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Building-to-building energy trading under the influence of occupant comfort

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ABSTRACT

Peer-to-peer energy trading is becoming an efficient methodology for trading flexibility between buildings due to the increasing utilisation of small-scale generation and storage technologies. In the buildings, however, this trading mechanism could be affected by occupant comfort and uncertainty around it, affecting the building operation and consumption. This study introduces a multi-level peer-to-peer energy trading framework for residential buildings under the influence of occupants preferences. The proposed method considers the effect of occupants comfort as an important factor on the control and energy management of buildings in local markets. The robustness of the proposed real-time control framework in face of uncertainty in a real-life building parameter (i.e. occupants comfort level) is improved through the-state-of-the-art information gap decision theory technique. This method requires very little information about uncertain parameters, making it a suitable technique for dealing with the uncertainty in parameters with unknown patterns. Finally, the operational models of energy storage and electric vehicles are adopted for full utilisation of available photovoltaic generation. The simulation results show that participating in the local energy trading can increase the robustness of the control systems in the residential microgrids in face of uncertainty in the occupant comfort level. Also, results show that 0.1% increase in the uncertainty radius of occupants comfort level requires a 6% increase in the energy bill. This shows the importance of considering the occupant comfort in the conventional building energy management strategies, and uncertainty around it on the energy bill.

1. Introduction

1.1. Motivation

Energy systems have been experiencing fundamental changes because of the urgent needs for decarbonisation of these structures. Complying with the requirements of decarbonisation has even targeted buildings as the end-users of the energy networks. With 36% of the global energy consumption, buildings are responsible for creating a considerable amount of CO_2 emissions worldwide [1]. In this regard, increasing the efficiency of building assets, installing small-scale generation and storage units, and electrification of heating/cooling systems considered as the substantial plans in the building sector. In addition, linking the transport sector to the energy grids through electric vehicles (EVs) could be another potential plan. These transitions can be efficiently managed by utilising building energy management strategies [2]. Under this paradigm, buildings can proactively manage their consumption and generation while exchanging energy with their interconnected distribution networks. These developments have enabled the introduction of local energy systems to the community of active buildings (ABs) that can trade energy internally under the peer-to-peer market framework [3]. Energy management of such communities, however, is more likely to be affected by internal and external factors such as user lifestyle and weather forecast respectively. Consequently, it is crucial for the local community managers to account for these variables while scheduling energy transactions between ABs and their incorporated elements.

1.2. Literature review

The peer-to-peer energy trading in the building sector (called B2B herein) can enable direct exchange of energy among dwellings. To this end, ongoing projects such as Piclo in the UK [4] and Brooklyn microgrid in the US [5], are investigating the advantages of this new paradigm in practice. The concept of B2B allows any type of ABs (e.g. commercial, residential) to manage their available PV and storage

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Nomenclature

Indices

b	Index of ABs
h	Index of home appliances
o	Operation period of variable power consumption appliances
t	Index of time periods

Sets

Ω_b	Set of buildings
Ω_h	Set of home appliances
Ω_o	Operation period of home appliances
Ω_t	Set of time periods

Parameters

$\eta_{ev}^{C/D}$	Charging/discharging efficiency of EV battery
T_t^{out}	Outdoor temperature
$\Delta D_{b,t}^{EV}$	Travel distance of EV
Δt	Duration f time periods
$\eta_I^{u/m}$	Utilisation/maintenance factor of lightening devices
$\eta_{es}^{C/D}$	Charging/discharging efficiency of BESS
η_{ev}^{t}	Driving efficiency of EV
κ_b	Number of lightening devices in building b
$\psi_{b,t}^{V/Th}$	Visual/thermal comfort weight coefficient
A_b	Illuminated space in building b
COP	Coefficient of performance of heat pump
D_b^{th}	Thermal capacitance of building b
$E_b^{ES_{Max/Min}}$	Maximum/minimum state of charge of BESS
$E_b^{EV_{Max/min}}$	Maximum/minimum state of charge of EV
f_b	Source flux value of building b
$OC_{b,t}^{AB_{\min}}$	Minimum occupants comfort index for each AB
$P_b^{HP_{\max}}$	Maximum power consumption of heat pump
$P_b^{C/D_{es}^{\max}}$	Maximum charging/discharging power of BESS
$P_b^{C/D_{ev}^{\max}}$	Maximum/minimum Charging/discharging power of EV
$P_t^{PV_F}$	Forecasted PV output
$P_{b,h,o}^{Ap}$	Power consumption of variable power consumption appliances in the operation cycle
$P_{b,h,t}^{Ap}$	Power consumption of home appliances
$P_{b,t}^{T_{ev}}$	EV Power consumption in transport vector
P_{MAx}^{I}	Maximum power consumption rate of lightening devices
R_b^{th}	Thermal reactance of building b
$T_b^{B_{\max/min}}$	Maximum/minimum temperature inside the building
$T_{b,t}^{Set}$	Temperature set point
V_t^{N}	Outdoor illuminance level
$V_{b,t}^{Set}$	AB illumination set point
$V_{b,t}^{B_{\max/min}}$	Maximum/minimum illuminance level of AB

Variables

$B_{b,h,t}^{Ap}$	Binary variable indicating the on/off status of home appliances
T_b^{oc}	Occupancy profile of building b
$T_{b,t}^{B}$	Indoor temperature
$V_{b,t}^{B}$	Indoor illuminance level
$H/C_{b,t}^{HP}$	Heating/cooling power consumption of heat pump

capacity along with the flexibility of their energy consumption units and trade it in a local market rather than selling it to the electricity retailers with low price tariffs. On the other hand, ABs that are not equipped with distributed energy resources can participate in the local market to fulfil their energy needs economically. In addition to the economic advantages for the prosumers and costumers, this trading methodology can defer generation investment in the higher grids and improve overall system reliability [6].

In order to enable B2B energy trading at the community level, it is critical to design a pricing mechanism which encourages market participants to trade energy locally while partially bypass the electricity supplier [7]. The mid-market rate and bill sharing mechanisms are the most popular frameworks that have been introduced for local energy pricing. The latter is defined based on the cost sharing for an individual peer, while the former defines the local price as the average value of importing and exporting prices from/to the main grid [8]. Although bill sharing mechanism is a suitable strategy for enabling local markets, it has been shown in [9] that the local sell prices are more likely to be lower than grid export prices; therefore, this method cannot guarantee the participation of prosumers in the local market. In [10] a surplus-to-demand ratio is defined for the pricing function of the P2P so as to reduce the price fluctuation in the real-time market.

It is important to note that validation of the local energy transaction depends on the availability of on-site generation such as PV units. Therefore, available literature designed their methodologies based on PV sharing in the community level [11]. It has been shown in [12] that a local market can optimise the efficiency of roof-top PV generation while minimising the energy exchange with the main grid. This efficient utilisation of PVs in the local market can defer system reinforcement in the network level [13]. A multi-objective optimisation model is introduced in [14] for efficient retrofitting plans in ABs, while advantages of PV units over the water heaters is demonstrated. The weighted sum method is utilised for handling the multi-objective optimisation, which is more likely to fail in solving the non-convex optimisation models [15]. A dynamic pricing scheme based on the supply and demand ratio of shared PVs is introduced in [16], which has resulted in cost saving for prosumers and improved efficiency of PV sharing. The availability of PV power, however, depends on the time of the day. The lack of storage technologies can result in curtailing PV power in case of excess generation. Authors in [17] investigated the effect of uncertainty in the PV generation on the community energy storage, where a multi-objective optimisation model is introduced to minimise the energy bill while considering occupants discomfort.

In this regard, the battery energy storage system (BESS) has gained popularity in the B2B energy trading due to its potential in mitigating the PV output. Ref. [18], proposed a B2B energy trading framework for optimising the operation of BESS and increasing the utilisation of PV units in the community of ABs. The proposed method brought about energy cost saving and peak demand reduction. Different ownership structures of BESS in the building sector and their application in the B2B is studied in [19]. In addition to the economic benefits of BESS in cutting down energy costs and PV utilisation efficiency, authors in [20] highlighted the social benefits of B2B in increasing the needs for storage unit equipment and indirectly rising the employment demand. The result obtained in [21] shows 28% of energy bill saving for ABs which are equipped with both PV and BESS. Therefore, utilisation of PV and storage technologies can benefit the building owners and their participation in the local markets. Wang et al. [22] introduced a virtual energy storage model based on thermal characteristics of the building

Table 1
Taxonomy of literature on peer-to-peer energy trading within buildings from 2020 to 2024: a comprehensive overview of relevant studies.

