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Pool trading model within a local energy community considering flexible loads, photovoltaic generation and energy storage systems

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ABSTRACT

This paper presents a pool trading model within a local energy community considering home energy management systems (HEMSs) and other consumers. A transparent mechanism for market clearing is proposed to incentivise active prosumers to trade their surplus energy within a rule-based pool market in the local energy community. A price-based demand response program (PBDRP) is considered to increase the consumers' willingness to modify their consumption. The mathematical optimization problem is a standard mixed-integer linear programming (MILP) problem to allow for rapid assessment of the trading market for real energy communities which have a considerable number of consumers. This allows for novel energy trading strategies amongst different clients in the model and for the integration of a pool energy trading model at the level of the local energy community. The objective function of the energy community is to minimize the overall bills of all participants while fulfilling their demands. Two different scenarios have been evaluated, independent and integrated operation modes, to show the impacts of coordination amongst different end-users. Results show that through cooperation, end-users in the local energy community market can reduce the total electricity bill. This is shown in a 16.63% cost reduction in the independent operation and a 21.38% reduction in the integrated case. Revenues for active consumers under coordination increased compared to independent operation of the HEMS.

1. Introduction

Current developments in the implementation of the Internet of Things (IoT) concept, Information and Communication Technologies (ICT) and smart grid technologies bring various opportunities for smart homes and residential energy communities to benefit from their smart home appliances. Utilising these new opportunities can improve the environmental sustainability and resilience of these communities (Duman, Erden, Gönül & Güler, 2021).

A. Context

One of the interesting features of smart energy buildings is that end-users can effectively control their appliances which are plugged into the electricity grid. There is an emerging technology developed for smart monitoring and controlling home appliances called "home energy management system (HEMS)", aimed at using smart plug systems to schedule and control the home appliances. The flexibility, replicability, and reliability of such systems make them much more attractive for smart buildings and residential energy communities. The combination of the smart metering systems and IoT technology transforms conventional distribution networks into smart grids since such technologies can provide real-time energy and data simultaneously (Lo & Ansari, 2012) and (Kienzle, Ahčin & Andersson, 2011).

Both demand response (DR) and HEMS bring new challenges and also opportunities for the smart grids and the active prosumers in the market (Javadi et al., 2020). This active management of distributed energy generation and demand is key to increasing the sustainability and well-being of residents of these energy communities (Perger, Wachter, Fleischhacker & Auer, 2021). Different challenges have arisen regarding the local energy markets such as the regulation,

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Nomenclature

Sets

i, NA	index/total number of appliances
j, NC	index/total number of energy communities
k, NS	index/total number of electrical energy storage
t, NT	index/total number of time intervals

Parameters

E^{Min}	minimum level of energy in the EES (kWh)
E^{Max}	maximum level of energy in the EES (kWh)
$P^{Ch.,\max}$	maximum charging power of the EES (kW)
$P^{Disch.,\max}$	maximum discharging power of the EES (kW)
$P^{D,Fix}$	hourly fixed demand power (kW)
P_j^{HVAC}	rated power of the HVAC system (kW)
$P_{j,t}^{PV}$	net injected power by the PV panel (kW)
$T_{i,j}$	utilization duration of appliances
$P_{i,j}$	rated power of controllable appliances (kW)
C^{ON}, C^{OFF}	on-off cost of controllable appliances ($)
LB, UB	lower/upper bound of operation time
ρ	electricity hourly tariff (TOU) ($/kWh)
α	grid operation service cost coefficient (%)
β	tax of energy consumption coefficient (%)
μ	building insulation coefficient (%)
ψ	building thermal coefficient (F/kWh)
$\eta^{Ch.}$	efficiency of EES in the charging mode
$\eta^{Disch.}$	efficiency of EES in the discharging mode
$\theta^{\min}, \theta^{\max}$	min/max comfort level of indoor temperature (F)
Δt	time interval (30-min)

Variables

PG^{G2H}	grid-to-home power injection (kW)
$PG_{s,t}^{H2G}$	home-to-grid power injection (kW)
PG^{C2H}	community-to-home power injection (kW)
PG^{H2C}	home-to-community power injection (kW)
$P_{j,t}^{D,Shift}$	shifted power of controllable appliances (kW)
$P_{j,t}^{D,HVAC}$	real power consumed by the HVAC system (kW)
$P_{j,k,t}^{Ch.}$	charging power of the EES (kW)
$P_{j,k,t}^{Disch.}$	discharging power of the EES (kW)
$E_{j,k,t}$	energy stored in the EES (kWh)
$\theta_{j,t}^{in}$	indoor temperature (F)
ON, OFF	turn on/off status of controllable appliances
$B_{i,j,t}$	binary decision variable for baseline loads
$S_{i,j,t}$	binary decision variable for shifted loads
I	corresponding binary variable
DI^{+}, DI^{-}	discomfort index regarding the shifted loads
δ	binary variable for HVAC derated power

Symbols and acronyms

DI	discomfort Index
EES	electrical energy storage
HEMS	home Energy management system
HVAC	heating, ventilation, and air conditioning
H2G	home-to-grid transactions
G2H	grid-to-home transactions
H2C	home-to-community transactions
C2H	community-to-home transactions
PV	photovoltaic

cyber-physical security issues, and energy trading management within the local energy community. On the other hand, flexible supply of the load demand, congestion alleviation, addressing the power mismatch, and improving the grid flexibility through increasing the reserve margin, are the main merits of unlocking the DR and flexible HEMS in the residential sector (Mendes et al., 2018).

Increasing concern over the environmental considerations since the last decades and maintaining the demands at the minimum level of pollution are the most important challenges for governmental energy providers (Estahbanati, 2014). With the ever-increasing penetration of solar photovoltaic (PV) panels into the residential sector, local energy communities can provide a considerable share of renewable and clean energy production (Osório et al., 2021). Moreover, to empower active prosumers to produce clean energy, market-based mechanisms will be required shortly to deal with the decentralized power generation and consumption within the community. Effective local markets are essential in such an environment to handle power and energy requirements between the active participants.

