Electric Vehicles Assisted Multi-Household Cooperative Demand Response Strategy

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***Abstract*—The recent ongoing development of electrical vehicles (EVs) offers vast benefits not only in environmental protection and economics, but also in demand response (DR) management on consumer side. Adopting EVs in DR enables householders to alleviate the load burden while reducing electric bill simultaneously. In this paper, we utilize EVs as temporary energy storage facilities to assist the power transaction, which ensures the flexibility and economic benefit. An innovative EVs assisted DR strategy including a neighbor energy sharing (NES) model is proposed, to jointly optimize the load distribution via vehicle to home (V2H) and vehicle to neighbor (V2N) connections, and economic cost for a residential network with multi-household. The effectiveness of the proposed DR strategy is verified by numerical results in terms of load balancing and cost reduction. It also significantly outperforms the previous DR approaches.**

I. INTRODUCTION

Electric vehicles (EVs) are becoming a trend in next generation of transportation due to their economic and environmental benefits, and the rapid advance of rechargeable battery technology [1]. Along with the worldwide application of dynamic pricing, an increasing adoption of EVs in residences brings about both opportunities and challenges for smart grid. Residences with EVs consume more electricity and react more elastically to electricity price [2]. According to the report provided by the U.S. Energy Information Association [3], the fast charging of an EV is equivalent to about 120 houses coming on line for half an hour, which is a severe issue to the power grid. On the other hand, the usage of EVs as energy storage units via vehicle-to-home (V2H) offers an effective solution to load shaping at demand side. In addition to this, the surplus energy of EVs can be delivered to neighbor via vehicle-to-neighbor (V2N) if it is enabled. Hence, householders are able to participate in load scheduling and may have multiple options in energy allocation.

Compared with the conventional energy storage system (ESS) and other energy production facilities, using EV as a temporary power source has advantages in employing flexibility and economic efficiency [4]. It does not expect extra investment besides the daily used EVs. Meanwhile, the power sharing is enabled from the V2N. The surplus energy of EVs can be shared to neighbor during peak price time and benefit for both sides. Therefore, the DR strategy with EVs holds wide prospects in practice not only for an individual household, but also for the multi-household network.

Much research has been conducted on demand response and there are many popular DR strategies being presented in literature, such as [5]–[7]. However, a shared limitation of the above DR programs is that the impacts of including EVs which is a significant component in residences recently have not been considered. In addition, a DR strategy with an EV auxiliary power supply (EV-APS) model was proposed in [4] and comprehensive factors were considered. In [8], authors focused on EVs' charging behaviors based on the collected data from EV charging session and different types of charging behaviors were derived. To analyze the potential usage of EVs in power grid, the optimal time of EVs' charging and discharging was explored in [9]. In addition to these, [10]–[12] also described a number of interesting DR programs coordinating with EVs. However, all the mentioned studies above are limited to the operation of an individual user and fail to attempt the EVs scheduling among a group of households in DR program.

In this paper, we propose an EVs assisted DR framework including a neighbor energy sharing (NES) model for a multi-household residential network. Compared with the previous research, the main contributions of this work can be summarized as follows:

(1) We utilize EVs as temporary energy storage facilities to assist the power transaction, which ensures the flexibility and economic benefit. Comprehensive affecting factors (*e.g.,* EVs behaviors, user preferences, load scheduling priorities, *etc.*) are considered in scheduling.
(2) Our DR framework is valid and effective not only for an independent household but also for a multi-household residential network, which can satisfy broader requirements compared with the conventional DR programs [4], [8], [10]–[12] in literature. The energy trading contract in neighborhood is also briefly declared in this work.
(3) The effectiveness of the proposed framework is verified by numerical results, which demonstrate that our approach significantly outperforms the methods [4] in literature in both load balancing and electricity cost reduction.

The rest of this paper is organized as follows. Section II presents the overall description of the DR framework for multiple households. In Section III, the mathematical modeling of system components is thoroughly discussed. Afterwards, a case study is carried out to evaluate the feasibility of the proposed approach. Finally, we briefly conclude the paper in Section VI.

