon/early evening between the hours of 17:00-20:00).

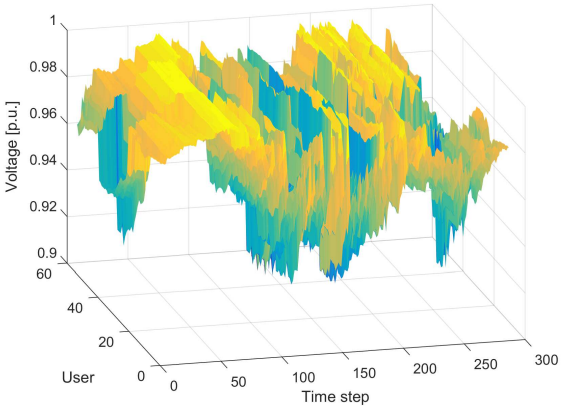


Figure 14: P2P energy trading case voltage profiles for all DN users at each five-minute time step in simulation.

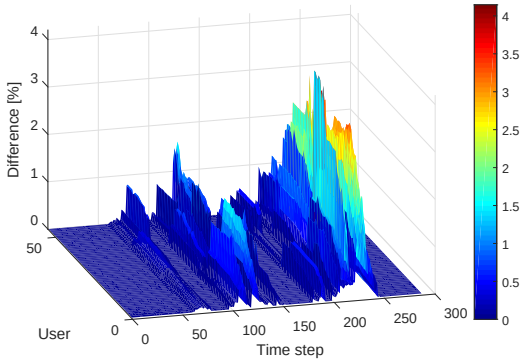


Figure 15: Difference between Base Case and P2P Case voltage profiles, expressed as percentage values.

6. Discussion and Conclusions

Peer-to-peer (P2P) energy trading schemes are designed to enable multi-bilateral trading between electricity network users in a neighbourhood or area, in order to balance energy surpluses and shortfalls locally. Such schemes could potentially enable greater choice for electricity consumers and facilitate increased levels of competition amongst large-scale and small-scale electricity generators and retailers, with the option

Table 3: Summary of DN Simulation Results.

Simulation result [Units]	Base Case	P2P Case	Difference
Net energy exported [kWh]	40.06	59.12	+19.06
Reactive power imported [kvarh]	41.07	34.85	-6.22
Max complex power [kVA]	148.73	149.32	+0.59
Active power losses [%]	3.33	3.40	+0.07
Phase Voltage Unbalance Rate [%]	8.866	8.665	-0.001

of electricity product differentiation based on consumer preferences.

The anticipated benefits of P2P energy trading include better utilisation of power network assets and reduction of energy losses due to shorter transmission distances. At the distribution network level, energy balancing can be achieved locally, reducing the need for grid import and upstream network asset investment.

However, the potential impacts of large-scale adoption of P2P energy trading on distribution network operation and planning are very unclear, and the co-simulation of local P2P energy trading markets and electricity distribution networks has not been investigated in the literature to date. The co-simulation approach presented in this paper provides a means of assessing the feasibility of large-scale adoption of P2P energy trading schemes, analysing their impacts on the distribution network, and validating their potential benefits.

In order for P2P energy trading to gain acceptance on a larger scale, it will be necessary for network operators and other stakeholders to have the capability to model its impacts on the distribution networks, and the potential effects on network performance and reliability. Accordingly, this paper presents a framework for co-simulation of a local P2P energy trading market mechanisms and electricity distribution networks. The analysis presented in Sections 4 and 5 provides a case study using this framework. P2P energy trading is carried out using a blockchain-assisted distributed double auction trading platform. The impacts of this energy trading are tested using a typical three-phase European LV suburban residential distribution system, where residential demand, PV and EV profiles based on measured data are employed in the analysis.

The paper demonstrates that this co-simulation approach can be used to analyse the impacts of P2P energy trading on network power flows and voltages. The results in Section 4 indicate that a moderate level of P2P energy trading did not have a significant impact on network operational performance in the European LV distribution network tested. Table 3 shows that the maximum demand recorded in the network over the 24 hours was not significantly affected, with the difference of less than 1 kVA between the Base Case and P2P Case. There was also very little difference in the phase voltage imbalance, with the PVUR equal to approximately 8.7% in both cases, Table 3. The results in Figs. 13-15 show only minor differences in the voltage profiles in the late afternoon/early evening hours (17:00-20:00).

The distribution network analysis in this paper is carried out over the course of one 24 hour period and does not examine the sensitivity to day types and seasonal factors. Future work will address these issues, and provide a more complete analysis of the impacts of various P2P energy trading mechanisms on network asset utilisation, reliability and power quality. Work is ongoing to fully integrate the co-simulation test-bed presented in this paper with Ethereum-based execution of transactions. The eventual aim of this research is to provide a comprehensive framework for examining the medium to long-term effects of local, decentralised electricity markets and P2P trading on distribution system planning and operation, and for comparing this with traditional, centralised market arrangements.