B. Literature review

Although there have been considerable research works in the field of HEMS, aiming at electricity bill reduction, few well-founded research studies have been devoted to investigating the flexibility of smart HEMSs in local energy markets (Khajeh, Laaksonen, Gazafroudi & Shafie-khah, 2019; Lotfi, Almeida, Javadi, Osório & Catalão, 2020; Mohandes, Mohandes, Moursi, Hatziargyriou & Khatib, 2019, 2020; Villar, Bessa & Matos, 2018). The flexibility provision through demand response programs (DRPs) at the residential level, considering the impacts of smart home appliances have been addressed (Jordehi, 2019). The application of HEMS in the presence of demand response programs has been extensively studied in the literature (Jin, Baker, Christensen & Isley, 2017; Mansouri et al., 2021; Tostado-Véliz, Icaza-Alvarez & Jurado, 2021). A comprehensive study has been carried out in Rezaee Jordehi, (2019) and a straightforward mathematical problem formulation has been introduced in (Javadi et al., 2020) to deal with the impacts of the discomfort index (DI) on the expected bill reduction using a multi-objective framework. To model the flexibility of the heat, ventilation, and air conditioning (HVAC) system for residential purposes, a mixed-integer linear programming (MILP) model has been developed by Antunes et al., (2020). The inverter-based HVAC system operation and flexibility provided by such a system have been studied by Hou, Wang, Huang, Wang and Wang, (2019). The presented model took into consideration the roles of all types of loads at the residential level, i.e. fixed, controllable and interruptible loads. To reduce the overall electricity bill and discomfort index, the combination of renewable energy sources (RESs) and electrical energy storage (EES) systems has been assessed in the literature for the sake of electricity bill reduction (Javadi, Lotfi, Gough & Catalão, 2019; Özkan, 2015; Shakeri et al., 2017; Tostado-Véliz, Gurung & Jurado, 2022). Mitigating the dependency on the grid and increasing the self-sustaining energy provision have been investigated in (Shakeri et al., 2017) while the peak load reduction issue has been discussed in (Özkan, 2015) and the optimal sizing and siting of the EES units have been done in (Javadi et al., 2019).

A comprehensive survey has been conducted in (Siano, De Marco, Rolan & Loia, 2019), addressing the potential of distributed ledger technology for power transactions in the local energy markets based on peer-to-peer (P2P) transactions. The main focus of the review article was on the development of a new distributed power transaction mechanism in the local market to mitigate the power mismatches in the local energy market.

The following studies examine the problem of a single HEMS acting to optimize a certain aspect of the HEMS. For example user behaviour estimation and the corresponding impacts on the electricity bill and emission reduction have been addressed in (Paridari, Parisio, Sandberg & Johansson, 2016). A new robust optimization model was suggested for smart appliances in active apartments and the impacts of the EES devices have been elaborated. To tackle the impacts of the uncertainties in the mentioned research, a trade-off between the cost of robustness and the protection against the uncertainties has been made. A bottom-up flexibility design framework has been presented in (Zhai, Wang, Yan & He, 2019) to manage the smart plug of home appliances, taking into account the effects of uncertainties of the user behaviour and measurement facilities.

In (Sharifi & Maghouli, 2019), a model for the optimal management of household appliances and energy storage systems was developed to minimize electricity costs, reduce the Peak-to-Average Ratio and maintain consumer comfort. The model considered Real-time-Pricing and a non-dominated sorting genetic algorithm (NSGA-II) to optimise the scheduling of various household appliances. Trading of energy within the community or technical constraints of the system were not considered.

(Duman et al., 2021) developed a HEMS model combined with smart thermostats to minimise household energy cost considering thermostatically controlled loads. The model considered a fuzzy logic thermostat to define the set-points for the thermostatically controlled loads. The authors did not consider the technical constraints of the grid or energy trading amongst different smart homes.

While not focused on optimizing a quantitative parameter, experimental research into the implementation of the IoT technology for the optimal HEMS operation has been investigated in (Li, Logenthiran, Phan & Woo, 2018) for self-learning consumers in order to increase consumer awareness of their energy use. A multi-agent communication system with a machine learning functionality has been proposed to address price forecasting, price clustering, as well as a smart alert system for the specific HEMS.

Moving from a single HEMS to a system for the optimal scheduling of domestic appliance for several residential consumers, work was developed by Lokeshgupta and Sivasubramani, (2019). The authors used a multi-objective model considering both the electricity cost as well as the peak demand of the households. The technical impacts of this scheduling on the distribution grid were not considered.

Considering microgrids, (Haghifam, Dadashi, Zare & Seyedi, 2020) presented a bi-level optimisation model for the scheduling of demand and supply in smart distribution networks considering both the microgrid operator and the Demand Response Aggregator. The model did not consider the potential for households to contribute to both the optimal scheduling of demand and generation and demand response services.

Work considering the wider energy community has begun to emerge. For example, a techno-economic assessment of energy communities in Turin, Italy was carried out by Viti, Lanzini, Minuto, Caldera and Borchiellini, (2020). The author's considered various distributed energy resources and different economic scenarios in the assessment and found that energy communities can increase the penetration of RES and have a positive economic impact on the members of the community. The authors did not consider optimising the demand profile of the community members to maximise the potential impact of the energy community on the distribution grid.

The optimal management of a diverse set of DERS owned by different stakeholders was considered by (Li & Yu, 2020). The authors considered demand response programs (both electrical and thermal loads) and the effects of a carbon tax to minimize the operational cost of the community while maximising the profits of each of the stakeholders. The authors did not consider the impacts of the energy community on the distribution grid.

A linear programming model for peer-to-peer energy trading within local energy communities was proposed by (Perger et al., 2021). The model sought to maximise the social welfare of the community through maximising the PV production of the community and then fairly allocating it to the members of the community. Results showed the economic viability of energy communities and their ability to participate in electricity markets.

A self-scheduling model for home energy management systems has been propsed by (Javadi et al., 2021) in which a novel formulation of a linearized DI has been proposed, incorporating the preferences of end-users in the daily operation of home appliances. The HEMS self-scheduling problem has been modelled as a multi-objective problem, aimed at minimizing the energy bill and DI.

Table 1 provides a summary of relevant literature in this field and how the current model extends the state of the art through various contributions. These contributions will be discussed in more depth in the next section.

C. *Paper contributions*

This paper presents a predefined tariff-based mechanism to manage transactions carried out by local energy market participants. This paper aims to demonstrate an environmentally sustainable local energy community that uses home energy management systems to optimally schedule several appliances. Also, the model utilizes local energy trading to improve the community's resilience and use of locally generated renewable energy sources. This framework utilizes smart grid concepts to actively manage the community's energy demand and generation from distributed energy resources benefiting from net energy metering https://doi.org/10.1016/j.energy.2021.121717. In this framework, a local energy trading centre is the responsible entity for settling the market based on the predefined rules. The market-clearing mechanism is explicit to the producers and consumers in this framework. A competitive price is considered according to the hourly time-of-use (TOU) tariff to clear the local market. In other words, it is a local pool market at the local energy community level and the market settler can effectively manage the power mismatches in the local area to reduce the total cost of consumers and increase the revenue of the active prosumers. The proposed model is based on a centralized optimization model to optimally supply the loads while incentivizing the active power suppliers in the local energy community to benefit from this opportunity provided by other consumers to buy their energy from the local energy market. At each client level, a HEMS system is modelled to address the DRP impacts on the electricity bills. It is noteworthy that the fixed, controllable and interruptible loads are considered at this level. As has been shown in the previous section and in Table 1, there is existing literature which has investigated this problem. However, none of the relevant research papers has addressed the problem comprehensively as is done in this model. To the best of the author's knowledge, the combination of allowing energy trading while incorporating DRPs and considering technical constraints has not been examined by previous work. In addition, the focus on energy communities is an important contribution as these communities are beginning to emerge as an interesting ecosystem for electricity generation and use and the number and importance of these communities is likely to grow in the future.

