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Enhancing PV Self-consumption within an Energy Community using MILP-based P2P Trading

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ABSTRACT The high penetration of Distributed Energy Resources (DERs) into the demand side has led to an increase in the number of consumers becoming prosumers. Recently, Peer-to-Peer (P2P) energy trading has gained increased popularity as it is considered an effective approach for managing DERs and offering local market solutions. This paper presents a P2P Energy Management System (EMS) that aims to reduce the absolute net energy exchange with the utility by exploiting two days-ahead energy forecast and allowing the exchange of the surplus energy among prosumers. Mixed-Integer Linear Programming (MILP) is used to schedule the day-ahead household battery energy exchange with the utility and other prosumers. The proposed system is tested using the measured data for a community of six houses located in London, UK. The proposed P2P EMS enhanced the energy independency of the community by reducing the exchanged energy with the utility. The results show that the proposed P2P EMS reduced the household operating costs by up to 18.8% when it is operated as part of the community over four months compared to operating individually. In addition, it reduced the community's total absolute net energy exchange with the utility by nearly 25.4% compared to a previous state-of-the-art energy management method.

INDEX TERMS Energy management system, energy independence, local consumption, mixed-integer linear programming, peer-to-peer energy trading, PV-battery systems.

NOMENCLATURE

N_{houses}	Number of houses in the community
$Pair_{no.}$	Number of available pair
$P_B(t)$	Battery discharge/charge power (kW)
$P_{B\text{-}rating}$	Maximum battery discharge/charge power (kW)
$P_B^{disch}(t)$	Battery discharge power (kW)
$P_B^{charg}(t)$	Battery charge power (kW)
$I(t)$	Battery charge/discharge current (Amp)
$P_{PV\text{-}1}(t)$	Forecasted PV generation for day1 (kW)
$P_{L\text{-}1}(t)$	Forecasted load demand for day1 (kW)
$P_{PV\text{-}2}(t)$	Forecasted PV generation for day2 (kW)
$P_{L\text{-}2}(t)$	Forecasted load demand for day2 (kW)
$SOC(t)$	Battery state of charge (%)
$E_{Day\text{-}f}$	Day-2 mid-peak and peak times energy forecast (kWh)
SOC_{max}	Maximum limit of the state of charge (%)
SOC_{min}	Minimum limit of the state of charge (%)
$E(t)$	Energy stored in the battery at time t (kWh)
$E(t\text{-}1)$	Energy stored in the battery at time t-1 (kWh)
$P_G(t)$	Power exchange with the utility grid (kW)
$P_G^{max\text{-}export}$	Maximum limit exported power to the utility grid (kW)
$P_G^{max\text{-}import}$	Maximum limit imported power from the utility grid (kW)
$P_G^{export}(t)$	Exported power to the utility grid (kW)
$P_G^{import}(t)$	Imported power from the utility grid (kW)
$\Phi_{export}(t)$	Binary variable to indicate the house is exporting power to the utility grid
$\Phi_{import}(t)$	Binary variable to indicate the house is importing power from the utility grid

$\Phi_{B\text{-}disch}(t)$	Binary variable to indicate the battery is discharging
$\Phi_{B\text{-}charg}(t)$	Binary variable to indicate the battery is charging
$B_{capacity}(t)$	Estimated battery capacity (kWh)
N_{cycle}	Battery cycle life
CC_B	Capital cost of the battery (£)
C_{BSS}	Battery degradation cost (£)
C_{buy}	Price of imported energy from the utility grid (£/kWh)
C_{sell}	Price of exported energy to the utility grid (£/kWh)
$f_{sell}(t)$	Tariff for selling energy to the utility grid (£/kWh)
$f_{buy}(t)$	Tariff for buying energy from the utility grid (£/kWh)
C_{bill}	Bill cost (£)
C_{house}	Optimization cost function for the individual house (£)
$C_{sum\text{-}P2P}$	Optimization cost function for the paired houses (£)
C_{P2P}	Cost of energy exchanged between the paired houses (£)
$f_{P2P\text{-}exp}(t)$	Export exchange tariff between the paired houses (£/kWh)
$f_{P2P\text{-}imp}(t)$	Import exchange tariff between the paired houses (£/kWh)
$P_{P2P}{}^{x\leftrightarrow y}(t)$	Power exchanged between the paired houses (kW)
$P_{P2P,max}(t)$	Maximum power exchanged between the houses (kW)
$б_{pos}{}^{x}(t)$	Energy flows from house (x) to house (y)
$б_{neg}{}^{x}(t)$	Energy flows from house (y) to house (x)
$C_{house\text{-}cost}{}^{individual(n)}$	Operational cost per day when a house is operating individually (£)
$C_{house\text{-}cost}{}^{P2P(n)}$	Operational cost per day when a house is operating as paired (£)
ΔT	Sample time (hr)
t_0	The time of the day starts at 12 AM (hr)
T	The time of the day ends after 24 hours (hr)
t	Current time (hr)
η_{conv}	Battery DC/DC converter efficiency (%)
η_c	Battery charging efficiency (%)
η_d	Battery discharging efficiency (%)
E_{import}	Imported energy from the utility grid (kWh)
E_{export}	Exported energy to the utility grid (kWh)

I. INTRODUCTION

The high penetration of Renewable Energy Sources (RESs) is changing electrical distribution networks from centralized, unidirectional markets to more decentralized, bidirectional markets which allows customers to become prosumers (producer + consumer) [1]. However, this shift in the energy systems structure/market creates new trends in the control of Distributed Energy Resources (DERs) which necessitate new local Energy Management Systems (EMSs) [2]. The main concerns with DERs are that they are intermittent and require a robust electrical network system [3]. High penetrations of DERs can cause numerous technical [4, 5] and operational challenges for the network operators. For example, it is reported that California over several days had to pay Arizona to take its excess solar power to avoid overloading its own power lines [6]. Germany had to introduce a "negative electricity price" rule to "ensure there is no incentive to generate electricity when supply exceeds demand" [7]. This is partially because there is not enough transmission capacity to transfer the generated wind energy from Northern Germany to its South [8]. It is reported that "Germany's negative electricity price rules have caused an estimated €50 million in losses for offshore wind projects in February 2020 alone" [7]. Therefore, to avoid the requirement for more transmission and distribution capacities, self-consumption, as a new trend, is encouraged by several countries such as the UK and Germany. This approach reduces the prosumers' dependency on the electricity network by reducing their exchanged energy with the grid. As the technology installation costs has being reducing, the generation tariff in the UK has been reduced from 54.17 p/kWh in 2010 to 3.79 p/kWh in 2019 [9, 10]. Moreover, the export tariff is reduced to one-third of the peak time electricity price and half of the off-peak electricity price [11]. This means that for new installs the most economically advantageous action is to maximize self-consumption of local renewable generation.

