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Towards a blockchain and machine learning-based framework for decentralised energy management

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ABSTRACT

In most domestic buildings, gas and electricity are supplied by energy and utility companies through centralised energy systems. This often results in a high burden on central management systems and has adverse effects on energy prices. Blockchain-based peer-to-peer energy trading platforms can deliver strategic operation of decentralised multi-energy network among multiple domestic buildings to reduce global greenhouse gas emissions and address global climate change issues. However, prevailing blockchain-based energy trading platforms focused on system implementation for peer-to-peer electricity trading while lacking predictive control and energy scheduling optimisation. Therefore, this paper presents an integrated blockchain and machine learning-based energy management framework for multiple forms of energy (i.e., heat and electricity) allocation and transmission, among multiple domestic buildings. Machine learning is harnessed to predict day-ahead energy generation and consumption patterns of prosumers and consumers within the multi-energy network. The proposed blockchain and machine learning-based decentralised energy management framework will establish optimal and automated energy allocation among multiple energy users through peer-to-peer energy transactions. This approach focuses on energy-matching from both the supply and demand sides while encouraging direct energy trading between prosumers and consumers. The security and fairness of energy trading can also be enhanced by using smart contracts to strictly execute the energy trading and bill payment rules. A case study of 4 real-life domestic buildings is introduced to determine the economic and technical potential of the proposed framework. In comparison to prevailing approaches, a key benefit from the proposed approach is an improved computational load/failure of a single point, energy trading strategy, workload, and capital cost energy. Findings suggest that energy costs reduced between 7.60% and 25.41% for prosumer buildings and a fall of 5.40%-17.63% for consumer buildings. In practical applications, the proposed approach can involve a larger number of prosumer and consumer buildings within the community to decentralise multiple energy trading, thus significantly contributing to the reduction of greenhouse gas emissions and enhancing environmental sustainability.

1. Introduction

1.1. Background and motivation

In 2020, energy use in buildings accounted for 42 % of Europe's overall energy consumption and 35 % of energy-related greenhouse gas emissions [1]. Many greenhouse gas emissions reduction strategies have been proposed at the individual building level, which include strategically scheduling energy appliances within the building [2] and retrofitting buildings with energy-efficient measures [3–8]. Beyond individual building optimisation, there has also been an urgent need to address climate change challenges at the community level so that local resources such as solar energy can be optimally harnessed while reducing the overall peak energy demand. Although some operating strategies have been proposed for collectively optimising the energy distribution among multiple users, a centralised agent is required to collect a heavy load of user information and determine energy schedules for each user. These operating strategies may face challenging issues such as user-privacy issues, scalability, and single point of failure. Moreover, the centralised energy management method may become quite complex when several flexible energy resources need to be considered.

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1.2. Research aim and paper structure

To overcome the limitations of conventional centralised energy management methods, the aim of this study is to propose an innovative blockchain and machine learning-based decentralised energy management framework for peer-to-peer trading of multiple energy within the local energy network. Each end-user has a local optimisation agent to determine its optimal schedule of multiple energy resources and energy trading rates.

The second section presents an overview of the state-of-the-art blockchain-based energy trading platforms, along with the identified research gaps and proposed research contributions. The third section illustrates the detailed design of the proposed blockchain and machine learning-based framework for decentralised multi-energy network management. The fourth section presents a case study to demonstrate the technical and economic potential of the proposed framework. The fifth section presents the practical implications and limitations of the conceptual framework, while the last section discusses the main research findings.

2. Literature review

2.1. Overview of the state-of-the-art blockchain-based energy trading platforms

Some researchers have investigated the feasibility of using blockchain in building energy management. For instance, Armon et al. [9] proposed a building heating management strategy to reduce the peaks-to-average ratio and energy consumption as well as improve thermal comfort in community buildings. A thermodynamic model was developed to reflect the transient energy consumption of each building. The key parameter (probability of the next hour) was shared on the blockchain, while smart contracts were adopted to access energy data from their neighbourhoods and determine the optimal operating schedule of boilers in order to decrease the peak-to-average ratio of load shape. The smart contract is a program running on a blockchain executed by multiple distributing nodes, without the need for a trusted third party, and relies on data to drive transactions. Armon's study adopted blockchain as the energy information sharing network to manage the energy consumption of neighbourhoods. Chenxi et al. [10] evaluated the framework of the wireless sensor network in the intelligent building energy management system, with a focus on designing a dynamic key management plan for smart buildings.

Apart from energy data sharing and dynamic key management, most recent research efforts have been contributing to using blockchain technology in peer-to-peer energy trading. For example, Olivier et al. [11] developed a decentralised framework for electrical energy management in a community of smart buildings and local renewable energy systems. The framework consisted of local optimisation processes and a smart contract to let participants collaboratively decide on a planning profile. A generic building model was developed to forecast building electricity demand based on the building load consumption from non-controllable parts and flexible parts, which was a simplification of the dynamic and complex energy performance. Meanwhile, based on different electricity tariffs, a local optimisation process was adopted to determine how much electricity could be bought from local electricity and power grid respectively. The Ethereum private blockchain was adopted as the energy trading platform. Yu-tian et al. [12] built a permissioned blockchain-based platform for peer-to-peer trading of renewable energy within the microgrids using Hyperledger Fabric. Hyperledger is the enterprise blockchain foundation's fundamental infrastructure, while the fabric design consists of highly scalable and flexible components such as ledge and smart contracts. The proposed platform can automate renewable electricity trading payment and settlement activities, as well as reduce trading clearing time and delivery loss. Yu-tian's study focused on fabric and the Paillier algorithm for energy trading and processing automation. Conversely, Eung et al. [13] delivered an automated decentralised renewable electricity trading platform within the microgrid using Ethereum blockchain. Don et al. [14] developed a peer-to-peer energy trading platform using Ethereum private blockchain, in which the double auction principle was adopted to enhance the vitality of the energy market. The major concern of Eung's [13] and Don's [14] studies was to develop a robust smart contract in facilitating closed bidding, energy exchange, settlement, and payment while building energy modelling and planning are not addressed. Similarly, Longze et al. [15] proposed a dynamic energy management strategy for distributed energy systems with high penetration of renewable energy using the Ethereum blockchain. Longze's study focused on developing a new consensus mechanism in blockchain, through energy contribution value to characterise credible transactions, emission reduction, demand response, and system operation contribution of energy prosumers. Qing et al. [16] developed a blockchain-based virtual power plant energy management platform to model energy trading and network services for domestic buildings with various loads, energy storages and local renewable energy generation devices. The sensor measurement was directly adopted to capture actual building energy consumption, while auxiliary variables and dual variables were adopted to reflect the electricity consumption of different energy devices. The buildings mainly relied on PV panels, the main grid, and a virtual power plant for electricity; thus, the optimisation was to determine the energy rate from the main grid, virtual power plant, and electricity storage, respectively. Using smart contracts, Abdullah et al. [17] proposed a microgrid market model to manage peer-to-peer electrical energy transactions. The prime concern of Abdullah's study was to develop a secure smart contract to facilitate participants to trade extra electricity with other participants. Price settlement between electricity providers and energy consumers was conducted on the basis of the mid-market method and supply-to-demand ratio-based pricing scheme. Miguel et al. [18] proposed a blockchain-based two-layer energy management strategy for community microgrids. The first layer managed the energy exchange among community members, while the second layer changed the network topology to reduce the energy injections to the main electricity power grid. Miguel's study sought to design an aperiodic execution flow to manage the smart contracts in a number of building clusters, while the real consumption data is directly used for testing purposes. Aparna et al. [19] developed a blockchain-based platform for peer-to-peer energy transactions among different houses. Aparna's study focused on designing the workflow of blockchain-based energy trading, such as request for energy trading, purchase of tokens from a controller node, pre-trading communication, as well as transaction creation and settlement. Based upon game-theoretic market rules and a blockchain-based transaction infrastructure, Moein et al. [20] developed a proof-of-concept for a peer-to-peer solar energy trading marketplace. The optimal power dispatching and price discovery process was determined by assuming that users were always willing to consume as much electricity power as needed to meet their demand. Based on cooperative game theory and blockchain technology, Md et al. [21] proposed an electricity trading platform to let users store renewable energy credits as assets in the blockchain and trade them with others. Existing dataset of electrical energy consumption was directly adopted to test the performance of blockchain for electricity trading, while game theory was adopted to select the appropriate prosumer for purchasing electricity. Yuling et al. [22] and Jingya et al. [23] proposed a distributed energy trading scheme based on consortium blockchain and game theory. However, their studies' approach was to develop an energy transaction matching mechanism and select optimal consumers and prosumers using different game theories. Using blockchain, Zixiao et al. [24] proposed a multi-microgrid electricity bidding trading model for a multi-seller and multi-buyer competitive spot market. Ant colony algorithm was adopted to determine the optimal energy flow among multiple microgrids. Xiaodi et al. [25] proposed a blockchain-based scheme for energy trading in a smart community. Conversely, Xiaodi's study focused on the multi-peer interaction process, including buyer request, seller reply, trading negotiation, community network validation, transaction settlement, and verification. A typical IEEE 13 bus system was adopted in Xiaodi's case study.

Previous work concerned with multi-energy management was mainly based on centralised control of distributed energy resources. For example, Valery et al. [26] developed a multi-agent approach to model an integrated energy system, where the complex multi-energy system was represented by a set of agents with their own individual behaviour. The agents interact with each other to determine the optimal operating schedule of each energy device. Similarly, Bin et al. [27] proposed a multi-agent method for interconnected multi-energy microgrid energy management. In the bottom layer, each agent operated independently to satisfy local customised energy demand, while the upper layer adopted a model predictive control method to determine the optimal power dispatching between microgrids and the main power grid.

2.2. Research gaps

These existing and emerging research efforts demonstrated the interest in blockchain technologies to secure data transmission and decentralization in electric energy systems and microgrids. Despite these efforts, the following research gaps have persisted:

(1) The thrust of efforts in this field focused primarily on electrical energy trading, thus neglecting or ignoring energy trading among multiple types of energy [11–25], such as heat. In reality, multi-energy systems can involve both heating and electrical energy types, while multi-type energy transmission can further reduce overall energy consumption and greenhouse gas emissions. For example, a cogeneration system can utilise exhaust heat from electricity generation to satisfy heating and cooling demand. If one building requires high electricity demand, while the other needs high heating energy demand, cogeneration system can be operated to supply electricity demand, while the exhaust heat can be traded to the other building with high heating demand. However, the existing research regarding decentralised multi-energy management mainly adopted a multi-agent method and was heavily based on a centralised control.

(2) Mainly because most of the previous research focused on developing and demonstrating the feasibility of using the blockchain-based platform for peer-to-peer energy trading, energy modelling was not considered [12–15,17,19,20,22,23]. Although energy modelling was adopted in some of the previous studies, they used generic thermodynamic models of hypothetical buildings to represent their real energy consumption [9,11], or assumed that future energy consumption patterns of real buildings were similar to their historical energy consumption profiles [16,18]. Existing databases [21,24] and IEEE bus systems [25] were also adopted for testing purposes. However, in practical applications, it is challenging to develop thermodynamic models for each individual building, while future energy consumption scenarios may also diverge from historical profiles, due to varying weather conditions and climate change.

(3) Existing research regarding blockchain-enabled peer-to-peer energy trading mainly focused on how to effectively utilise blockchain for system development, including trading process and workflow [12,19,21,25], bidding price scheme [11,20,22–24], smart contract development [13,14,17,18] and consensus mechanism development [15]. There was no research that can guide buildings or participants to determine how much energy they should buy or sell. When a multi-energy system was adopted to satisfy multiple forms of energy, it would be challenging for building users to determine the operating capacity or status of each energy device. In other words, participants on the state-of-the-art blockchain energy trading platform might not be able to reach the optimal solution to reduce overall energy consumption and greenhouse gas emissions, without mathematical optimisation.

2.3. Main contribution

The aim of this paper is to develop a blockchain and machine learning-based framework for decentralised energy trading within the multi-energy network. To overcome the above-mentioned 3 research gaps, the following 3 features are proposed for the developed framework:

1. Ethereum blockchain is used to facilitate peer-to-peer multi-type energy trading among different users. For example, if Participant A uses a cogeneration system to satisfy its peak electrical energy demand, the extra heat from the cogeneration system can be exported to Participant B who has a relatively high heat demand. Meanwhile, if Participant B has extra electricity generation from its PV panel, participant B can also trade electricity to Participant A to satisfy its high electricity demand.
2. Machine learning models are adopted to predict heating and electrical energy demands from buildings based on their historical energy consumption data. These machine learning models can be adopted in practice to predict day-ahead energy demands to facilitate energy planning of the participating buildings. Therefore, no expertise or experience is needed in developing thermodynamic models for each participating building. By collecting historical energy consumption data from smart meters and the latest weather forecast from local weather stations, machine learning models can generate accurate energy predictions by identifying the latest changes in energy consumption patterns.
3. Particle swarm optimisation (PSO) is adopted to help each participant select its optimal energy planning and operating schedule. For example, the prosumer can simultaneously use a PV panel and a cogeneration system, as well as import electricity from the main power grid and other prosumer buildings to satisfy its electrical energy demand. Meanwhile, prosumers can simultaneously use a solar heater, a cogeneration system, a biomass boiler, or import from other participants to meet their heating energy demand. Therefore, the PSO algorithm is adopted to determine the optimal energy schedule of different energy devices and resources.

3. Blockchain and machine learning-based framework for decentralised energy management

As shown in Fig. 1, the blockchain and machine learning-based framework mainly consists of 3 core parts, including the blockchain for peer-to-peer multiple energy trading, machine learning for multiple energy prediction, and PSO for energy scheduling optimisation. For each building, multiple machine learning models are developed for heating energy prediction, electrical energy prediction, PV electricity generation, and solar heater heating energy generation, respectively. Relying on collecting energy consumption and production data from smart meters and weather forecast data from local weather stations, day-ahead energy demands from buildings and energy generations from renewable energy devices can be predicted. Each building is equipped with a PSO for scheduling the operating capacity of each local energy device, as well as proposing importation and exportation rates of electrical and heating energy. The predicted energy demands and generations from machine learning models are used as input datasets in PSO. The proposed importation and exportation rates of each prosumer and consumer are communicated through the blockchain to determine the actual importation and exportation rates of each building.

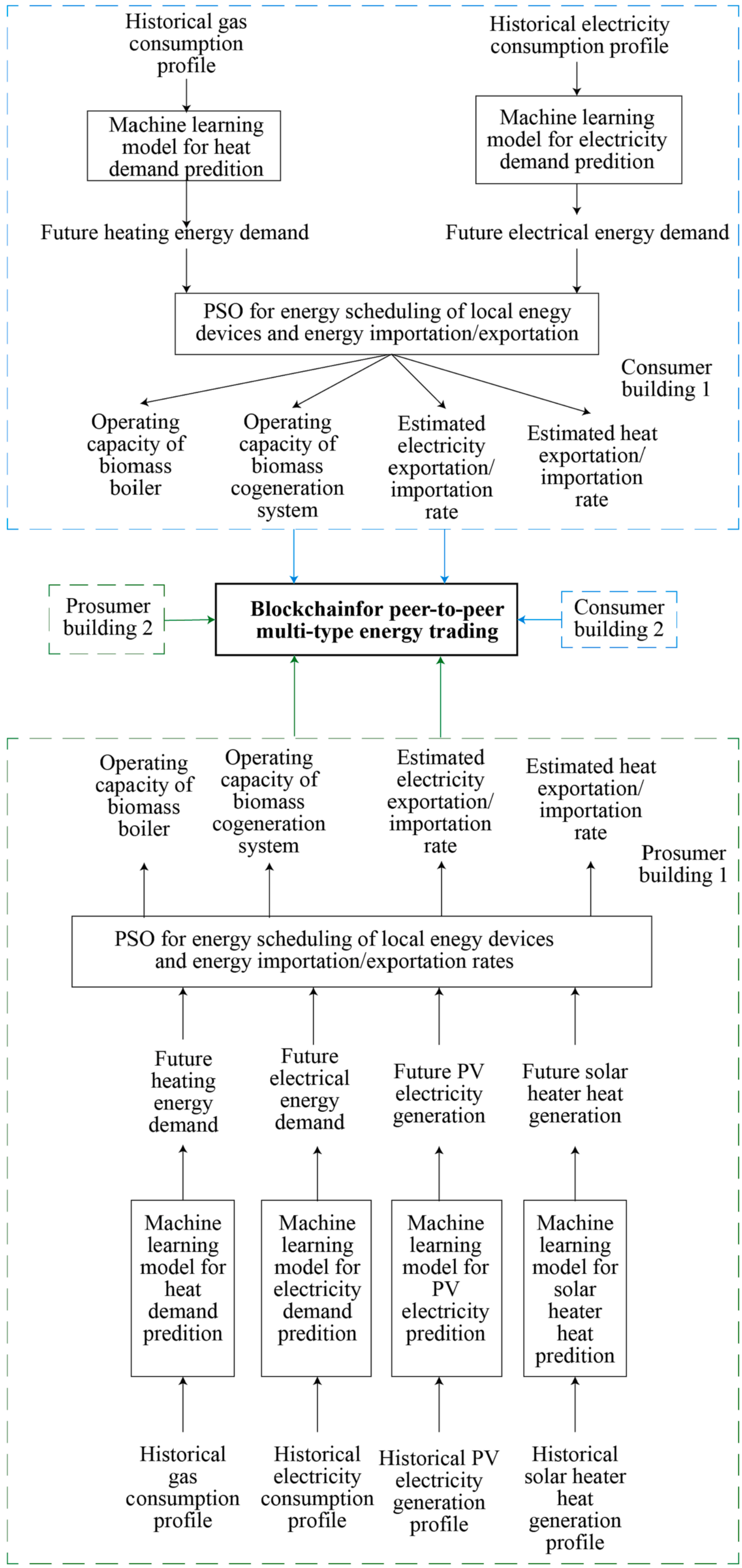


Fig. 1. Framework of blockchain and machine learning-based decentralised energy management.

3.1. Multi-energy network

The multi-energy network consists of distributed prosumer buildings and consumer buildings. Consumer buildings do not have renewable energy generation devices and heavily rely on consuming primary energy (i.e., natural gas or biomass), importing electricity from main power grids, and importing energy from other prosumer buildings. Prosumer buildings are able to both generate and consume energy. As rooftop PV panels and solar heaters have been demonstrated to have good life-cycle performance under UK weather conditions [5], they are adopted to convert buildings from consumers to prosumers. To enhance building energy efficiency and transform conventional buildings towards renewable energy, biomass-driven cogeneration systems, and biomass boilers can be installed in both consumers and prosumers. A typical example of a multi-energy network is illustrated in Fig. 2. The localised multi-energy network can eliminate the inefficiencies of a monolithic centralised electricity generation system by reducing energy loss through transmission lines and alleviating the high burden on central management systems.

3.2. Blockchain for multi-type energy trading

Blockchain is a chain of immutable blocks to ensure the integrity and security of transactions [28]. The blocks are generally chained through block hash values, while the data and transactions in a block are generally immutable [29]. As a blockchain is a distributed ledger, each participating member of the blockchain has the same and complete copy of the blockchain. Meanwhile, smart contracts can be used to automate the purchasing and selling of energy based on energy supply and demand from different participants. In this study, blockchain is adopted to facilitate peer-to-peer trading for multiple types of energy amongst various prosumer and consumer buildings. Therefore, participating buildings on the multi-energy network can conduct the direct exchange of surplus heating and electrical energy.

As public blockchains are permissionless and anyone can join them, it is not able to guarantee the privacy of each participating building. Consequently, the private blockchain is used to secure energy transactions and prevent participants' privacy, mainly because only authorised members can participate in energy trading. Any new building (i.e., energy node) that wants to participate in the multi-energy network needs to be authorised by the private chain central operator. The central operator is the blockchain provider, who is in charge of user administration. Once a node is authorised to become a legal node, it can participate in the transaction. To be more specific, if new building A wants to join the private blockchain, first, it needs to use an asymmetric encryption algorithm to generate a pair of public and private keys and send the former to the central operator. The central operator will then use its private key to verify and save the identity information of building A. Building A can create an account and join the private blockchain upon validation and receiving the certificate from the central operator.

In the multi-energy network, if the participating building has excess energy (i.e., heating, cooling, and/or electricity), it can broadcast the sellable energy and intended selling price. Conversely, the participating building, which is short of heat or electricity, can also broadcast its requirements and intended purchase price. If the requirements and intended purchase price match the sellable energy and selling price, respectively, the smart contract can facilitate the atomic transaction of energy and payment. The atomic transaction means that two sides of trade fulfill all predefined conditions before the trade can be completed, which indicates that the energy transaction and payment transaction are simultaneously completed [30].

3.3. Machine learning model for energy prediction

The energy performance of the building itself, renewable energy generation units, and energy conversion units are highly correlated with weather conditions. The historical energy performance such as heating and electrical energy demands from different buildings, electricity generating rates from rooftop PV panels, as well as heating energy generating rates from solar heaters can be collected from various smart meters. Due to the time-series characteristics of building energy demands and energy generation units, long short-term memory networks are developed to predict the day-ahead multiple energy demands of each building and energy generation rates from different renewable energy devices. LSTM model uses input gate, output gate, forget gate, and self-connected memory cells to reveal the time-based dependences in time-series data, through feedback connections [31]. As LSTM models are adopted for time-series energy data prediction, if there are missing values during certain hours, it is assumed that the energy data of that particular hour would be equal to the previous time step.