There are some new features added to the model, compared to the previous studies. The HEMS model developed in this paper is organized within a standard MILP framework to reduce the computational burden while taking into account a considerable number of smart end-users for real test systems. Furthermore, a fair market clearing mechanism is introduced in this study to increase the tendency of the producers and consumers to participate in the local market.

This paper aims to provide a pool trading framework in such a way as to handle the surplus energy of the active prosumers at a low-voltage level with a limited power injection possibility. In this framework, the clearing mechanism for all participants has been settled by the DSO, addressing the key factors, like tax and grid service costs. In addition, there is a possibility for the DSO to handle the peak hour prices by the real contribution of the active prosumers in the community https://doi.org/10.1007/s00500-020-05093-2. The idea behind the pool trading framework is to activate the consumer engagements in the local energy

Table 1
Summary table of relevant literature.

Paper	Focus	Objective function	Type of optimization	Devices considered	Energy trading	Demand response considered	Technical constraints considered
Özkan (2015)	Single home	Reduce power imports, reduce peak load	MILP	PV, BESS	No	No	No
Shakeri et al. (2017)	Single home	Min electricity costs	MILP	PV, BESS	No	No	No
Jordehi (2019)	Single home	Min electricity costs	Modfied particle swarm optimisation	PV, Wind	No	No	Yes
Hou et al. (2019)	Single home	Min electricity costs, maintain comfort	MILP	PV, ESS, EV	No	No	No
Rezaee Jordehi (2019)	Single home	Min electricity costs, maintain comfort	Enhanced leader particle swarm optimisation	PV, EV	No	No	Yes
Zhai et al. (2019)	Single home	Max system flexibility	Intrusive load monitoring	EV	No	No	No
Li et al. (2018)	Single home	Increase energy awareness	Machine learning	EV	No	Yes	No
Paridari et al. (2016)	Single home	Min costs and emissions	MILP	ESS	No	No	No
Javadi et al. (2020)	Single home	Min costs maintain comfort	MILP	EV	No	No	No
Antunes et al. (2020)	Single home	Min costs and maintain comfort	MILP	NA	No	No	Yes
Sharifi and Maghouli (2019)	Single home	Min costs, min PAR, max comfort	NSGA-II	ESS	No	No	No
Duman et al. (2021)	Single home	Min costs	MILP	PV, BESS, EV	Yes	No	Yes
Lokeshgupta and Sivasubramani (2019)	Multiple homes	Min electricity cost and peak demand	MILP	BESS	No	No	No
Haghifam et al. (2020)	Microgrids	Min operating costs	MINLP	Wind, PV, ESS	No	Yes	Yes
Viti et al. (2020)	Energy community	Max Production/Load ratio	Techno-economic assessment	PV	Yes	No	No
Li and Yu (2020)	Energy communities	Min costs/ max stakeholder profit	Analytical target cascading algorithm	PV	Yes	No	Yes
Perger et al. (2021)	Energy communities	Max the self-consumption of the community	Linear optimization	PV, BESS	Yes	No	No
This paper	Energy communities	Min cost of operations	MILP	PV, EV, ESS	Yes	Yes	Yes

Max- Maximize, Min- Minimize, BESS- Battery Energy Storage System, EV- Electric Vehicle, ESS- Energy Storage System, PAR- Peak-to-Average Ratio.

community to benefit from the local power generation while reducing the peak power procurement from the upstream network. Thus, a pre-defined exchange tariff has been elaborated by the DSO to enhance the power exchange possibility within the community, activating demand response programs at the community level and strategic saving and consumption by the dedicated end-users to reduce their electricity bills, while respecting their consumption preferences. To simulate the pool trading within the local energy community, a centralized model based on the MILP optimization structure is presented in this paper. Two different scenarios have been provided to show the effectiveness of ‘independent’ and ‘integrated’ clearing strategies. In the independent model, each HEMS can optimize its electricity bill by optimally scheduling the home appliances’ operation while in the integrated model, the HEMS operator can participate in a local market in the energy community.

D. Paper organization

The rest of the paper is categorized as follows: the conceptual model of the local energy community is addressed in Section 2. The main principles of the local energy community and end-user’s interactions in this local market are explained in this section as well as the mathematical formulation of the optimal HEMS operation problem in the local energy community, taking into consideration the stand-alone and integrated operating modes of the end-users. The interactions between the HEMSs and the local energy community are addressed as well. Section 3 addresses the simulation results and case studies. Lastly, the Conclusion of the paper is presented in Section 4.

2. Formulation of local energy communities

Local energy communities are emerging entities in the new market structures. The main role of energy communities is to sustain energy provision and reduce energy poverty. An ideal energy community can easily fulfil the electricity demand within the local area. An energy community can have energy transactions in the community and benefit from the collaboration of all active consumers in the market as well.

In this respect, energy community members would benefit from cheaper energy prices and distributed flexibility while they could share local energy production and benefit from reduced grid tariffs. The end-users can have renewable power generation installations in the energy community like PV panels and small wind turbines as well as small Energy Storage Systems (ESS) to store energy. Also, it is assumed that each consumer has some home appliances and these appliances would be used by the consumers during the day.

Fig. 1 shows the conceptual model of home appliances at one of the energy community members. As can be observed, there are diverse home appliances together with an electric vehicle (EV) in which the operation of such appliances can be managed by the HEMS in the local energy community.

To have a fair market, the trading cost of energy within the local energy community is supposed to be identical for either buying or selling, and the cost is considered different from that relating to transactions with the distribution grid. In this regard, the cost of electricity provided by the distribution grid is higher than that of the electricity trading within the local energy community. Besides, the selling price to the grid excludes tax and therefore, it is lower than the electricity price for trading in the local energy community. This pricing mechanism proves that the end-users tend to trade their electricity in the local

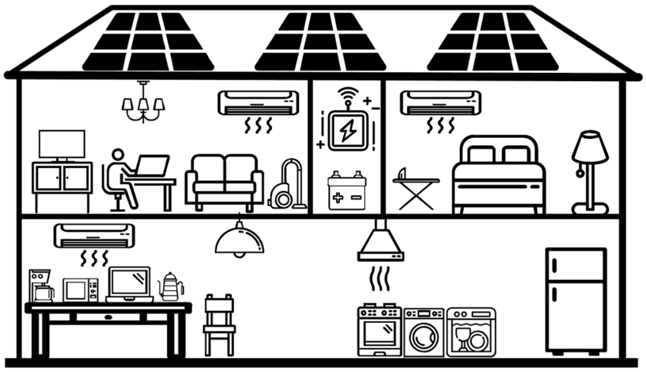

Fig. 1. Home appliances installed at one of the residential energy community members.

energy community rather than trading with the distribution network. In the worst case, consumers have to trade their electricity with the distribution grid, resulting in a lower economic benefit compared to the case with trading in their local energy community.

A. Interactions within the local community

This section presents the mathematical formulation of the HEMSs, besides their interactions with the local energy community and distribution grid. The problem formulation is proposed in an integrated model and it can be solved in both independent and integrated states. In the independent model, each HEMS can optimize its electricity bill by optimally scheduling the home appliances' operation while in the integrated model, the HEMS operator can participate in a local market in the energy community. In this state, it is possible to have transactions with the local energy community as well as the distribution grid. Thus, the central controller of the local energy community is responsible for the transaction with the community.