Ref.	Occupants comfort		Real-time	Energy vector			Flexibility		Pricing mechanism			Uncertainty Modelling	
	I[a]	TZ[a]		E[a]	H[a]	T[a]	D[a]	G[a]	MMR[a]	BS[a]	Other	Method	Parameter
[7]	x	x	✓	✓	✓	✓	✓	x	✓	x	x	x	x
[10]	x	✓	✓	✓	✓	x	✓	x	x	x	✓	x	x
[12]	x	x	x	✓	x	x	✓	✓	x	x	✓	x	x
[17]	✓	x	x	✓	✓	x	✓	✓	x	x	x	SB[a]	REG[a]
[18]	x	x	✓	✓	x	x	✓	✓	✓	✓	✓	x	x
[19]	x	x	✓	✓	x	x	✓	✓	x	x	✓	x	x
[20]	x	x	✓	✓	x	x	✓	✓	x	x	✓	x	x
[22]	x	✓	✓	✓	✓	✓	✓	✓	x	x	✓	x	x
[26]	x	x	✓	✓	x	x	✓	✓	x	x	✓	x	x
[27]	x	x	✓	✓	x	x	✓	✓	x	✓	x	RO[a]	REG[a]
This study	✓	x	✓	✓	✓	✓	✓	✓	✓	x	x	IGDT[a]	OP[a]

[a] I: Index, TZ: Temperature Zone, E: Electricity, H: Heating, T: Transport, D: Demand,G: Generation, MMR: Mid-market Rate, BS: Bill Sharing, SB: Scenario Based, REG: Renewable Energy Generation, RO: Robust Optimisation IGDT: Information Gap Decision Theory, OP: Occupancy Profile.

to investigate the influence of P2P on the penetration level of renewable energy sources.

The efficient utilisation of generation and storage technologies, as well as local pricing mechanisms depends on the control mechanism. The current literature suggests using real-time energy management techniques [23,24]. To this end, ongoing practical projects [4,5] are utilising the real-time energy management and pricing. Authors in [25] proposed a receding horizon control (RHC) for real-time energy management of ABs. The proposed structure allows the participants in the local market to adjust the generation and demand based on the real-time energy price and renewable energy generation. A hierarchical energy management strategy is introduced in [26] for coordination of BESS and shiftable home appliances to achieve energy cost saving. Although adaptation of RHC real-time methods could be an efficient methodology for optimising the energy management of generation and storage technologies, the issue of uncertainty in the input data should not be neglected. In [27], a robust optimisation problem is suggested for uncertainty of renewable generation in the B2B market. By stressing the uncertainty of renewable generation in B2B trading, Ref. [28] proposed a pricing mechanism for trading the forecasted and real-time PV output in the local market separately. In addition to the uncertainty in the renewable generation, however, there are other sources of uncertainty in the building side that can be challenging. Uncertainty in occupant preferences is one of these uncertain parameters which is difficult to predict or build a pattern for.

1.3. Research gap

The taxonomy of recent papers on the community-based B2B energy trading is given in Table 1. Although significant research has been published in this area, there are several important factors which requires further investigation. Despite the acknowledged importance of occupants comfort in building energy management [29], its impact on B2B trading models remains largely unexplored. Existing studies addressing occupants comfort often rely on simplistic temperature-based comfort metrics, overlooking the complex thermodynamic dynamics of buildings. Moreover, the visual comfort is mainly neglected while the effect of occupant comfort on P2P trading at the community level has been overlooked. Furthermore, while real-time energy management methods have been employed in previous research, they predominantly focus on addressing uncertainty in renewable generation. However, the variability in building users' behaviour introduces significant uncertainty in occupant comfort levels, which can profoundly influence real-time energy management and B2B energy trading strategies. Lastly, the ongoing electrification of heating and transportation systems introduces additional complexities to the electricity network, thereby impacting B2B energy trading dynamics. It is imperative to investigate the effects of optimising multiple energy vectors on local energy trading dynamics to ensure the resilience and sustainability of community-based energy systems.

1.4. Contribution

This article addresses the aforementioned research gap by proposing a multi-level energy management strategy for building to building (B2B) energy trading in residential microgrids (RMGs). The proposed method uses the RHC method for real-time hierarchical energy management of RMGs. The conceptual explanation of model predictive control based RHC method is given in [30]. Due to the potential uncertainty in the occupant comfort level (even in real-time energy management) the proposed method tries to improve the immunity (i.e. robustness) of the objective function for the local trading against uncertainty in occupant comfort level. This means that the immunity of objective function is guaranteed if the occupant comfort level experiences variation within an unknown threshold. The process of solving the optimisation is given in Fig. 1. In the first level, an energy bill minimisation model is solved for each individual building without consideration for B2B energy trading. Considering this level, the ABs participate in the B2B trading if it can bring about lower energy bill for them. Then, the second level solves the model in a deterministic environment without consideration for uncertainty in the RHC method. Finally, third level solves the optimisation in an uncertain environment, while maximising the robustness in face of uncertain occupants comfort level using the notion of information gap decision theory technique. The detailed description of the optimisation framework is given in Section 2. The application of this method and its advantages over other methods is explained in [31]. The proposed framework considers the operational characteristics of building assets (e.g. washing machine) and uses the thermo-dynamic building model for formulating ABs thermal comfort model. It also considers the effect of heating and transport vectors on the B2B trading by considering heat pump and EVs as the linking assets of each vector respectively. Buildings are classified based on different occupancy profiles and asset utilisation. The methodology investigates the influence of building users' preferences as a real-life social factor on the real-time control of residential microgrids and the incorporated local markets. To summarise, the main contributions of this paper are:

- A novel multi-level framework is designed to optimise community-based B2B energy trading. This approach utilises a hierarchical control process that respects both building-specific constraints and overarching community-level requirements. By considering the intricate characteristics of individual building assets, this method enables flexibility on both the demand and generation sides of energy exchange. This framework lays the groundwork for efficient and equitable energy trading within communities, accommodating diverse asset portfolios and ensuring adherence to local constraints.
- The significance of incorporating occupants comfort as a pivotal factor in B2B energy trading strategies is underscored. Moreover, the challenge posed by uncertainty in occupancy profile is addressed, recognising it as a critical determinant affecting

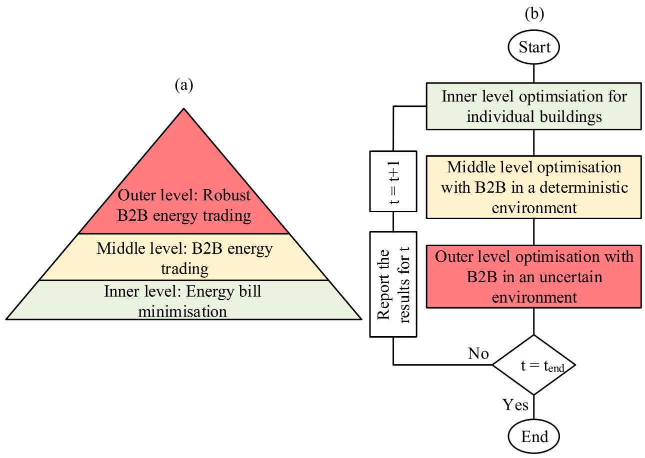

Fig. 1. Conceptual illustration of control process.

local energy exchange dynamics. To mitigate this uncertainty, a robust methodology is introduced to enhance the resilience of the RHC method. By integrating occupants comfort considerations and robustness measures, this approach fosters more reliable and adaptive energy management practices, ultimately enhancing the satisfaction and well-being of building occupants while ensuring the robustness of the energy system.

- This study explores the operational intricacies of Battery Energy Storage Systems (BESS) and Electric Vehicles (EVs) within the context of B2B energy trading. Different adopt operational models are introduced to leverage the full potential of rooftop PV generation, optimising energy utilisation and distribution. Furthermore, the impact of EVs on B2B energy dynamics is investigated, shedding light on their role as both consumers and contributors to local energy exchange. Through comprehensive analysis, the synergistic effects of BESS, EVs, and rooftop PV generation on enhancing the efficiency and sustainability of community-based energy systems are analysed.

1.5. Article structure

The reminder of this paper is organised as follows. Section 2 gives an overview of the RMG. The operational model of RMG is given in Section 3. Section 4 introduces the proposed robust B2B. Section 5 discusses the simulation results. Finally, Section 6 draws a conclusion.

2. Residential microgrid outline

The conceptual illustration of the RMG is shown in Fig. 2. A number of residential ABs in a close geographical location which are connected to the same substation form the RMG. These ABs are connected together through distribution lines. They can exchange energy, money, and information together and with the main grid. It is assumed that the RMG is equipped with the information and communications technologies to facilitate secure and fast data exchange. Based on a community-based B2B framework [9], dwelling units form a local market to exchange energy together. Under this community market, a controller collects the information from the ABs and incentivises them to participate in the market by defining the local price signals. Therefore, price signals indirectly guide the ABs to participate in the B2B energy trading.

Each AB is equipped with a heat pump which provides the heating energy requirements. Also, different types of home appliances (e.g. washing machine, fridge, computer, etc.) in terms of power consumption pattern are considered for each AB. ABs are clustered into three groups based on their available generation and storage technologies and occupancy profile. More information related to occupancy profile can be found in [32,33]. The detailed information of each cluster is assumed as follows:

1. Cluster 1: unoccupied from 9:00 AM to 2:00 PM. The ABs classified into this group are equipped with PV and EV.
2. Cluster 2: occupied the whole day. The ABs in this cluster installed a BESS and a PV.
3. Cluster 3: unoccupied during office hours (i.e. 9:00 AM to 5:00 PM). The ABs in this cluster are equipped with PV, EV, and BESS.