II. DEMAND RESPONSE FRAMEWORK FOR MULTI-HOUSEHOLD RESIDENTIAL NETWORK

The block diagram of the proposed DR framework with the EVs assisted NES model is showed in Fig. 1. In this study, it is assumed that each household in the residential community is registered in the network and controlled by the corresponding automatic control unit (ACU) which plays the role as an instructor of each household. ACU regulates the power supplying and the operating time of the household appliances (HAs, *e.g.,* shiftable appliances and nonshiftable appliance [13]) based on the dynamic load information which is received from the smart meter, and other request signals (*e.g.,* EV status, scheduling priority, DP, *etc.*). In addition, the centralized control unit (CCU) that is the highest controller in the network globally monitors the status of the ACUs and optimally manages the EVs assisted NES model through the information flows.

In the proposed DR framework, customers in the network are registered for two types of connections: V2H connection and V2N connection. Specifically, the householders buy electricity from the power grid for the daily consumption including HAs supplying and EVs charging, under the DP tariff. On the one hand, the domestic appliances are directly powered by the public power grid in general. However, the household which is outfitted with EV is able to provide power from EV battery for their HAs on appropriate occasions, such as peak demand periods or power grid outage, via V2H connection. On the other hand, since limited number of the households are equipped with EV at their premises, the households without energy storage unit may need power assistance from NES model via V2N connection, particularly in peak demand time.

When there is surplus energy available being detected in EVs, the CCU determines when and how to allocate the surplus energy to the personal house or the neighbor's houses who have the energy assistance requirements. In general, the EV energy will satisfy the demand of the EV owner in priority. The energy transaction in neighborhood happens when the power grid is not able to fulfill the demand or the serving load at high charges in peak demand periods. Thus, a customer can receive the power from a neighbor at comparatively lower prices. The trading contract between end-user customers will be explained in Section III.

III. SYSTEM MODELS

The EVs are utilized as the flexible energy storage units to ensure the energy trading in neighborhood. The following subsections present the mathematical modeling of the system components in details.

A. Global Energy Balance Model

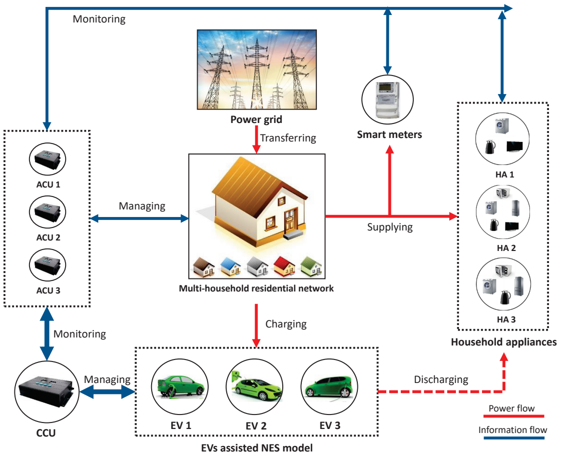


Fig. 1. Block diagram of the proposed DR framework for a multi-household network.

In order to precisely present the energy transactions between each component in the network with K households, W_t^{grid} and $W_{k,t}^{\text{grid}}$ are assumed as the total energy consumption of the entire network and the k^{th} household, respectively, in a time period $[t_{\text{in}}, t_{\text{term}}]$. Afterwards, the global energy model can be proposed as:

$$W_t^{\text{grid}} = \sum_{k=1}^{K} W_{k,t}^{\text{grid}} \tag{1}$$

where

$$W_{k,t}^{\text{grid}} = \int_{t_{\text{in}}}^{t_{\text{term}}} P_{k,t}^{\text{grid}} \cdot d(t) \tag{2}$$

where $P_{k,t}^{\text{grid}}$ is the power rate of the k^{th} household at time t. Moreover, considering the specific power including nonshiftable appliance ($P_{k,t}^{\text{NS}}$), shiftable appliance ($P_{k,t}^{\text{S}}$), EV charging ($P_{k,t}^{\text{EV,c}}$) and EV discharging ($P_{k,t}^{\text{EV,d}}$) into the network, $P_{k,t}^{\text{grid}}$ can be extended as in Equations (3) - (4).