In the local energy community, the end-users can also control the electricity consumption according to price signals, which are based on the TOU mechanism in this study. Therefore, operators of HEMSs can determine the best strategy for electricity consumption. Besides, if the end-users install PV panels or EES units, they can manage the electricity trading within the local energy community, and in the worst case, they can sell the surplus energy to the distribution grid. The overall objective function of this model can be represented as (1):

$$Min$$

$$\sum_{t=1}^{NT}\sum_{j=1}^{NC}\left(\underbrace{\left[\rho_t^{TOU}P_{j,t}^{G2H}-(1-\alpha-\beta)\rho_t^{TOU}P_{j,t}^{H2G}\right]\Delta t}_{Electricty\ Trading\ with\ Distribution\ Grid}+\underbrace{\left[(1-\alpha)\rho_t^{TOU}P_{j,t}^{C2H}-(1-\alpha)\rho_t^{TOU}P_{j,t}^{H2C}\right]\Delta t}_{Electricty\ Trading\ within\ Local\ Energy\ Community}\right)+\underbrace{\sum_{t=1}^{NT}\sum_{j=1}^{NC}\sum_{i=1}^{NA}\left[ON_{i,j,t}C_{i,j}^{ON}+OFF_{i,j,t}C_{i,j}^{OFF}\right]-\sum_{j=1}^{NC}\sum_{i=1}^{NA}\left[C_{i,j}^{ON}+C_{i,j}^{OFF}\right]}_{Turn-on\ and\ Turn-off\ Cost} \quad (1)$$

The objective function is comprised of three parts; the first item states the cost of transactions with the distribution grid, the second one deals with the transactions within the energy community, and the last one is considered for the HEMS's controllable loads to avoid multiple turn-on and turn-off during the operation intervals. As previously mentioned, the hourly time tariffs are considered in this paper, i.e., the TOU pricing mechanism. The grid cost, α, and tax, β, are considered in the TOU tariff. Thus, for selling the surplus electricity to the grid, the grid service cost and tax would be excluded.

For those transactions within the local energy community, the grid cost has remained fixed and the terms relating to the tax would be excluded. The optimization constraints are divided into two sub-problems. The first sub-problem relates to the HEMS scheduling while the latter deals with the constraints relating to the transactions within the local energy community and distribution grid as well.

B. HEMS scheduling constraints

The optimal scheduling of home appliances in the HEMS needs to be managed by the HEMS operator according to the TOU tariff and the preferences of the operator. For the controllable loads, the operator can modify the plug-in time and bills can be minimized accordingly. In this paper, a binary decision variable is assigned to each time interval to show the operating time intervals for each appliance. The corresponding constraints of the HEMS sub-problem are as follows:

$$B_{i,j,t}=\begin{cases}0 & t<LB_{i,j,b}\\ 1 & LB_{i,j,b}\le t\le UB_{i,j,b}\\ 0 & t>UB_{i,j,b}\end{cases} \quad B_{i,j,t}\in\{0,1\} \quad (2)$$

$$S_{i,t}\le\begin{cases}0 & t<LB_{i,j,s}\\ 1 & LB_{i,j,s}\le t\le UB_{i,j,s}\\ 0 & t>UB_{i,j,s}\end{cases} \quad S_{i,j,t}\in\{0,1\} \quad (3)$$

$$\sum_{t=1}^{NT}B_{i,j,t}=T_{i,j} \quad \forall i=1,2,\dots,NA \quad (4)$$

$$\sum_{t=1}^{NT}S_{i,j,t}=T_{i,j} \quad \forall i=1,2,\dots,NA \quad (5)$$

$$\sum_{i=1}^{NA}S_{i,j,t}P_{i,j}=P_{j,t}^{D,\,Shift} \quad (6)$$

$$ON_{i,j,t}-OFF_{i,j,t}=S_{i,j,t}-S_{i,j,t-1} \quad \forall t>1 \quad (7)$$

$$DI_{i,j}^{-}\ge\frac{1}{T_{i,j}}\left[\sum_{t=1}^{NT}t\times B_{i,j,t}-\sum_{t=1}^{NT}t\times S_{i,j,t}\right] \quad (8)$$

$$DI_{i,j}^{+}\ge\frac{1}{T_{i,j}}\left[\sum_{t=1}^{NT}t\times S_{i,j,t}-\sum_{t=1}^{NT}t\times B_{i,j,t}\right] \quad (9)$$

$$0\le P_{j,k,t}^{Ch.}\le I_{j,k,t}^{Ch.}P_{j,k}^{Ch.,\max} \quad (10)$$

$$0\le P_{j,k,t}^{Disch.}\le I_{j,k,t}^{Disch.}P_{j,k}^{Disch.,\max} \quad (11)$$

$$0\le I_{j,k,t}^{Ch.}+I_{j,k,t}^{Disch.}\le 1 \quad (12)$$

$$E_{j,k,t}=E_{j,k,t-1}+\eta_{j,k}^{Ch.}P_{j,k,t}^{Ch.}\Delta t-\frac{1}{\eta_{j,k}^{Disch.}}P_{j,k,t}^{Disch.}\Delta t \quad (13)$$

$$E_{j,k,1}=E_{j,k,T} \quad (14)$$

$$E_{j,k}^{\min} \le E_{j,k,t} \le E_{j,k}^{\max} \tag{15}$$

$$\theta_{j,t}^{in} = \theta_{j,t-1}^{in} + \mu_j\left(\theta_{j,t}^{out} - \theta_{j,t-1}^{in}\right) - \psi_j P_{j,t}^{D,HVAC}\Delta t \tag{16}$$

$$\theta_j^{\min} \le \theta_{j,t}^{in} \le \theta_j^{\max} \tag{17}$$

$$\theta_{j,1}^{in} = \theta_{j,initial}^{in} \tag{18}$$

$$P_{j,t}^{D,HVAC} = \left[0.2\delta_{j,t}^{(1)} + 0.4\delta_{j,t}^{(2)} + 0.6\delta_{j,t}^{(3)} + 0.8\delta_{j,t}^{(4)} + \delta_{j,t}^{(5)}\right]P_j^{HVAC} \tag{19}$$

$$\delta_{j,t}^{(1)} + \delta_{j,t}^{(2)} + \delta_{j,t}^{(3)} + \delta_{j,t}^{(4)} + \delta_{j,t}^{(5)} \le 1 \tag{20}$$

$$P_{j,t}^{G2H} - P_{j,t}^{H2G} + P_{j,t}^{PV} + P_{j,t}^{C2H} - P_{j,t}^{H2C} = P_{j,t}^{D,\,Fix} + P_{j,t}^{D,\,Shitf} + P_{j,t}^{D,HVAC} + \left[\sum_{k=1}^{NS} P_{j,k,t}^{Ch.} - \sum_{k=1}^{NS} P_{j,k,t}^{Disch.}\right] \tag{21}$$

For instance, for fixed loads, the corresponding binary variables are supposed to be predetermined and they can be addressed as binary parameters. The binary decision variables for controllable and interruptible loads should be determined by the optimization problem. For controllable appliances, the predefined time intervals have been determined according to the consumer's preferences. Such time intervals are assumed as baseline operating intervals. Consequently, the permissible operating intervals could be determined by the consumers, taking into account their preferences.