3.4. PSO algorithm for energy scheduling

For passive energy-generating units, such as rooftop PV panels and solar heaters, the energy-generating rates depend on actual weather conditions. Conversely, for active energy-generating units, such as biomass cogeneration systems, ground source heat pumps, and biomass boilers, the energy-generating rates are controllable through part-load operation. The passive energy-generating units and active energy-generating units can work together to satisfy multiple energy

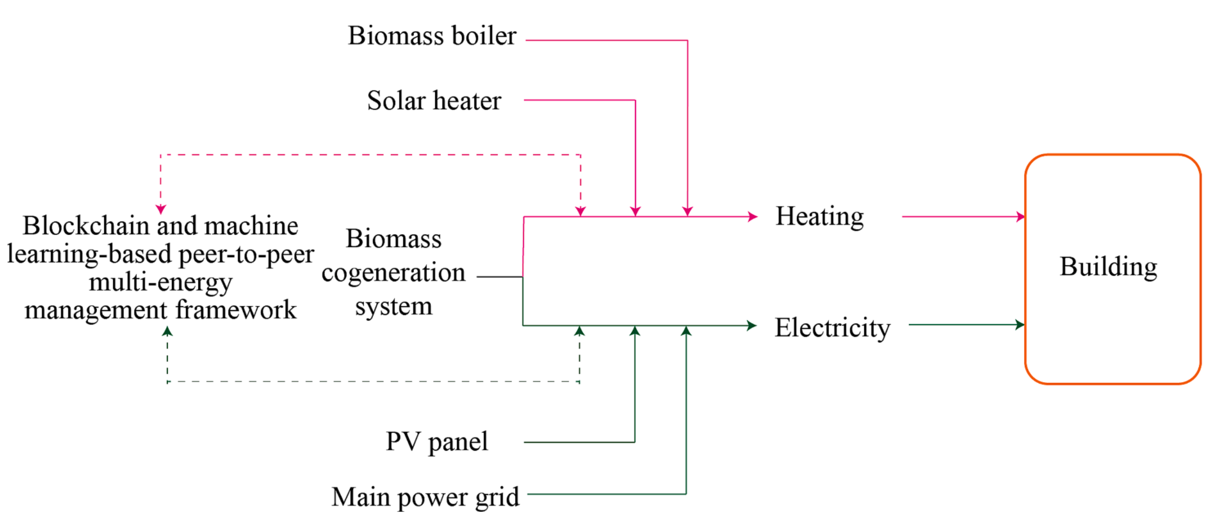


Fig. 2. Energy and information flow within the multi-energy network and proposed framework.

demands. For example, the electrical energy demands can be satisfied by the collaboration from rooftop PV panels, biomass cogeneration systems, electricity imported from the main power grid, and electricity imported from other participated buildings; while the heating energy demands can be satisfied by biomass boiler, heat utilisation from biomass cogeneration system, and heat imported from other participating buildings.

It is important to determine the optimal energy schedule of each energy-generating unit to minimise overall energy costs. PSO algorithms have been increasingly adopted to solve sophisticated engineering problems owing to their robustness, faster convergence speed, and lower computing load [32]. As demonstrated in [2,3,6], PSO was effectively adopted to determine the energy schedule of the multi-energy system in an individual domestic building, and office building. In this study, each building is equipped with an individual PSO optimiser to determine the optimal operating parameters of the biomass cogeneration system, and biomass boiler, along with electricity importing rate from the main power grid, electrical and heating energy importing rates from other buildings within the multi-energy network.

3.5. Deployment of the blockchain energy-trading platform

In order to test the feasibility and performance of the blockchain and machine learning-based decentralised energy management framework shown in Fig. 1, Solidity is adopted to develop and deploy the Ethereum private blockchain. Meanwhile, a smart contract is implemented to facilitate the atomic peer-to-peer energy trading and energy cost transactions. Ethereum is a decentralized platform that runs smart contracts and applications without censorship and third-party interference. However, Solidity is an advanced programming language for smart contracts [33].

4. Case study

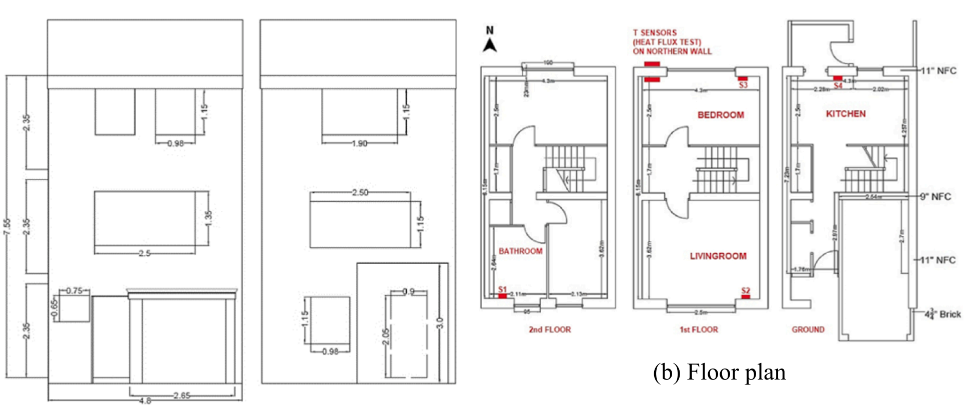
4.1. Basic information on case study buildings

In order to demonstrate the feasibility of the developed energy management framework, 4 domestic buildings are connected through the multi-energy network and can conduct peer-to-peer energy transactions with each other. The 4 case study buildings were built in 1971 and located in Bristol, United Kingdom. They have the same floor area, construction structure, and internal layout. The main differences in energy performance result from occupancy behaviour. The electricity and gas consumption were monitored in their natural settings. The floor plan and elevation plan are shown in Fig. 3. The case study domestic buildings were built with no-fines concrete walls and finished with paramount plasterboard. The ground floor was built with solid concrete slab while roofs were built using pitched trussed rafters and insulated at ceiling level. The internal garages, loft, and back porch were not heated. As these 4 domestic buildings are located in the south UK, cooling is not required. Thus, this research only focuses on heating and electrical energy supply.

4.2. Building energy demands and renewable energy production

The historical hourly electricity and gas consumption data in 2016 of the four domestic buildings is collected to develop the LSTM energy prediction models. The year-round hourly electricity power generation from the PV panel, along with the thermal power generation from the solar heater, was also obtained from two nearby PV panels and solar heaters in 2016. The descriptive information of the collected electricity and gas consumption profile of 4 case study buildings, along with the renewable energy production profile from 2 nearby PV panels and solar heaters, is summarised in Table 1. As there were 366 days in 2016, while hourly energy consumption and production data were collected, the total number of observations is $366 \times 24 = 8774$ for each type of data. The average gas consumption rate is 2871, 1736, 563 and 1579 W, respectively, while the average electricity consumption rate is 1775, 482, 682 and 274 W, respectively for each case study building. The total gas consumption is 25222, 5248, 4949, and 13,870 kWh, respectively, while the total electricity consumption is 15592, 4231, 5993 and 2403, respectively for each case study building. The total electricity production from PV1 and PV2 is 11,198 and 4702 kWh, respectively, while the total heating energy production from solar heater 1 and solar heater 2 is 2218 and 940 kWh, respectively.

The energy consumption profiles of each building are summarised in Fig. 4. For building 1, the electricity consumption rate is lower than 2000 W during most of the time, as shown in Fig. 4(a). There is no electricity consumption recorded during the middle of May due to sensor disconnection. The gas consumption rate is lower than 2000 W or between 8000 and 10000 W during most of the time, as shown in Fig. 3(b), mainly due to low heating demand at daytime and high heating demand at nighttime during the cold seasons. For building 2, as shown in Fig. 3 (c), the electricity consumption rate from January to early May is much higher than the remaining periods, with the highest rate being 6193 W. There is no electricity consumption during early to middle July, and middle August to early September. It may be due to the fact that the electricity meter was disconnected. As shown in Fig. 4(d), the gas consumption rate is discrete owing to the precision of certain gas meters. The gas consumption is much higher during January to early May, November and December than the other months, with the highest rate being 12000 W. For building 3, as shown in Fig. 4(e), the electricity consumption rate is relatively evenly distributed over the year, except for the fact that there was no electricity recorded from the middle of



(b) Floor plan

(a) Elevation plan

Fig. 3. Elevation plan and floor plan of 4 case study buildings [34].

Table 1
Descriptive information of energy profiles.

Statistics	Building 1				Building 2				Building 3		Building 4	
	Ele.	Heat	PV panel	Solar heater	Ele.	Heat	PV panel	Solar heater	Ele.	Heat	Ele.	Heat
Count	8784	8784	8784	8784	8784	8784	8784	8784	8784	8784	8784	8784
Mean (W)	1851	2311	2735	547	611	1389	745	153	692	640	282	1300
Std. (W)	1718	3240	4897	979	1212	2252	1934	387	749	1241	238	1943
Min. (W)	0	0	0	0	0	0	0	0	0	0	0	0
25 % (W)	708	27	0	0	0	0	0	0	0	29	99	5
50 % (W)	1204	400	10	2	51	0	0	0	533	198	217	158
75 % (W)	2315	4656	3193	639	648	2000	40	8	991	570	447	1889
Max. (W)	8115	12,493	21,100	4220	6193	12,000	9590	1918	3725	5791	1178	10,898
Total (kWh)	16,261	20,301	24,021	4804	5460	12,198	24,021	1344	6077	5623	2478	11,422

June to late July, as well as after November. As shown in Fig. 4(f), the gas consumption rate is lower than 1000 W during most time of the year. From January to May, November and December, the gas consumption rate is much higher than the other months. For building 4, as shown in Fig. 4(g), the electricity consumption rate is lower than 447 W during most time of the year, while the peak value is 1178 W. There only exists a small period of electricity sensor data disconnection during middle July. As shown in Fig. 4(h), from January to May and October to December, the gas consumption is much higher than the other periods of the year. There only exists a small period of gas sensor disconnection during the middle of December.

As shown in Fig. 5, during the summer season, the electricity generation rate from PV panels and thermal energy generation rate from solar heaters is relatively higher than that during the winter season. There also exists a lack of energy generation records during early to middle July, and middle August to early September.

4.3. Prediction performance of LSTM models

In the case study buildings, when gas and electricity consumption profiles are collected, the conventional gas-fuelled boiler is adopted to provide heat demand, while electricity is purely imported from the main power grid. To estimate the electricity and heating energy demands of the buildings, it is assumed that the gas boiler has a constant efficiency of 80 %. The historical electricity and gas consumption data of each building is adopted to train the LSTM prediction model. As the electricity and gas consumption datasets do not follow the normal distribution as seen from Fig. 4, the min–max scaling approach is adopted to normalise the datasets into the scale of 0–1.80 % of the data is adopted for training, while 20 % of the data is adopted for testing. A single LSTM layer is adopted, with the number of neurons being 100, activation function being sigmoid, learning rate being 0.05 and dropout rate being 0.5. The prediction performance of each LSTM model is summarised in Table 2. Meanwhile, the training and testing performance of LSTM models during 2 representative weeks for each building are summarised in Figs. A1 and A2 in the Appendix, for electricity and heating respectively. The blue line indicates the measured historical energy data from energy meters, while the purple line represents the prediction results.

4.4. Design parameters of the multi-energy network

To increase renewable energy production, rooftop PV panels and solar heaters are installed on Building 1 and Building 2 to convert them from consumers into prosumers, while Building 3 and Building 4 remain as consumers. To increase energy utilisation efficiency and make better use of renewable energy, a biomass cogeneration system, and biomass boiler is adopted in each building to provide electrical and thermal energy for the respective buildings. The 4 buildings are also permitted to import electricity and heating energy from other buildings while exporting electricity and heating energy to other buildings. Based on the historical electricity and gas consumption of the case study buildings, the design parameters of the multi-energy network are summarised in Table 3. Meanwhile, the energy performance of the biomass cogeneration system and the biomass boiler is estimated from the manufacturing data [35].

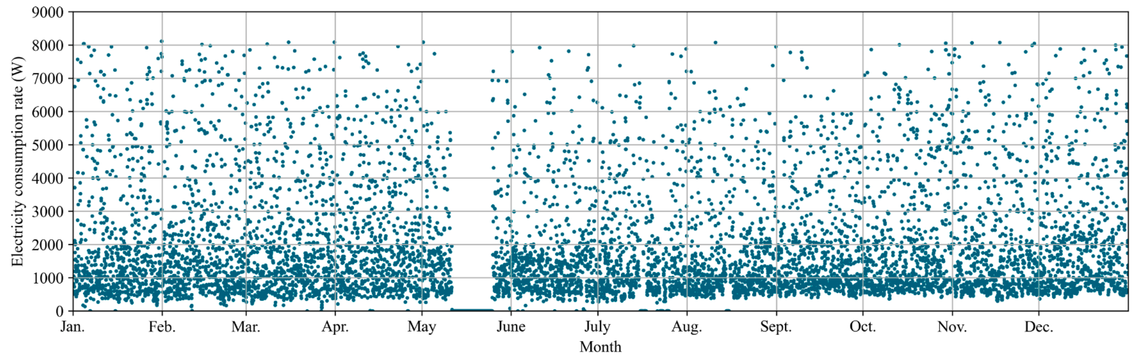
4.5. Performance evaluation of evolutionary optimisation

The PSO algorithm is adopted to determine the operating capacity of the biomass cogeneration system, operating capacity of biomass boiler and electricity importing rate from the power grid. The inertial, individual and social weights are randomly generated within the value between 0 and 1, while the other PSO parameters are summarised in Table 4. The price of each energy resource is summarised in Table 5. This case study assumes that the heat and electricity exchange costs are 0.017 and 0.1 £/kWh, respectively. In practical application, these exchange costs are determined by the actual participants through the blockchain platform.

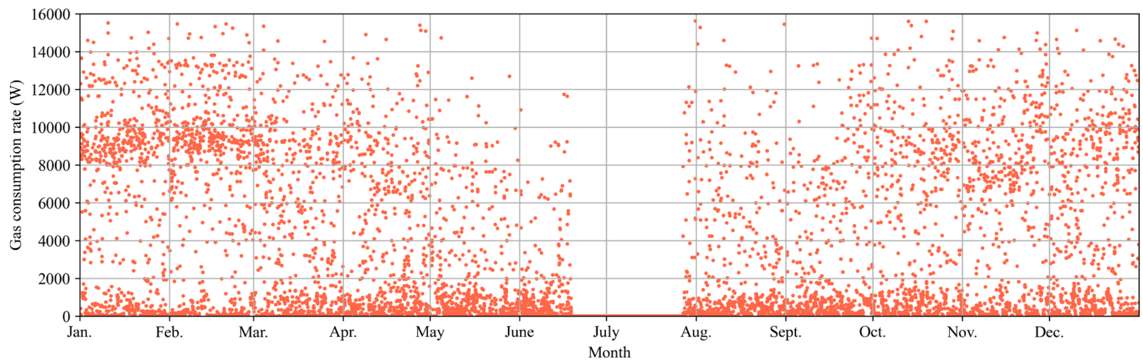
The energy allocation among different energy devices of each building during representative week (Week 29) is summarised in Fig. 6. The energy allocation during other weeks for Buildings 1, 2, 3, and 4 are summarised in Figs. A3-A6 in Appendix. In terms of electricity allocation, D_e indicates electrical energy demand, Q_{pv}, Q_g, Q_{CHP}, $Q_{imp,e}$ and $Q_{exp,e}$ indicates electricity generation rate from PV panel, main power grid, biomass cogeneration system, imported electricity from other buildings and exported electricity to other buildings, respectively. Regarding heating allocation, D_h indicates heating energy demand, Q_{SH}, Q_{BB}, Q_{CHP}, Q_{imp} and Q_{exp} indicates thermal energy generation rate from solar heater, biomass boiler, biomass cogeneration system, imported heat from other buildings and exported heat to other buildings, respectively.

As shown in Fig. 6(a), during nighttime, the electricity demand of Building 1 is low. Thus, it is mainly provided by biomass cogeneration system and biomass boiler, while little amount of electricity is exported. Throughout the daytime, PV panel is primarily used to satisfy electricity demand. When electricity production from PV panels is low due to low solar radiation, the power grid and cogeneration system will be used. When electricity production from PV panel is large due to high solar radiation, the extra electricity can be exported to other buildings. During 0–7 h, extra thermal energy from the cogeneration system is mainly utilised to provide heat for the building as its heating demand is quite low. Throughout other periods, thermal energy from the solar heater and the cogeneration system is primarily used to satisfy heating demand for the building. If it is not sufficient, the biomass boiler will be used. As the heating energy provided by solar heaters is relatively lower than the actual heating demand, heating energy is seldom exported.

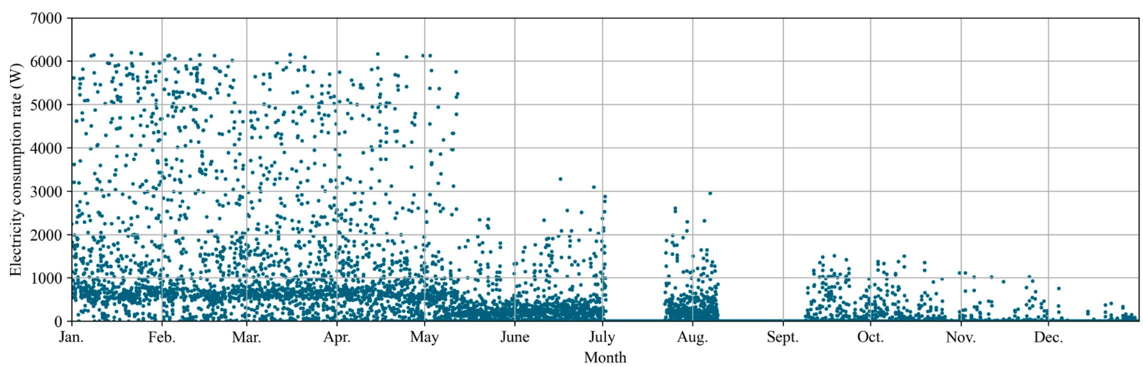
In terms of Building 2, the electricity demand is always lower than the PV electricity production during daytime, as shown in Fig. 6(b). Therefore, it is frequently exported to provide electricity for other buildings. During the nighttime, when electricity demand is quite low, the extra electricity energy from the cogeneration system would be exported. This is because the cogeneration system is operated to provide heating energy due to its high energy utilisation ratio. During the daytime, when heating demand is quite high and solar heater is not able to



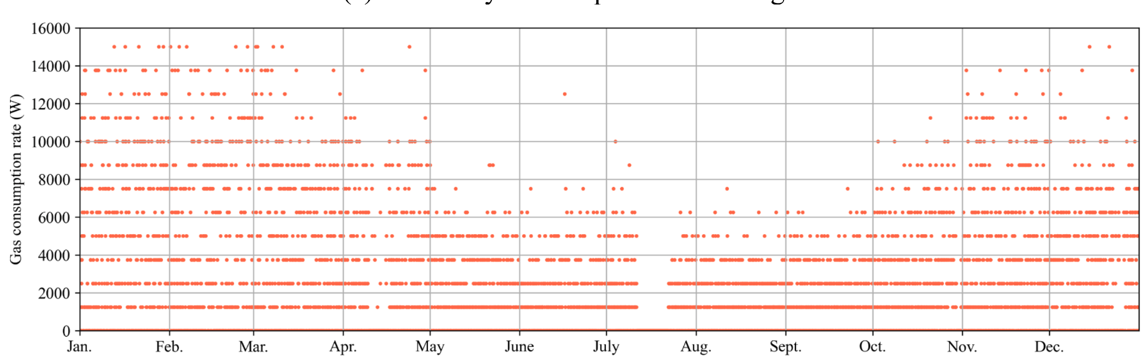
(a) Electricity consumption of building 1



(b) Gas consumption of building 1

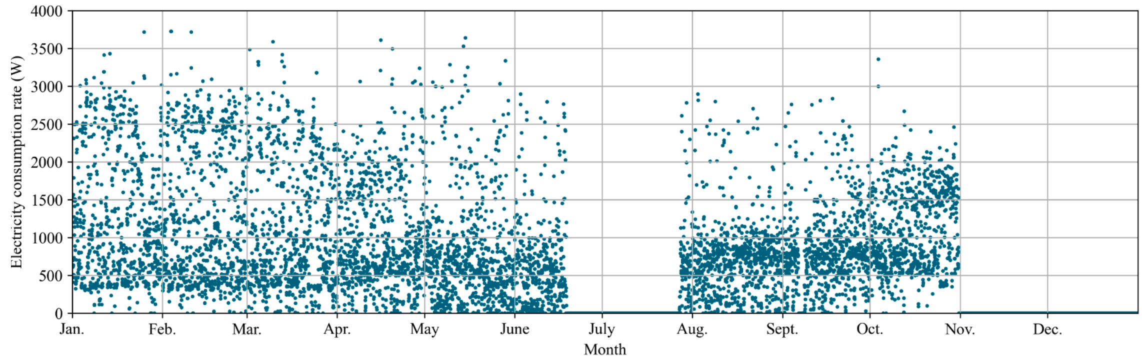


(c) Electricity consumption of building 2

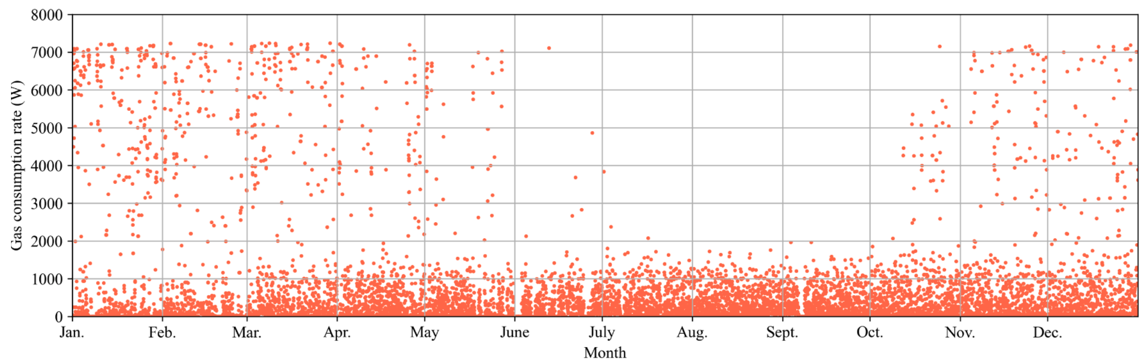


(d) Gas consumption of building 2

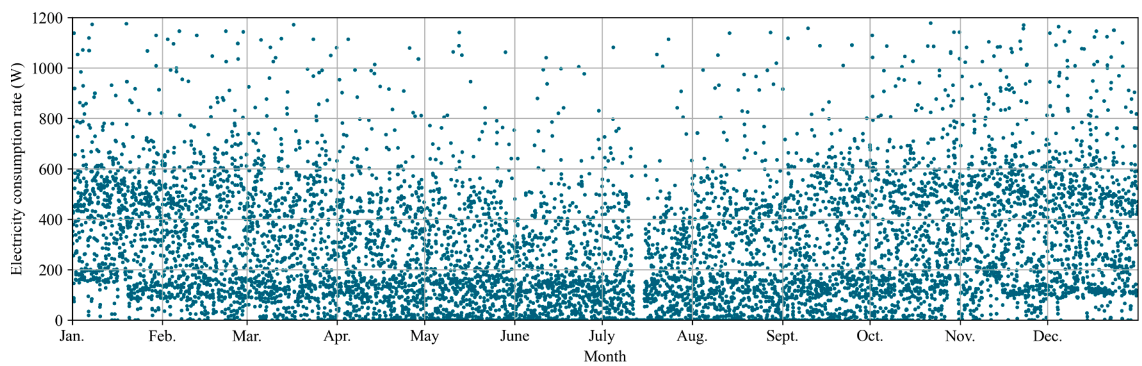
Fig. 4. Electricity and gas consumption of 4 buildings.