7. Acknowledgements

The authors acknowledge the contributions from the International Energy Research Centre (IERC) project "EnerPort" industry partners Systemlink Technologies Ltd., mSemicon Teoranta, and Verbatm. This work has been funded in part by Enterprise Ireland (contract number TC-2013-0002B), Science Foundation Ireland (grant number SFI/12/RC/2289, co-funded by the European Regional Development Fund), and the Department of Communications, Climate Action and Environment of the Government of Ireland. This work was also supported by the Department of Agriculture, Food and the Marine on behalf of the Government of Ireland under Grant Number SFI 16/RC/3835.

References

[1] F. Rahimi, A. Ipakchi, F. Fletcher, The changing electrical landscape: End-to-end power system operation under the transactive energy paradigm, IEEE Power and Energy Magazine 14 (3) (2016) 52–62. doi:10.1109/MPE.2016.2524966.

[2] NIST, Transactive Energy Challenge.
URL https://pages.nist.gov/TEChallenge/community/

[3] M. A. Mustafa, S. Cleemput, A. Abidin, A local electricity trading market: Security analysis, in: 2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2016, pp. 1–6. doi:10.1109/ISGTEurope.2016.7856269.

[4] N. Z. Aitzhan, D. Svetinovic, Security and privacy in decentralized energy trading through multi-signatures, blockchain and anonymous messaging streams, IEEE Transactions on Dependable and Secure Computing PP (99) (2016) 1–1. doi:10.1109/TDSC.2016.2616861.

[5] B. Hayes, I. Melatti, T. Mancini, M. Prodanovic, E. Tronci, Residential demand management using individualized demand aware price policies, IEEE Transactions on Smart Grid 8 (3) (2017) 1284–1294. doi:10.1109/TSG.2016.2596790.

[6] C. Burger, A. Kuhlmann, P. Richard, J. Weinmann, Blockchain in the energy transition: A survey among decision-makers in the German energy industry (2016).

[7] S. Thakur, J. G. Breslin, Peer to peer energy trade among microgrids using blockchain based distributed coalition formation method, Technology and Economics of Smart Grids and Sustainable Energy 3 (1) (2018) 5. doi:10.1007/s40866-018-0044-y.

[8] S. Thakur, B. P. Hayes, J. G. Breslin, Distributed double auction for peer to peer energy trade using blockchains, in: Proceedings of the 5th International Symposium on Environment Friendly Energies and Applications, 2018.

[9] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, E. Hossain, Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains, IEEE Transactions on Industrial Informatics 13 (6) (2017) 3154–3164. doi:10.1109/TII.2017.2709784.

[10] J. J. Sikorski, J. Haughton, M. Kraft, Blockchain technology in the chemical industry: Machine-to-machine electricity market, Applied Energy 195 (2017) 234 – 246.

[11] Brooklyn microgrid.
URL https://www.brooklyn.energy/

[12] Powerpeers community energy trading platform.
URL https://powerpeers.nl/

[13] PowerLedger: A blockchain-based peer-to-peer energy trading platform.
URL https://powerledger.io/

[14] M. Andoni, V. Robu, D. Flynn, S. Abram, D. Geach, D. Jenkins, P. McCallum, A. Peacock, Blockchain technology in the energy sector: A systematic review of challenges and opportunities, Renewable and Sustainable Energy Reviews 100 (2019) 143 – 174. doi:https://doi.org/10.1016/j.rser.2018.10.014.

[15] Electric Power Research Institute, OpenDSS Simulation Tool.
URL http://smartgrid.epri.com/SimulationTool.aspx

[16] IEEE European Low Voltage Test Feeder, IEEE PES Distribution Test Feeder Working Group (2015).
URL https://ewh.ieee.org/soc/pes/dsacom/testfeeders/

[17] Y. Parag, B. K. Sovacool, Electricity market design for the prosumer era, Nature Energy 1 (4) (2016) 1–6.

[18] T. Morstyn, A. Teytelboym, M. D. McCulloch, Bilateral contract networks for peer-to-peer energy trading, IEEE Transactions on Smart Grid (2018) 1–1doi:10.1109/TSG.2017.2786668.

[19] Y. Wang, W. Saad, Z. Han, H. V. Poor, T. Basar, A game-theoretic approach to energy trading in the smart grid, IEEE Transactions on Smart Grid 5 (3) (2014) 1439–1450. doi:10.1109/TSG.2013.2284664.

[20] J. Ma, J. Deng, L. Song, Z. Han, Incentive mechanism for demand side management in smart grid using auction, IEEE Transactions on Smart Grid 5 (3) (2014) 1379–1388. doi:10.1109/TSG.2014.2302915.

[21] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, J. Lei, Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers, IEEE Transactions on Power Systems 32 (5) (2017) 3569–3583. doi:10.1109/TPWRS.2017.2649558.

[22] D. Papadaskalopoulos, G. Strbac, Decentralized participation of flexible demand in electricity markets - part i: Market mechanism, IEEE Transactions on Power Systems 28 (4) (2013) 3658–3666. doi:10.1109/TPWRS.2013.2245686.