Eqs. ((2)–(5)) deal with the associated binary variables for the baseline and shifted operation. For the baseline, the appliance '*i*' in the community '*j*' at time '*t*' would be in service for the given time interval, and for the other periods it would be disconnected (2). The same equation is proposed to change the operation time. However, the appliance can be operated in the permissible time interval, suggested by the end-user (3). Eqs. (4) and (5) confirm that for each appliance, the ON state must be equal to the operating period of that specific appliance.

The controllable share of the total demand is modelled by (6), incorporating the associated binary variable and the apparent power of the appliance. Eq. (7) deals with the ON and OFF switching states using the corresponding binary decision variables. For a given controllable appliance, the discomfort index is considered to deal with the total time intervals for shifted operation by (8) and (9). It is evident that for the baseline operation, the corresponding discomfort index would be zero while for shifted operation, one of the positive variables would be nonzero.

Eqs. ((10)–(15)) have been assigned to the model and they relate to the EES devices. Eqs. (10) and (11) state the charging and discharging constraints while Eq. (12) removes the conflicting state of the EES operation https://doi.org/10.1002/er.5867. The energy balance equation is indicated in (13) https://doi.org/10.1016/j.ijepes.2021.107912 while the initial energy stored in the EES should be remained fixed at the end of the operation horizon, and it is represented by (14). The lower and upper bounds on the energy stored in the EES are addressed in (15) (Jordehi, Javadi & Catalão, 2021).

In this study, the HVAC system is also considered a controllable load. The HVAC system's constraints are stated in Eqs. ((16)–(20)).

The indoor temperature constraint, taking into consideration the impacts of the outdoor and the insulation system is characterized in Eq. (16) Hou et al., 2019). The dead band for the convenience temperature is provided by ((17), while (18) addresses the initial indoor temperature at the beginning of the scheduling problem.

The exact power consumed by the inverter-based HVAC system is modelled in (19). The inverter-based HVAC can operate at different levels relative to the rated power 10.1109/EEEIC/ICPSEurope49358.2020.9160629. Therefore, additional binary decision variables have been introduced to represent the operating point of the HVAC system. Eq. (20) states one operating point at the same time, addressing the corresponding binary variable (Antunes et al., 2020).

The load balance equation, considering the bidirectional power flow between HEMS and distribution grid and local energy community, fixed, controllable and controllable demands, as well as PV power generation, is modelled by (21). The power balance equation is the most critical constraint of the HEMS operation at each time interval.

C. Energy transaction constraints

The power transaction within the energy community and the distribution grid is managed by the local energy controller. The local energy community controller is responsible for all transactions within the controlled area. The active consumers, i.e., HEMS operators, in this case, can trade electricity with other end-users through the central controller. The corresponding constraints of the energy transaction are as follows:

$$0 \le P_{j,t}^{G2H} \le P_j^{Trans.} I_{j,t}^{G2H} \tag{22}$$

$$0 \le P_{j,t}^{H2G} \le P_j^{Trans.} I_{j,t}^{H2G} \tag{23}$$

$$0 \le I_{j,t}^{G2H} + I_{j,t}^{H2G} \le 1 \tag{24}$$

$$0 \le P_{j,t}^{C2H} \le P_j^{C} I_{j,t}^{C2H} \tag{25}$$

$$0 \le P_{j,t}^{H2C} \le P_j^{C} I_{j,t}^{H2C} \tag{26}$$

$$0 \le I_{j,t}^{C2H} + I_{j,t}^{H2C} \le 1 \tag{27}$$

$$\sum_{j=1}^{NC} P_{j,t}^{C2H} = \sum_{j=1}^{NC} P_{j,t}^{H2C} \tag{28}$$

$$0 \le I_{j,t}^{G2H} + I_{j,t}^{H2C} \le 1 \tag{29}$$

Eqs. ((22)–(24)) address the constraints regarding the power transaction between the distribution grid and HEMS. These constraints state that at each time interval, the unidirectional power flow is allowed and the maximum power that can be transacted is limited by the capacity of the power transformer, connecting the HEMS to the distribution network. The same constraints are assigned to the model to characterize the power transaction between the HEMS and the local energy community. Eqs. ((25)–(27)) represent these constraints. The power transaction strategy is in real-time and therefore, the hourly balance constraint is one of the critical constraints.

Thus, the total power injected into the local energy community must be consumed by another end-user within the community (28). According to the agreement between the local energy community and distribution grid, buying electricity from the distribution network and selling to the local energy community at the same time is prohibited (29), while the surplus power injection from the end-user's side to both distribution network and local energy community is allowed.

3. Simulation results

The proposed model has been evaluated in this section to show the effectiveness of the DRPs and the local energy community power transaction in the end-user's bills reduction. For the sake of clarifying the mathematical model, two different case studies have been assessed. The first case study includes three HEMSs and one school in the local energy community and the daily bill assessment is carried out accordingly. The second case study considers a larger energy community to verify the effectiveness of the performance of the proposed model for real energy communities.