To manage the surplus generation in a prosumer situation one or more of the following actions can be taken:

a) Installing a Battery Storage System (BSS) to store the surplus energy and use it later when needed. The cost of the battery, its efficiency, and the battery management system must all be considered before adoption [12-15].
b) Adopting a demand-side management approach where some loads are turned on during high generation and are turned off during low generation. An example of this is water heating immersion elements. This is not possible for all consumers/loads as it is a function of their daily behavior and responsibilities.
c) Trading energy with a local community of prosumers rather than with the utility grid.

Peer-to-Peer (P2P) energy trading has gained popularity at the community level as it is considered an effective approach for managing DERs and offering local market solutions. There are several initiatives worldwide that support P2P energy trading between prosumers. These include Piclo in the UK, Mosaic in the US, SonnenCommunity in Germany, and Vandebron in the Netherland [16-18].

Based on recent studies, P2P energy trading schemes are categorized into four main techniques [19]:

a) Game theory: a set of techniques and models that are used to examine interactions between different participants in the P2P energy market [20, 21].

b) Auction theory: a method that allows buyers and sellers to interact with each other and trade their electricity [22, 23].
c) Blockchain technology: a distributed database that can securely host critical information/transactions that can be shared securely among members. Blockchain enables decentralized and secure energy trading in a P2P network [24-26].
d) Constrained optimization algorithms: a mathematical formulation of the problem based on certain constraints that must be met during optimization.

This study focuses on the constrained optimization approach. There are several works related to the mathematical formulation of the P2P problem. For example, the authors in [1] proposed a hierarchical EMS using the Mixed Integer-Linear Programming (MILP) for P2P energy trading. The main objective of [1] is to reduce the operating costs of the four houses in the community. However, the import/export tariff for the energy exchanged between the paired houses is set to zero, which is not acceptable by prosumers as it means they sell their energy without gaining a profit. The authors in [16] proposed P2P energy sharing and a three-stage evaluation methodology to reduce operating costs. Their work, however, didn't consider the health of the batteries in cost evaluation. In [27] the MILP is used to formulate the P2P problem for a community consisting of four houses, while the decision-making is performed by feeding all necessary information about the relevant houses into a central controller. The main objective of [27] is to minimize the operating cost. In [28] a two-stage aggregated control is proposed to control the battery settings. The main objective of [28] is to minimize the energy bill of the community and reduce the electricity export to the utility grid. A simple rule-based P2P trading is proposed in [29] to choose the best pairs of houses. Similarly, the authors in [30] used MILP-based EMS to choose the best house pairs according to their consumption profiles and the distance between houses. The main target of [30] is to minimize the peak load demand and reduce the electricity bills. Authors in [31] proposed a P2P energy trading between industrial, commercial, and residential energy hubs in the distribution system. The main objective of [31] is to minimize the energy cost; however, their system didn't consider the health of the batteries in the optimization process. Authors in [32] proposed a P2P EMS for a community consisting of 5 prosumers, which aims to reduce the bill cost. However, their system does not consider battery degradation cost and the cost evaluation has been done for one day only. Authors in [33] proposed a P2P EMS for energy exchange between 5 buildings aims to reduce the energy costs. However, their system does not considered BSSs, where BSS allows building to store its surplus energy and use it in high price tariff.

One of the advantages of a centralized EMS is that since optimal control settings are determined at the decision-making level, conflicts during system operation are minimized. In addition, centralized EMSs can be considered as a global optimization since the cost function is minimized considering all constraints of the system. In contrast, a local optimization in a decentralized EMS cannot provide a solution to minimize the overall cost function of the whole system. The decentralized part used in the local optimization serves the overall target of the centralized system optimization. Therefore, this study proposed a hybrid P2P EMS, where the decentralized part of the algorithm provide the local data to the centralized system, which is tasked to minimize the total energy transactions of the community with the grid.

Based on published literature most of the optimization mechanisms focus on maximizing the economic benefits of peers while simultaneously maximizing the usage of RESs. However, there is a limited number of published works focused on minimizing the net energy exchange with the utility as the main target. As the penetration of prosumers increases, minimizing the net exchange energy, which represents energy independence, becomes more crucial [34]. The more independent prosumer (or a community of prosumers) implies less requirement for central generation, storage, transmission, and distribution capacities [12]. However, enhancing a self/local-consumption approach necessitates more usage of the battery system, which may deteriorate battery health and increase the total operating cost of each home (due to the current price of batteries) compared to the works that maximize the economic benefits. On other hand reducing operating costs increases the exchange energy with the grid and necessitates more distribution/transmission and storage capacity at the network side, which increases the whole network operating costs. Therefore, if network operators aim to enhance the self/local-consumption approach, the energy tariff and/or storage price must change accordingly.

This study focuses on P2P transactions at the community level. The proposed P2P EMS maximizes the local/self-consumption by coordinating the distributed BSSs. In addition, the net energy exchanged with the grid is minimized by exchanging the excess energy within the community while two days-ahead forecast is utilized in the optimization process. Moreover, considering day-2 energy forecast reduces the house energy costs as it charges the BSS from the PV surplus power, neighbors, or grid at the low tariff periods and use that energy when required.

The main contributions of this work can be summarised as:

a) Proposing a P2P EMS that utilizes the two days-ahead forecasts for each house.
b) Proposing a MILP-based P2P energy management algorithm that maximizes the energy independence of the community by minimizing the exchanged energy with the utility, which in turn:
   i. Reduces the required central generation, storage, transmission, and distribution capacities.
   ii. Reduces the distribution/transmission losses.

This paper is organized as follows. Section II illustrates the community configuration. Section III presents the proposed

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EMS structure. Section IV presents the individual Home Energy Management System (HEMS). The central control that includes the P2P EMS is presented in section V and section VI presents the simulation results and discussions. Finally, section VII presents the conclusions of this work.

II. COMMUNITY CONFIGURATION

This study uses the measured data from six houses located in London, UK as a case study [35]. The community consists of six residential prosumers equipped with solar panels and batteries of 4 kWh each, connected to the main electricity grid as shown in Fig. 1. The rated charge/discharge power ($P_{B\text{-}rating}$) of the BSS is 2.7 kW [36]. The capital cost of each BSS is assumed to be £3,000 [37], while the battery prices are expected to reduce further up to 50% in 2025 [38]. The number of the battery's life cycle is 5000 [36]. The maximum SOC (SOC_{max}) and the minimum SOC (SOC_{min}) limits are set to 98% and 20%, respectively [12]. Table I presents the location of each house, PV rated power, and the total load energy for four months (June to September 2014).

III. ENERGY MANAGEMENT SYSTEM STRUCTURE

The main objective of the proposed EMS in this paper is to minimize the absolute net energy exchanged between the community and the utility to enhance the local-consumption while reducing the operating costs of each house. The proposed method consists of two layers as shown in Fig. 1:

(1) Home energy management system: A HEMS is installed in each house, enabling the user(s) to monitor their energy production and consumption. In this stage, the daily energy exchanged with the utility is minimized for each household without exchanging the excess energy within the community (i.e., each house operates individually). The results for the HEMS are uploaded to the central controller as shown in Fig. 1.