$$P_{k,t}^{\text{grid}} = P_{k,t}^{\text{HA}} + \alpha \cdot \left(\beta \cdot P_{k,t}^{\text{EV,c}} - (1-\beta) \cdot P_{k,t}^{\text{EV,d}}\right) \tag{3}$$

$$P_{k,t}^{\text{HA}} = \sum_{j=1}^{m} P_{k,t,j}^{\text{NS}} + \varepsilon_i \cdot \sum_{i=1}^{n} P_{k,t,i}^{\text{S}} \tag{4}$$

Subject to:

$$\forall t,\ P_{k,t}^{\text{grid}} \leqslant P_{k,\max}^{\text{grid}} \tag{5}$$

$$\forall t,\ \sum_{k=1}^{K} P_{k,t}^{\text{grid}} \leqslant P_{\max}^{\text{grid}} \tag{6}$$

where $P_{k,t}^{\text{HA}}$ in Equation (4) denotes the load of electrical appliances consisting of the nonshiftable load $P_{k,t,j}^{\text{NS}}$ and the shiftable load $P_{k,t,i}^{\text{S}}$ at time t, where j and i are the indexes of the appliances. The parameter ε_i which indicates the scheduling priority of the shiftable appliances equals to small positive values (*e.g.,* 1+e^{-8}, 1+2e^{-8} and 1+3e^{-8}) and it is determined by the householders according to their scheduling preferences. Besides, the maximum power rate of an individual household $P_{k,\max}^{\text{grid}}$ and the maximum power rate of the network

$P_{\max}^{\text{grid}}$ are proposed in Equation (5) and (6), respectively, to limit the real-time load for the safety consideration. Binary parameters α and β in Equation (3) are both used to indicate the EV status that is given as:

$$\text{EV Status} = \left\{ \begin{array}{lll} \text{Disabled}, & \text{if } \alpha = 0, \ \beta = \forall \\ \text{Charging}, & \text{if } \alpha = 1, \ \beta = 1 \\ \text{Discharging}, & \text{if } \alpha = 1, \ \beta = 0 \end{array} \right\} \tag{7}$$

B. EVs Assisted NES Model

In a residential community, different classes of customers exist. It is not possible for every household to purchase an EV. Thus, it is assumed that only a part of houses are installed with EV and indexed as $\hat{k}$, and the rest houses without EV are indexed as $\tilde{k}$. Afterwards, we define $W_{\hat{k}}^{\text{EV,(1)}}$ and $W_{\hat{k}}^{\text{EV,(2)}}$ as the initial energy within EV battery when EV leaves home of the 1st day and the 2nd day, respectively. $W_{\hat{k}}^{\text{EV,rem}}$ represents the remaining energy within an EV. The energy cost on the daily trip is proposed as $W_{\hat{k}}^{\text{EV,trip}}$. Additionally, $D_{\hat{k}}^{\text{trip}}$ and $D_{\hat{k}}^{\max}$ are proposed to indicate the actual travel distance of the vehicle and the maximum travel distance with a fully charged EV. Moreover, the energy charging to the EV and discharging from the EV are assumed as $W_{\hat{k}}^{\text{EV,c}}$ and $W_{\hat{k}}^{\text{EV,d}}$, respectively. Afterwards, the EV balance model with the relevant constrains for a single house can be proposed as:

$$W_{\hat{k}}^{\text{EV,rem}} = W_{\hat{k}}^{\text{EV,(1)}} - W_{\hat{k}}^{\text{EV,trip}} \tag{8}$$

$$W_{\hat{k}}^{\text{EV,trip}} = \frac{D_{\hat{k}}^{\text{trip}}}{D_{\hat{k}}^{\max}} \cdot W_{\hat{k}}^{\text{EV,max}} \tag{9}$$

$$W_{\hat{k}}^{\text{EV,(2)}} = W_{\hat{k}}^{\text{EV,rem}} + W_{\hat{k}}^{\text{EV,c}} - W_{\hat{k}}^{\text{EV,d}} \tag{10}$$