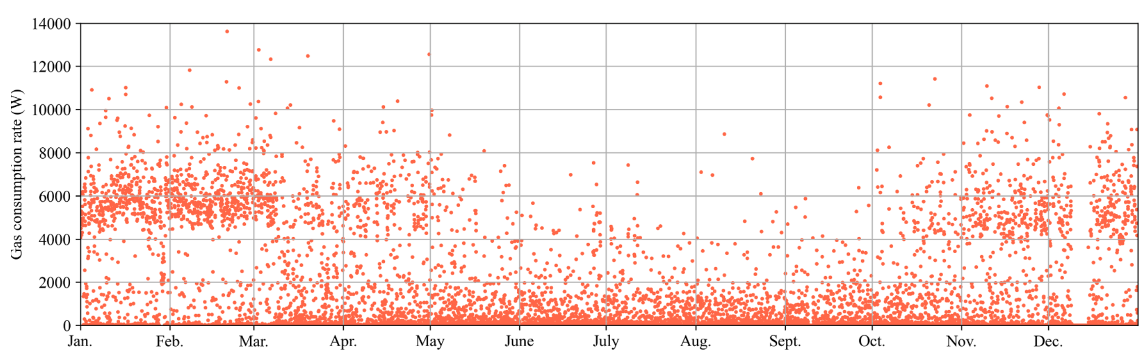
(e) Electricity consumption of building 3



(f) Gas consumption of building 3



(g) Electricity consumption of building 4

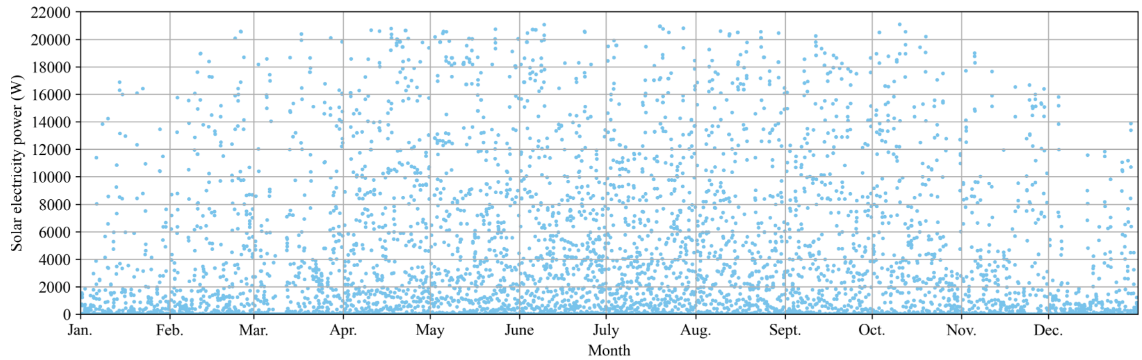


(h) Gas consumption of building 4

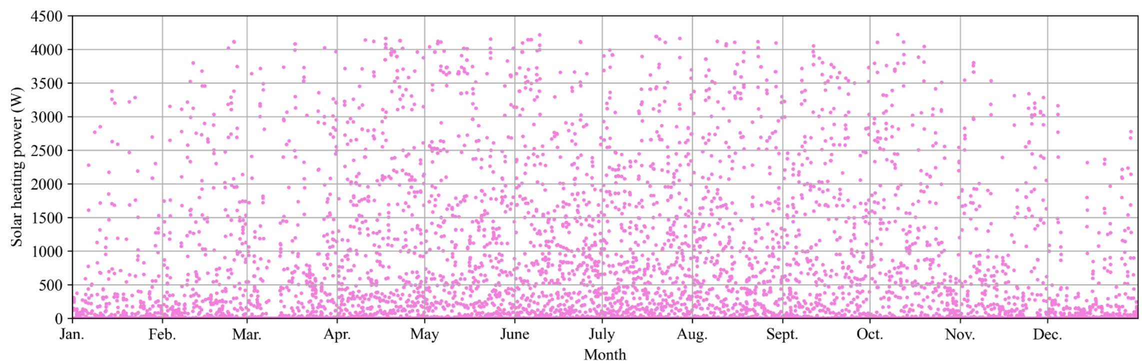
Fig. 4. (*continued*).

provide sufficient heating energy, the cogeneration system, and biomass boiler would be utilised to supplement heat.

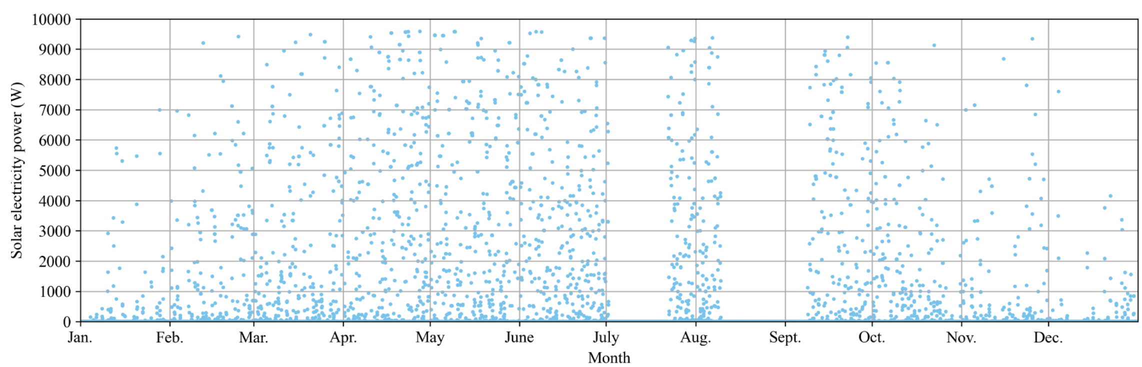
For building 3 and building 4, as shown in Fig. 6 (c) and (d), respectively, a large amount of electricity is imported from other buildings, while the power grid and cogeneration system are also adopted to provide electricity if the available electricity from peer-to-



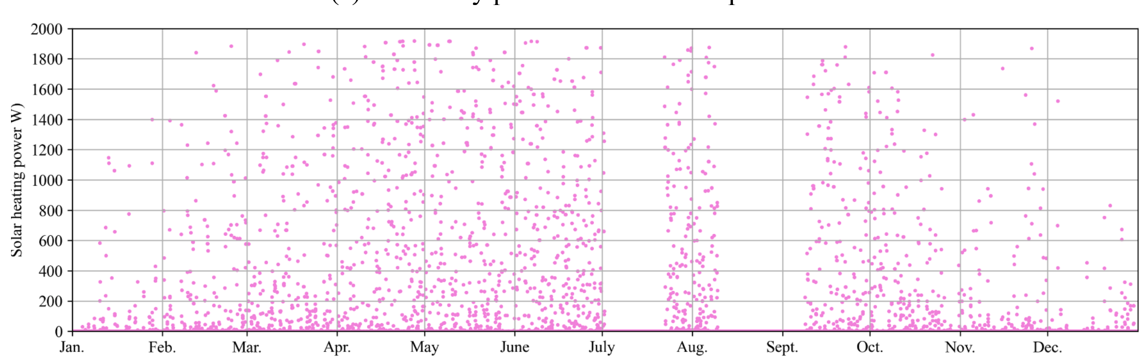
(a) Electricity production from PV panel 1.



(b) Heating production from solar heater 1.



(c) Electricity production from PV panel 2.



(d) Electricity production from PV panel 2.

Fig. 5. Renewable energy production from energy devices.

Table 2
Prediction performance of LSTM models.

Evaluation metrics	Datasets		Building 1	Building 2	Building 3	Building 4
Mean absolute error (W)	Electricity	Training	712	341	275	99
		Testing	976	83	79	157
	Heating	Training	1035	722	294	1072
		Testing	2073	2034	680	1277
Root mean squared error (W)	Electricity	Training	1300	755	535	166
		Testing	1669	206	165	284
	Heating	Training	2652	1805	681	843
		Testing	3787	5134	1686	1997

Table 3
Design parameters of multi-energy networks for case study buildings.

Design parameters	Unit	Value
Electrical efficiency of cogeneration system	%	15
Thermal efficiency of cogeneration system	%	65
Nominal capacity of biomass boiler for building 1	W	10,000
Nominal capacity of biomass boiler for building 2	W	11,000
Nominal capacity of biomass boiler for building 3	W	10,000
Nominal capacity of biomass boiler for building 4	W	2000

Table 4
PSO parameters.

Population	100
Maximum iterations	40
Fitness criterion	0.01

Table 5
Price of different energy resources (£/kWh).

Biomass	0.0211
Electricity	0.1310
Heat exchange with other buildings	0.017
Electricity exchange with other buildings	0.1

peer energy trading platform is not sufficient. For building 3, the heating demand of the building is primarily supplied by the cogeneration system due high energy efficiency of the cogeneration system. For building 4, heating demand is also supplied by biomass boiler as the available thermal energy from peer-to-peer energy trading platform and cogeneration system is not sufficient.

4.6. Performance evaluation of the proposed energy trading framework

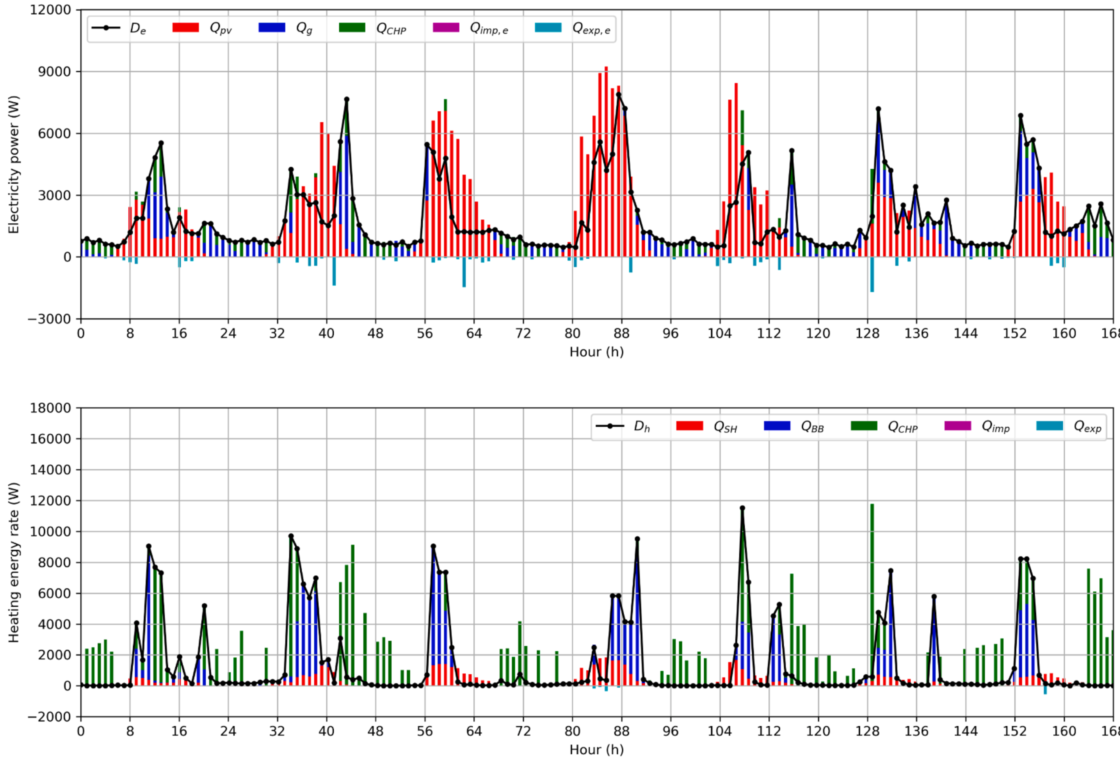
To investigate the economic potential of the proposed energy trading framework, its overall performance is compared with 4 reference buildings that do not have access to peer-to-peer energy trading. The 4 reference buildings are assumed to have the same electricity and heating demand as our case study buildings. Buildings 1 and 2 can use rooftop PV panels, the main power grid, and the biomass cogeneration system for electricity supply, while the solar heater, the biomass boiler, and the biomass cogeneration system are harnessed for heat supply. Meanwhile, Buildings 3 and 4 only use the biomass cogeneration system, the biomass boiler and the power grid for energy supply. The energy costs for the reference buildings (i.e., without peer-to-peer energy trading) and the proposed framework are summarised in Table 6. It is seen that 7.96 %-18.18 %, 7.60 %-25.41 %, 5.40 %-9.01 %, and 12.46 %-17.63 % reduction in energy costs can be achieved for Buildings 1, 2, 3, and 4, respectively, through adopting the proposed framework.

5. Practical implications and future work

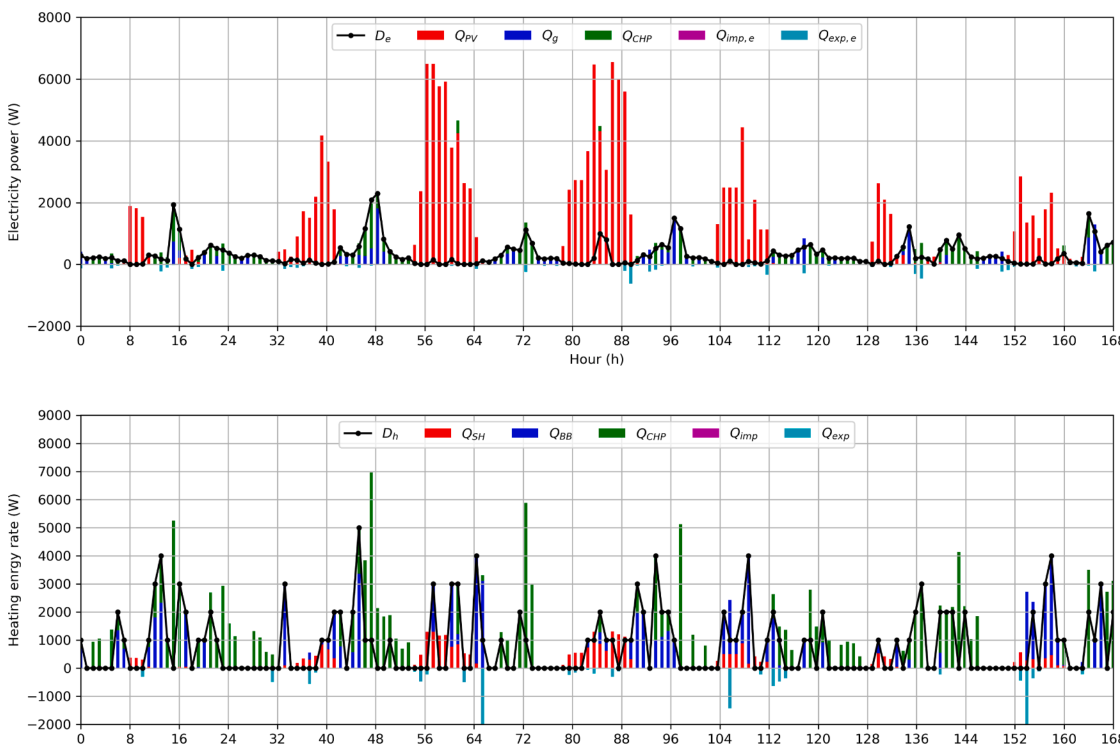
This study demonstrated the economic and technical potential of a blockchain and machine learning-based framework to enable multi-type energy allocation and transmission among different buildings. In practical applications, the building needs to be equipped with electricity and gas meters to collect its historical electricity and gas consumption for at least one year. Based on the hourly energy consumption profile, LSTM models can be developed to predict day-ahead electricity and heating energy demand for the building. If the building is equipped with rooftop PV panels and solar heaters, their electricity and thermal energy generating rate can also be estimated through day-ahead weather forecasts. Based on the day-ahead electricity and heating demand of the consumer building, or energy demand and renewable energy production of the prosumer building, day-ahead energy scheduling of different energy devices such as the biomass boiler, the biomass cogeneration system, electricity importation from the power grid, as well as heat and electricity importation and exportation rate from other buildings can be estimated by the PSO energy scheduling algorithm. Based on the estimated heat and electricity importation rate, buildings can conduct multi-type (i.e., heat and electricity) energy trading with nearby buildings, using a smart energy trading platform based on the proposed framework.

Despite the proven cost-saving attributes of the proposed blockchain and machine learning framework, further developments are required. Future research is needed to develop a fully functional platform in terms of energy modelling, algorithm development, software design, hardware implementation, scalability testing, and practical application.