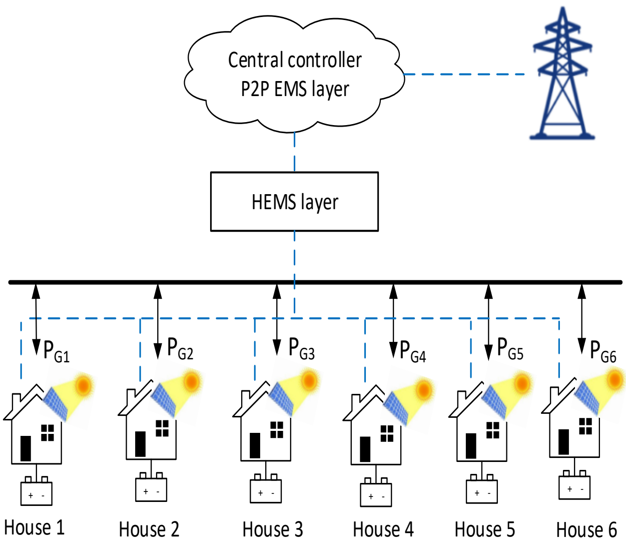

FIGURE 1. Community structure.

TABLE I
LOCATIONS AND PARAMETERS OF THE SIX HOUSES [35]

House location and number	PV rating (kW_p)	Four months load energy (kWh)
Maple Drive East (House no.1)	0.45	430
Suffolk Road (House no. 2)	0.50	1072
Bancroft Close (House no. 3)	3.50	870
Alverston Close (House no. 4)	3.0	1212
YMCA (House no. 5)	4.0	1252
Forest Road (House no. 6)	3.0	732

(2) Central controller: In the central controller a P2P energy trading is used for optimizing the sequential functioning of each pair of houses using data accessible to the central controller. In this stage, the house pairs are formed and selected, aimed to minimize the energy exchange with the utility and the operational costs. The number of available pairs combinations ($Pair_{no.}$) is:

$$Pair_{no.} = \frac{N_{houses}(N_{houses}-1)}{2} \tag{1}$$

where N_{houses} is the number of houses in the community, here N_{houses} = 6, resulting on 15 different combination pairs. The optimization process is executed for each pair of houses to establish: (1) the lowest cost of the energy consumed by a given pair, and (2) a daily profile with a sample time (ΔT) of 10 min to provide reference values for energy exchanged between the pairs and power drawn from the utility. The selection of pairs is made in the central controller. After the optimal settings are obtained from the selected house pairs, the signals are sent to each house.

IV. HOME ENERGY MANAGEMENT SYSTEM

In the HEMS, each house is optimized as a single system to determine its own minimum energy exchange with the utility. The problem is formulated using MILP. The proposed HEMS follows the steps detailed below:

- First, the initial SOC of the BSS and two days-ahead forecasted data are input: day-1 PV generation ($P_{PV\text{-}1}$), day-1 load demand ($P_{L\text{-}1}$), day-2 PV generation ($P_{PV\text{-}2}$), and day-2 load demand ($P_{L\text{-}2}$).
- Then, the HEMS calculates the day-2 energy forecast ($E_{Day\text{-}f}$) by summing the high tariff intervals i.e., mid-peak (from 6 AM – 4 PM and 7 PM – 11 PM) and peak times (from 4 PM-7 PM), from forecasted data using (2):

$$E_{Day\text{-}f} = \int_{t=6\text{ AM}}^{t=11\text{ PM}} (P_{PV\text{-}2}(t) - P_{L\text{-}2}(t))\, dt \tag{2}$$

  where $P_{PV\text{-}2}(t)$ and $P_{L\text{-}2}(t)$ are, respectively, the forecasted PV power and the load demand for day-2.
- Next, the HEMS performs the MILP optimization for one day-ahead (i.e., day-1) to obtain the BSS setting.
- Finally, the HEMS obtains the decision variables and sends the result to the central controller to proceed with P2P optimization.

A. PROBLEM FORMULATION of HEMS

The HEMS in this study is reported in [39] and is summarized in this subsection for clarity :

The objective function focuses on minimizing the cost function (C_{house}), which includes the cost of the energy purchased from the utility (C_{buy}), the cost of the energy transferred to the utility (C_{sell}), and the BSS degradation cost (C_{BSS}).

$$C_{house}= |C_{buy}|+|C_{sell}|+C_{BSS} \tag{3}$$

C_{house} considers C_{buy} and C_{sell} as absolute values to reduce the net energy exchange with the utility (i.e., reducing total energy transactions). C_{BSS} is included in the expression for C_{house} to take into account the battery lifetime. The respective costs of selling and purchasing the energy are:

$$C_{buy}=\sum_{t_0}^{T}\Delta T\times f_{buy}(t)\times P_G(t),\quad P_G(t)>0 \tag{4}$$

$$C_{sell}=\sum_{t_0}^{T}\Delta T\times f_{sell}(t)\times P_G(t),\quad P_G(t)<0 \tag{5}$$

where the t_0 is the time of day commencing at 12 AM, T is the duration of 24 hours, ΔT (hr) is the sampling time, $f_{buy}(t)$ is the cost of the energy purchased from the utility (£/kWh), $f_{sell}(t)$ is the tariff (£/kWh) for energy fed into the utility, and $P_G(t)$ is power exchange with the utility grid (kW). The balance of power in the system is represented as in (6):

$$P_{L\text{-}1}(t)\text{-}P_{PV\text{-}1}(t) = P_G(t)+P_B(t) \tag{6}$$

where $P_B(t)$ is the battery power.

B. HEMS BATTERY CONSTRAINTS

The following equations represent the BSS model. The degradation cost of each charging/discharging cycle is represented by (7) [39]:

$$C_{BSS}= \sum_{t_0}^{T}\frac{\mathrm{CC_B}\times\eta_{Conv}\times\eta_c\times\Delta T\times\left|P_B^{charg}(t)\right|}{2\times N_{cycle}}+\frac{\mathrm{CC_B}\times\Delta T\times P_B^{disch}(t)}{\eta_{Conv}\times\eta_d\times 2\times N_{cycle}} \tag{7}$$

where the $\mathrm{CC_B}$ represents the initial cost of the battery (£) (without considering power converters), N_{cycle} is the number of battery's life cycles, η_{conv} represents battery DC/DC converter efficiency (%), P_B^{disch} is the battery discharge power (kW), P_B^{charg} is the battery charge power (kW), η_d is the efficiency of the battery when discharging (%), and η_c is the charging efficiency of the battery (%). Note that P_B^{charg} has a negative value and P_B^{disch} has a positive value. The estimated stored energy in the BSS, SOC of the battery [39], and the current battery capacity are [40]:

$$E(t)= E(t\text{-}1) - \frac{\Delta T\times P_B^{disch}(t)}{\eta_d} - \Delta T\times\eta_c\times P_B^{charg}(t) \tag{8}$$

$$SOC(t)=\frac{E(t)}{B_{capacity}(t)}\times 100 \tag{9}$$

$$B_{capacity}(t) = \frac{1}{SOC(t_\alpha)\text{ - }SOC(t_\beta)}\int_{t_\alpha}^{t_\beta} I(t)\,dt \tag{10}$$

where $E(t)$ is battery energy at time t, $E(t\text{-}1)$ is battery energy at time $t\text{-}1$, $B_{capacity}$ is the estimated battery capacity, and $I(t)$ is the battery charge/discharge current, $SOC(t_\alpha)$ is the battery SOC at time t_α, SOC(t_β) is the battery SOC at time t_β. The new capacity is updated after each charge/discharge cycles and is fed back into (9) to estimate the SOC accordingly.