Subject to:

$$\forall t, \ W_{\hat{k}}^{\text{EV,min}} \leqslant W_{\hat{k}}^{\text{EV,rem}} \leqslant W_{\hat{k}}^{\text{EV,max}} \tag{11}$$

$$\tau \cdot W_{\hat{k}}^{\text{EV,max}} \leqslant W_{\hat{k}}^{\text{EV,(2)}} \leqslant W_{\hat{k}}^{\text{EV,max}} \tag{12}$$

where $W_{\hat{k}}^{\text{EV,min}}$ and $W_{\hat{k}}^{\text{EV,max}}$ in (11) represent the minimum and the maximum allowed EV battery capacity, respectively. However, constraint (12) is proposed to ensure the EV leave home with an appropriate energy storage level, where τ is a threshold parameter (*e.g.,* $\tau = 0.95$).

Moreover, considering the power impacts on the grid, $P_{\hat{k},t}^{\text{EV,c}}$, $P_{\hat{k},t}^{\text{EV,d,v2h}}$ and $P_{\hat{k},t}^{\text{EV,d,v2n}}$ are utilized to describe the power rates of EV charging, EV discharging via V2H and EV discharging via V2N at time t, respectively. Therefore, $W_{\hat{k}}^{\text{EV,c}}$ and $W_{\hat{k}}^{\text{EV,d}}$ can be extended as:

$$W_{\hat{k}}^{\text{EV,c}} = \eta_{\hat{k}}^{\text{c}} \cdot \left\{ \sum_{l=1}^{L} \int_{T_{\hat{k},l}^{\text{c,1}}}^{T_{\hat{k},l}^{\text{c,2}}} P_{\hat{k},t}^{\text{EV,c}} \cdot d(t) \right\} \tag{13}$$

$$\begin{aligned} W_{\hat{k}}^{\text{EV,d}} = \frac{1}{\eta_{\hat{k}}^{\text{d,v2h}}} \cdot \left\{ \sum_{m=1}^{M} \int_{T_{\hat{k},m}^{\text{d,1}}}^{T_{\hat{k},m}^{\text{d,2}}} P_{\hat{k},t}^{\text{EV,d,v2h}} \cdot d(t) \right\} \\ + \frac{1}{\eta_{\hat{k}}^{\text{d,v2n}}} \cdot \left\{ \sum_{n=1}^{N} \int_{T_{\hat{k},n}^{\text{d,1}}}^{T_{\hat{k},n}^{\text{d,2}}} P_{\hat{k},t}^{\text{EV,d,v2n}} \cdot d(t) \right\} \end{aligned} \tag{14}$$

Subject to:

$$\eta_{\hat{k}}^{\text{c}}, \ \eta_{\hat{k}}^{\text{d,v2h}} \text{ and } \eta_{\hat{k}}^{\text{d,v2n}} \in (0, 1) \tag{15}$$

$$\forall t \in [T_{\hat{k},m}^{\text{d,1}}, T_{\hat{k},m}^{\text{d,2}}], \ P_{\hat{k},t}^{\text{EV,d,v2h}} \leqslant P_{\hat{k}}^{\text{EV,rated}}, \ P_{\hat{k},t}^{\text{EV,d,v2h}} \leqslant P_{\hat{k},t}^{\text{act}} \tag{16}$$

$$\forall t \in [T_{\hat{k},n}^{\text{d,n}}, T_{\hat{k},n}^{\text{d,2}}], \ P_{\hat{k},t}^{\text{EV,d,v2n}} \leqslant P_{\hat{k}}^{\text{EV,rated}}, \ P_{\hat{k},t}^{\text{EV,d,v2n}} \leqslant P_{\tilde{k},t}^{\text{act}} \tag{17}$$