(1) Regarding energy modelling, the constant operating efficiency was assumed for the biomass boiler, and biomass cogeneration system, while the heat-to-electricity output ratio of the biomass cogeneration system was also static. In a practical situation, the efficiency of the biomass cogeneration system and biomass boiler would be much lower during part-load operation. The heat-to-electricity output ratio may also be changed at a low part-load ratio. Dynamic models of biomass boilers and cogeneration systems should be developed to reflect the real situation and account for the possible energy loss through part-load operations.
(2) In terms of algorithm development, a set of fixed parameters is used in LSTM models for different buildings in this study. Due to the featuring characteristics in energy consumption among different buildings, different parameters, such as the number of LSTM neurons, activation functions, learning rate, and dropout rate, can be chosen for different buildings. Moreover, different evolutionary optimisations algorithms, such as artificial bee colony [36,37], ant colony [38], and genetic optimisation [39], can be used and compared to select the most appropriate algorithm in determining energy schedules of the multi-energy network.
(3) As far as smart contract development is concerned, the maximum allowable energy rate through both the main power grid and distribution transmission grid (i.e., peer-to-peer energy trading grid) should be set in the smart contract to make sure the energy transmission grids do not exceed their bearable loads. Moreover,

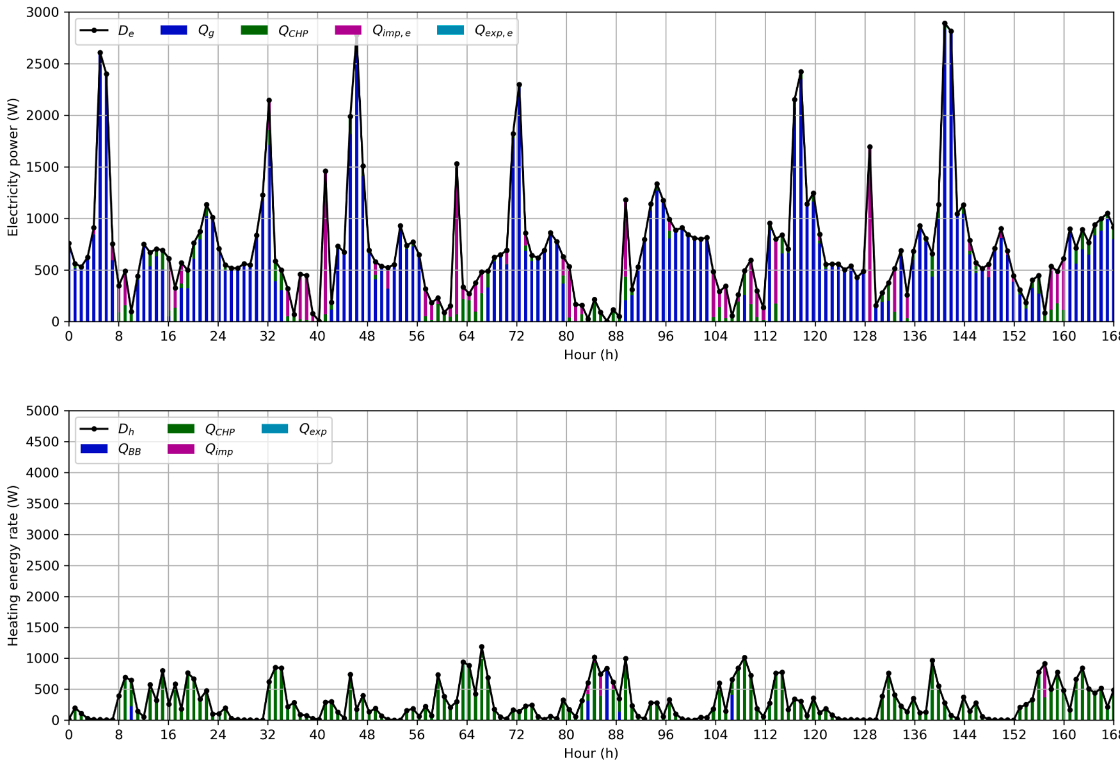


(a) Building 1

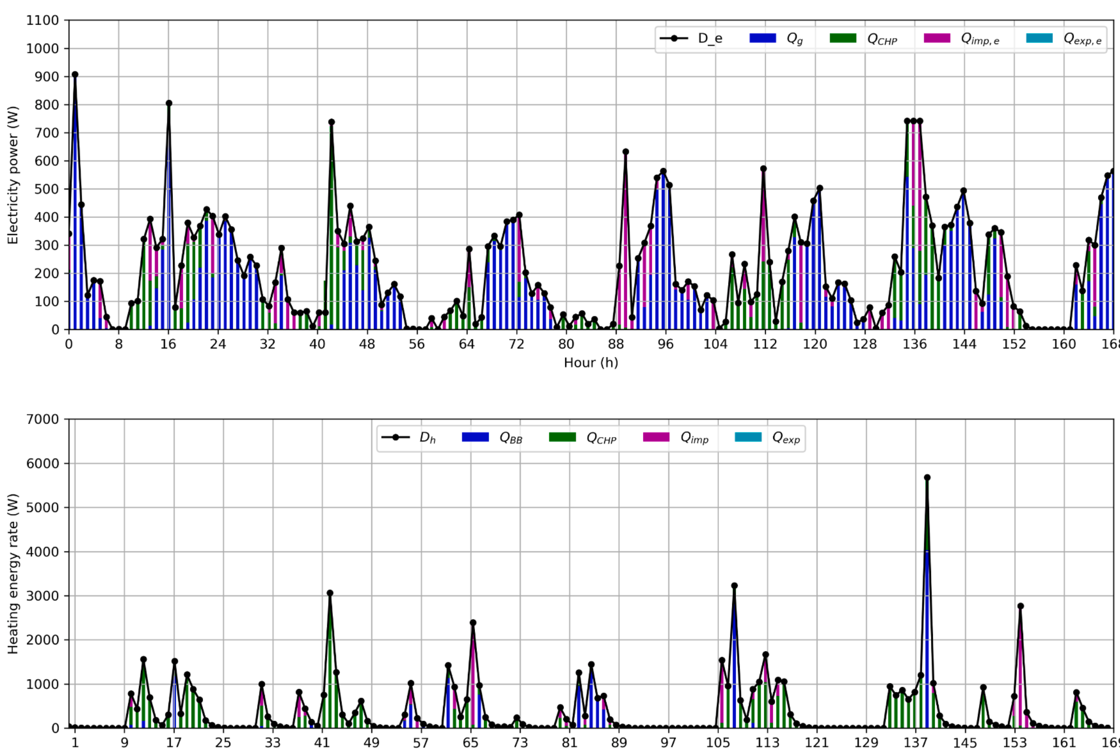


(b) Building 2

Fig. 6. Electrical and heating energy allocation and transmission among 4 domestic buildings.



(c) Building 3

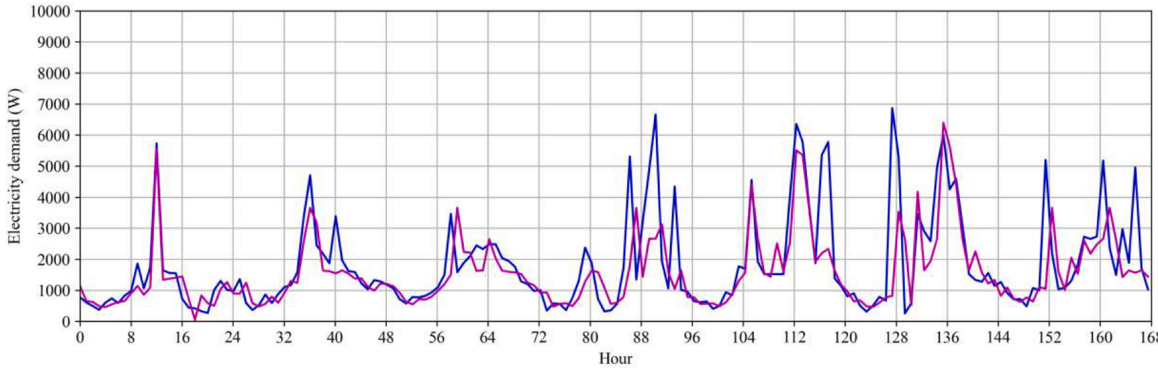


(d) Building 4

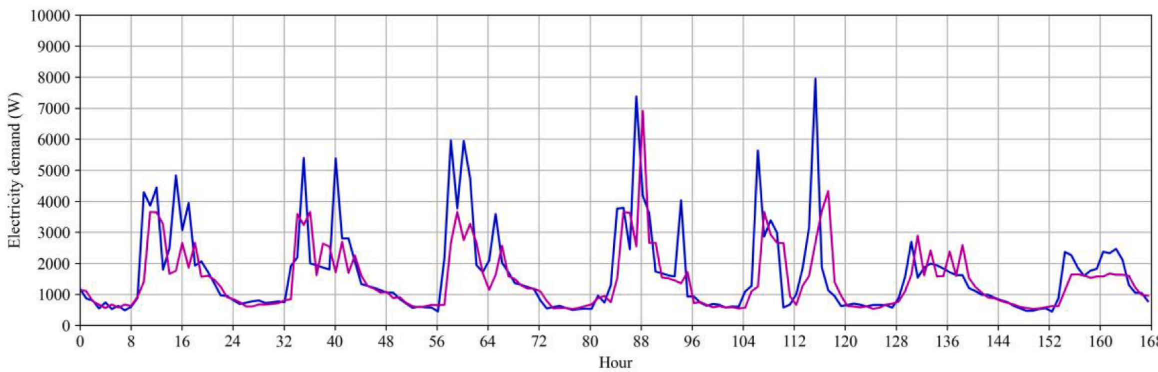
Fig. 6. (*continued*).

the asset response rate [40] and asset ramp rate [41] of main power grids, energy transmission grids, and multi-energy systems should also be taken into consideration in the smart contract.

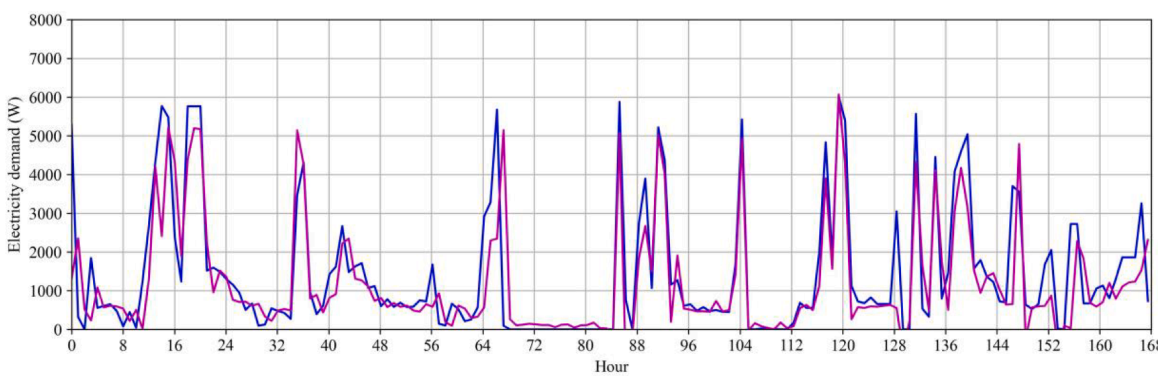
(4) Regarding software development, fully functional software needs to be developed so that participants can visualise the predicted day-ahead energy consumption and explore how peer-to-peer



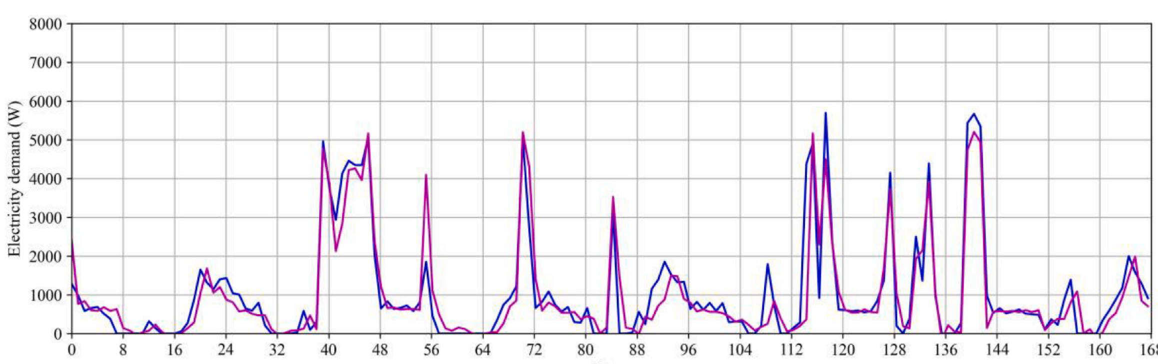
(a) Training, Building 1



(b) Testing, Building 1

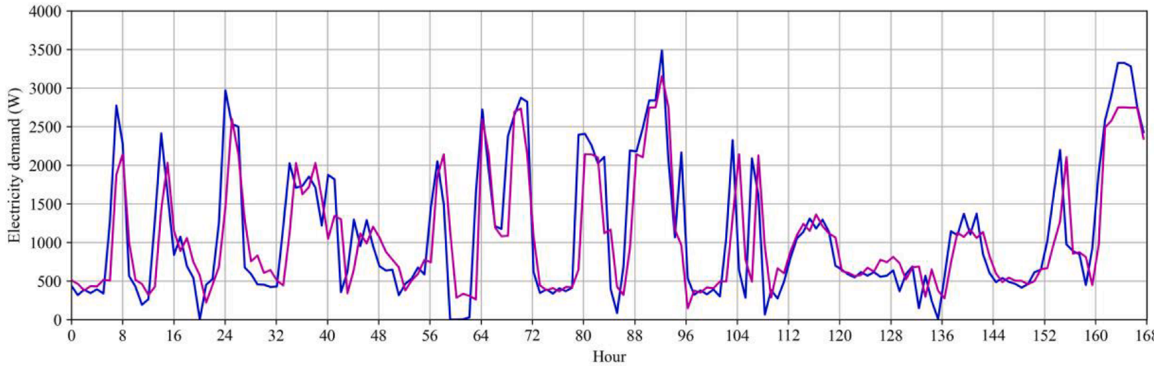


(c) Training, Building 2

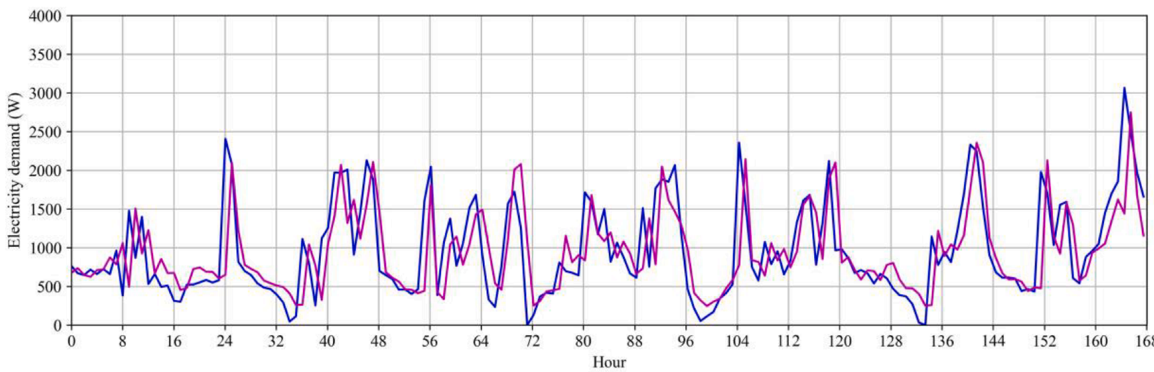


(d) Testing, Building 2

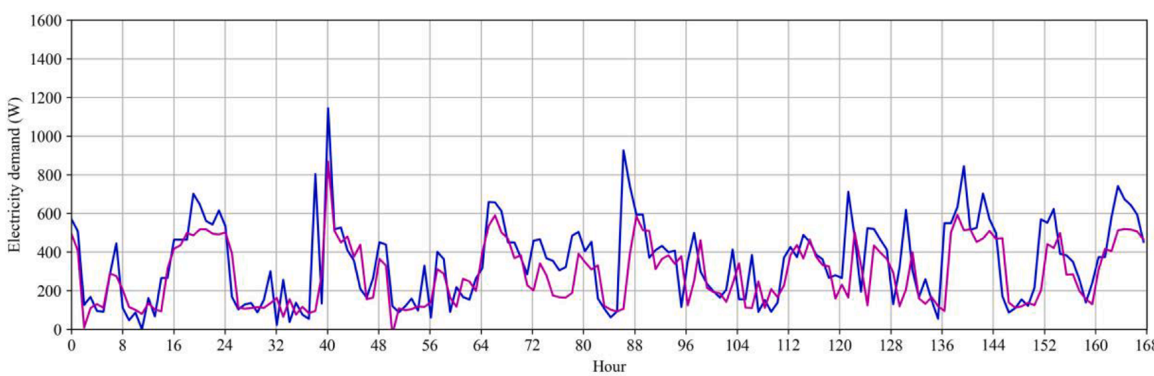
Fig. A1. LSTM prediction performance of building electricity demand.



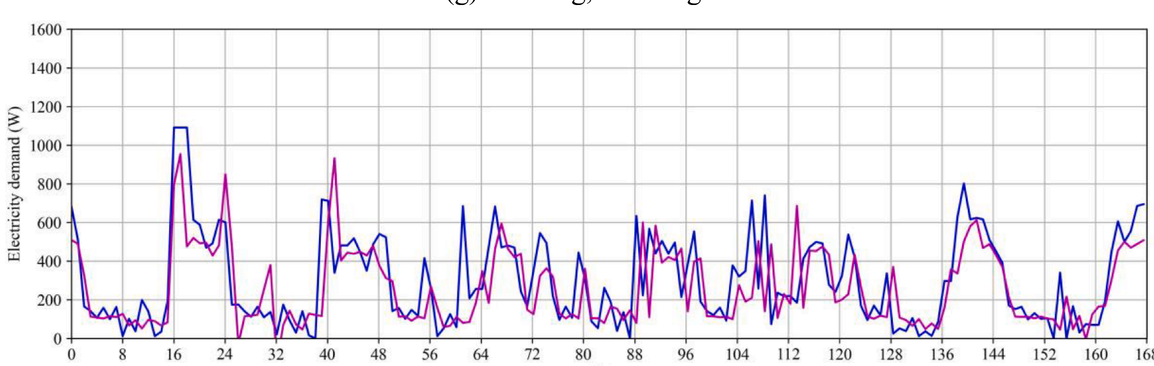
(e) Training, Building 3



(f) Testing, Building 3

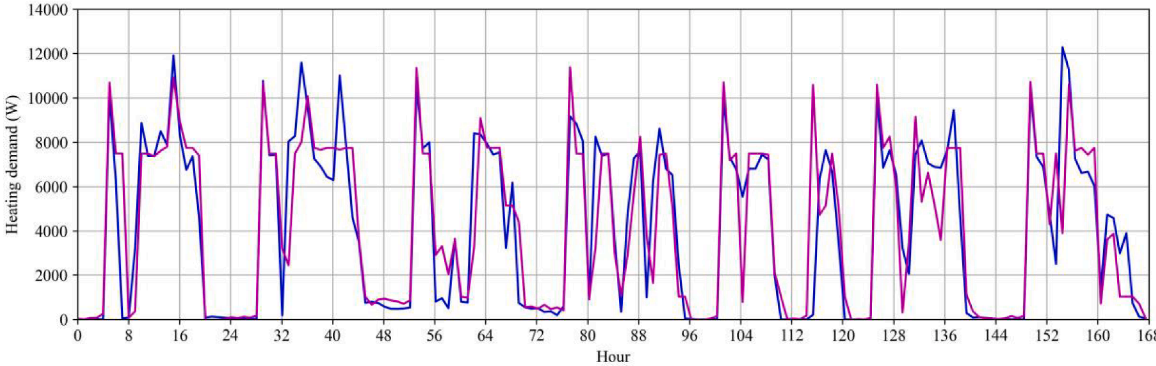


(g) Training, Building 4

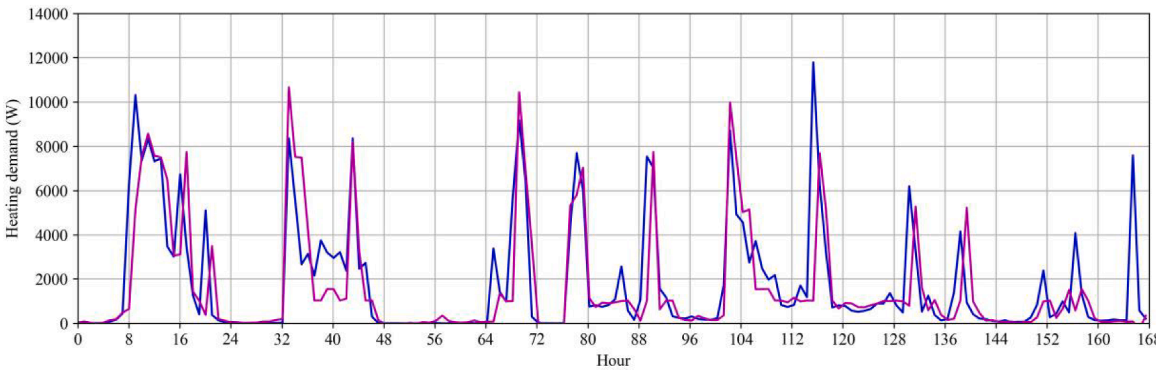


(h) Testing, Building 4

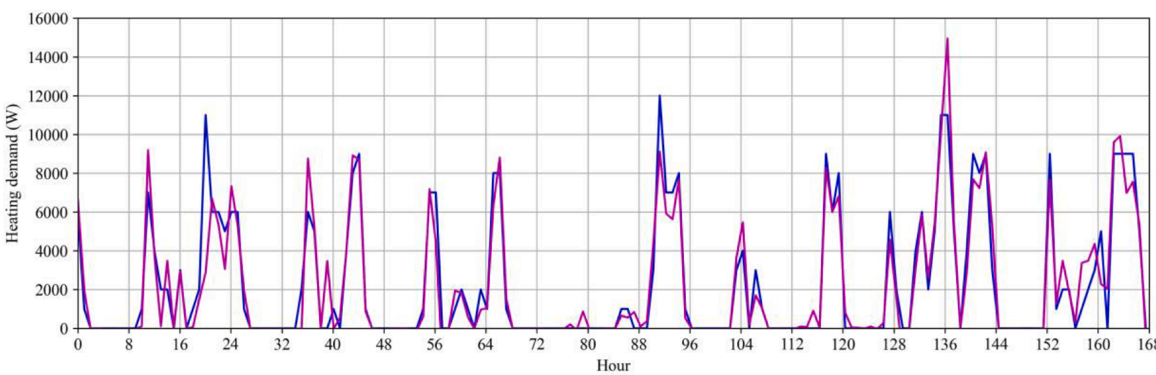
Fig. A1. (*continued*).