During mid-peak and peak times, the battery is discharged to its minimum limit (i.e., SOC_{min}) to reduce the energy purchased from the utility at a high price. The permissible limits for the SOC during mid-peak and peak times are given by (11):

$$SOC_{min}\leq SOC(t)\leq SOC_{max} \tag{11}$$

During the off-peak times, the proposed algorithm uses the day-2 required energy forecast for mid-peak and peak times (i.e., $E_{Day\text{-}f}$). To ensure that the forecast energy required is stored in the BSS during the off-peak times, (12) is used [39]:

$$SOC_{min}+\left(100\times\frac{E_{Day\text{-}f}}{B_{capacity}}\right)\leq SOC(t)\leq SOC_{max} \tag{12}$$

The power exchange with the battery is computed using (13) [39]:

$$P_B(t)= P_B^{disch}(t)\times\eta_{Conv}+\frac{P_B^{charg}(t)}{\eta_{Conv}} \tag{13}$$

The maximum allowable charge/discharge power of the battery is limited using (14) and (15) [39]:

$$0\leq P_B^{disch}(t)\leq P_{B\text{-}rating} \tag{14}$$

$$\text{-}P_{B\text{-}rating}\leq P_B^{charg}(t)\leq 0 \tag{15}$$

C. SYSTEM CONSTRAINTS FOR HEMS

The battery and utility power constraints for each household are described in this section. Four binary variables $\Phi_{B\text{-}disch}$, $\Phi_{B\text{-}charg}$, Φ_{import} and Φ_{export} are used as state flags to indicate the transitions of the battery and utility. $\Phi_{B\text{-}disch}$ and $\Phi_{B\text{-}charg}$ are used for battery discharge and charge modes, respectively. Φ_{import} and Φ_{export} are used for import from and export to the utility.

Constraints (16) to (18) are used to ensure that the battery can't be charging and discharging at the same instant [39].

$$\Phi_{B\text{-}disch}(t)+\Phi_{B\text{-}charg}(t)\leq 1 \tag{16}$$

$$\Phi_{B\text{-}disch}(t)=\begin{cases}1 & ,P_B(t)>0\\ 0 & ,P_B(t)<0\end{cases} \tag{17}$$

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$$\Phi_{B\text{-}charg}(t)=\begin{cases}1 & ,P_B(t)<0\\ 0 & ,P_B(t)>0\end{cases} \tag{18}$$

The battery is discharging when $\Phi_{B\text{-}disch}(t)$ is equal to one, and when $\Phi_{B\text{-}charg}(t)$ is equal to one the battery is charging. It is worth noting that when the $\Phi_{B\text{-}disch}(t)$ and $\Phi_{B\text{-}charg}(t)$ are equal to zero the BSS is neither in charging or discharging modes (hence $P_B=0$).

Constraints (19) and (20) link binary variables and battery power [39]:

$$P_B^{disch}(t)\leq \Phi_{B\text{-}disch}(t)\times(P_{B\text{-}rating}) \tag{19}$$

$$P_B^{charg}(t)\leq \Phi_{B\text{-}charg}(t)\times(-P_{B\text{-}rating}) \tag{20}$$

Constraints (21)-(23) are used to ensure that the system only imports or exports power at one time [39].

$$\Phi_{import}(t)+\Phi_{export}(t)\leq 1 \tag{21}$$

$$\Phi_{import}(t)=\begin{cases}1 & ,P_G(t)>0\\ 0 & ,P_G(t)<0\end{cases} \tag{22}$$

$$\Phi_{export}(t)=\begin{cases}1 & ,P_G(t)<0\\ 0 & ,P_G(t)>0\end{cases} \tag{23}$$

When the system takes power from the grid, $\Phi_{import}(t)$ is equal to one, otherwise, $\Phi_{import}(t)$ equals zero. Similarly, if the system is transferring power to the grid, $\Phi_{export}(t)$ is equal to one, otherwise, $\Phi_{export}(t)$ equals zero.

Constraints (24) and (26) link binary variables and grid power [39]:

$$P_G^{import}(t)\leq\Phi_{import}(t)\times P_G^{max\text{-}import} \tag{24}$$

$$P_G^{export}(t)\leq\Phi_{export}(t)\times P_G^{max\text{-}export} \tag{25}$$

$$P_G(t)=P_G^{import}(t)\text{-}P_G^{export}(t) \tag{26}$$

where $P_G^{import}(t)$ and $P_G^{export}(t)$ are power transferred from and power transferred to the utility, respectively. $P_G^{max\text{-}export}$ and $P_G^{max\text{-}import}$ are the limits of power transferred to and imported from the grid, respectively (in this study the limit is set to infinity).

To avoid discharging the battery when the PV system is transferring surplus power to the grid, constraint (27) is used.

$$\Phi_{B\text{-}disch}(t)+\Phi_{export}(t)\leq 1 \tag{27}$$

where $\Phi_{B\text{-}disch}(t)$ is equal to one when the battery is discharging and otherwise equals zero. $\Phi_{export}(t)$ is equal to one when the house transfers power to the utility and otherwise is equal to zero.

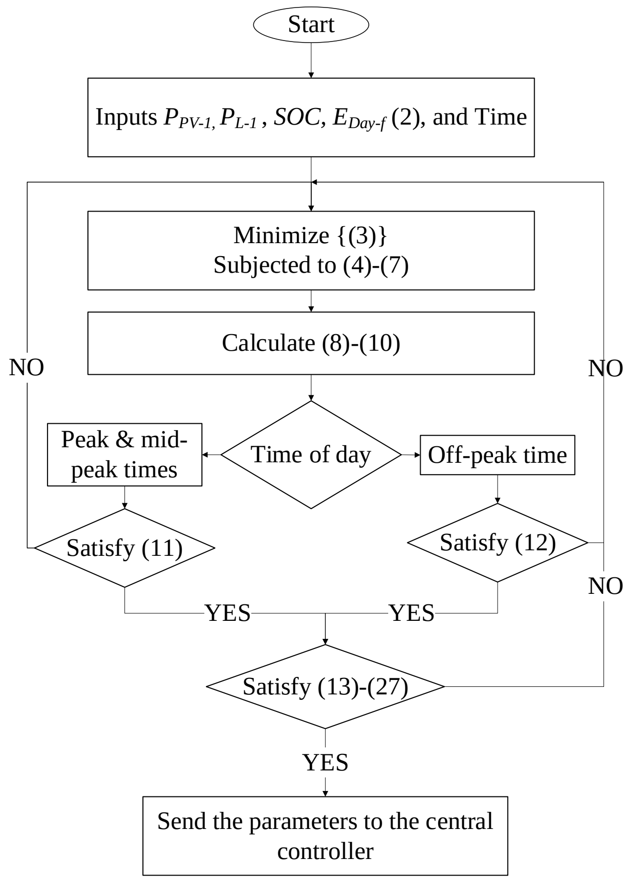

FIGURE 2. Flowchart of the HEMS [39].