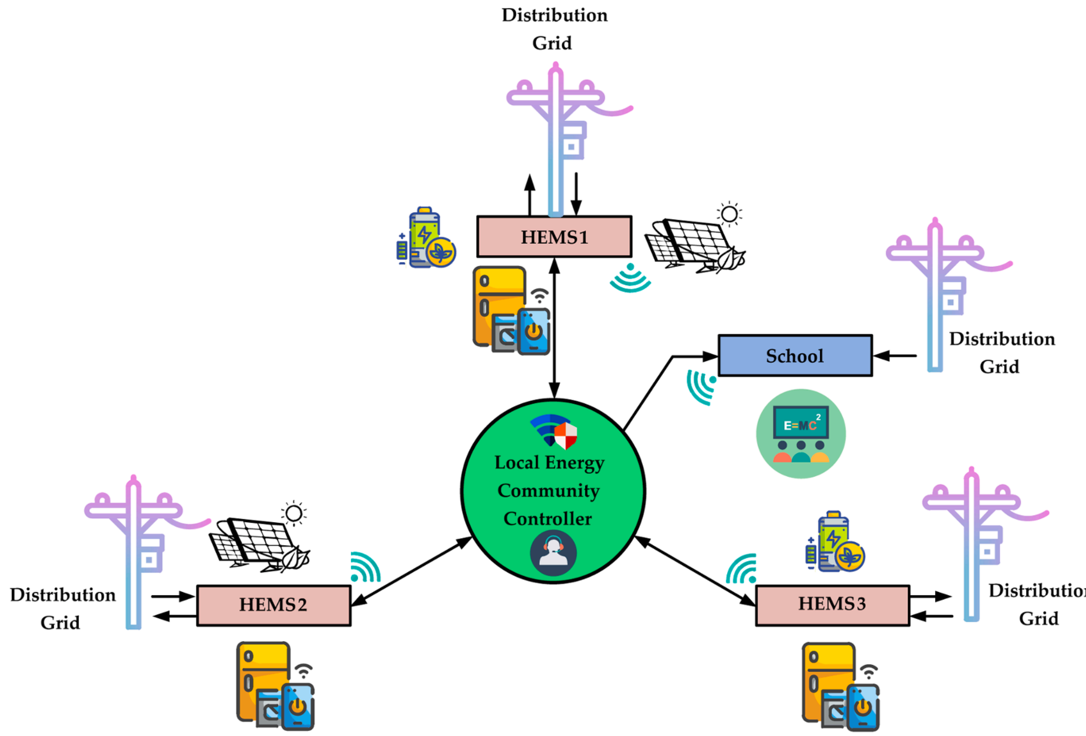

Fig. 2. Local energy community and the interconnection between the agents in this study.

A. Small energy community-daily bill assessment

As mentioned above, this case study addresses the daily bill calculation under different operating modes, considering the impacts of the local energy community and the corresponding internal market as well as DRPs. The test system includes three HEMSs and one school as flexible and non-flexible end-users respectively. Fig. 2 illustrates the conceptual representation of this case study. There are two PV panels with capacities equal to 5 kW and 3 kW installed at HEMS 1 and HEMS 2, respectively. Besides, there are two EES units installed at HEMS 1 and HEMS 3 with the rated capacity of 4 kWh and 3 kWh respectively. The school load is not flexible while the end-users with HEMS are flexible and their bills can be effectively controlled by effective responses to the price signals, besides their efficient roles as prosumers in the market. It is supposed that each consumer has predefined load patterns and the preferences of the consumers are identified. The specific load profiles for the flexible end-users are provided in Tables 2–4. In these tables, the flexible home appliances, nominal power, baseline and acceptable bands of operation are provided accordingly.

There are two different bounds in the mentioned tables. The first one is related to the 'base' and the second one is associated with the 'shiftable' one. For example, in Table 2, for the 'Dishwasher', the end-user prefers to utilize this appliance between time slots 19–22 and it will be utilized for '4′ time slots, i.e. 2 h. The end-user can use this appliance between time slots 15–33, however, it must be operated for 4 consecutive time slots to avoid any interruptions during the operation. Also, the daily load profile of the school is illustrated in Fig. 3

Besides, the HVAC demand is categorized into interruptible loads for all consumers. It is noteworthy that the duration of a single time interval is 30 min. In this case study, two different scenarios have been studied. In the first scenario, the daily bill assessment has been done for the base

Table 2
The specifications of controllable loads- (HEMS 1).

HEMS#1	P_i(kW)	T_i	LB_b	UB_b	LB_s	UB_s
Dishwasher	2.5	4	19	22	15	33
Washing Machine	3.0	3	19	21	16	23
Spin Dryer	2.5	2	27	28	25	35
Cooker Hob	3.0	1	17	17	16	17
Cooker Oven	5.0	1	37	37	36	37
Microwave	1.7	1	17	17	16	17
Laptop	0.1	4	37	40	33	47
Desktop Computer	0.3	6	37	42	31	47
Vacuum Cleaner	1.2	1	19	19	18	33
Electric Vehicle	3.5	6	37	42	31	47

Table 3
The specifications of controllable loads- (HEMS 2).

HEMS#2	P_i(kW)	T_i	LB_b	UB_b	LB_s	UB_s
Washing Machine	2.4	8	2	9	2	12
Spin Dryer	3.0	4	15	18	12	23
Cooker Hob	1.2	1	16	16	15	16
Television	0.25	2	26	27	24	28
Microwave	1.8	1	26	26	24	26
Dishwasher	2.2	4	26	29	23	35
Vacuum Cleaner	1.8	1	33	33	32	34
Electric Vehicle	3.2	6	37	42	31	47
Cooker Oven	1.2	1	38	38	35	45
Treadmill	1.6	1	40	40	39	42

Table 4
The specifications of controllable loads- (HEMS 3).

HEMS#3	P_i(kW)	T_i	LB_b	UB_b	LB_s	UB_s
Dishwasher	2.4	16	2	17	2	20
Washing Machine	3.0	4	15	18	12	23
Microwave	1.2	1	17	17	16	17
Laptop	0.28	10	18	27	17	30
Rice Cooker	1.8	2	21	22	21	22
Hair Dryer	1.5	1	22	22	22	23
Food Processor	0.8	2	23	24	21	27
Television	0.2	10	24	33	20	40
Iron	1.4	2	38	39	14	44
Sewing Machine	0.5	2	38	40	35	44

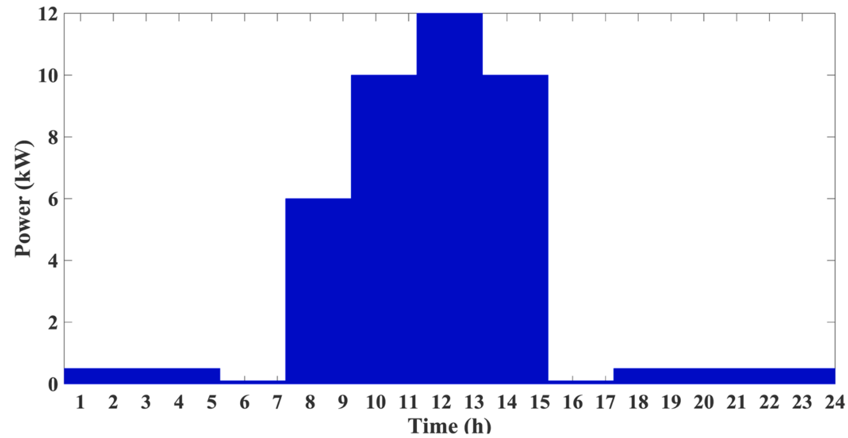

Fig. 3. Daily load profile of the school.

Table 5
Daily bill assessment in the energy community.

Daily Bill	*Independent Operation*		*Integrated Operation*	
	Base	*DRP*	*Base*	*DRP*
HEMS 1	0.686 $	0.288 $	0.660 $	0.252 $
HEMS 2	1.012 $	0.758 $	0.998 $	0.747 $
HEMS 3	1.302 $	1.209 $	1.285 $	1.190 $
School	3.564 $	3.564 $	3.560 $	3.548 $
Total	6.564 $	5.819 $	6.503 $	5.737 $

case and when the DRPs are implemented. In the second scenario, the impacts of the power transaction in the energy community have been assessed for the base case and DRP implementation. The simulation results for the base case and the DRP are obtained by considering the DI and penalty as a big value and zero respectively. It means that for the DRP implemented, the consumers are fully engaged and the cost reduction is of the highest priority for the engaged end-users. Simulation results derived in this case are addressed in Table 5 for both scenarios. The daily bills are calculated for all types of end-users loads, i.e., fixed, flexible and interruptible loads. Additionally, the effects of power transaction in the internal market of the local energy community have been elaborated. The obtained simulation results confirm that the collaboration of the end-users in the local energy community market can successfully mitigate the daily bill of all consumers. Also, the consumer's response to the DRPs results in more than 11% reduction in the cost for

Table 6
Bill assessment in the energy community.