The controller receives different AB settings including the preferred comfort level, occupancy profile, the scheduled time window of home appliances (e.g. washing machine, dishwasher). It also receives external weather data and retailer import/export prices. This information drives the transaction of money, and energy. By performing a real-time simulation, the controller defines the local prices and sends them to each AB. Each AB participates in the market if it can bring its energy bill down. The detailed explanation of market mechanism is given in Section 4. The control system reports information to each AB through the information and communications technologies infrastructure, assuming no delay in the transformation of data.

The process of solving the optimisation model by the controller is shown in Fig. 1. As illustrated in Fig. 1-(a), each time step of the control horizon passes through three different levels. In the inner level, the model is solved for each building without consideration for B2B. This level minimises the energy bill of buildings which practically affects the energy scheduling of building assets so as to derive less energy from the upper grid. The results of this level are used as a reference for the middle level which tries to activate the local market to achieve lower costs. No change in occupants behaviour is considered in the second level, therefore, it is a deterministic optimisation. Finally, the third level takes into account the uncertainty in the preferences of occupants. This level improves the robustness in face of uncertainty while considering the costs obtained in the lower levels. The process is based on rolling horizon and it is repeated until the last time period. The flow chart for solving the optimisation method is given in Fig. 1-(b). This methodology is a real-time control technique which considers a real-life social scenario (i.e. occupants comfort level) as the uncertain parameter of optimisation.

3. Residential microgrid operational model

The operational characteristic of the RMG (described in Section 2), consisting of a number of ABs and their incorporated distributed energy resources is discussed in this section. The detailed description of symbols is given in the Nomenclature.

3.1. Home appliances

The consumption pattern of home appliances can be categorised into two groups: (a) those which consume fixed power during the day (e.g. fridge), and (b) those which have cycle operation (e.g. washing machine). While operation of some loads in the first category is shiftable (e.g. vacuum cleaner), the loads in the second category create better degree of flexibility. The operation of latter loads can be shifted based on preferred time-window.

The operation of fixed power consumption tasks is defined based on their starting (i.e. t_{st}) and ending (i.e. t_{en}) time, as follows:

$$\sum_{t_{st}\in\Omega_t}^{t=t_{en}} B^{Ap}_{b,h,t} = 1 \tag{1}$$

where $B^{Ap}_{b,h,t}$ is a binary variable indicating the on/off status of home appliances.

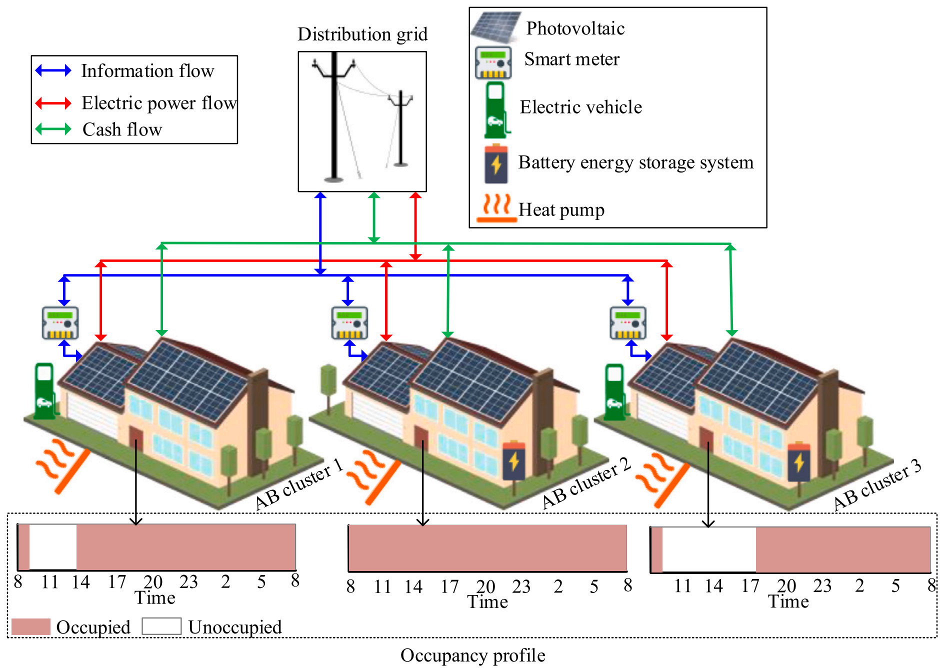

Fig. 2. The conceptual illustration of RMG and its incorporated AB clusters.

In order to model the operation of variable power consumption tasks, there is a need to consider an important fact: their operation cannot be interrupted once they start working. Therefore, the binary variable $B^{Ap}_{b,h,t}$ derives the power consumption of each appliance (i.e. $P^{Ap}_{b,h,t}$) to satisfy required demand of each unit during the whole operation cycle (i.e. $P^{Ap}_{b,h,o}$), as follows:

$$\sum_{t_{st}\in\Omega_t}^{t=t_{en}} B^{Ap}_{b,h,t} P^{Ap}_{b,h,t} = \sum_{o\in\Omega_o} P^{Ap}_{b,h,o} \tag{2}$$

3.2. Photovoltaic units

The output power of these units for each AB is obtained based on the predicted value on a real-time basis. Their output power can be used for supplying the internal load of an AB, traded in the B2B market, traded with the main grid, and stored in the BESS/EV for the similar application in the future time periods. The output power of PV units is constrained as below:

$$0 \le P^{PV_{av}}_{b,t} \le P^{PV_F}_{t} \tag{3}$$

$$0 \le P^{PV}_{b,t} \le P^{PV_{av}}_{b,t} \tag{4}$$

where constraint (3) represents the available PV power based on the real-time prediction, while constraint (4) limits the value of PV output at time period t which is used for supplying load demand, participating in the B2B trading, and exported to the main grid.

3.3. Battery energy storage system

BESS can play a considerable role in the ABs. Application of this technology in the power system has been proven before [34]. This technology can be also efficient in the local markets by storing excess PV generation of an AB and selling it to the other ABs in the community for increasing the profit of owners. The BESS model is given in the following.

$$E^{ES}_{b,t} = E^{ES}_{b,t-1} + \Delta t P^{C_{es}}_{b,t} \times \eta^{C}_{es} - \Delta t P^{D_{es}}_{b,t} \Big/ \eta^{D}_{es} \tag{5}$$

$$E^{ES_{Min}}_{b} \le E^{ES}_{b,t} \le E^{ES_{Max}}_{b} \tag{6}$$

$$E^{ES}_{t_{st}} = E^{ES}_{t_{en}} \tag{7}$$

$$0 \le P^{C_{es}}_{b,t} + P^{C^{pv}_{es}}_{b,t} \le B^{es}_{b,t} \times P^{C^{\max}_{ess}}_{b} \tag{8}$$

$$0 \le P^{D_{es}}_{b,t} + P^{D^{b2b}_{es}}_{b,t} \le (1 - B^{es}_{b,t}) \times P^{D^{\max}_{ess}}_{b} \tag{9}$$

$$0 \le P^{C^{pv}_{es}}_{b,t} \le P^{PV_{av}}_{b,t} - P^{PV}_{b,t} \tag{10}$$

$$0 \le P^{D^{b2b}_{es}}_{b,t} \le \sum_{t_1\in\Omega_t}^{(t-1)\in\Omega_t} P^{C^{pv}_{es}}_{b,t} \tag{11}$$

where constraint (5) shows the state of charge of BESS in AB based on charged/discharged power and state of charge in the previous time period; constraints (6) limits the upper and lower state of charge of BESS; constraint (7) ensures that state of charge of battery at the end of period is equal to that of beginning so as to prevent net accommodation. The charging and discharging power of BESS is limited by constraints (8) and (9) respectively, with binary variable $B^{es}_{b,t}$ preventing simultaneous charge and discharge. Note that in constraint (8), the variable $P^{C^{pv}_{es}}_{b,t}$ is the excess PV output at time period t that is charged to the BESS, which is limited by constraint (10). This charged power can be used for supplying internal demand, exporting to the main grid, or trading in the B2B market. This constraints enables the full utilisation of available PV power. Finally, Constraint (11) shows the contribution of each building into the local market based on their excess PV generation.

3.4. Heat pumps

Heat pumps are environmentally friendly sources of providing heating and cooling energy. They can draw heating or cooling from the environment and provide buildings with their energy needs. These units consume electricity and their operation is modelled as:

$$B^{HP}_{b,t} H^{HP}_{b,t} + (1 - B^{HP}_{b,t}) C^{HP}_{b,t} \le P^{HP}_{b,t} COP \tag{12}$$

$$P^{HP}_{b,t} \le P^{HP_{\max}}_{b} \tag{13}$$

where constraint (12) shows the operation of heat pump for providing heating or cooling, and constraint (13) limits the electric power consumption of heat pump.