Fig. 2. illustrates the above steps and constraints for HEMS.

V. CENTRAL CONTROLLER

The central controller is responsible for the P2P EMS and the selection of the pairing of the houses.

In the P2P optimization, the selected pair of houses export the excess energy from the PV to the grid after satisfying the demands of the given pair of houses and charging the batteries based on the day-2 forecast (i.e., $E_{Day\text{-}f}$). The energy consumption priorities are listed below from high to low:

1. Each house consumption.
2. Each house required SOC limit at the end of the day based on $E_{Day\text{-}f}$.
3. Paired house consumption.
4. Paired house required SOC limit at the end of the day based on $E_{Day\text{-}f}$.
5. Export to the gird.

The P2P problem is also formulated using MILP. The proposed P2P EMS follows the steps detailed below:

- First, input the initial SOC of the BSS for a given pair of houses (x) and (y).
- Obtain the forecast data for the next two days for houses (x) and (y) and calculate $E_{Day\text{-}f}$ for those houses using equation (2).
- Next perform the MILP optimization for one day-head (i.e., day-1) to obtain the BSS setting for houses (x) and (y).

- Finally, the decision variables are sent to the selection level to choose the best pairs.

A. P2P EMS PROBLEM FORMULATION

For the paired houses (i.e., house (x) and house (y)) the cost function that needs to be minimized is presented as (28):

$$C_{sum\text{-}P2P} = \sum_{n=x,y} |C_{buy}{}^{n}|+|C_{sell}{}^{n}|+C_{BSS}{}^{n} - |C_{P2P}{}^{n}| \tag{28}$$

$$C_{P2P}=\begin{cases} \Delta T\times \sum_{to}^{T} f_{P2P\text{-}exp}(t)\times P_{P2P}{}^{x\leftrightarrow y}(t)\ ,\ P_{P2P}{}^{x\leftrightarrow y}(t)>0 \\ \Delta T\times \sum_{to}^{T} f_{P2P\text{-}imp}(t)\times P_{P2P}{}^{x\leftrightarrow y}(t)\ ,\ P_{P2P}{}^{x\leftrightarrow y}(t)<0 \end{cases} \tag{29}$$

where n is referring to the house (x) and (y), C_{P2P} is the cost per day of the energy exchanged between the paired houses (x) and (y). $f_{P2P\text{-}exp}(t)$ is the export exchange tariff between the paired houses (£/kWh). $f_{P2P\text{-}imp}(t)$ is the import exchange tariff between the paired houses (£/kWh). $P_{P2P}{}^{x\leftrightarrow y}(t)$ is the power exchanged between houses (x) and (y) (kW), this value is positive when the power is flowing from house (x) to (y) and is negative if it is flowing in the opposite direction. The P2P energy balance equations for each house and for the pair are:

For house (x):

$$P_{L\text{-}1}{}^{x}(t)\text{-}P_{PV\text{-}1}{}^{x}(t) = P_{G}{}^{x}(t)+P_{B}{}^{x}(t)\text{-}P_{P2P}{}^{x\leftrightarrow y}(t) \tag{30}$$

For house (y):

$$P_{L\text{-}1}{}^{y}(t)\text{-}P_{PV\text{-}1}{}^{y}(t)=P_{G}{}^{y}(t)+P_{B}{}^{y}(t)\text{-}P_{P2P}{}^{y\leftrightarrow x}(t) \tag{31}$$

For houses (x) and (y):

$$\sum_{n=x,y} P_{G}{}^{n}(t)+P_{B}{}^{n}(t) = \sum_{n=x,y} P_{L\text{-}1}{}^{n}(t)\text{-}P_{PV\text{-}1}{}^{n}(t) \tag{32}$$

B. P2P EMS BATTERY CONSTRAINTS

As mentioned above, (8) and (9) are used to estimate energy stored and SOC of each BSS in houses (x) and (y). During mid-peak and peak times, the battery is discharged down to its SOC_{min} according to (11). Off-peak times in Day-1, (12) is used for each BSS to store only the energy required for the next mid-peak and peak times.

C. SYSTEM CONSTRAINTS FOR P2P EMS

To ensure that the flow of power between houses (x) and (y) is always in one direction, constraints (33-35) are used for house (x) and similar constraints are applied for house (y) [1].

$$б_{Pos}{}^{x}(t)+б_{neg}{}^{x}(t)\leq 1 \tag{33}$$

$$б_{pos}{}^{x}(t)= \begin{cases} 1\ ,\ P_{P2P}{}^{x\leftrightarrow y}(t)>0 \\ 0\ ,\ P_{P2P}{}^{x\leftrightarrow y}(t)\leq 0 \end{cases} \tag{34}$$

$$б_{neg}{}^{x}(t)= \begin{cases} 1\ ,\ P_{P2P}{}^{x\leftrightarrow y}(t)<0 \\ 0\ ,\ P_{P2P}{}^{x\leftrightarrow y}(t)\geq 0 \end{cases} \tag{35}$$

where $б_{pos}{}^{x}(t)$ equals one if, during the time interval (t), the energy flows from the house (x) to the house (y) and equals zero otherwise. The binary variable $б_{neg}{}^{x}(t)$ is equal to one if, during the time interval (t), the energy flows from the house (y) to the house (x) and equals zero otherwise.

Constraints (36) and (37) link binary variables and exchanged power (in this study there is no limit for power exchange between paired houses) [1]:

$$P_{P2P}{}^{x\leftrightarrow y}(t)\leq б_{pos}{}^{x}(t)\times P_{P2P,max}(t) \tag{36}$$

$$P_{P2P}{}^{x\leftrightarrow y}(t)\leq б_{neg}{}^{x}(t)\times P_{P2P,max}(t) \tag{37}$$

where $P_{P2P,max}(t)$ is the maximum permissible value for power exchanged between the houses (x) and (y) and this value is set to infinity unless specified.

To ensure that batteries are not used to export energy to the grid, the following constraint (38) is introduced [1]:

$$б_{B\text{-}disch}{}^{x}(t)+ \Phi_{export}{}^{x}(t)\leq 1 \tag{38}$$

where $б_{B\text{-}disch}{}^{x}(t)$ equals zero if the battery in the house (x) is not discharging, otherwise, it equals one. The binary $\Phi_{export}{}^{x}(t)$ equals zero if the battery (x) is not transferring power to the grid, otherwise, it equals one. To avoid the condition where one house in a pair receives power from the grid whilst simultaneously exporting power to the other house, constraint (39) is applied [1].

$$б_{pos}{}^{x}(t)+ \Phi_{import}{}^{x}(t)\leq 1 \tag{39}$$

where $\Phi_{import}{}^{x}(t)$ is equal to one if the house (x) is importing power from the main grid otherwise it is equal to zero.