$$\forall [T_{\hat{k},l}^{\text{c,1}}, T_{\hat{k},l}^{\text{c,2}}] \cap \forall \left\{ [T_{\hat{k},m}^{\text{d,1}}, T_{\hat{k},m}^{\text{d,2}}] \cup [T_{\hat{k},n}^{\text{d,1}}, T_{\hat{k},n}^{\text{d,2}}] \right\} = \emptyset \tag{18}$$

where $\eta_{\hat{k}}^{\text{c}}$, $\eta_{\hat{k}}^{\text{d,v2h}}$ and $\eta_{\hat{k}}^{\text{d,v2n}}$ denote the efficiencies of the corresponding EV behaviors. Since the EV behaviors are discontinuous and may execute at different periods, different time labels are proposed. For example, time parameters $T_{\hat{k},l}^{\text{c,1}}$ and $T_{\hat{k},l}^{\text{c,2}}$ in Equation (13) represent the start time and the end time of the l^{th} charging period. Meanwhile, the definitions of the time parameters in EV discharging periods are similar to Equation (13).

Furthermore, the discharging power via V2H connection ($P_{\hat{k},t}^{\text{EV,d,v2h}}$) cannot exceed the rated power ($P_{\hat{k}}^{\text{EV,rated}}$) nor the actual power required of the household ($P_{\hat{k},t}^{\text{act}}$) as it is shown in constrain (16). Constraint (17) is similar to (16). However, $P_{\tilde{k},t}^{\text{act}}$ represents the actual load demand of the neighbor household which receives the power assistance from the EV household via V2N connection. Besides, as shown in constraint (18), the EV charging and discharging are not allow to operate simultaneously for the purpose of protecting the EV battery from damage.

C. Energy Trading Model in Neighborhood

The proposed EVs assisted NES model ensures the energy trading in neighborhood via V2H and V2N connections. However, it is necessary to declare key points of the trading contract in neighborhood which is shown as follows in advance.

(1) The EV energy will be provided to satisfy the power demand of the household which owns the EV in priority .
(2) After (1), the surplus EV energy will be used to supply the households which are not equipped with any energy storage units (*e.g.,* EVs.) in priority .
(3) If multiple EVs have surplus energy, the EV with the most energy reserve will be adopted to assist neighbors' power demand in priority .
(4) The allocation of the EV energy will follow the principle of maximizing the benefits of the EV provider.

In addition to these, $B_{\hat{k}}^{\text{NES}}$ and $B_{\tilde{k}}^{\text{NES}}$ are proposed to describe the obtained benefits of the households who sold EV energy and received energy assistance, respectively, via NES model. Hence, $B^{\text{NES}}_{\hat{k}}$ and $B^{\text{NES}}_{\tilde{k}}$ can be formulated as follows.

$$B^{\text{NES}}_{\hat{k}} = \theta\% \cdot (C^{\text{dmd}}_{\tilde{k}} - C^{\text{EV,c}}_{\hat{k}}) \tag{19}$$

$$B^{\text{NES}}_{\tilde{k}} = (1 - \theta\%) \cdot (C^{\text{dmd}}_{\tilde{k}} - C^{\text{EV,c}}_{\hat{k}}) \tag{20}$$

subject to:

$$C^{\text{dmd}}_{\tilde{k}} - C^{\text{EV,c}}_{\hat{k}} > 0 \tag{21}$$

where $C^{\text{dmd}}_{\tilde{k}}$ is the cost for electricity demand without EV sharing within a none EV household and $C^{\text{EV,c}}_{\hat{k}}$ is the cost for EV charging of the energy sharing part. θ is a profit distribution parameter and normally $\theta\% = 0.5$, which means the participants in energy trading share the profits equally. The energy transaction via NES model occurs only when it is profitable as shown in Equation (21). Obviously, this type of EVs based energy sharing model is beneficial for the trading participants in both sides.