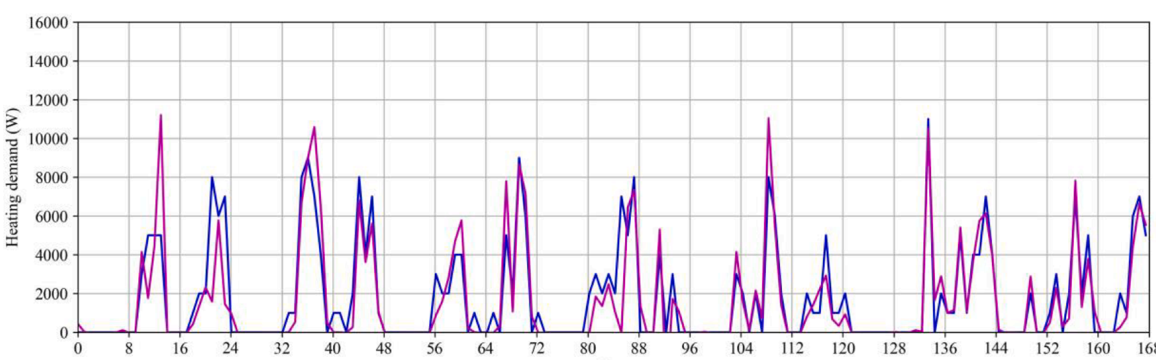
(a) Training, Building 1



(b) Testing, Building 1

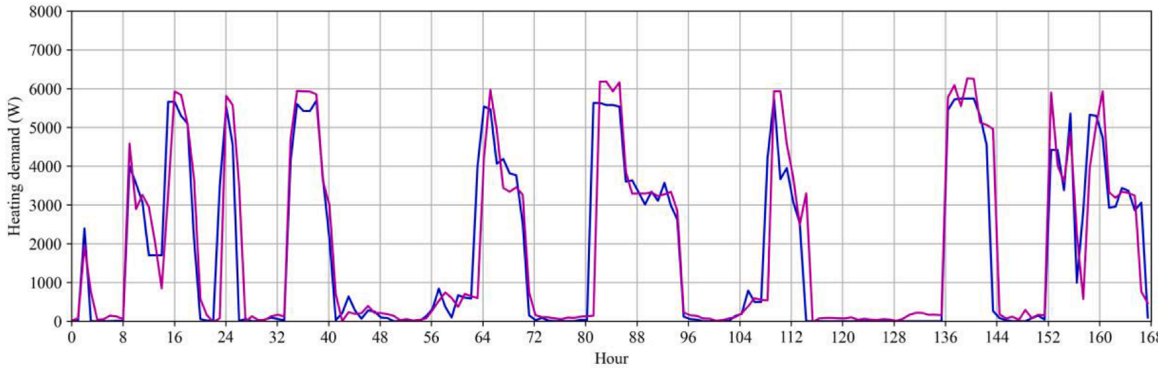


(c) Training, Building 2

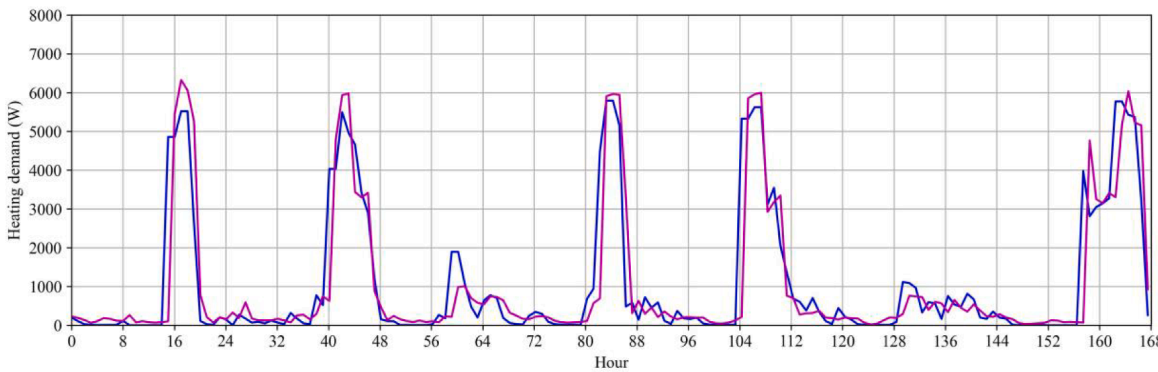


(d) Testing, Building 2

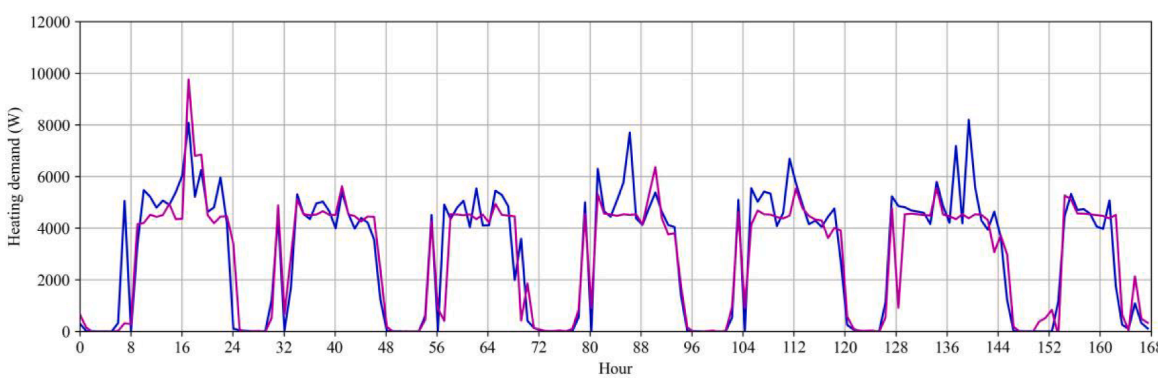
Fig. A2. LSTM prediction performance of building heating demand.



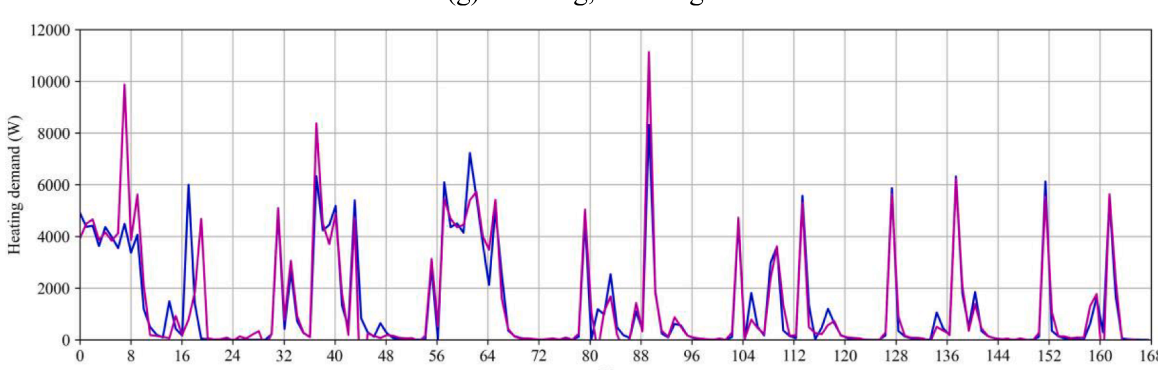
(e) Training, Building 3



(f) Testing, Building 3

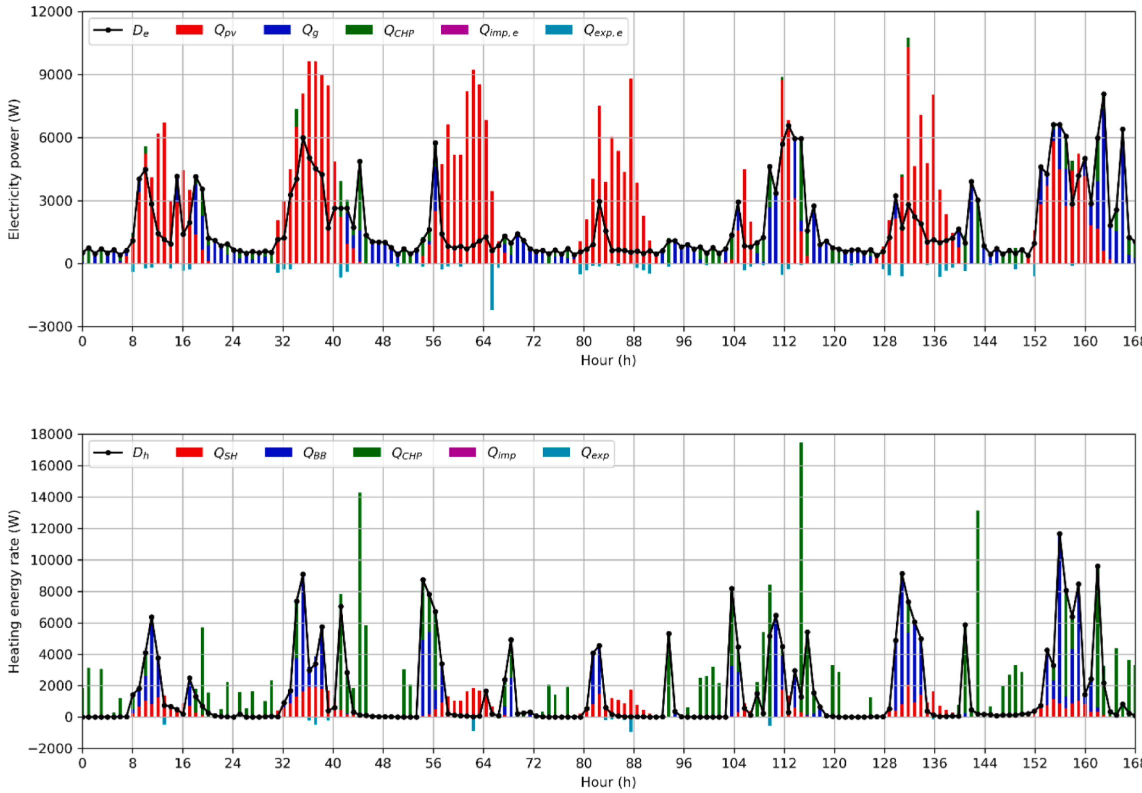


(g) Training, Building 4

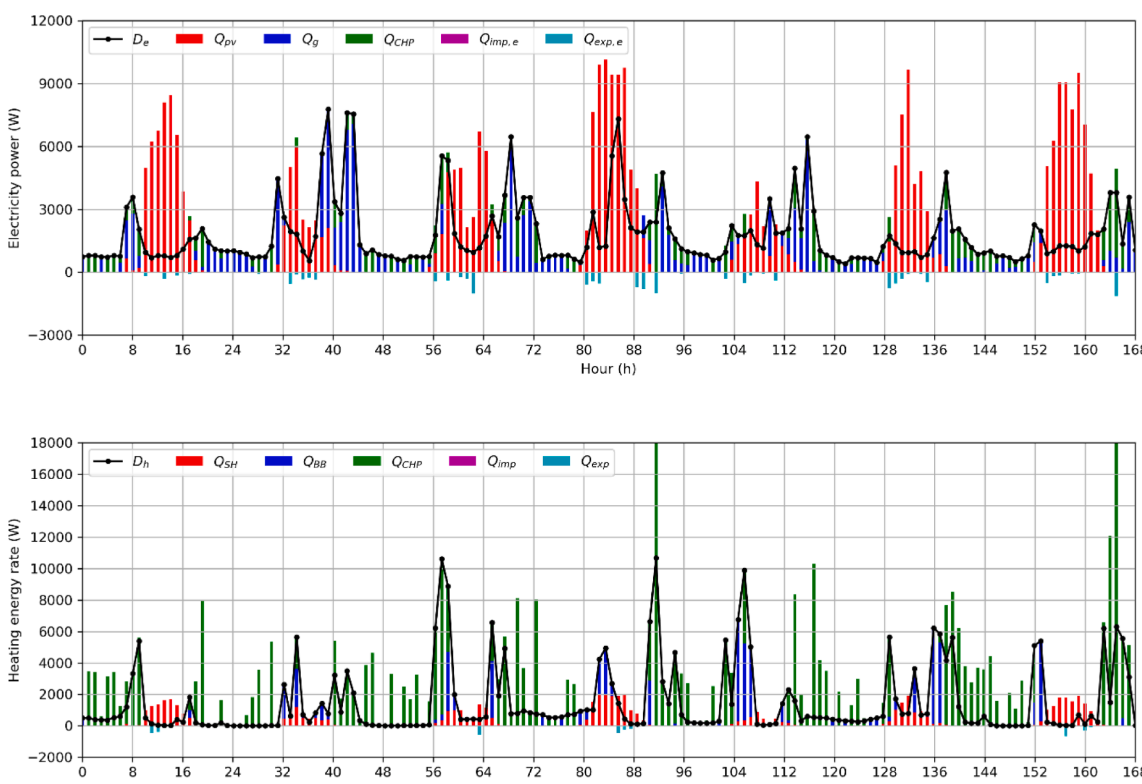


(h) Testing, Building 4

Fig. A2. (*continued*).

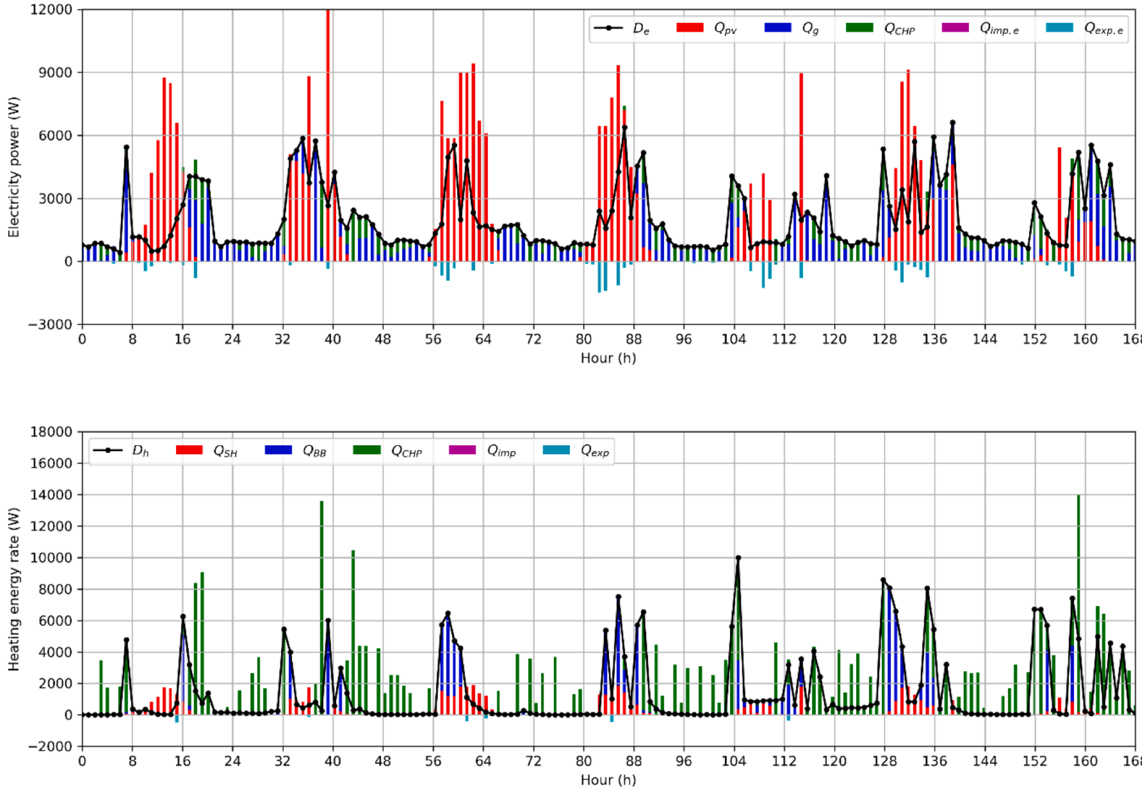


(a) Week 30

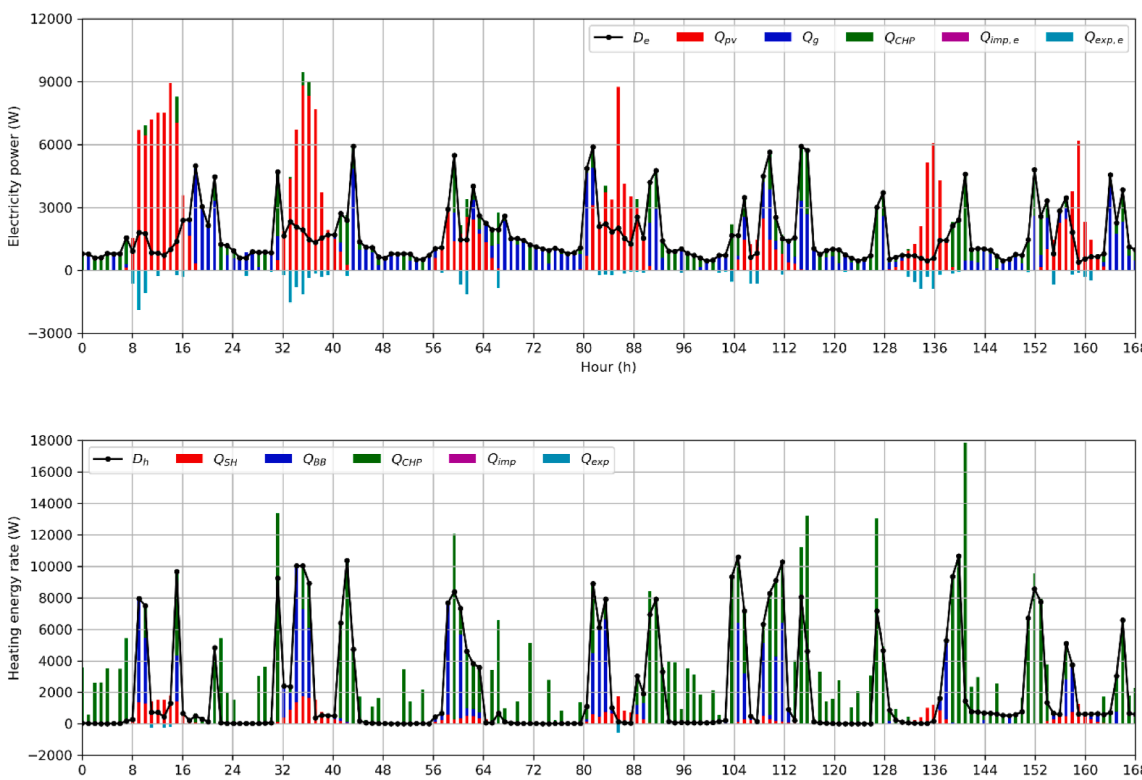


(b) Week 35

Fig. A3. Electrical and heating energy allocation of Building 1 in Weeks 30 and 35–39.

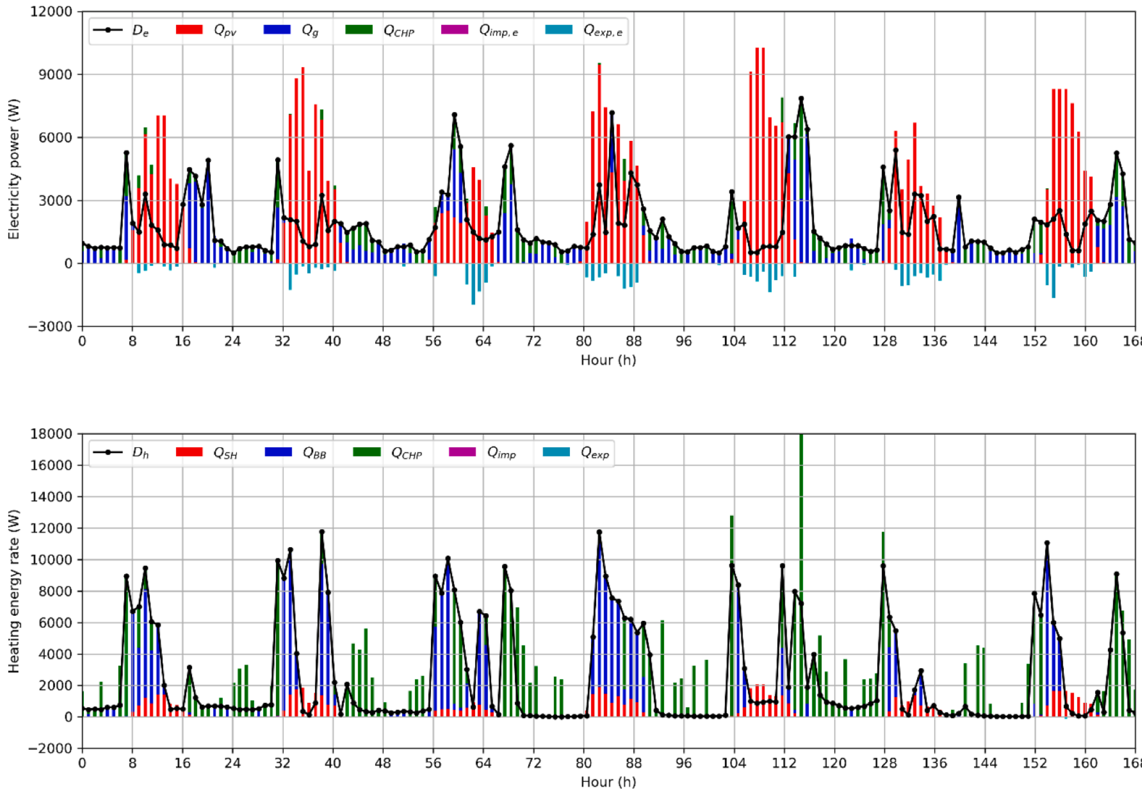


(c) Week 36

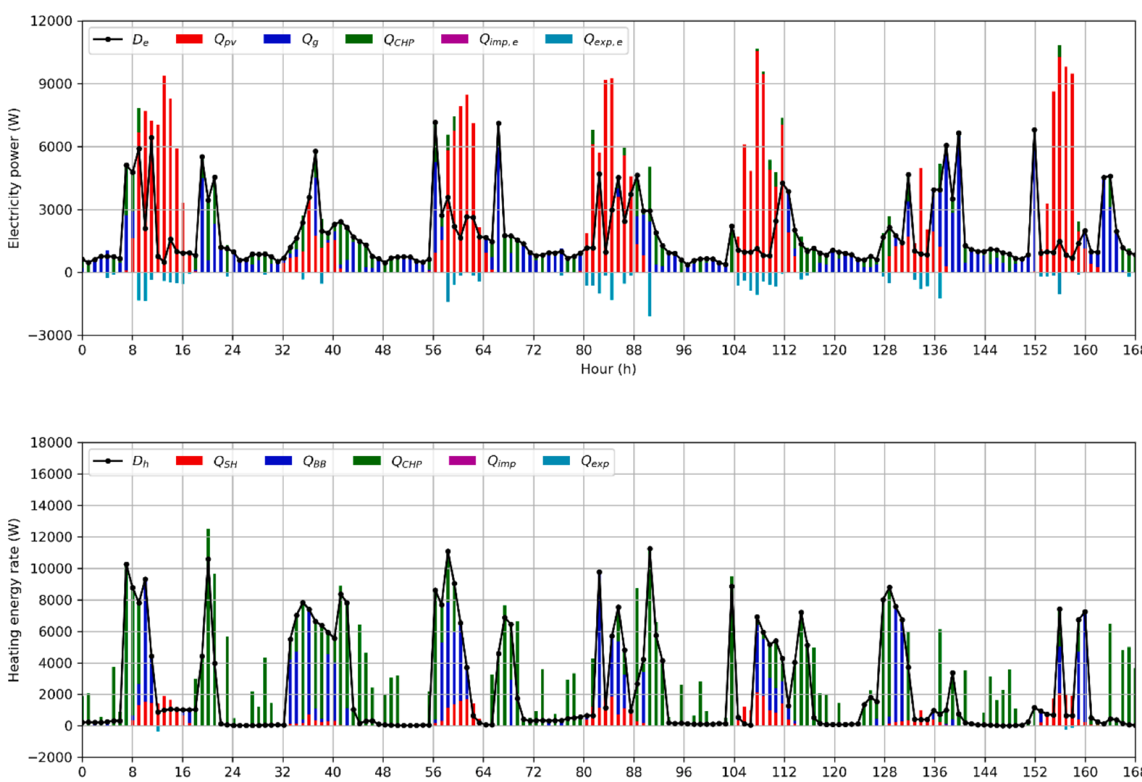


(d) Week 37

Fig. A3. (*continued*).