To avoid the condition where one house in a pair transmits power to the grid whilst simultaneously receiving power from the other house, constraint (40) is applied [1].

$$б_{neg}{}^{x}(t)+ \Phi_{export}{}^{x}(t)\leq 1 \tag{40}$$

To be worthwhile, any solution provided by P2P optimization for houses (x) and (y) must be more beneficial in terms of energy costs than when the house operates individually. Such a condition is met when the following constraint is satisfied (41):

$$C_{house\text{-}cost}{}^{P2P(n)} \leq C_{house\text{-}cost}{}^{individual(n)} \tag{41}$$

where n is referring to the house, here (x) and (y), $C_{house\text{-}cost}{}^{individual(n)}$ is the operational cost per day of energy consumed

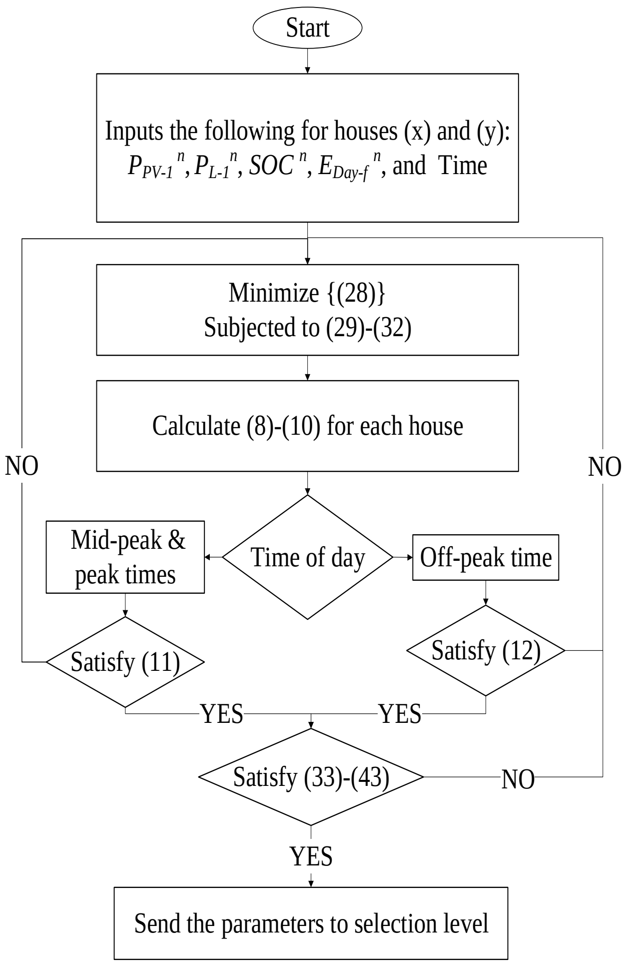

FIGURE 3. Flowchart of the P2P EMS.

when a house is operating individually (i.e., HEMS) and calculated as:

$$C_{house\text{-}cost}{}^{individual(n)} = C_{buy}{}^{n} + C_{sell}{}^{n} + C_{BSS}{}^{n} \tag{42}$$

Note that $C_{sell}{}^{n}$ is a negative value. For the n[th] house in the P2P optimization, the operational cost per day of energy consumed is $C_{house\text{-}cost}{}^{P2P(n)}$ and calculated as:

$$C_{house\text{-}cost}{}^{P2P(n)} = C_{buy}{}^{n} + C_{sell}{}^{n} + C_{BSS}{}^{n} - C_{P2P}{}^{n} \tag{43}$$

Fig. 3. Illustrates the above steps and constraints for P2P EMS.

D. MIXED-INTEGER LINEAR PROGRAMMING

The main target of the proposed P2P EMS is to minimize the total energy exchanged between the houses in the community and the grid. The decentralized sub-system as a first step simplifies the centralized optimization problem and supports quick convergence of the global solution. The proposed system is formulated using MILP optimization and the Gurobi®

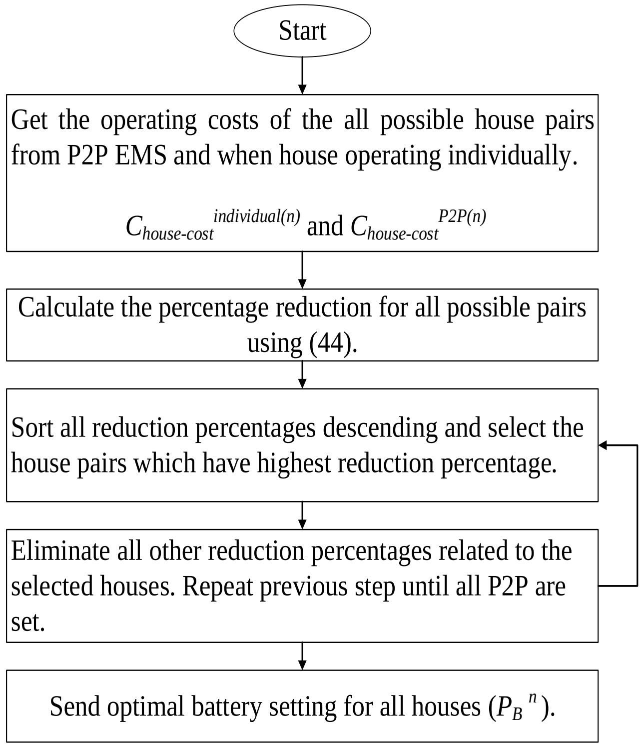

FIGURE 4. Flowchart of the Selection Level.

Optimizer tool in the MATLAB software. There are three different approaches to solve a MILP problem, namely: Branch and Bound, Cutting Plane, and Feasibility Pump [41], [42]. The Branch and Bound algorithm (or Tree Search) is used in this study to find the optimal day-ahead setting for the BSS for each house based on $E_{Day\text{-}f}$, while the cost function in (27) is optimized by three steps. First, the solution of the problem is obtained without any limitations, this stage is called relaxation of the original Linear Programming (LP) problem. Second, the limitations are applied over the obtained results to remove the infeasible solutions. And finally, the optimal solution is obtained using the produced feasible solutions, while tightening the variables constrains further for conducting another search iterations within the obtained variables values to solve the problem again, until the optimal solution is achieved.

E. SELECTION LEVEL

Figure. 4 shows the steps taken to identify the chosen pairs of houses from the P2P results, which are detailed in the below steps:

1. Obtain operating costs for all possible house pairs from P2P EMS and costs for each house operating individually from HEMS.
2. Calculate the reduction percentage for all possible pairs using (44):

$$\frac{\sum_{n=x,y} C_{house\text{-}cost}{}^{individual(n)} - \sum_{n=x,y} C_{house\text{-}cost}{}^{P2P(n)}}{\sum_{n=x,y} C_{house\text{-}cost}{}^{individual(n)}} \times 100\% \tag{44}$$

3. Sort all reduction percentages descending and select the house pairs which has the highest reduction percentage.
4. Eliminate all other reduction percentages related to the selected houses to prevent the same house being a member of multiple pairs and repeat the previous step (step 3) until all P2P are determined.
5. Send optimal battery setting for all houses.