The objective of this work as shown in Equation (22) is to minimize the total daily cost for energy usage of the residential network as well as shaping the load to a proper level in peak demand time. The mixed-integer linear programming (MILP) which is the most appropriate technique has been used to obtain the optimal solution.

$$\text{Minimize } TC = \int_{T_{\text{in}}}^{T_{\text{term}}} W_{\text{grid}} \cdot P_{\text{tariff}} \cdot d(t) \tag{22}$$

where W_{grid} represents the total energy bought from the power grid in time period $[T_{\text{in}}, T_{\text{term}}]$ and P_{tariff} is the real-time electricity prices.

IV. CASE STUDY

This section proposes a case study to evaluate the feasibility of the proposed approach in terms of saving electric bills and alleviating the load burden in peak demand time simultaneously.

A. Simulation Setup

In the case study, the selected time interval for the optimization is set as 3 minutes. The adopted multi-household network is assumed to comprise 5 households for convenience. For each household, over 15 types of common used domestic appliances covering both shiftable and nonshiftable scenarios are accounted. However, it has been proved that the proposed approach is also valid for a larger scale of households.

In addition to these, the ε parameter which is used to indicate the scheduling priority of the shiftable appliances (*e.g.,* hot water tank, dish-washing machine, washer, *etc.*), is randomly selected to simulate various circumstances. The objective scheduling time for the shiftable appliances is set between 5 p.m. to 12 p.m. according to users' preferences.

Moreover, as not all the users are able to purchase an electrical vehicle, only 3/5 of the households are assumed to be equipped with EVs to support the neighbor energy sharing. For each EV device, a battery capacity of 35 kWh is employed. The charging and discharging (via V2H and V2G) efficiencies are all considered to be 0.95 for convenience. The minimum remaining energy in EV is restricted to 10% of the battery capacity to avoid the deep discharging. Besides, the parameters about the EV status, time of arriving (ToA), time of leaving (ToL), charging rate (CR), discharging rate (DCR) and energy remaining of arriving home (ERoA) of the specific EV within each household, are given in Table I.

TABLE I
ELECTRICAL VEHICLE PARAMETERS SPECIFICATION

Parameters	House #1	House #2	House #3	house #4	House #5
EV Status	Active	Active	Active	Disable	Disable
ToA (1st day)	5 p.m.	6 p.m.	7 p.m.	-	-
ToL (2nd day)	8 a.m.	9 a.m.	10 a.m.	-	-
CR (kW)	7.5	6.5	5.5	-	-
DCR (kW)	3.5	3	2.5	-	-
ERoA (kWh)	26	24	22	-	-

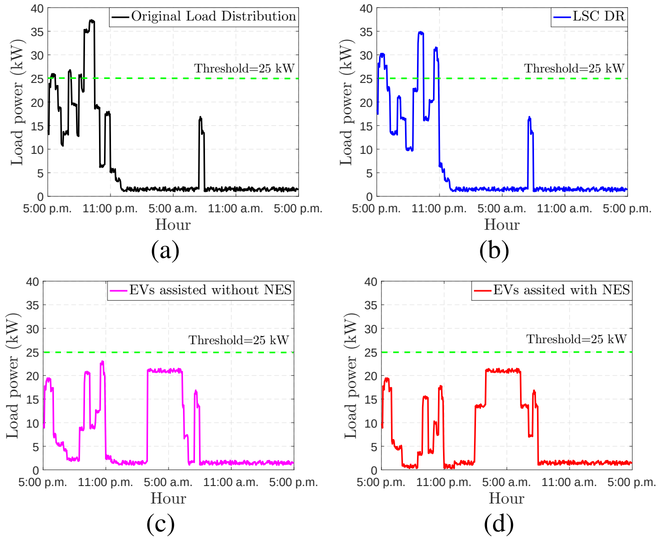
In this case, the basic household load data is provided by [4] and the UK dynamic pricing data of a typical day can be found in [14]. The simulation results are also compared with the literature DR programs [4], [13].