Asset	#	Upper	μ	Lower	Upper	σ	Lower
WM	85	16	10	8	4.00	1.50	0.50
SD	40	16	14	10	2.00	1.25	1.00
TD	25	18	12	10	3.00	1.50	1.00
DW	67	23	20	18	2.50	1.00	0.80
CK1	75	14	12	10	1.30	0.85	0.70
CK2	80	22	20	18	1.60	0.90	0.80
OV	25	13	12	11	0.75	0.65	0.50
GR	10	15	14	13	0.75	0.70	0.60
HB	24	22	19	18	1.20	0.95	0.90
MW	72	9	8	7.5	1.20	1.00	0.90
IR	26	22	18	16	2.00	1.50	1.00
LT	48	23	18	10	3.00	2.00	0.10
PC	40	23	18	10	4.00	2.50	0.50
VC	80	23	20	18	2.00	1.00	0.95
FP	54	12	10	8	1.00	0.50	0.25
HD	24	20	18	16	1.25	0.75	0.50
TV1	75	18	16	14	1.25	1.00	0.75
TV2	40	23	21	19	1.50	1.10	0.78
RC	38	12	11	10	1.50	1.00	0.75
O/A	284	20	14	10	4.50	3.00	0.50

Algorithm for HEMS Consumption Modeling

for HEMS#j=1: NC
    Generate the number of controllable assets # i
    for i=1: NA
        Generate the number of Switching {0, 1, 2,…}
        Generate P_i
        Generate T_i, $LB_{i,b}$, $UB_{i,b}$, $LB_{i,s}$, and $UB_{i,s}$
    end
    Set the $EES_{j,k}$ Parameters if available
    Set the HVAC Parameters if available
    Set the PV system parameters if available
    Generate the PV power based on irradiation
    if PV is available
        Generate the rated power of EV, P_i
        Generate T_i, $LB_{i,b}$, $UB_{i,b}$, $LB_{i,s}$, and $UB_{i,s}$
    end
    Generate the daily fixed demand
end

Fig. 4. Consumption patterns generation algorithm.

each scenario Eq. (30), Tables 3, 6.

B. *Large-scale energy community*

In this case study, a large-scale local energy community, including 98 consumers has been studied. This local energy community has 3 schools and one dormitory with 12 clients. In order to generate the end-users' consumption patterns, a comprehensive scenario generation has been stimulated for each consumer. It is assumed that each consumer can have fixed, controllable and interruptible loads. The occupant behaviour modelling approach for residential consumers has been proposed in (Yilmaz, Firth & Allinson, 2017). The algorithm for the end-users' consumption pattern generation is depicted in Fig. 4. In this study, the normal probability density function (PDF) has been used to generate the HEMS consumption patterns according to the normal distribution. The normal distribution is parameterized with the corresponding mean, μ, and the variance, σ^2, as follows:

$$f(x;\mu,\sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{30}$$

Fig. 5 illustrates the PDF of the mentioned controllable appliances in the whole community.

For the WM dataset, the corresponding PDF for the rated power, operation duration, permissible bound, and the total number of daily switching actions are illustrated in Fig. 6.

The daily bills of all consumers in this study for both cases are provided in Table 7. The simulation results confirm that the proposed local market can convincingly reduce the daily bills, and also increase the

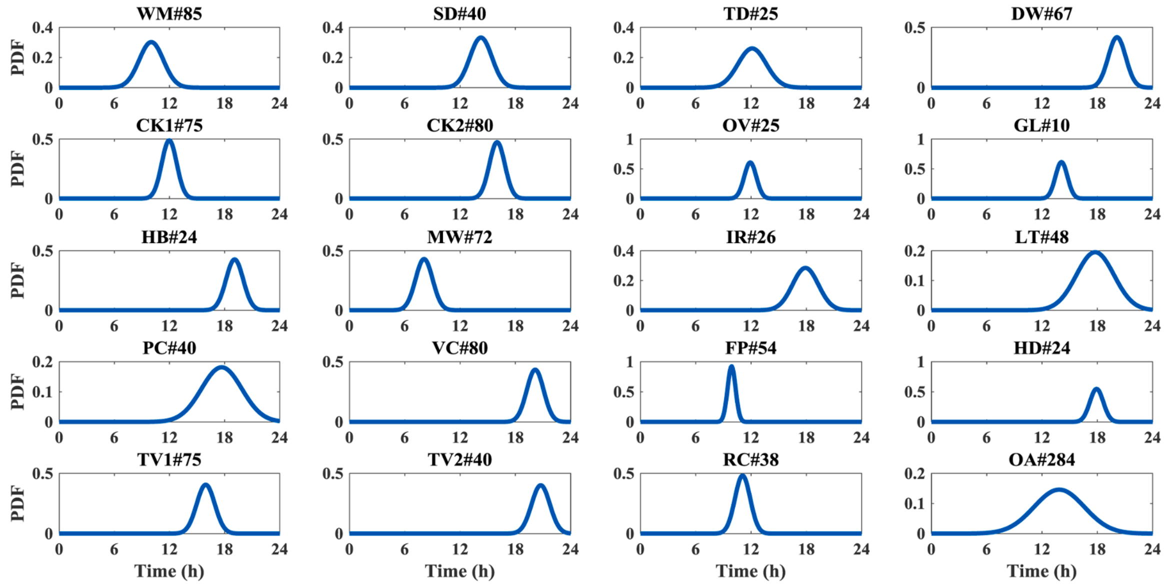

Fig. 5. The normal distribution PDFs for controllable appliances. Washing Machine (WM), Spin Dryer (SD), Tumble Dryer (TD), Dish Washer (DW), Cooker (CK), Oven (OV), Grill (GL), Hob (HB), Microwave (MW), Laptop (LT), Personal Computer (PC), Vacuum Cleaner (VC), Food Processor (FP), Hair Dryer (HD), Television (TV), Rice Cooker (RC), Other Appliance (O/A).