VI. RESULTS AND DISCUSSIONS

The proposed method has been implemented in the MATLAB software environment and compared with the proposed system in [1]. Work proposed in [1] is chosen for comparison because it has similar system configuration (i.e., P2P EMS at consumption level) and aims to reduce the energy costs. The data used in this work is for four months (June to September 2014) and with ΔT of 10 min. The Time of Use (TOU) tariff scheme obtained from [1] is used as shown in Table II. The export tariff from RES to the utility is 3.79 p/kWh **[11]**. The import/export tariff for the energy exchanged between the coupled houses is chosen as 4 p/kWh. Several methods already exist in the literature to predict PV generation and load consumption. For example, Artificial Neural Network [43], Differential Evolution, and Particle Swarm Optimization [44] are all used for day-ahead forecasts. In addition, the authors in [45] have proposed two days-ahead forecasts for a wind turbine. This study imposes normally distributed random numbers on the historical data to represent forecast data [12, 46]. The Mean Absolute Percentage Error (MAPE) of forecasted energy is assumed to be 30% over the four months.

TABLE II
TARIFF RATES [1]

Tariff	Time of Day	Price per kWh
Off-peak	11 PM - 6 AM	4.99 p
Mid-peak	6 AM – 4 PM 7 PM – 11 PM	11.99 p
Peak	4 PM – 7 PM	24.99 p

A. PERFORMANCE COMPARISON

This section shows the performance of the proposed P2P EMS on four houses chosen from the six houses (houses no. 1, 2, 3 and 4) for two days. Figs. 5 (a-1), (b-1), and (c-1) represent the P_{PV} and P_L for houses no. 1, 2, and 3, respectively, for the two test days (17th and 18th June 2014). The solid orange line represents P_L and the solid blue line represents P_{PV}. Figs. 5 (a-2), (b-2), and (c-2) represent the optimal BSS settings for each house and the exchanged power in the community (i.e., P_{P2P}) for house no. 1, 2, and 3, respectively, for the two days (17th and 18th of June 2014). The solid red and dashed blue lines represent *SOC* and P_{P2P}, respectively. Figs. 5 (a-1), (b-1) show that energy consumption for house no. 1 and 2 are higher than their generation most of the time during day 1 and 2. However, house no. 3 generation is more than its consumption as shown in Fig. 5 (c-1). Figs. 5 (a-2), (b-2), and (c-2), show that house no. 1 exchanges power with house no. 2 during day-1 and with house no. 3 during day-2. As shown from Fig. 5 (b-2), during day 2 house no.2 does not exchange energy with neighbors (P_{P2P}=0). Instead during off-peak the BSS is charged to just above 40% and maintains the charge from 5AM to 8AM, when it is charged up again (in accordance to the next day forecast) from the PV surplus power (red solid line). Similarly, house no. 3 does not exchange energy with neighbors in day 1 as shown in Fig. 5 (c-2).

Fig. 6 shows the performance of house no. 4 for the same two test days. The solid red, solid black, and dashed blue lines represent *SOC*, P_{PV}-P_L, and P_{P2P}, respectively. As shown in-Fig. 6, during day-1, the generation is higher than demand ($P_{PV} > P_L$), the BSS is charged by the surplus energy. In addition, it maintains a SOC of 45% during off-peak time as it has prior knowledge of day-2 forecast (i.e., $E_{Day\text{-}f}$). Therefore, during day-1 and day-2 house no.4 did not share the excess energy with the neighbors. This process maximizes self-consumption and reduces the absolute net energy exchanged with the utility. In addition, storing the energy required for day-2 avoids purchasing unnecessary energy from the utility or from neighbors. Table III compares the total operating costs for four months (June to September 2014) of each household when they are operating as part of the community, compared to operating individually. Results show that the proposed method reduces the operating costs of all houses by up to 18.8%. As shown in Table III, the total operational cost of the community is reduced by 7.6% when compared to the six houses being operated individually.

Table IV compares the total operating costs of the proposed method in [1] for four months (June to September 2014) of each household when they are operating as part of the community, with that when the house operates individually. Results show that the proposed method in [1] reduces the operating costs of all houses by up to 45%. As shown in Table IV, the total operational cost of the community is reduced by 11.8% when compared to the six houses being operated individually. As it can be seen from Tables III and IV, the operating costs of [1] is less than that of the method proposed in this paper. This is simply because this paper is aimed to reduce the exchanged energy with the grid, not the operating costs. Since this paper enhances a self/local-consumption approach, it will use the BSSs more frequently compared with [1], which increases the operating cost for each home. However, since [1] exchanges more energy with the grid (see Table V), it necessitates more distribution/transmission and storage capacity at the network side, which increases the whole network operating costs. Therefore, if the network operators want to encourage the self/local-consumption approach, the energy tariff and/or storage price must change accordingly.