[23] X. Ayon, J. Gruber, B. Hayes, J. Usaola, M. Prodanovic, An optimal day-ahead load scheduling approach based on the flexibility of aggregate demands, Applied Energy 198 (2017) 1 – 11. doi:https://doi.org/10.1016/j.apenergy.2017.04.038.

[24] R. de Sa Ferreira, L. A. Barroso, P. R. Lino, M. M. Carvalho, P. Valenzuela, Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach, IEEE Transactions on Smart Grid 4 (4) (2013) 2285–2295. doi:10.1109/TSG.2013.2241087.

[25] B. P. Majumder, M. N. Faqiry, S. Das, A. Pahwa, An efficient iterative double auction for energy trading in microgrids, in: 2014 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG), 2014, pp. 1–7. doi:10.1109/CIASG.2014.7011556.

[26] M. Marzband, F. Azarinejadian, M. Savaghebi, E. Pouresmaeil, J. M. Guerrero, G. Lightbody, Smart transactive energy framework in grid-connected multiple home microgrids under independent and coalition operations, Renewable Energy 126 (2018) 95 – 106. doi:https://doi.org/10.1016/j.renene.2018.03.021.

[27] H. Wang, J. Huang, Incentivizing energy trading for interconnected microgrids, IEEE Transactions on Smart Grid 9 (4) (2018) 2647–2657. doi:10.1109/TSG.2016.2614988.

[28] J. Li, C. Zhang, Z. Xu, J. Wang, J. Zhao, Y. A. Zhang, Distributed transactive energy trading framework in distribution networks, IEEE Transactions on Power Systems 33 (6) (2018) 7215–7227. doi:10.1109/TPWRS.2018.2854649.

[29] M. Pilz, L. Al-Fagih, Recent advances in local energy trading in the smart grid based on game-theoretic approaches, IEEE Transactions on Smart Grid 10 (2) (2019) 1363–1371. doi:10.1109/TSG.2017.2764275.

[30] E. Sorin, L. Bobo, P. Pinson, Consensus-based approach to peer-to-peer electricity markets with product differentiation, IEEE Transactions on Power Systems (2018) 1–1doi:10.1109/TPWRS.2018.2872880.

[31] T. Morstyn, M. McCulloch, Multi-class energy management for peer-to-peer energy trading driven by prosumer preferences, IEEE Transactions on Power Systems (2018) 1–1doi:10.1109/TPWRS.2018.2834472.

[32] A. Luth, J. M. Zepter, P. C. del Granado, R. Egging, Local electricity market designs for peer-to-peer trading: The role of battery flexibility, Applied Energy 229 (2018) 1233 – 1243. doi:https://doi.org/10.1016/j.apenergy.2018.08.004.

[33] Y. Zhou, J. Wu, C. Long, Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework, Applied Energy 222 (2018) 993 – 1022. doi:https://doi.org/10.1016/j.apenergy.2018.02.089.

[34] E. Mengelkamp, J. Garttner, K. Rock, S. Kessler, L. Orsini, C. Weinhardt, Designing microgrid energy markets: A case study: The brooklyn microgrid, Applied Energy 210 (2018) 870 – 880. doi:https://doi.org/10.1016/j.apenergy.2017.06.054.

[35] S. Lavrijssen, A. C. Parra, Radical Prosumer Innovations in the Electricity Sector and the Impact on Prosumer Regulation, Sustainability 9 (7) (2017) 1–21.

[36] P. Siano, G. De Marco, A. Rolan, V. Loia, A survey and evaluation of the potentials of distributed ledger technology for peer-to-peer transactive energy exchanges in local energy markets, IEEE Systems Journal (2019) 1–13doi:10.1109/JSYST.2019.2903172.

[37] R. McAfee, A dominant strategy double auction, Journal of Economic Theory 56 (2) (1992) 434 – 450.

[38] S. Nakamoto, Bitcoin: A peer-to-peer electronic cash system, http://www.bitcoin.org/bitcoin.pdf.

[39] A. Back, M. Corallo, L. Dashjr, M. Friedenbach, G. Maxwell, A. Miller, A. Poelstra, J. Timón, P. Wuille, Enabling blockchain innovations with pegged sidechains, 2014.

[40] K. P. Schneider, B. A. Mather, B. C. Pal, C. W. Ten, G. J. Shirek, H. Zhu, J. L. R. P. J. C. Fuller, L. F. Ochoa, L. R. de Araujo, R. C. Dugan, S. Matthias, S. Paudyal, T. E. McDermott, W. Kersting, Analytic considerations and design basis for the IEEE distribution test feeders, IEEE Transactions on Power Systems 33 (3) (2018) 3181–3188.

[41] Electricity North West, Low Voltage Network Solutions (LVNS) (2015).
URL `https://www.enwl.co.uk/lvns`

[42] P. Pillay, M. Manyage, Definitions of voltage unbalance, IEEE Power Engineering Review 21 (5) (2001) 49–51. doi:10.1109/MPER.2001.4311362.