3.5. Electric vehicles

The operational model of the EV battery is similar to that of BESS. However, considering the power consumed by transport vector and its effect on the availability of EVs in providing services for the ABs, the operational model of these units should be adopted. Also, participation of an AB in the B2B market is similar to the BESS. The mathematical model of EVs is given in the following.

$$E_{b,t}^{EV} = E_{b,t-1}^{EV} + \Delta t P_{b,t}^{C_{ev}} \times \eta_{ev}^{C} - \Delta t P_{b,t}^{D_{ev}} \Big/ \eta_{ev}^{D} - \Delta t P_{b,t}^{T_{ev}} \tag{14}$$

$$E_{b}^{EV_{Min}} \leq E_{b,t}^{EV} \leq E_{b}^{EV_{Max}} \tag{15}$$

$$0 \leq P_{b,t}^{C_{ev}} + P_{b,t}^{C_{ev}^{pv}} \leq B_{b,t}^{C_{ev}} \times P_{b}^{C_{ev}^{\max}} \tag{16}$$

$$0 \leq P_{b,t}^{D_{ev}} + P_{b,t}^{D_{ev}^{b2b}} \leq B_{b,t}^{D_{ev}} \times P_{b}^{D_{ev}^{\max}} \tag{17}$$

$$B_{b,t}^{D_{ev}} + B_{b,t}^{C_{ev}} \leq 1 \tag{18}$$

$$B_{b,t_{dr}}^{C_{ev}} = B_{b,t_{dr}}^{D_{ev}} = 0 \tag{19}$$

$$0 \leq P_{b,t}^{C_{ev}^{pv}} \leq P_{b,t}^{PV_{av}} - P_{b,t}^{PV} \tag{20}$$

$$0 \leq P_{b,t}^{D_{ev}^{b2b}} \leq \sum_{t_1 \in \Omega_t}^{(t-1)\in\Omega_t} P_{b,t}^{C_{ev}^{pv}} \tag{21}$$

where Eq. (14) denotes the state of charge of EV, which is defined based on the value of energy in the previous time period, charging/discharging power, and the power consumed for the transportation. Note that this model is only applicable for those buildings which have EVs. Constraint (15) limits the state of charge of EV, while constraints (16) and (17) limit the charging and discharging power of EV. Constraint (18) prevents simultaneous charge and discharge while (19) indicates that no charging and discharging happens in the time periods that the EV is on the road (i.e. t_{dr}). Finally, constraints (20) and (21) guarantee the full utilisation of PV power and show the contribution of each building into the local market based on their excess PV generation respectively.

3.6. Occupants comfort

Occupants comfort is a critical factor in energy management of dwelling units [29]. Therefore, the willingness of building users to participate in any market should be considered in control and optimisation of ABs. In this study, the occupants comfort is modelled by an index which represents the thermal and visual comfort of ABs, as below:

$$OC_{b,t}^{AB} = \left(\psi_{b,t}^{V} \times I_{b,t}^{V} + \psi_{b,t}^{Th} \times I_{b,t}^{Th}\right) \Big/ T_{b}^{oc} \tag{22}$$

$$OC_{b,t}^{AB_{\min}} \leq OC_{b,t}^{AB} \tag{23}$$

$$I_{b,t}^{V} = 1 - \left(\frac{V_{b,t}^{T} - V_{b,t}^{Set}}{V_{b,t}^{Set}}\right)^2 \tag{24}$$

$$V_{b,t}^{T} = V_{b,t}^{B} + V_{t}^{N} \tag{25}$$

$$V_{b,t}^{B} = \frac{\kappa_b P_{b,t}^{I} f_b \eta_I^u . \eta_I^m}{A_b} \tag{26}$$

$$V_{b,t}^{B_{\min}} \leq V_{b,t}^{T} \leq V_{b,t}^{B_{\max}} \tag{27}$$

$$0 \leq P_{b,t}^{I} \leq P_{Max}^{I} \tag{28}$$

$$I_{b,t}^{Th} = 1 - \left(\frac{T_{b,t}^{B} - T_{b,t}^{Set}}{T_{b,t}^{Set}}\right)^2 \tag{29}$$

$$T_{b,t+1}^{B} = T_{b,t}^{B} + \frac{\Delta t}{R_b^{th} D_b^{th}} \left(T_t^{out} - T_{b,t}^{B}\right) + \frac{\Delta t}{D_b^{th}} Q_{b,t}^{th} \tag{30}$$

$$Q_{b,t}^{th} = B_{b,t}^{th} \times H_{b,t}^{th} - (1 - B_{b,t}^{th}) \times C_{b,t}^{th} \tag{31}$$

$$T_b^{B_{\min}} \leq T_{b,t}^{B} \leq T_b^{B_{\max}} \tag{32}$$

Eq. (22) shows the general comfort index of each AB, which is obtained based on thermal and visual comfort indices. According to Constraints (23), the occupant comfort index should meet the requirements of building users. Eq. (24) shows the visual comfort index. The illuminance level inside each AB is obtained based on the outside level of illuminance and that of lighting devices in Eq. (25). The illuminance level provided by lighting devices is obtained by Eq. (26) [35]. Constraint (27) limits the total illumination level of each AB. Constraint (28) limits the power consumption of lightning devices. The thermal comfort index is shown by Eq. (29), while constraint (30) represents the indoor temperature based on the building reactance/capacitance thermo-dynamic model [35]. The heating/cooling requirement of AB is modelled by constraint (31). Finally, constraint (32) limits the temperature inside each AB.

3.7. Energy balance

The power provided by different distributed energy resources in the RMG, as well as that of importing/exporting from the main grid is utilised to supply the demand inside the community. The following energy balance constraints are considered.

$$\begin{aligned} &\textstyle\sum_{h\in\Omega_h} \left(B_{b,h,t-o}^{Ap} P_{b,h,o}^{Ap}\right) + P_{b,t}^{I} + P_{b,t}^{D_{es}} + P_{b,t}^{D_{ev}} + P_{b,t}^{G_E} + P_{b,t}^{HP} \\ &= P_{b,t}^{G_I} + P_{b,t}^{PV} + P_{b,t}^{C_{es}} + P_{b,t}^{C_{ev}} \end{aligned} \tag{33}$$

$$\begin{cases} H_{b,t}^{HP} = H_{b,t}^{th} \\ C_{b,t}^{HP} = C_{b,t}^{th} \end{cases} \tag{34}$$

$$P_{b,t}^{T_{ev}} = \Delta D_{b,t}^{EV} \times \eta_{ev}^{t} \tag{35}$$

where constraint (49) is the electric power balance constraint containing of different power consumption and generation parts. The technical models of each asset have been provided in the preceding subsections. Constraint (34) shows the heating/cooling energy balance. Finally, Eq. (35) represents the power consumption in the transport vector based on driving distance and efficiency of EV. Note that the heat pump is the linking variable between electricity and heating/cooling energy sector, while variable $P_{b,t}^{T_{ev}}$ is the linking variable between electricity and transport vectors.

4. Robust building-to-building mechanism

In this study, a community-based B2B energy trading method is developed for the RMG. In this framework, ABs share their information with a central controller which coordinates the market. This controller encourages ABs to participate in the local market by sending them the local price signals. Therefore, ABs participate in the market in a decentralised manner [7]. In this paradigm, ABs first share their available consumption and generation requirements, and then, the remaining energy surplus/need will be shared with the main grid. This process is modelled in three phases: individual building level, community level, and transaction with the main grid.

4.1. Building level

In addition to the PV units as the local generation, the potential of BESS and EVs in storing generated PV and trading it locally in another time is taken into account. The B2B process starts from individual ABs, where they calculate their available generation and demand capacity. Eqs. (36) and (37) represent the available demand and generation of each AB respectively. It is worth mentioning that the AB demand in this study is a variable, rather than a fixed parameter.

$$P_{b,t}^{Dem} = \sum_{h\in\Omega_h}\left(B_{b,h,t-o}^{Ap} P_{b,h,o}^{Ap}\right) + P_{b,t}^{I} + P_{b,t}^{C_{es}^{pv}} + P_{b,t}^{C_{ev}^{pv}} + P_{b,t}^{HP} \tag{36}$$

$$P_{b,t}^{Gen} = P_{b,t}^{PV} + P_{b,t}^{D_{es}^{b2b}} + P_{b,t}^{D_{es}^{b2b}} \tag{37}$$

4.2. Community level

At the community level, ABs share their energy surplus or requirements with each other locally. This transaction should be subjected to: (a) available capacity of ABs (i.e. the import/export power from the main grid cannot be traded in the B2B), (b) role of an AB as a buyer or a seller at a specific time period. Also, the amount of shared energy in the local market should be equal to that of received at each time interval. These conditions are mathematically described as follows:

$$P_{b,t}^{Net} = \min\left\{P_{b,t}^{Gen}, P_{b,t}^{Dem}\right\} \tag{38}$$

$$P_{b,t}^{b2b^-} \le B_{b,t}^{b2b}\left(P_{b,t}^{Gen} - P_{b,t}^{Net}\right) \tag{39}$$

$$P_{b,t}^{b2b^+} \le (1 - B_{b,t}^{b2b})\left(P_{b,t}^{Dem} - P_{b,t}^{Net}\right) \tag{40}$$

$$P_{b,t}^{B2B} = P_{b,t}^{p2p^+} - P_{b,t}^{p2p^-} \tag{41}$$

$$\sum_{b\in\Omega_b} P_{b,t}^{B2B} = 0 \tag{42}$$

The amount of surplus/deficit power of each building is obtained by (38). Based on the value of $P_{b,t}^{Net}$, constraints (39) and (40) represent the role of ABs as provider or receiver in the B2B market respectively. The binary variable $B_{b,t}^{b2b}$ prevents simultaneous selling and buying of energy by an individual AB at each time period. Eq. (41) shows the total value of B2B for each AB. Finally, according to Constraint (41), the amount of energy shared in the B2B transaction should be equal to the energy received among all ABs in the community. This constraint is a necessary condition of a community-based B2B energy trading optimisation which (a) actualise B2B trading based on internal capacity of community, and (b) guarantees that the energy transaction within the community would not affect the upper grid.