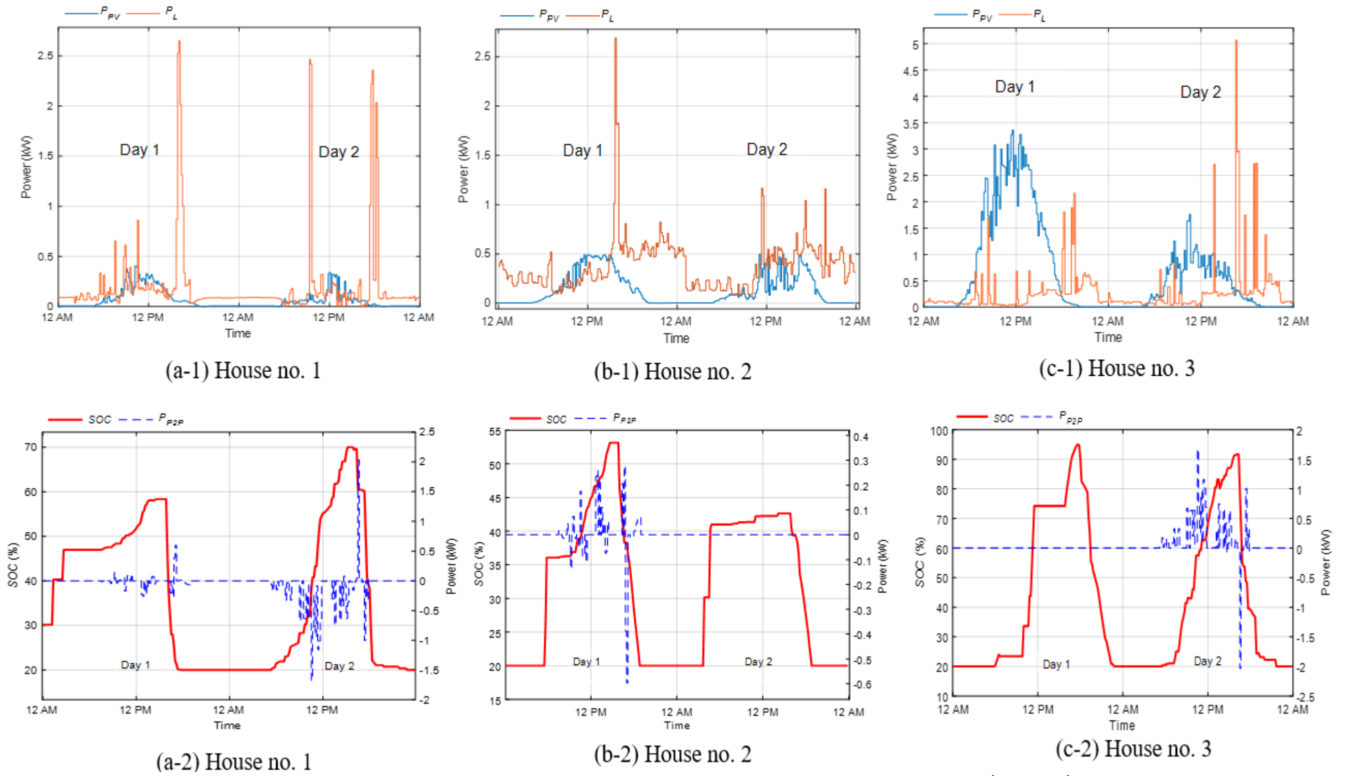

FIGURE 5. **Power and SOC plots for the proposed P2P EMS systems applied to houses no. 1, 2, and 3 for the 17th and 18th of June 2014. Figs (a-1), (b-1), and (c-1) represent the P_{PV} and P_L for house no.1, 2, and 3, respectively. The solid orange line represents P_L and the solid blue line represents P_{PV}. Figs (a-2), (b-2), and (c-2) represent the *SOC* and P_{P2P} for houses no. 1, 2 and 3, respectively. The solid red and dashed blue lines represent *SOC* and P_{p2p}, respectively.**

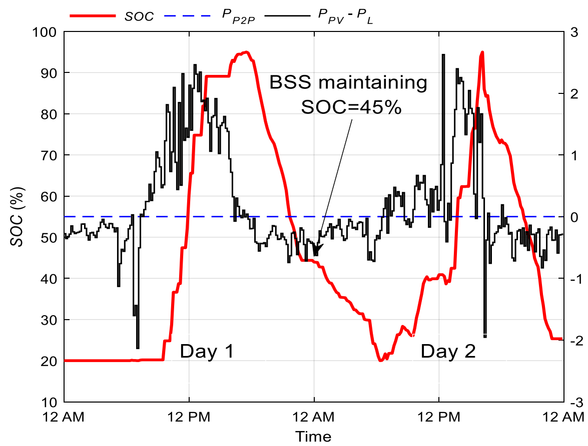

FIGURE 6. **The proposed P2P EMS for house no. 4 for the two test days 17th and 18th of June 2014. The solid red, solid black, and dashed blue lines represent *SOC*, P_{PV} - P_L, and P_{P2P}, respectively.**

B. COMPARING ENERGY EXCHANGED WITH PREVIOUS STATE-OF-THE-ART STRATEGY

Table V compares the total absolute energy exchange of the proposed P2P EMS with the P2P EMS adopted in [1] for the four months from June to September 2014. The proposed method reduces the total absolute energy exchange for the six houses by nearly 25.4 % compared to the P2P EMS proposed in [1].

TABLE III
PROPOSED METHOD

Community	Energy costs for individual operation (HEMS) (£)	Energy costs for P2P operation (£)	Reduction (%)
House 1	32	26	18.8
House 2	112	96	14.2
House 3	32	31	3.1
House 4	47	49	4.3
House 5	47	48	2.1
House 6	61	56	8.2
Total	331	306	7.6

TABLE IV
PROPOSED METHOD IN [1]

Community	Energy costs for individual operation (HEMS) (£)	Energy costs for P2P operation (£)	Reduction (%)
House 1	19	18	5.2
House 2	116	105	9.5
House 3	40	22	45
House 4	32	31	3.1
House 5	27	27	0
House 6	63	62	1.6
Total	297	265	11.8

TABLE V
ABSOLUTE ENERGY EXCHANGE WITH THE UTILITY FOR FOUR MONTHS

Community	Energy exchanged (kWh) ([1])	Energy exchanged (kWh) (Proposed P2P)	Reduction (%)
House 1	1166	818	29.9
House 2	681	624	8.4
House 3	1427	1052	26.3
House 4	1378	964	30
House 5	1660	1188	28.4
House 6	351	328	6.6
Total	6663	4974	25.4

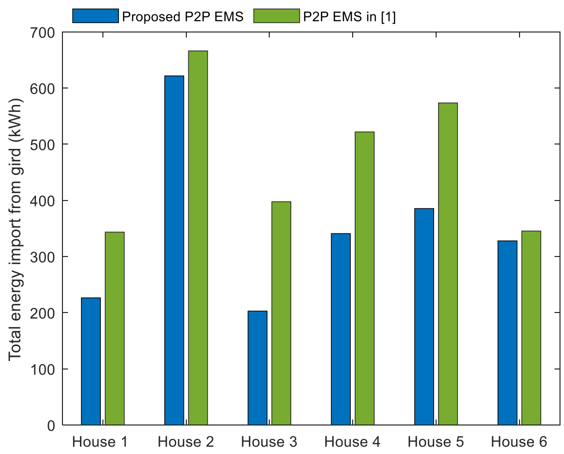

FIGURE 7. **Total imported energy during peak and mid-peak times for four months period (June to September 2014). The blue and green bars represent proposed P2P EMS and P2P EMS reported in [1] for the six houses.**

Fig. 7 shows the total imported energy during peak and mid-peak times for the four months period. The blue and green bars represent the proposed P2P EMS and the P2P EMS in [1], respectively. As illustrated in Fig. 7, the proposed P2P EMS reduces the overall imported energy from the grid during peak and mid-peak times.

VII. Conclusion

The proposed EMS based on energy trading between prosumers enhances a local-consumption approach, which: (1) reduces unnecessary energy exchanges with the utility, (2) reduces the operating costs of every house in the community compared to operating individually, (3) reduces distribution/transmission losses and the required central transmission, storage and generation facilities. The proposed P2P EMS can supply the demand during the next day by discharging the battery or purchasing from neighbors rather than importing from the utility. In addition, by including the next day-ahead forecast (i.e., day-2) the self-consumption of each house in the community is maximized. However, enhancing a self/local-consumption approach may not be economical for individual home (with today energy tariff and storage costs). Therefore, if the network operators aim to enhance the self/local-consumption, the energy tariff and/or storage price must change accordingly.

Research gaps need to be addressed in the future work are (a) investigating the impacts of the integration of plug-in Electric Vehicles in the system, (b) investigating the economic analysis of the system considering the overall system component costs and the profit from the EMS.

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