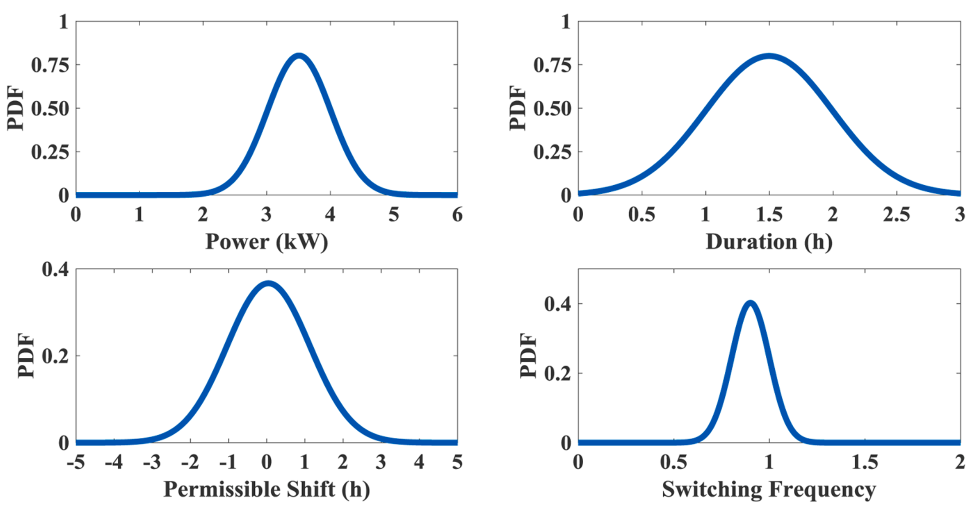

Fig. 6. The normal PDFs for washing machines in this study.

Table 7
Daily bills in the large-scale energy community.

Daily Bill	*Independent Operation*		*Integrated Operation*	
	Base	*DRP*	*Base*	*DRP*
Residential	103.719 $	84.095 $	93.841	72.078 $
School 1	3.564 $	3.564 $	3.375 $	3.291 $
School 2	5.046 $	5.046 $	4.760 $	4.408 $
School 3	−1.778 $	−1.778 $	−2.090 $	−3.015 $
Dormitory	13.021 $	12.094 $	12.732 $	11.775 $
Total	123.572 $	103.021 $	112.618 $	88.537 $

revenue of the active prosumers. For instance, School 3 has an installed PV panel with a rated capacity of 30 kW and the net daily bill is negative since the total injection to the grid or community is greater than the total consumption. Fig. 7 depicts the daily power trading between the distribution network and the local energy community for both independent and integrated operation modes. The simulation results confirm that in the independent operation mode without any DRP, the energy consumption in the community is reasonable, while the DRP reduces the power consumption and the cost accordingly.

In this case, taking into account the internal transactions in the local energy community, the total power purchased from the distribution grid substantially reduces. The DRP, in this case, reduces the power consumption during the peak hours and it shifts the power demand to off-peak hours. In this case, the local energy community is self-sustained for at least one hour with the DRP implementation.

4. Conclussion

This paper investigated a pool-based market for the local energy communities to incentivize internal trading between active prosumers and end-users in the local market. To model the home energy management system (HEMS), fixed, controllable and interruptible loads have been modelled in the proposed framework. A pool-based market was developed for all transactions within the local energy community to reduce requirements on the grid. A mixed-integer linear programming (MILP) framework was presented to model the HEMS, addressing price-

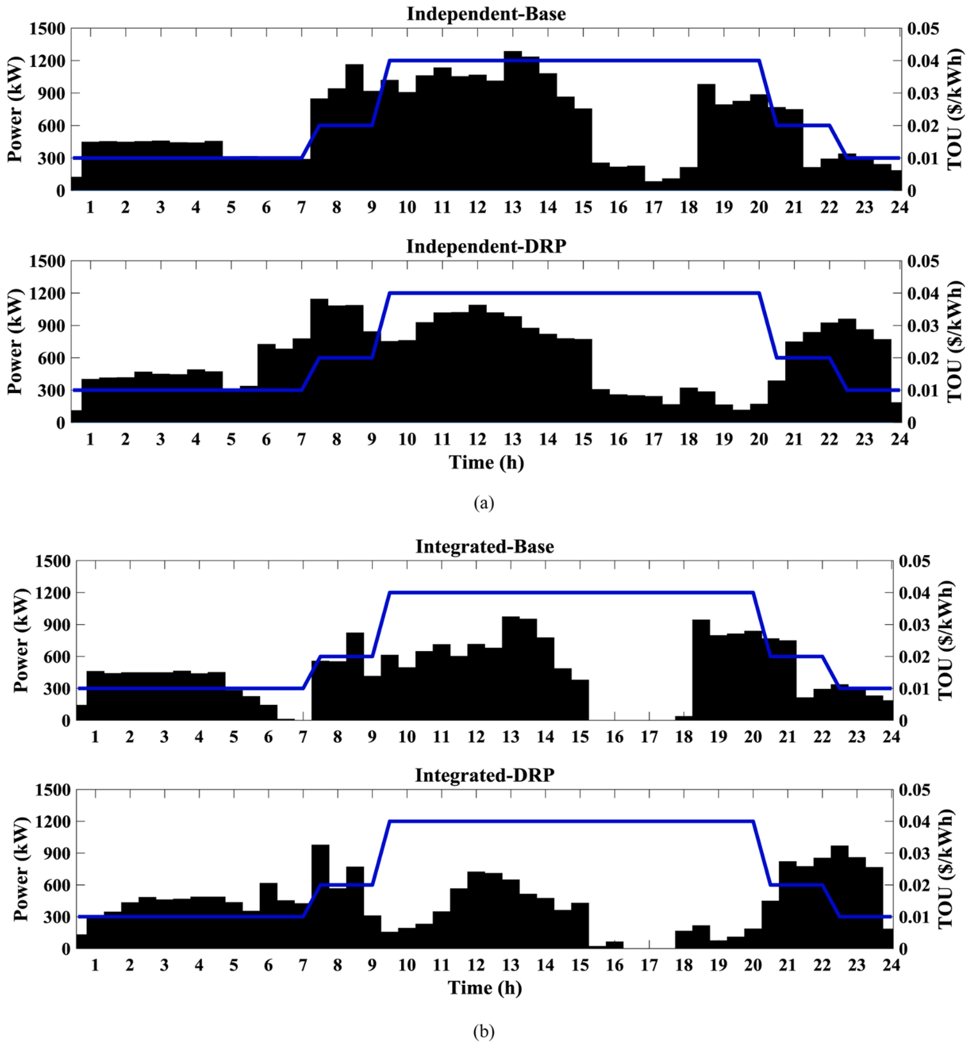

Fig. 7. The net grid-to-community electricity selling, (a) independent operation mode; (b) integrated operation mode.

based demand response programs (DRPs). The feasibility and compatibility of the developed framework have been examined through two different case studies. The first case study was assessed to show the interactions between the clients in a simple manner, while the second case study verified that the model is fast and reliable enough for real case studies. To model the consumer's behaviour, a scenario-based strategy was adopted in the second case study to stimulate the consumption patterns of the end-users. Two different scenarios have been evaluated, independent and integrated operation modes, to show the impacts of coordination amongst different end-users. Results show that through cooperation, end-users in the local energy community market can reduce the total electricity bill. This is shown in a 16.63% cost reduction in the independent operation and a 21.38% reduction in the integrated case. Revenues for active consumers under coordination increased compared to independent operation of the HEMS. Taken together, results from this model show that pool trading models may be applie to local energy communities and bring about significant benefits to the members of the pool. The structure and level of coordination are key to maximizing these benefits and so careful attention should be paid during the development of such markets.

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.

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