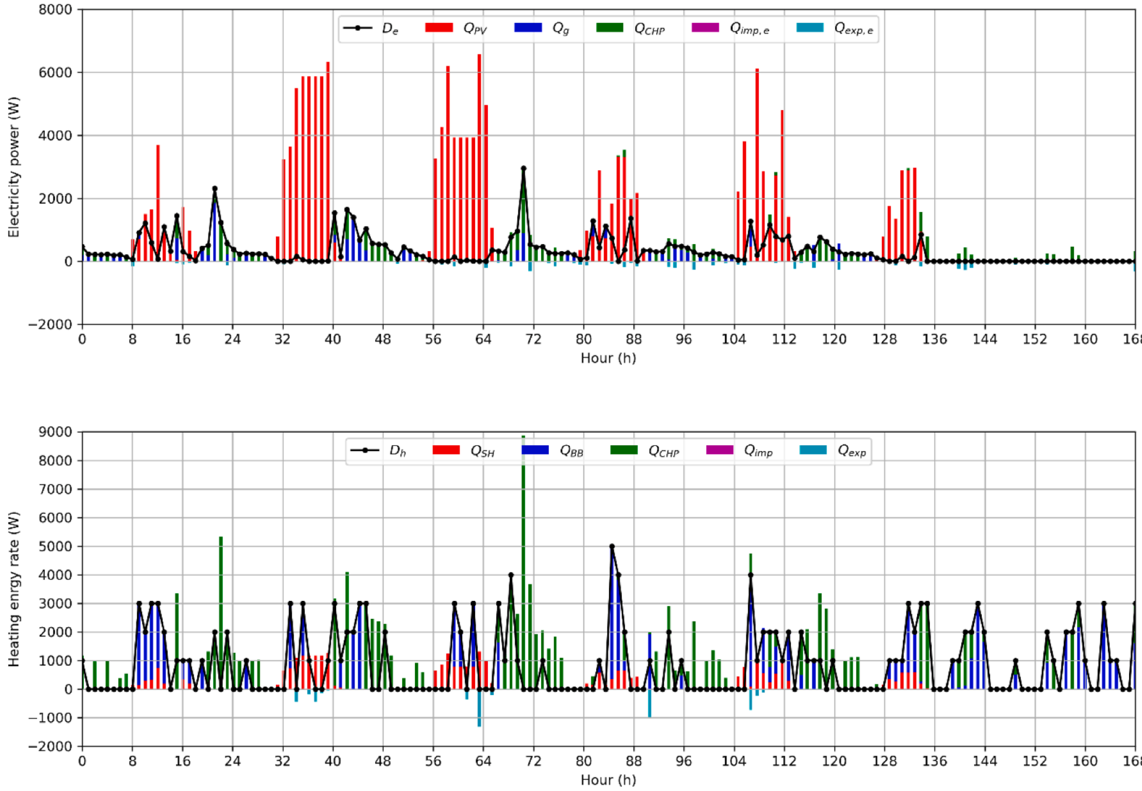


(e) Week 38

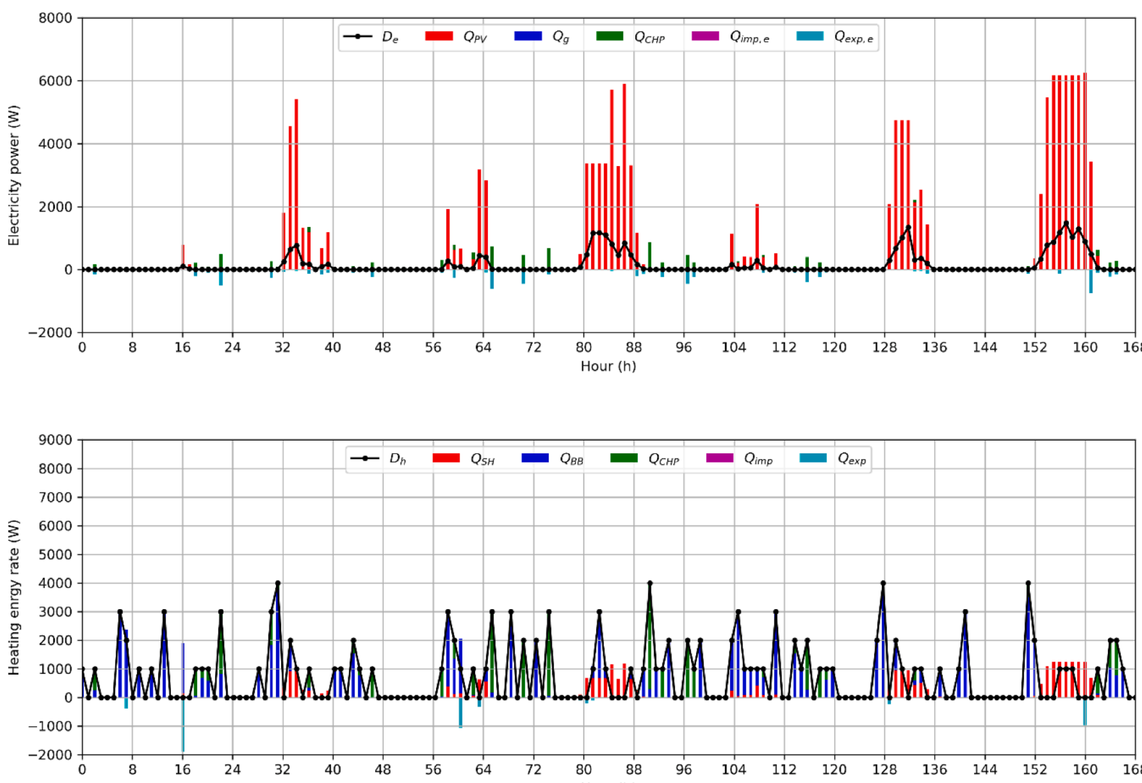


(f) Week 39

Fig. A3. (*continued*).

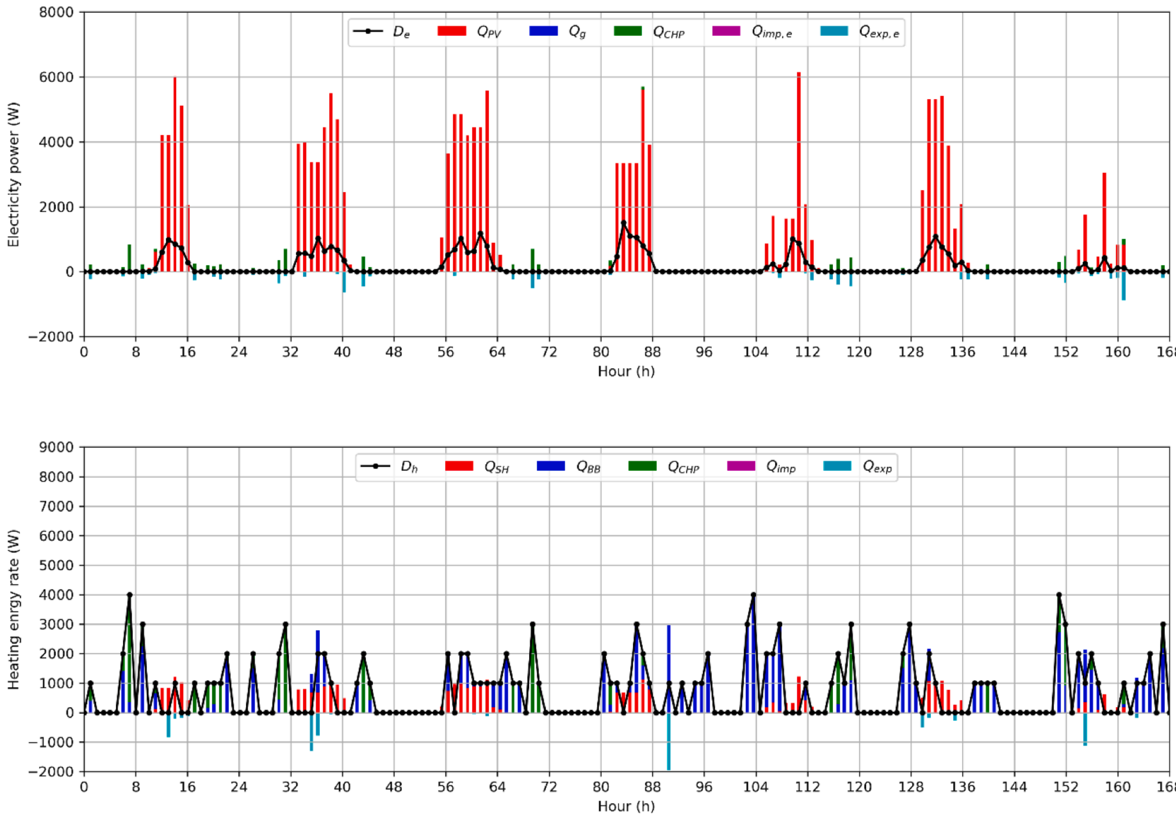


(a) Week 30

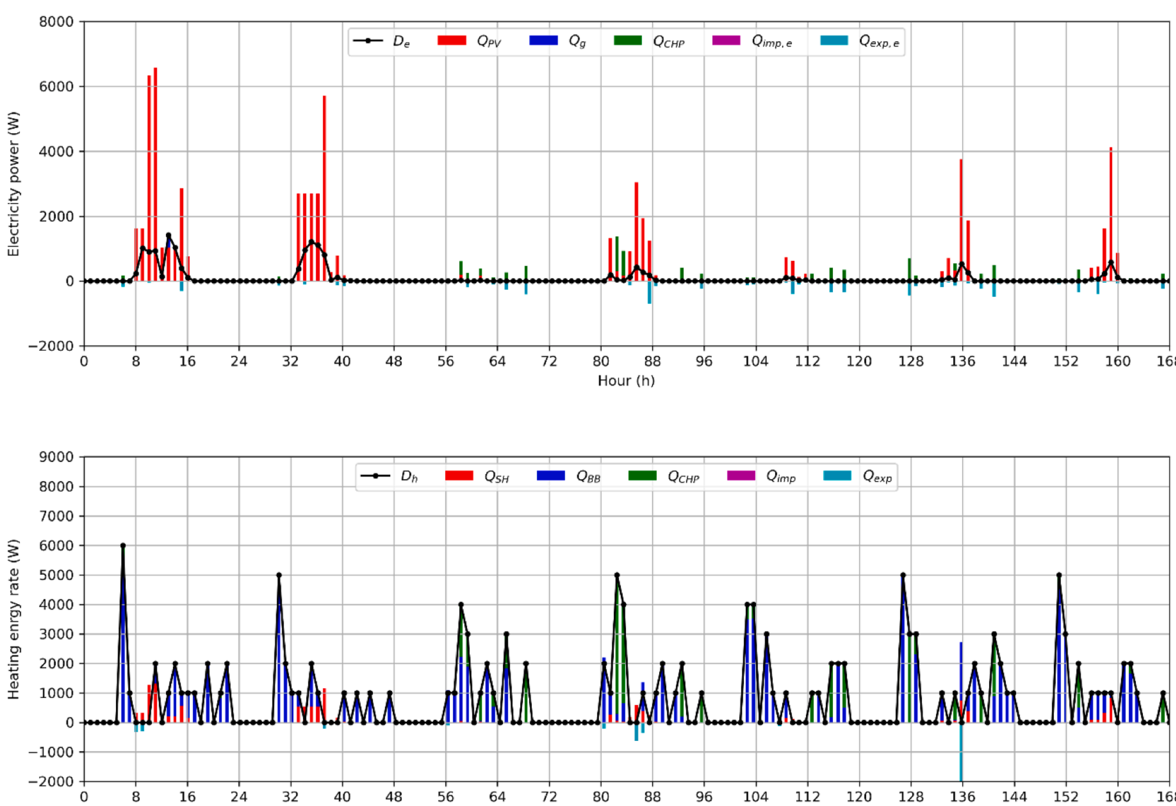


(b) Week 35

Fig. A4. Electrical and heating energy allocation of Building 2 in Weeks 30 and 35–39.

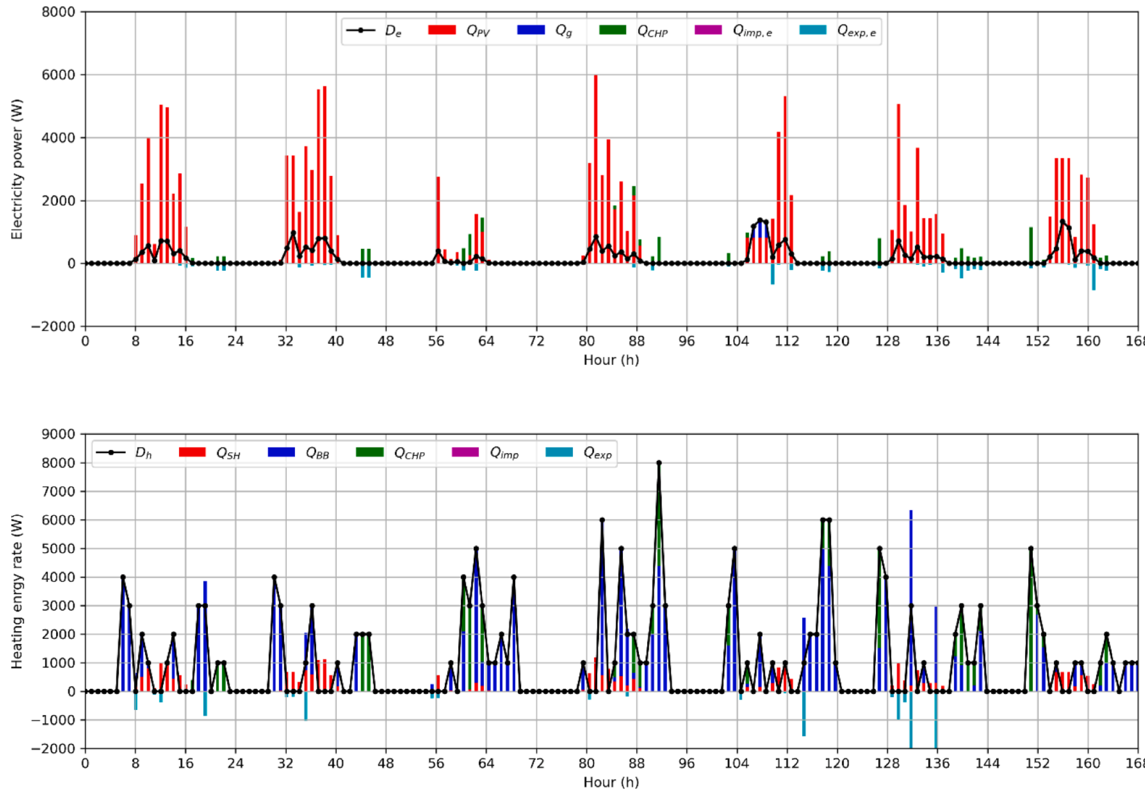


(c) Week 36

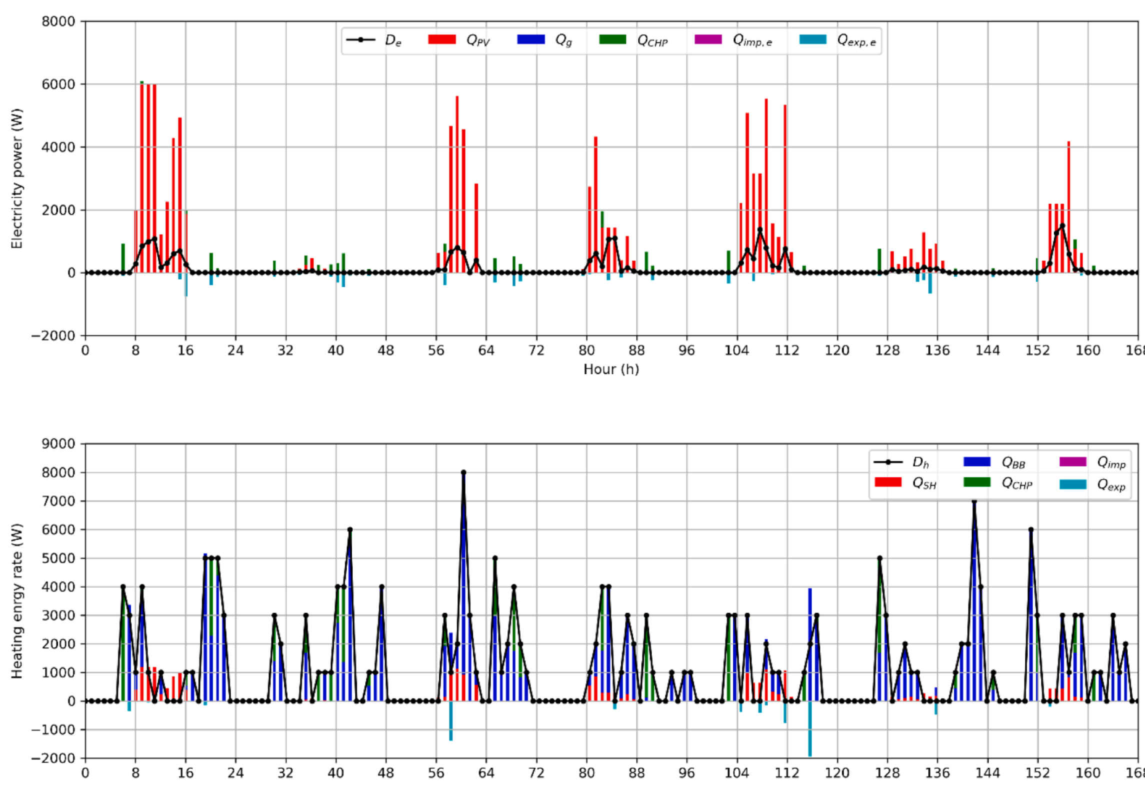


(d) Week 37

Fig. A4. (*continued*).