4.3. Transaction with the main grid

Finally, the excess generation or demand of the community is received/provided by the main grid, as below:

$$\begin{aligned} &P_{b,t}^{G_I} + P_{b,t}^{Gen} + P_{b,t}^{P2P} + P_{b,t}^{D_{es}} + P_{b,t}^{D_{ev}} \\ &= P_{b,t}^{G_E} + P_{b,t}^{Dem} + P_{b,t}^{C_{ev}} + P_{b,t}^{C_{es}} \end{aligned} \tag{43}$$

4.4. Local pricing method

In a community-based B2B energy trading, participating in the local market is encouraged by the control system through determining the local prices. These price signals should be economically beneficial for the ABs to participate in the market, while the energy surplus/need is still traded with the main grid based on national market prices. Bill sharing and mid-market rate frameworks are the most common local pricing methods that are used in the literature. The superiority of mid-market rate over bill sharing method in terms of properly incentivising the participants to take part in the market is demonstrated in [9]. Therefore, the mid-market rate method is utilised in this study for defining the local price signals.

In the mid-market rate method, the local buy and sell prices are defined based on the available generation (i.e. $\sum_b P_{b,t}^{Gen}$) and demand (i.e. $\sum_b P_{b,t}^{Dem}$) within the community. Considering $\gamma_t^{G_b}$ and $\gamma_t^{G_s}$ as the buying and selling prices from/to the main grid respectively, if the local generation matches the demand, the local buy (i.e. $\gamma_t^{C_b}$) and sell (i.e. $\gamma_t^{C_s}$) prices will be defined as the average of grid buy and sell prices, as below:

$$\gamma_t^{C_b} = \gamma_t^{C_s} = \gamma_t^{C_{mid}} = \left(\gamma_t^{G_b} + \gamma_t^{G_s}\right)\Big/2 \tag{44}$$

However, local generation or demand could be higher in some intervals. Therefore, the mid-market rate method suggests two different strategies.

If the local demand is higher that generation, the main grid supplies the deficit energy with the contract prices, and the local buy and sell prices are defined as follows:

$$\gamma_t^{C_b} = \frac{\sum_{b\in\Omega_b}\left(P_{b,t}^{Gen} \times \gamma_t^{C_{mid}}\right) + \sum_{b\in\Omega_b}\left(P_{b,t}^{Dem} - P_{b,t}^{Gen}\right) \times \gamma_t^{G_b}}{\sum_{b\in\Omega_b} P_{b,t}^{Dem}} \tag{45}$$

$$\gamma_t^{C_s} = \gamma_t^{C_{mid}} \tag{46}$$

If the local generation is higher than demand, the main grid buys the surplus energy with the contract prices, and the local buy and sell prices are defined as follows:

$$\gamma_t^{C_s} = \frac{\sum_{b\in\Omega_b}\left(P_{b,t}^{Dem} \times \gamma_t^{C_{mid}}\right) + \sum_{b\in\Omega_b}\left(P_{b,t}^{Gen} - P_{b,t}^{Dem}\right) \times \gamma_t^{G_s}}{\sum_{b\in\Omega_b} P_{b,t}^{Gen}} \tag{47}$$

$$\gamma_t^{C_b} = \gamma_t^{C_{mid}} \tag{48}$$

4.5. Energy bill

Based on the described pricing mechanism, the energy bill of each individual AB is obtained as below:

$$EB_b = \sum_{t\in\Omega_t}\left[\Delta t\left(\gamma_t^{G_b} P_{b,t}^{G_I} - \gamma_t^{G_s} P_{b,t}^{G_E}\right) + \Delta t\left(\gamma_t^{C_b} P_{b,t}^{p2p^+} - \gamma_t^{C_s} P_{b,t}^{p2p^-}\right)\right] \tag{49}$$

where the first two terms are cost and income of energy exchange with the main grid based on the retail prices, while the third and fourth terms are respectively cost of buying and selling energy in the B2B market. In the proposed optimisation, this equation is considered as the objective function, which is minimised by the RMG controller.

4.6. Robust control optimisation

A real-time control framework is required for energy management of RMGs. This will allows the main grid controller to send the security control signals to the distributed local controllers. The import/export power from the main grid is an important decision variable which can limit the energy transaction with the main grid on a real-time basis. Based on this criterion and the price signals, local controllers can guide their incorporated communities so as to achieve an optimised solution.

Besides, the real-time control method allows the controllers to receive real-time input data and compile their optimisation. This includes the output power of PV units, weather related inputs, and the price signals. The controller can define the local price signals and report them to the ABs. Although the RHC based methods are suitable for dealing with input variation, in the building sector, there is still one source of uncertainty which is difficult to predict and describe: the occupants' related inputs.

Due to the importance of building occupants in any optimisation related to the AB sector, they can create challenges. On the other hand, since human behaviour is highly unpredictable, it is difficult to model the uncertainty of such denominators. In addition, it has been argued in [30] that there is a need to account for uncertainty in the RHC-based methods. Therefore, in this study, considering the occupant comfort level as the indicator of building users, a robust methodology is introduced for improving the robustness of B2B energy trading optimisation. To do so, the information gap decision theory technique is utilised for improving the RMG controller robustness in face of occupant comfort level.

The information gap decision theory presents an effective approach for characterising uncertainties that lack substantial information and cannot be adequately modelled using probability distribution functions [36]. Unlike stochastic and probabilistic methods, this approach does not necessitate extensive information about uncertain parameters and offers significantly reduced computational time compared to techniques like the scenario-based approach [31]. Given the limited information available regarding uncertainty in occupancy profiles, this study employs information gap decision theory to manage uncertainties related to user behaviour. The general optimisation model associated with this approach is outlined below:

$$f = \max_{x}(f(X,\kappa)) \tag{50}$$

$$E(X,\kappa) \leq 0 \tag{51}$$

$$I(X,\kappa) = 0 \tag{52}$$

$$\kappa \in U(\bar{\kappa},\alpha) = \left\{ \kappa : \left| \frac{\kappa - \bar{\kappa}}{\bar{\kappa}} \right| \leq \alpha \right\} \tag{53}$$

where X denotes the set of decision variables in the optimisation problem, while κ represents the vector representing the uncertain parameter. E and I respectively signify equality and inequality constraints within the optimisation framework, and U denotes the uncertainty set. α represents the maximum allowable deviation of the predicted uncertainty parameter from its estimated value, as described by Eq. (53).

The first step in addressing a problem using information-based decision theory involves solving the following optimisation problem under the assumption of no deviation between the uncertain parameter and its predicted value.

$$f_b = \max_{x}(f(X,\bar{\kappa})) \tag{54}$$

$$E(X,\kappa) \leq 0 \tag{55}$$

$$I(X,\kappa) = 0 \tag{56}$$

The result of this optimisation problem yields the baseline value of the objective function. However, given the adverse impact of uncertainty in occupant behaviour on the objective function, a risk-averse strategy is employed to enhance the robustness of the objective function in the presence of uncertainty in the input parameters. Therefore, in this approach, the decision variable X is determined in such a manner that it ensures the robustness of the objective function even if the uncertain parameter κ deviates from its predicted value (i.e., $\bar{\kappa}$). This strategy is mathematically described as below:

$$\max_{x} \alpha \tag{57}$$

$$E(X,\kappa) \leq 0 \tag{58}$$

$$I(X,\kappa) = 0 \tag{59}$$

$$f(X,\kappa) \geq f_b(X,\kappa) \times (1-\beta) \tag{60}$$

$$0 \leq \beta \leq 1 \tag{61}$$

It is worth mentioning that β influences decision-makers' risk preferences by reflecting their attitudes towards uncertainty. In situations where the consequences of decisions are uncertain, individuals may exhibit varying levels of risk aversion or risk tolerance. β allows for the incorporation of these risk preferences into decision-making frameworks, enabling decision-makers to weigh the potential risks and rewards associated with different courses of action.

According to the principles of the information gap decision theory, the controller solves the following optimisation for the RMG.

$$\max_{DV} \left\{ \sum_{t\in\Omega_t} \frac{\alpha_t}{\Delta t} \left(\min \sum_{b\in\Omega_b} EB_b \times (1+\beta) \geq \sum_{b\in\Omega_b} EB_b \right) \right. \tag{62}$$

$s.t$:

$$(1+\alpha_t)OC_{b,t}^{AB_{\min}} \leq OC_{b,t}^{AB} \tag{63}$$

$$0 \leq \beta \leq 1 \tag{64}$$

$$(5)\text{–}(22), (24)\text{–}(49) \tag{65}$$

Eq. (62) is the objective function of the proposed control framework, where the uncertainty radius is maximised in face of occupants behaviour while the energy bill is kept within a permissible value. In order to improve robustness, the energy bill is increased. The amount of increase in the energy bill is defined by the controller, which is agreed between ABs in the community. This increase is called cost of system robustness. Constraint (63) shows the effect of uncertainty radius on the occupants comfort index, which reflects the user preferences. Solving this optimisation derives a set of decision variables which define the operation of different AB assets, local market prices, the energy scheduling of different assets, and the robustness factor.