B. Results

Fig. 2 presents the overall load shaping results by using different DR programs. We assume that the threshold of the overall load demand is 25 kW. Specifically, it can be seen that the LSC DR program can slightly alleviate the load burden, particularly around 9 p.m., since limited appliances are scheduled and none of EVs are adopted in the LSC DR program. However, the load shaping performances of using EVs without and with NES in (c) and (d), respectively, are better than the results in (a) and (b). The load demand of the entire network in both (c) and (d) has remained below the threshold apparently due to the EVs discharging contributions.

In addition, compared with the load distribution in (c), the load demand in (d) approaches to a lower level in peak time around 7 p.m. to 9 p.m. This is because the households without EVs received the energy assistance from neighbors via V2N so that the overall load demand on the grid decreases. As a consequence, it is obvious to see that the EVs take more time to charge the batteries in off-peak time for the usage of the 2nd day. Moreover, since the EVs plays a great role in power transaction within the network, the real-time energy remaining variations of EVs (#1, #2 and #3) at parking station are illustrated in Fig. 3.

In terms of the daily electricity cost, the proposed approach has more benefits compared with the literature DR programs as shown in Table II. Apparently, the proposed DR with an EVs assisted NES model performs the best with the lowest cost in the comparison for all cases. Specifically, as the house #1 does not participate in the energy trading in neighborhood due to the lower distributing priority, there is not any cost difference between using EVs with and without NES. Nonetheless, as the energy providers in the transaction, the costs of house #2 and house #3 are reduced by 47.3% and 46.1%, respectively, by adopting the EVs assisted NES model compared with the original cost. Additionally, about 10.5% and 7.4% cost reduction can be achieved compared with the method of using EVs without NES. On the other side of the trading, house #4 and house #5 that are not equipped with EVs also obtain the benefits from the energy sharing. About £0.24 and £0.32 which are equivalent to 10.4% and 13.7% cost saving can be gained during the transaction for house #4 and house #5, respectively.



(a) (b) (c) (d)

Fig. 2. Overall load shaping results by using different DR programs. The load profiles of (a) without DR; (b) by LSC DR; (c) by EV without NES DR; (d) by EV assisted NES DR.

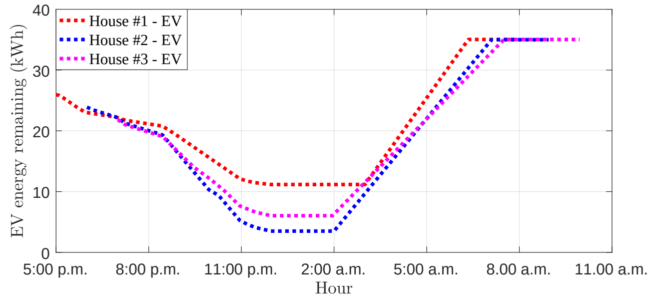


Fig. 3. Real-time energy remaining variations of EVs at parking station.

TABLE II
DAILY COST (£) COMPARISON BY ADOPTING DIFFERENT DR PROGRAMS .

Methods	House #1	House #2	House #3	House #4	House #5
Original	3.15	3.55	3.88	2.31	2.34
LSC	3.09	3.49	3.73	2.24	2.26
EVs without NES	1.83	2.09	2.30	-	-
EVs assisted NES	1.83	1.87	2.13	2.07	2.02

In an overview, for this selected residential community including 5 individual households, the total payment saving is about £5.31 which is equivalent to 34.9% in this case. Obviously, the adopted EVs based NES model is benefit for the energy trading participants on both sides and significant improvements can be achieved comparing with the literature DR programs.

V. CONCLUSION

In this work, a DR strategy considering an EVs assisted NES model has been studied. The effectiveness of the proposed methodology has been verified by numerical results, which demonstrates that the load can be significantly shaped to an appropriate level and the daily electric cost of the entire network can be reduced by 34.9%. On the basis of the achieved results, we can conclude that the proposed DR strategy is an energy-efficient tool and can fulfill the tasks of load balancing and saving bills for the multi-household network.

VI. ACKNOWLEDGEMENT

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