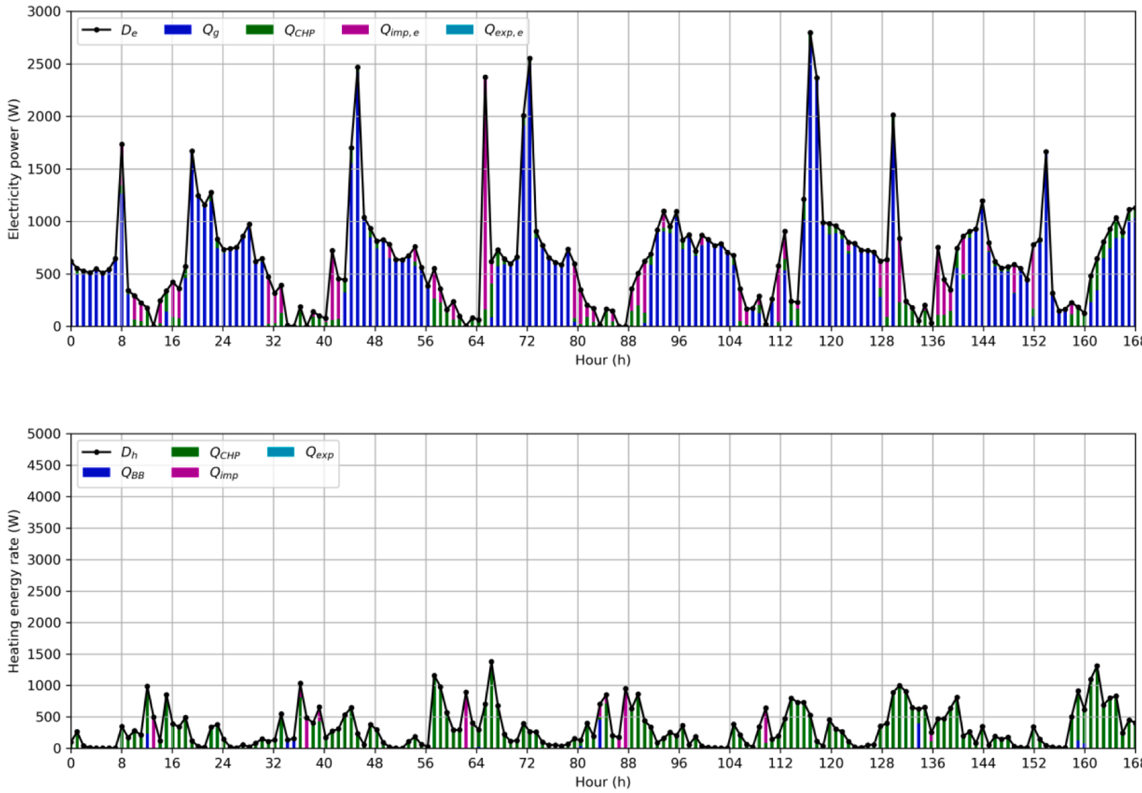


(e) Week 38

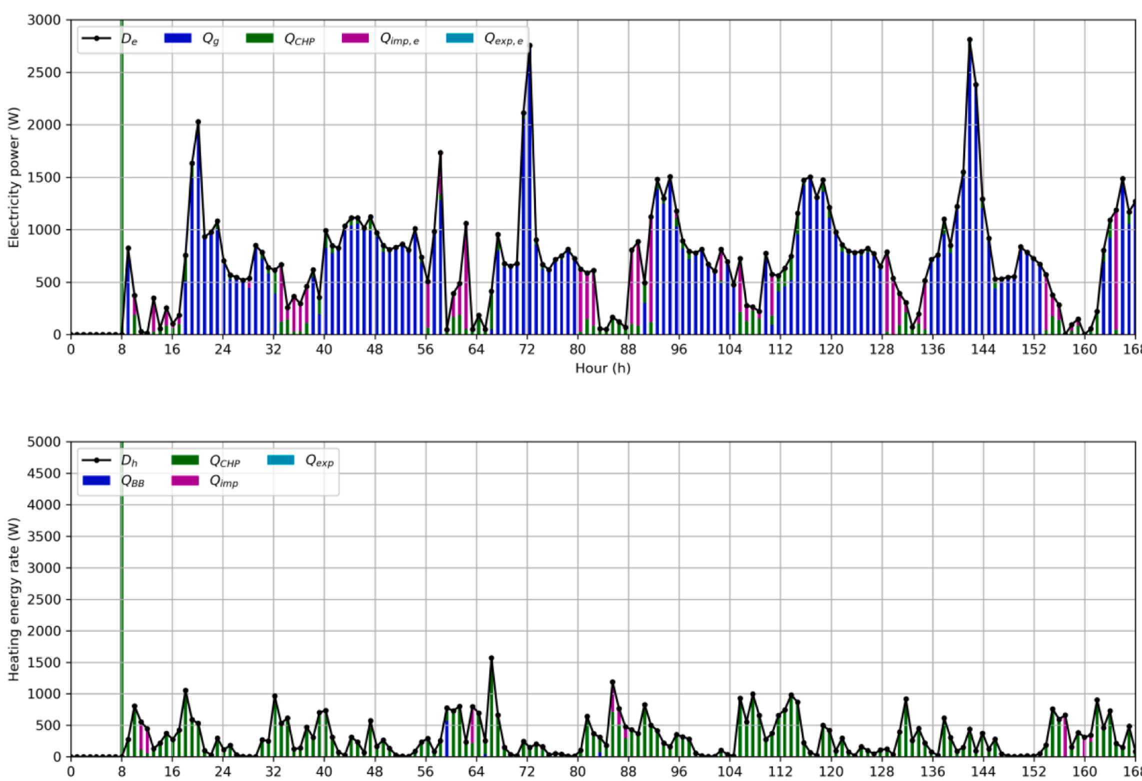


(f) Week 39

Fig. A4. (*continued*).

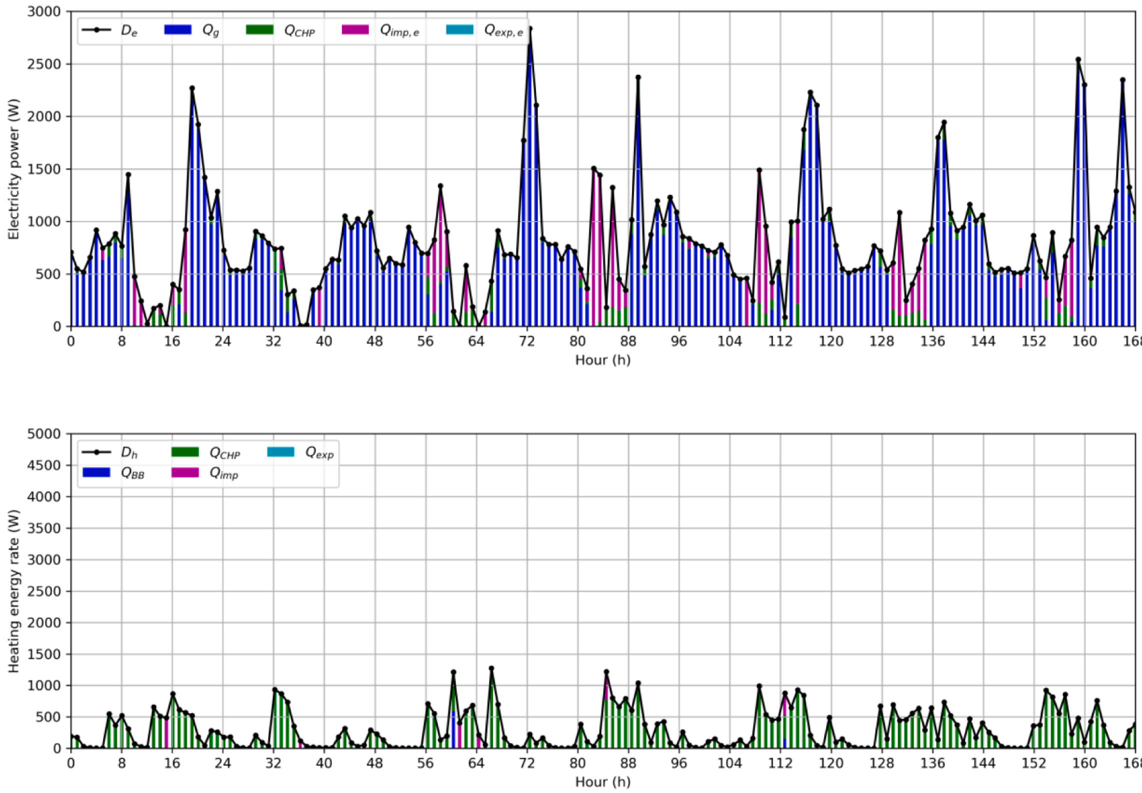


(a) Week 30

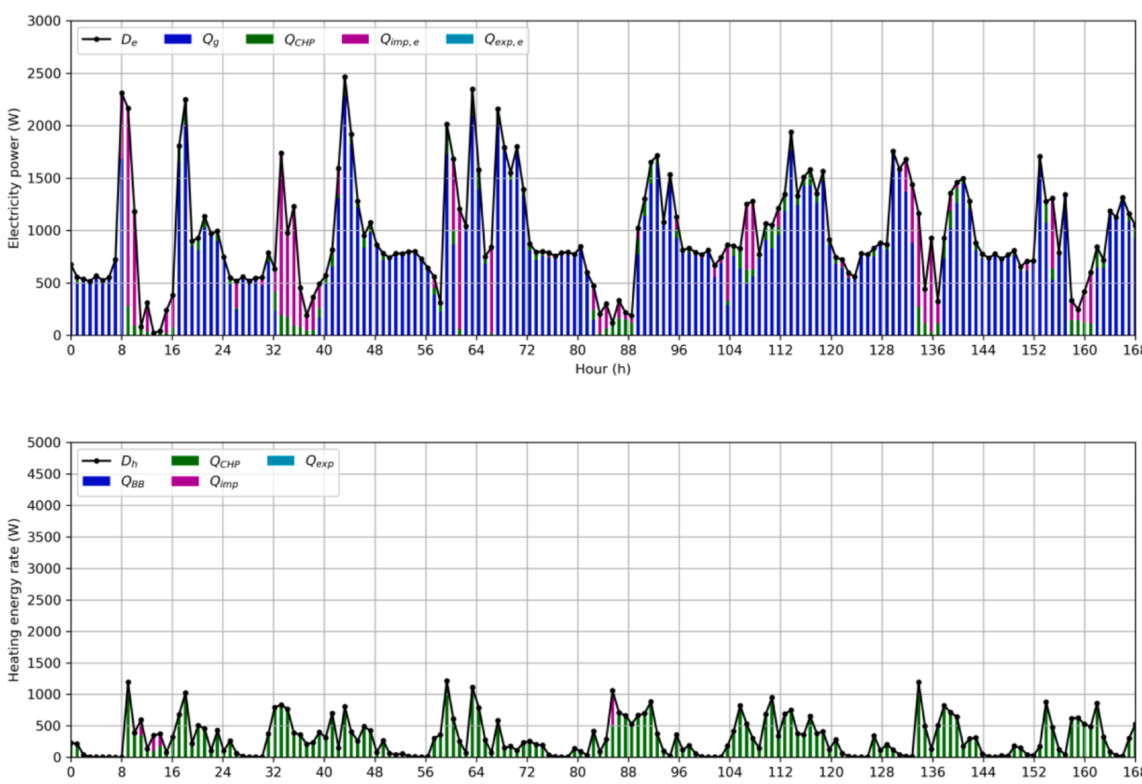


(b) Week 35

Fig. A5. Electrical and heating energy allocation of Building 4 in Weeks 30 and 35–39.

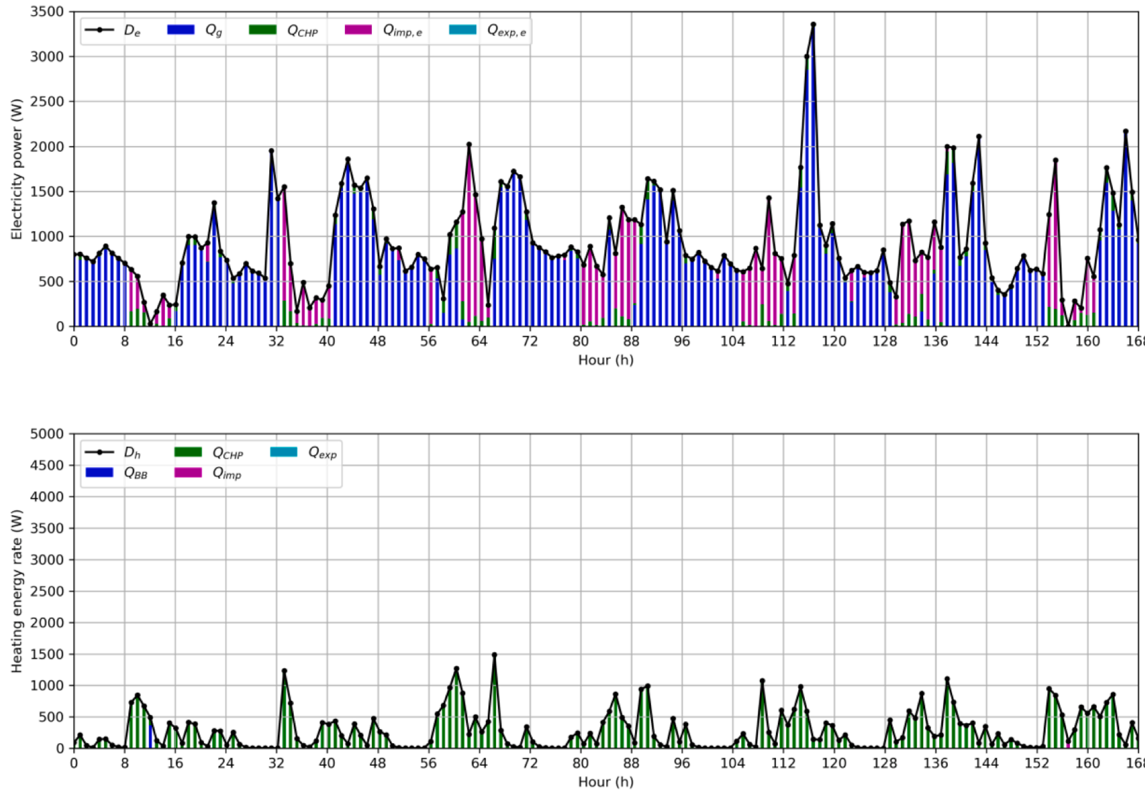


(c) Week 36

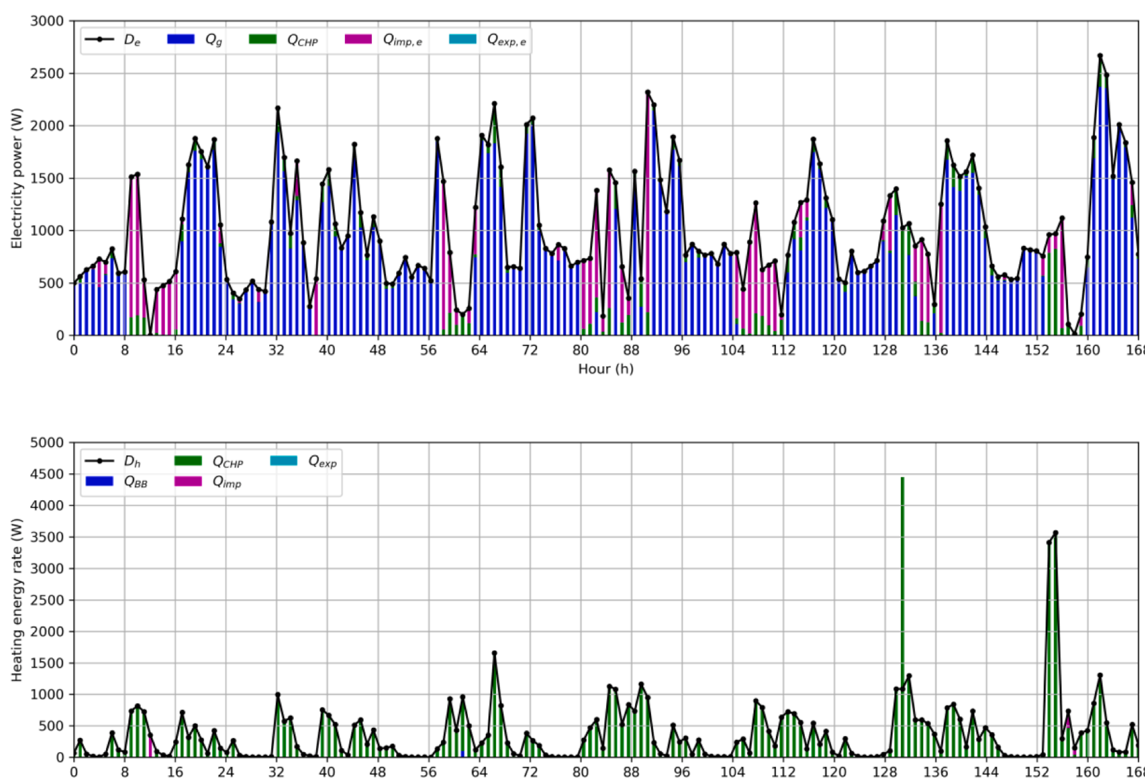


(d) Week 37

Fig. A5. (*continued*).

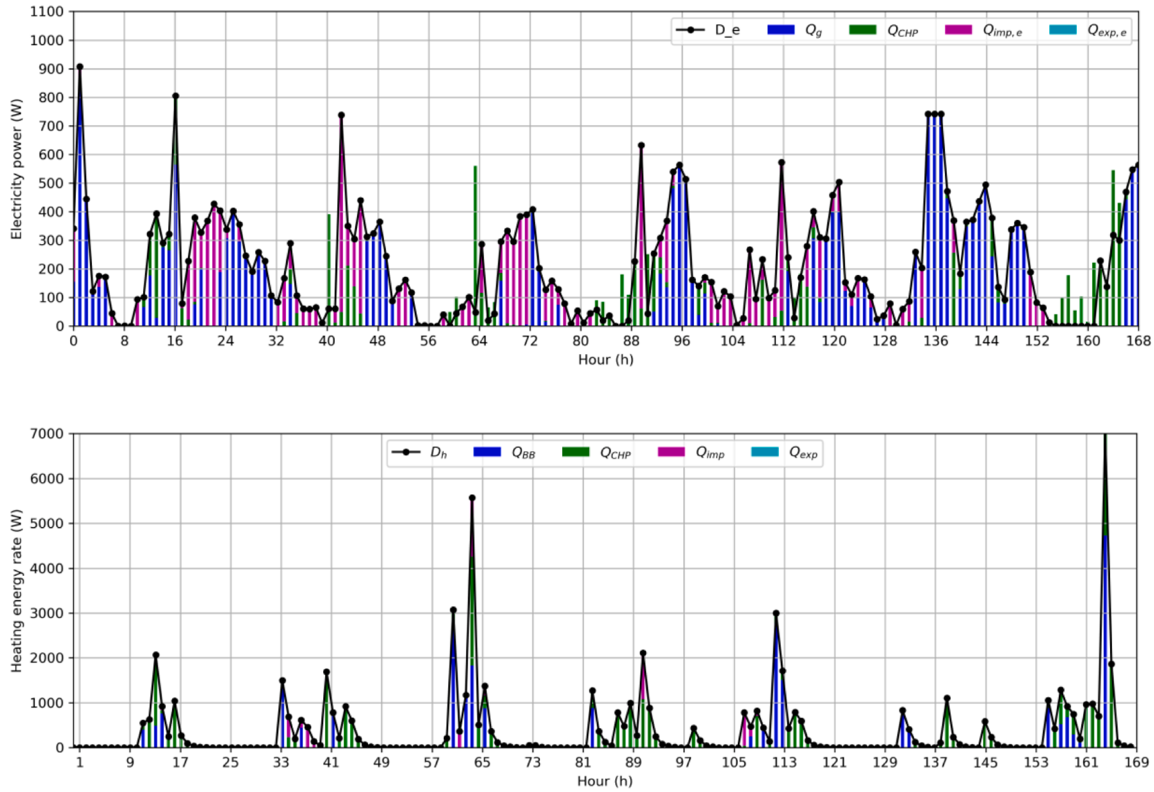


(e) Week 38

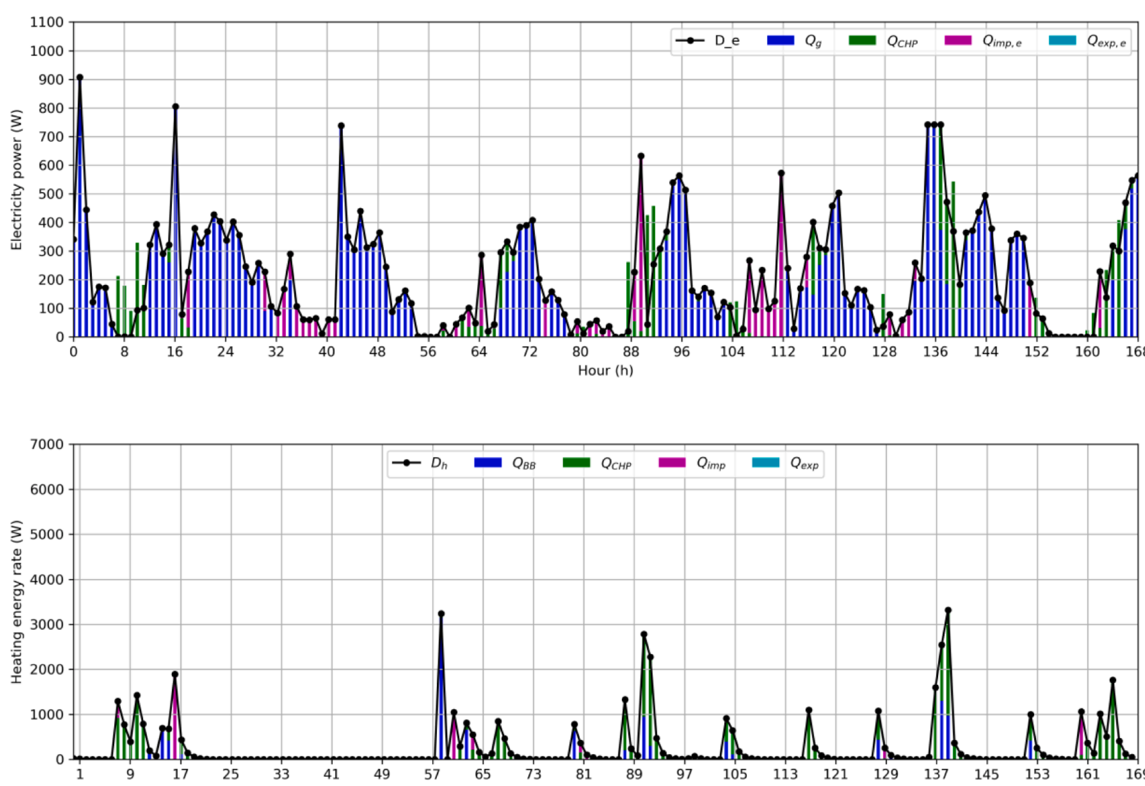


(f) Week 39

Fig. A5. (*continued*).