5. Simulation results

The proposed methodology is tested for a community of ABs, consisting of 10 residential buildings. Note that the proposed model can be solved for any number of buildings. ABs are connected to the main grid at the point of integration. As discussed, ABs are clustered based on their occupancy profile and installed distributed energy resources. The information on the AB clusters, and the inclusion of different home appliances in each building is summarised in Table 2. The characteristic of EVs and BESS is given in Table 3 [7], while the driving distance of EVs is taken from [37].

The import and export prices from/to the main grid are taken from [18], where the import price is defined based on time-of-use tariff structure and export prices are defined based on feed-in-tariff. The PV outputs are defined using the PV Watts Calculator [38]. The parameters of thermal and visual comfort indices are provided in Table 4 [2,35].

The proposed optimisation is a mixed integer non-linear programming (MINLP) model which is coded in general algebraic modelling system (GAMS) [39] using DICOPT solver. The system is compiled for 24 h, in 30-minute time interval, starting from 8:00 AM. The simulation is examined on a personal computer with an Intel Core i7-3.00 GHz and 8 GB of RAM.

In order to evaluate the performance of the proposed method, the following case studies are analysed.

Case I: This case study is solved without consideration for B2B energy trading.

Case II: This case study considered B2B energy trading. It is solved in a deterministic environment.

Case III: This case study considered B2B energy trading, but without consideration for occupant comfort.

Case IV: This case study provides a robust solution where occupant comfort level is an uncertain input.

Table 2
Building clusters and their incorporated appliances.

building No.	Cluster No.	Included appliances	Appliance No.	Description
b_1	2	$h_1 - h_{10}$	h_1	Dishwasher
b_2	3	$h_1 - h_6, h_{10}$	h_2	Washing machine
b_3	3	$h_7 - h_{10}$	h_3	Spin dryer
b_4	1	$h_1 - h_4, h_6 - h_7, h_{10}$	h_4	Cooker hob
b_5	1	$h_4 - h_{10}$	h_5	Cooker oven
b_6	2	$h_1 - h_{10}$	h_6	Microwave
b_7	1	$h_1 - h_4, h_8 - h_{10}$	h_7	Laptop
b_8	1	$h_1 - h_4, h_6 - h_{10}$	h_8	Desktop
b_9	2	$h_1 - h_{10}$	h_9	Vacuum cleaner
b_{10}	3	$h_5 - h_7, h_9 - h_{10}$	h_{10}	Fridge

Table 3
Technical parameters of EVs, and BESSs [7].

EV		BESS	
Parameter	value (unit)	Parameter	value (unit)
$E_b^{EV_{Max}}$	15 (kWh)	$E_b^{ES_{Max}}$	10 (kWh)
$E_b^{EV_{Min}}$	5 (kWh)	$E_b^{ES_{Min}}$	5 (kWh)
$P_b^{C_{ev}^{\max}}$	6 (kW)	η_{es}^C	95 (%)
$P_b^{D_{ev}^{\max}}$	6 (kW)	η_{es}^D	95 (%)
η_{ev}^C	93 (%)	$P_b^{C_{es}^{\max}}$	4 (kW)
η_{ev}^D	93 (%)	$P_b^{D_{es}^{\max}}$	4 (kW)
η_{ev}^t	(1/6) (kW/km)		

Table 4
Parameters of thermal and visual comfort indices [2,35].

Parameter	value (unit)	Parameter	value (unit)
R_b^{th}	18 (°C/kW)	κ_b	20
D_b^{th}	0.525 (kWh/C°)	A_b	150 (m^2)
$T_b^{B_{\min}}$	18 (C°)	η_I^u	0.8
$T_b^{B_{\max}}$	25 (C°)	η_I^u	0.8
$T_{b,t}^{Set}$	22.5 (C°)	f_b	5000
$P_b^{HP_{\max}}$	1.5 (kW)	$V_{b,t}^{B_{\min}}$	500 (lux)
$V_{b,t}^{Set}$	650 (lux)	$V_{b,t}^{B_{\max}}$	900 (lux)

Table 5
Energy bill in different case studies.

Case study	Case I	Case II	Case III	
Energy bill (£)	4.47	4.27	3.30	4.42

This section aims at evaluating the performance of the introduced method. The proposed method (i.e. Case IV) is compared with other cases so as to demonstrate its effectiveness, particularly in terms of the impact of occupants comfort and uncertainty on community energy exchange. In addition, application of EVs in the B2B energy trading is evaluated. Finally, the sensitivity of uncertainty in occupant comfort level is examined against the robustness budget.

5.1. Economic analysis

Table 5 illustrates the cumulative energy bills of the RMG across different case studies. In Case IV, the robustness band is assumed to be 5%. A comparison between Cases I and II reveals that participation in B2B energy trading led to a lower energy bill, with costs reduced by 4.5%. Additionally, despite aiming to enhance robustness within a specific budget, the energy bill in Case IV remains lower than that of Case I. This underscores the economic efficiency of our proposed method in achieving robust solutions at minimal cost, indicating that B2B can enhance the robustness of local control systems. Lastly, it is notable that neglecting the occupants comfort index reduced the energy bill to £3.30, marking a 23% decrease compared to Case II.

5.2. Importance of occupant comfort and uncertainty management

Fig. 3 depicts the cumulative imported and exported power from/to the main grid for different case studies. A notable observation is the reduction in power imported from the main grid in Case II compared to Case I, accompanied by an increase in cumulative power export. This indicates that B2B energy trading decreases the reliance on power imports from the main grid while facilitating greater power export. Additionally, the comparison between cases II and III reveals an increase in power demand from the main grid when considering the occupant comfort index. Furthermore, when comparing Case IV with Case II, there is a noticeable increase in imported power from the main grid, particularly evident at 1:30 AM. This reflects the RMG's need to enhance robustness in response to uncertainty in occupant behaviour, opting for more reliable generation sources over volatile renewable generation within the community. Overall, the comparisons between cases III and IV with Case II underscore the impact of considering occupants comfort and uncertainty in occupant behaviour on the increased need for importing power from the main grid.

The local energy exchange between ABs is illustrated in Fig. 4. This visualisation demonstrates how the occupants comfort index and uncertainty in occupancy profiles impact B2B power exchange dynamics. The exchange predominantly occurs during hours of high energy demand, notably in the evening. ABs engage in power exchange based on their grouped clusters, considering their equipped assets and occupancy profiles. For example, Building b_1 serves as a power receiver due to its daytime occupancy and lack of EV assets. Conversely, Building b_2 operates in the opposite role, sharing excess energy with other ABs as it remains unoccupied during office hours and possesses diverse assets. Comparing Case III to Case II, it is evident that the participation of buildings in local energy exchange increases, reflecting the impact of occupants comfort in reducing B2B exchange values. Additionally, there is a higher level of power exchange in the robust solution, indicating that ABs actively participate in the local market to enhance robustness against uncertainty in occupants comfort levels. Given the significant role of B2B in reducing energy bills (as shown in Table 5), increased participation occurs in the robust solution to lower costs.

Fig. 5 illustrates the local buy and sell prices for cases II (without consideration for uncertainty) and IV (robust solution). This visualisation sheds light on the impact of uncertainty in occupants behaviour on local pricing dynamics. During time periods when PV generation exceeds demand for each AB (from 7:00 AM to 3:00 PM), as observed in the deterministic case (Case II), local sell prices fluctuate based on the interplay between generation and demand. However, in the robust case, fluctuations in occupant comfort levels alter demand patterns, prompting ABs to utilise available PV generation to satisfy comfort requirements. Consequently, local sell prices stabilise around the average value of import and export grid prices during these periods. Conversely, during peak-load periods when most ABs are occupied (from 3:00 PM to 12:00 AM), local demand outstrips generation capacity. As a result, local buy prices rise above the average value during this timeframe. Notably, the local buy prices in Case IV surpass those in Case II during these peak-load periods, underscoring the influence of occupant comfort on price signals. This analysis underscores the intricate interplay

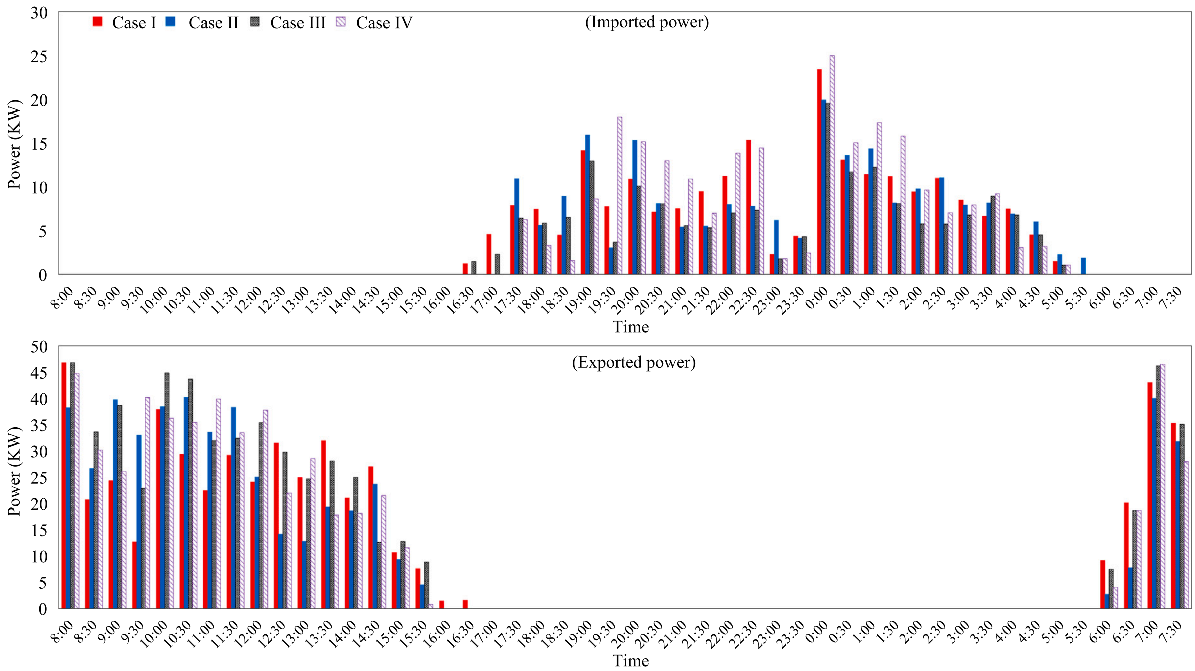

Fig. 3. Cumulative power exchange with the main grid in different case studies.

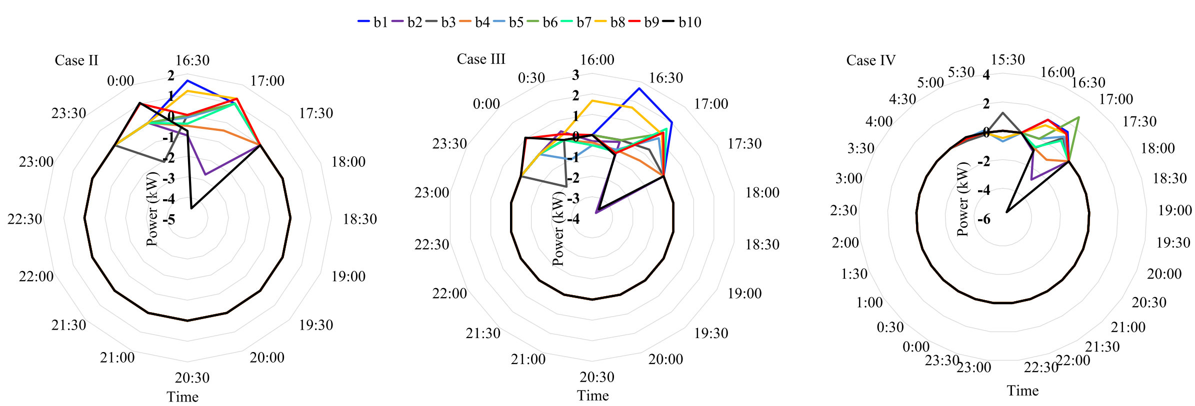

Fig. 4. Energy exchange between ABs in different strategies.

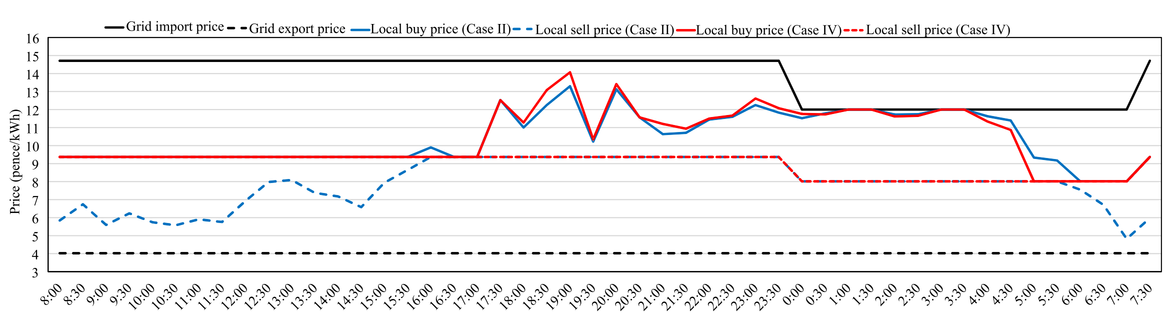

Fig. 5. Local buy and sell prices in deterministic and uncertain environment.

between occupants comfort levels, energy demand, and local pricing dynamics, emphasising the need for robust solutions that can adapt to uncertainties in occupants behaviour to ensure stable and equitable pricing mechanisms within the community.

The indoor temperature values of AB b_1 across different case studies are illustrated in Fig. 6. A comparison between cases I and IV reveals that despite ABs engaging in the B2B strategy and the system's robustness improving, the indoor temperature is higher in the latter case. Additionally, the indoor temperature in Case IV exceeds that of Case II. These results indicate that the proposed robust solution achieves better occupant satisfaction. Furthermore, the figure highlights how ABs can adapt to demand patterns, with temperatures rising above the

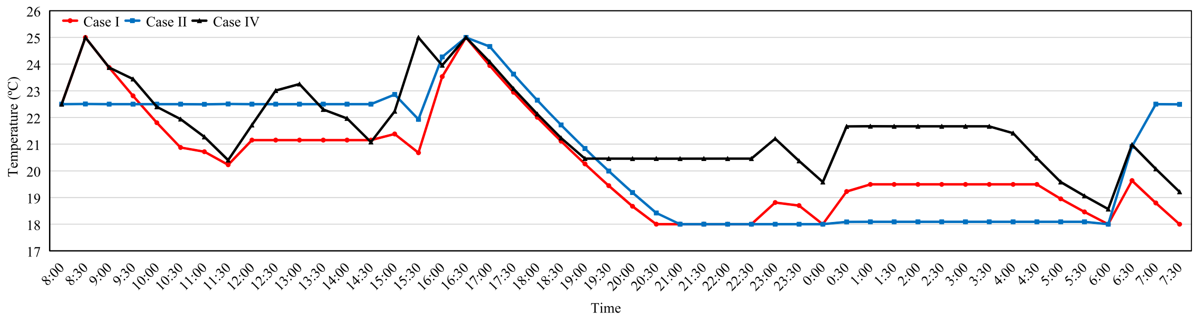

Fig. 6. Indoor temperature of AB b_1 in different case studies.

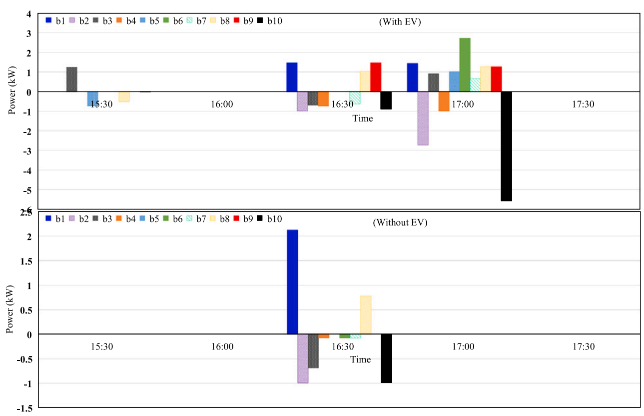

Fig. 7. Energy exchange between ABs with and without EV participation.

setpoint (i.e., 22.5 °C) during off-peak periods (i.e., from 8:00 AM to 4:30 PM) and gradually decreasing during on-peak periods (i.e., from 5:00 PM to 9:30 PM). This flexibility allows AB owners to leverage the thermodynamic characteristics of their properties, effectively using ABs as virtual storage assets to participate in various energy markets. Overall, this analysis underscores the potential for optimising indoor temperature management within ABs to enhance energy efficiency and maximise benefits in dynamic energy trading scenarios.

5.3. Role of electric vehicles

To underscore the significance of integrating the transport vector into P2P energy trading among ABs, we focus on a specific time-frame characterised by heightened local energy transactions (from 3:30 PM to 5:30 PM), as highlighted in Fig. 7 for Case III, with and without EVs. This visualisation reveals that the participation of EVs has notably augmented the local energy exchange between ABs within this time-frame. Moreover, the absence of EVs has had a cascading effect, influencing the participation of ABs that do not possess any vehicles, particularly those in Cluster 2. By examining this critical period, we gain insights into how the inclusion or exclusion of EVs impacts the dynamics of local energy exchange among ABs. This underscores the crucial role of integrating the transport vector into P2P energy trading schemes, not only for ABs with EV assets but also for those without, thereby fostering a more comprehensive and impactful energy ecosystem within the community.