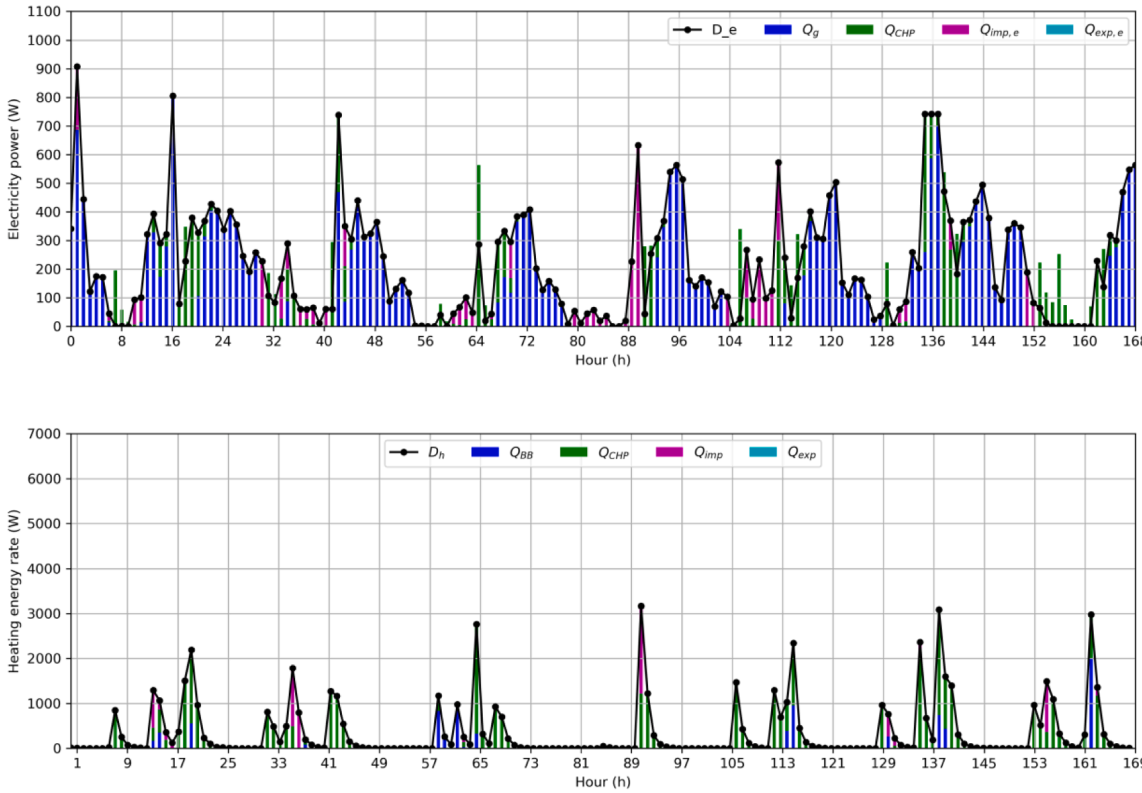


(a) Week 30

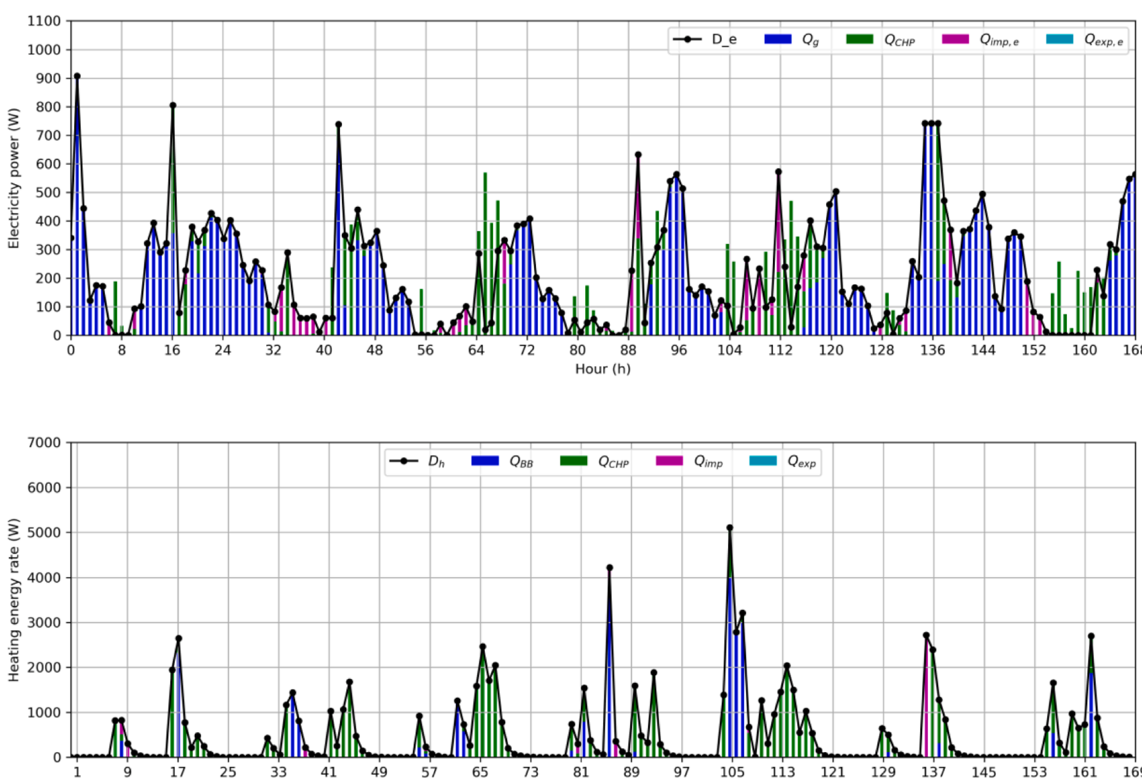


(c) Week 35

Fig. A6. Electrical and heating energy allocation of Building 4 in Weeks 30 and 35-39.

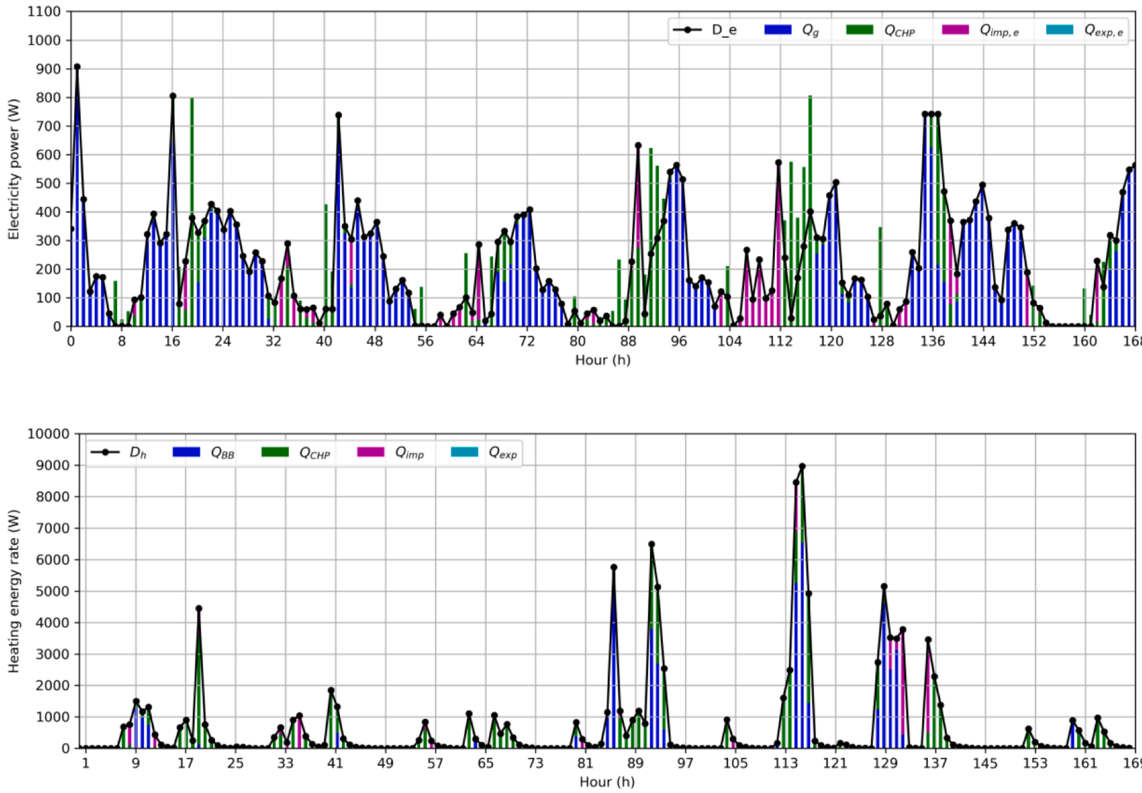


(d) Week 36

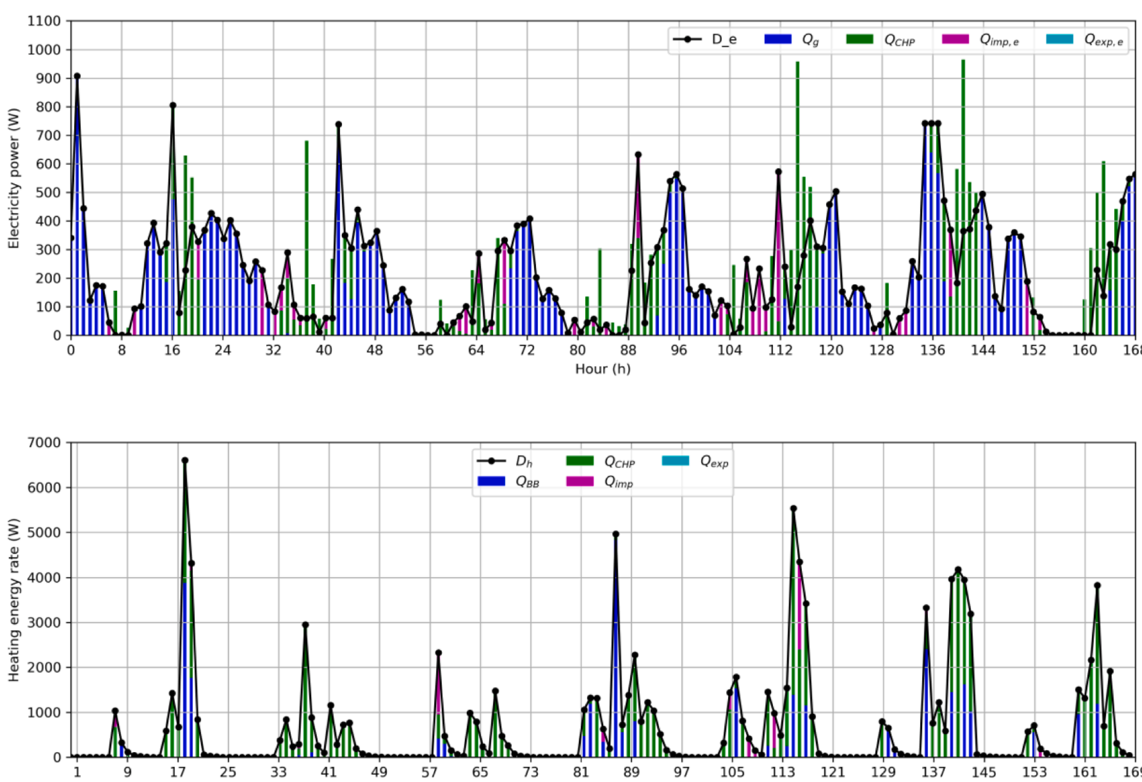


(e) Week 37

Fig. A6. (*continued*).



(f) Week 38



(g) Week 39

Fig. A6. (*continued*).

Table 6
Energy costs of different buildings (£).

Period	Method	Building 1	Building 2	Building 3	Building 4
Week 29	Reference method	21,240	8353	17,180	6167
	Proposed framework	19,550	7418	15,794	5208
	Reduction	7.96 %	11.19 %	8.07 %	15.55 %
Week 30	Reference method	22,490	7649	15,673	6578
	Proposed framework	20,213	7067	14,261	5758
	Reduction	10.12 %	7.60 %	9.01 %	12.46 %
Week 35	Reference method	29,905	2443	16,727	6549
	Proposed framework	27,130	1987	15,824	5727
	Reduction	9.28 %	18.68 %	5.40 %	12.55 %
Week 36	Reference	29,270	2299	19,196	7646
	Proposed framework	26,112	1715	17,722	6490
	Reduction	10.79 %	25.41 %	7.68 %	15.12 %
Week 37	Reference	31,924	2840	22,123	8356
	Proposed framework	27,004	2425	20,494	7087
	Reduction	15.41 %	14.62 %	7.36 %	15.19 %
Week 38	Reference	31,083	3569	21,495	8500
	Proposed method	25,433	3191	19,526	7188
	Reduction	18.18 %	10.60 %	9.16 %	15.43 %
Week 39	Reference	32,036	3884	23,362	8987
	Proposed method	27,126	3563	21,385	7403
	Reduction	15.33 %	8.26 %	8.46 %	17.63 %

energy trading to help them make profits and achieve cost savings. Three Python algorithms are developed separately for energy prediction, planning optimisation, and blockchain transaction, respectively. However, a dataset is saved as a.h5 file to communicate between different Python files. In practical applications, there may exist implementation and maintenance challenges for integrating these three techniques (i.e., blockchain, machine learning, and PSO optimisation). For example, the communication protocols need to be coordinated among IoT sensors, machine learning modules, blockchain modules, and PSO optimisation modules [42]. In practice, each building has a tailored python-based optimisation module, and a distributed and all the participated buildings will conduct peer-to-peer multi-type energy trading through the blockchain-based platform. As illustrated in Fig. 1, the tailored Python-based optimisation module consists of 4 machine learning models for heat demand prediction, electricity demand prediction, PV electricity production prediction, and solar heater heat production prediction, as well as one PSO model for scheduling local energy devices and energy importation and exportation rate. The input dataset to this tailored optimisation module mainly includes smart energy sensor measurement, while the output dataset consists of values regarding energy rates of local energy devices, importation energy from other buildings, and exportation energy to other buildings. The blockchain platform is an open-source decentralised system and can enable peer-to-peer transactions among multiple participants, while the importation and exportation energy rates obtained from each optimisation module will be automatically set as input dataset to the blockchain platform.

(5) In relation to hardware development, the actual energy transmission grids need to be implemented to perform real-time heating and electrical energy trading. Meanwhile, blockchain-specific hardware and network infrastructure should also be developed and adopted in practical applications. In addition, other renewable energy devices such as ground source heat pumps and building-integrated wind turbines [5] might also play an important role in heat and electricity production. The impacts of their participation on overall cost-saving potential should be investigated.

Table 7
Performance comparison between existing methods and proposed framework.

Conventional methods	Features of conventional methods	Features of the proposed approach	In which aspect the proposed method outperforms conventional methods
Multi-agent method based multi-energy management system	Relies on centralised control	Machine learning and optimisation modules are distributed in each participated building	Computational loadFailure of a single point
blockchain-based energy trading platform	Based on participants' experience in determining energy trading rate	Optimal energy importation and exportation rate is determined by optimisation algorithm	Energy trading strategy
Thermodynamic models for building energy prediction	Model is needed for each building based on its unique architecture, energy system and thermal properties	Easily personalised to each individual building by training its historical energy consumption profiles.	Workload
Individual building energy management	Relies on energy storages to reschedule the peak and valley demand	Peer-to-peer energy sharing to reschedule the peak and valley demand	Capital cost energy efficiency

(6) Regarding scalability testing, as only 4 domestic buildings participated in this study, the renewable energy utilisation rate is still quite low. As different types of buildings may have different peak times for electricity and heating demand, it is interesting to see how energy utilisation rate can be further improved if different types of buildings are included in the peer-to-peer energy trading.

(7) In terms of practical application, the error between predicted and actual values of both energy demands and generating rates should also be considered. In the case that the predicted energy demand is smaller than the actual energy demand, a higher operating capacity of biomass boiler should be adopted to supplement the heat demand, as a result, electricity should be imported from the main power grid. Moreover, cooling demands may also be required for domestic buildings or other types of buildings under different climate conditions. The proposed conceptual framework may be further extended to include cooling energy trading, while biomass trigeneration systems, absorption chillers and electric chillers can be installed to satisfy cooling energy demands.

As demonstrated in Table 7, the proposed blockchain and machine learning-based framework for decentralised energy management outperforms various state-of-the-art approaches. The developed framework performs better than the multi-agent method, based multi-energy management system in terms of computational load. This is mainly because the proposed machine learning and optimisation modules are distributed in each participated building so that no centralised control is required. The decentralised feature can also prevent the management system from single point of failure.

The developed framework can also outstrip the state-of-the-art blockchain-based energy trading platform, which relies heavily on participants' experience in determining energy trading rate. In the proposed framework, the optimal scheduling of local energy devices and importation/exportation rate are estimated by PSO algorithm for each building, while this optimal energy importation and exportation rate is used for peer-to-peer energy trading.

In terms of building energy prediction, conventional thermodynamic models tend to model for each building, based on its unique architecture, energy system and thermal properties, which is proven to be both cumbersome and time-consuming. However, the developed machine learning models provides a step change as it can be easily personalised to each individual building by training its historical energy consumption profiles.

The proposed blockchain framework also provides improvements in comparison to existing smart energy management for individual buildings. Those individual energy management systems mainly rely on energy storages to reschedule the peak and valley demand, and they fail to cooperate with other buildings. The proposed peer-to-peer energy sharing can avoid the energy storages, which may lead to higher capital cost and energy loss.

6. Conclusion

Traditionally, gas and electricity are generally supplied through centralised energy systems, which are operated by major energy and utility companies. These central management systems always result in a high computational load, while energy prices are fully decided by those companies and may increase rapidly due to economic inflation. In addition, a large fraction of energy losses through long-distance energy transmission occurs. Conversely, the strategic operation of decentralised energy systems among different buildings can reduce global greenhouse gas emissions, and address climate change issues. Although blockchain has been adopted in various energy trading platforms to facilitate peer-to-peer electricity transactions, most of the existing research focused on workflow, smart contracts and consensus mechanism development, while there may be a lack of predictive control, optimal energy planning, and multi-energy trading.

The key innovation of this study is to integrate blockchain and machine learning to develop an energy management conceptual framework for decentralised multi-type energy (i.e., heat and electricity) allocation and transmission among a range of domestic buildings. LSTM models are adopted to predict day-ahead energy consumption rates of different buildings and energy generation rates of renewable energy devices, within the multi-energy network. PSO algorithms are adopted to determine the schedules of operating capacity of controllable energy devices, as well as energy importation and exportation rates of each participating building. Meanwhile, blockchain is adopted to establish peer-to-peer energy transactions among different buildings. This novel framework focuses on global energy-matching between supply and demand sides from a range of buildings through encouraging direct energy trading between prosumers and consumers. The privacy, security, and fairness of energy management are also enhanced through smart contracts to strictly execute the energy trading and bill payment rules.

This study determined the economic and technical potential of peer-to-peer multi-type energy trading under a given set of tariff circumstances, with a case study of 4 real-life domestic buildings. The results of testing the proposed framework in the case study buildings revealed that there was a 7.96 %-18.18 %, 7.60 %-25.41 %, 5.40 %-9.01 % and 12.46 %-17.63 % reduction for Buildings 1, 2, 3 and 4, respectively. In practical application, the proposed framework can involve a larger number of prosumer and consumer buildings within the community to decentralise multiple energy trading, reduce greenhouse gas emissions and enhance environmental sustainability.

Findings revealed that in comparison to prevailing methods including multi-agent method-multi-energy management system, blockchain-based energy trading platform, and thermodynamic models for building energy prediction, the proposed framework performs better in terms of computational load/failure of a single point, energy trading strategy, workload, and capital cost energy.

A strong case was made for the economic and technical potential of a blockchain and machine learning-based framework to enable multi-type energy allocation and transmission among different buildings. Above all, it confers significant potential to contribute to the reduction of greenhouse gas emissions and enhancing environmental sustainability.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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