5.4. Building operation characteristics

The comparison of available generation and demand for buildings b_1 (Cluster 2) and b_2 (Cluster 3) is depicted in Fig. 8. This comparison provides insights into the role each building plays in the local energy market. Building b_1 exhibits higher energy demand, particularly noticeable between 4:00 PM and 6:00 PM, as illustrated in Fig. 8. Consequently, during this timeframe, b_1 functions as an energy receiver, requiring support from the grid. Conversely, building b_2 showcases a surplus in generation during the same period. Therefore, b_2 assumes the role of an energy provider, contributing excess energy to the local market. Furthermore, the surplus generation predominantly occurs during hours of lower energy demand, as evident from the data. Consequently, buildings like b_2 export excess power to the main grid during these periods, as depicted in Fig. 3. This analysis highlights the dynamic interaction between energy generation and demand among different buildings within the community, underscoring the importance of efficient energy management strategies to optimise resource utilisation and minimise reliance on external energy sources.

The ON/OFF status of shiftable power appliances, such as washing machines and dishwashers, for buildings b_1 (Cluster 2) and b_2 (Cluster 3) is visualised in Fig. 9. This depiction offers insights into the timing of appliance usage in relation to B2B energy trading activities. Building b_2 exhibits a strategy of shifting its appliances' ON/OFF status to a period preceding the participation of ABs in the local market, specifically between 4:00 PM and 6:00 PM. Conversely, building b_1 adjusts its appliances' status to coincide with the time period of energy trading in the local market. As a result, b_1 demonstrates flexibility not only in energy generation but also in demand, aligning appliance usage with opportunities for participation in local energy markets. This analysis underscores the significance of flexible energy consumption patterns enabled by shiftable power appliances, contributing to the optimisation of energy utilisation and enhancing the efficiency of B2B energy trading within the community.

5.5. Sensitivity analysis

The tolerable value of robustness (denoted as β) plays a crucial role in expanding the uncertainty radius, thereby enhancing system robustness. Fig. 10 illustrates the relationship between the uncertainty radius and variations in β. It is evident from this figure that increasing the value of β results in a corresponding increase in system robustness. However, achieving a higher level of robustness while ensuring occupants satisfaction poses a significant challenge. For instance, to elevate the robustness degree from 1.05% to 1.15% (i.e., a 0.1% increase), the controller must increase β by 6%. This phenomenon is attributed to the substantial portion of building energy consumption dedicated to providing occupants comfort. This finding underscores the profound impact of even marginal changes in occupants behaviour on the energy management of buildings and their participation in local energy markets.

6. Conclusion

This paper presents a multi-level energy management strategy for building participation in peer-to-peer energy trading. Recognising the pivotal role of occupants in building-level decision-making, occupants comfort is integrated as a crucial consideration in the optimisation

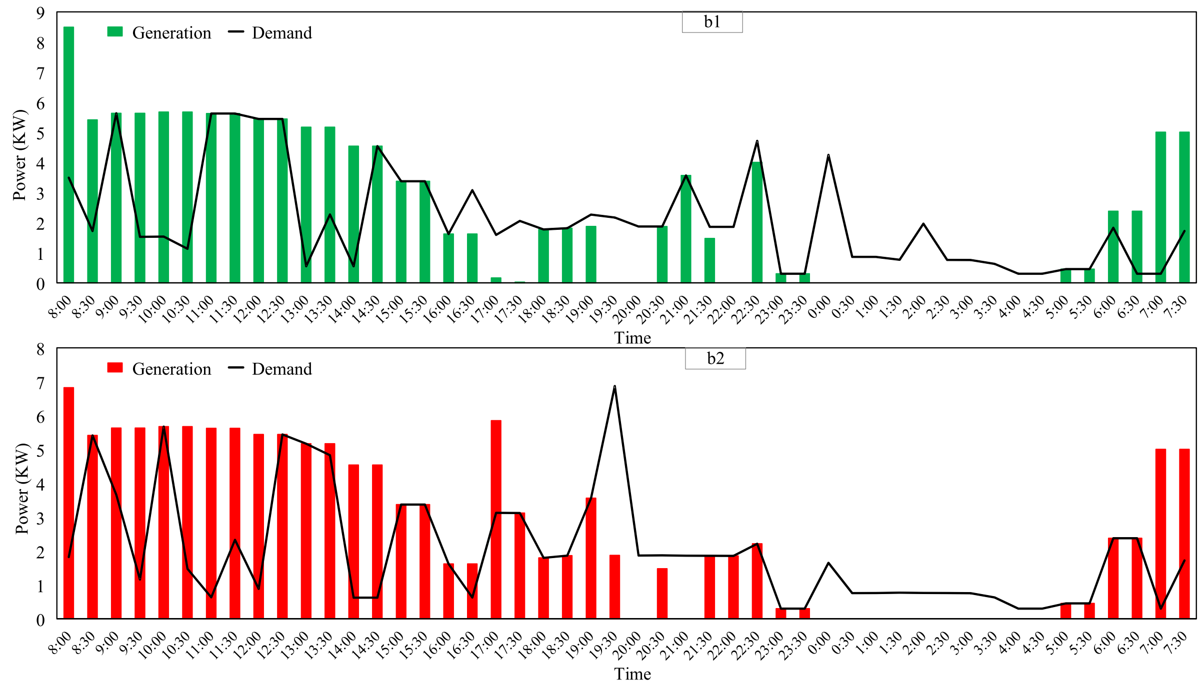

Fig. 8. Generation and demand capacity of ABs b_1 and b_2.

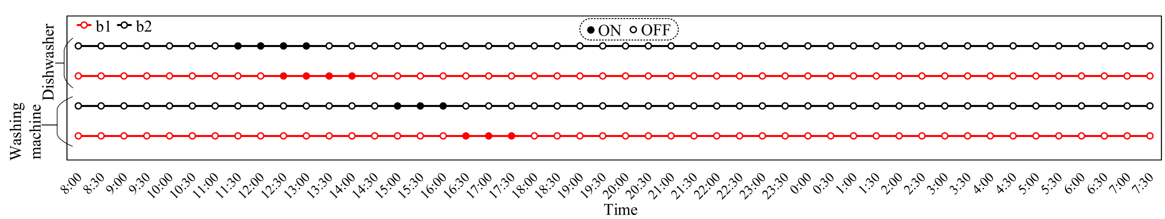

Fig. 9. ON/OFF status of shiftable home appliance for ABs b_1 and b_2.

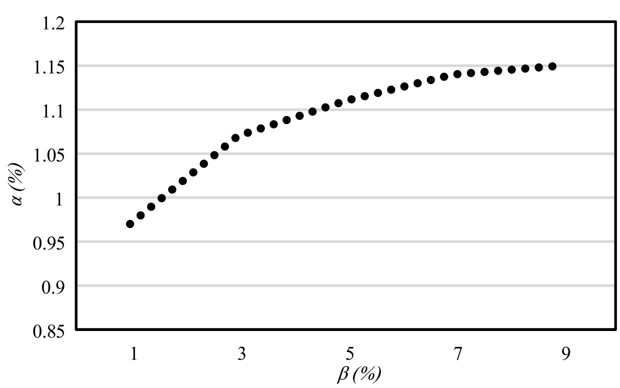

Fig. 10. Variation of robustness degree over the changes in β.

framework. Moreover, the impact of uncertainty in occupant comfort levels is investigated using the information gap decision theory method. To address this uncertainty, a robust receding horizon control method is proposed, enhancing the real-time control mechanisms' robustness. Simulation results demonstrate that the proposed building-to-building energy trading approach can reduce energy bills by 4.5% while improving control system robustness. Building participation in such energy trading schemes proves beneficial for improving robustness in the face of uncertainty in occupancy profile, underscoring the advantages of local energy markets. The significance of occupants comfort in building-to-building energy trading is evident, as neglecting this factor can increase participation in community energy exchange. However, integrating occupants comfort indices can enhance the robustness of the community control system against uncertainty in occupancy profiles. Additionally, the simulation results highlight the role of occupants comfort degree in enhancing the robustness of residential microgrids. Furthermore, the presence of electric vehicles in a community significantly influences the value of local energy exchange between buildings, emphasising the importance of considering electric vehicles in energy management strategies. Lastly, it is observed that enhancing the control mechanism's robustness in response to occupant comfort level uncertainty entails a challenging decision-making process with significant budget implications. For instance, active building community needs to increase its total energy bill by 6% in order to achieve 0.1% increase in the robustness against uncertainty of occupant comfort level, necessitating careful consideration by building community managers.

The future research direction could focus on exploring the application of online optimisation methods in futuristic community energy management, considering the exponentially growing number of decision factors, and investigating the security of energy transactions between buildings in the presence of various uncertainties. These research directions offer promise for advancing the understanding and implementation of robust and efficient community energy systems.

CRediT authorship contribution statement

Saman Nikkhah: Conceptualization, Data curation, Formal analysis, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Adib Allahham:**

Formal analysis, Funding acquisition, Resources, Writing – review & editing, Conceptualization. **Arman Alahyari:** Formal analysis, Investigation, Software, Validation, Writing – review & editing. **Charalampos Patsios:** Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing. **Philip C. Taylor:** Funding acquisition, Resources, Supervision, Writing – review & editing. **Sara L. Walker:** Funding acquisition, Resources, Supervision, Writing – review & editing. **Damian Giaouris:** Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

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

Data will be made available on request.

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