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Plugged-in electric vehicle-assisted demand response strategy for residential energy management

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Abstract

Demand response (DR) management systems are a potentially growing market due to their ability to maximize energy savings by allowing customers to manage their energy consumption at times of peak demand in response to financial incentives from the electricity supplier. Successful execution of a demand response program requires an effective management system where the home energy management system (HEMS) is a promising solution nowadays. HEMS is developed to manage energy use in households and to conduct the management of energy supply, either from the grid or the alternative energy sources like solar or wind power plants. With the increase of vehicle electrification, in order to achieve a more reliable and efficient smart grid (SG), cooperation between electric vehicles (EVs) and residential systems is required. This cooperation could involve not only vehicle to grid (V2G) operation but a vehicle to home (V2H) too. V2H operation is used to transfer the power and relevant data between EVs and residential systems. This paper provides an efficient HEMS enhanced by smart scheduling and an optimally designed charging and discharging strategy for plugged-in electric vehicles (PEVs). The proposed design uses a fuzzy logic controller (FLC) for smart scheduling and to take the charging (from the grid)/discharging (supply the household appliances) decision without compromising the driving needs. Simulations are presented to demonstrate how the proposed strategies can help to reduce electricity costs by 19.28% and 14.27% with 30% and 80% state of charge (SOC) of the PEV respectively compared to the case where G2V operation only used along with the photovoltaic (PV) production, improve energy utilization by smoothing the energy consumption profile and satisfy the user's needs by ensuring enough EV battery SOC for each planned trip.

Keywords: Fuzzy logic controller, Home energy management system, Energy storage systems, Vehicle-to-home, Smart home, Smart grid

Introduction

The demand for electricity due to industrialization and the shift from conventional grids to smart ones is exponentially growing nowadays. Meanwhile, the use of renewable energy sources (RESs), EVs, and energy storage systems (ESSs) is also increasing. To influence customer use of electricity in ways that will produce desired changes in the

utility's load profile, demand side management (DSM) is used for those utility designed activities. Moreover, time-of-use pricing (TOU) encourages consumers to move their charging from peak to off-peak periods. DR strategies are considered one of the most important DSM solutions, it is gaining more attention in power system operations recently, driven by the increasing interest in implementing the SG concept. Therefore, in order to remodel and adapt to increasing load levels, DR is a promising long-term solution to improve energy efficiency and reducing energy loss. It also plays an important role in both balancing energy supply and demand and enhancing the reliability in the SG (Jabir et al. 2018; Paterakis et al. 2015; Durvasulu and Hansen 2018; Hou et al. 2019; Cui et al. 2014).

Recent research considers HEMS as an integral part of the SG that plays a key role in implementing DR applications for residential consumers, which aim to minimize electricity bills and improve energy efficiency. HEMS offers economic incentives for users to manage their electricity consumption by shifting the operational time of household appliances during peak demand in response to electricity price signals (Zhou et al. 2016), as most customers do not have time to manage, control and monitor their electricity consumption. Many researchers are working on the development of efficient and reliable HEMS using different strategies and optimization techniques. For example, to solve the scheduling problem (Aslam et al. 2018; Antunes 2018; Foroozandeh et al. 2020) used mixed integer linear programming (MILP). While Ahmad et al. (2017) proposed an optimal home energy management system using a genetic algorithm (GA) where the constrained optimization problem is mathematically formulated by using the multiple knapsack problems. In ref Lokeshgupta and Sivasubramani (2018) game theory approach is used to minimize both the consumer's energy bill and the system peak demand simultaneously by scheduling the residential energy consumption. However, these strategies are computationally complex. Therefore, they are not favorable for real-time applications.

Recently, a wide variety of applications that have been made based on the FLC emphasized its effectiveness as it is easy to implement and much closer in logic to human thinking and natural language than the traditional logical systems (Rajeswari and Janet 2018; Chandran et al. 2016; Rahman et al. 2014). FLC is widely adopted for home energy management techniques. For example, in order to avoid overriding the autonomous thermostat decision, an Adaptive Fuzzy Logic Model (AFLM) is developed for residential energy management in the SG environment to adapt to the new user's preferences. The proposed study has offered the user a control capability, it did not consider the cost reduction as a preference though. Fuzzy et al. (2018) proposed an FLC for HEMS to minimize electricity cost by managing the energy from the PV to supply home appliances in the grid-connected PV battery system. In this study, automatic tuning of the fuzzy membership functions using the Genetic Algorithm is developed to improve performance, but the FLC is developed by the distributed approach where each home appliance has its own FLC make it more complex to implement compared to a fuzzy logic controlling all the appliances. Moreover, Khalid et al. (2019) designed HEMS using fuzzy logic to manage the energy consumption of the heating, ventilation, and air conditioning (HVAC) and illumination while the rest of the household appliances is managed using heuristic optimization techniques. This design is not fully automated control

where some parameters require a regular update from the user. Chekired et al. (2017) elaborated a strategy to manage home energy demand using a fuzzy logic technique that mainly depends on the PV available energy and according to an established load priority. The proposed strategy has saved 26.49% and 25.54% of energy. The author here has not considered the price signal in order to maintain cost reduction where the reduction in the consumed energy does not ensure the cost reduction because the price is changed in different periods.

DR provides the controllable functionality over some appliance's activities but does not reduce the total demand. Consequently, PEVs and PVs technologies and DR can be engaged to the load profile and achieve a greater energy balance. Recently, the implementation of EVs integrated into residential applications is rapidly growing thanks to their power flexibility, storage properties, and the tax breaks or rebates to EV owners which leads to economic and environmental benefits (Verma et al. 2015). As stated in the Future Energy Scenarios (FES) report published by the UK National Grid, the number of EVs in the UK is expected to increase significantly to 11 million by 2030 and to 36 million by 2040. Consequently, the electricity network can be affected due to the random charging of EVs during peak hours causes an electricity price increase, additional load, and force serious stress on the distribution grid (Denai 2019). However, EVs could also serve as temporary energy storage with a bi-directional capability to provide auxiliary power fed to the household appliances, other EVs, and/or utility grids when needed. However, other than the disruption of the EV availability for travel needs, EVs taking part in bi-directional power flow could result in more charge cycles. Thus, battery deterioration will be more severe depending on the depth and frequency of the charging and discharging cycles (Storage et al. 2018; Khan et al. 2019). Therefore, to maintain an efficient energy balance, advanced management of the EV battery need to be investigated. In this context, Irena (2017) used the term smart EV charging as "adapting the charging cycle of EVs to both the conditions of the power system and the needs of vehicle users". This facilitates the integration of EVs while meeting mobility needs and encourages EV owners to adopt their EVs to serve as a DR resource. The development of modern automation technology offers vast benefits not only in economics and environmental protection but also in employing DR (Radu et al. 2017). For example, Nour et al. (2019) and Sachan et al. (2020), smart charging strategies of EVs are proposed, in which the EV charging process benefits both electric utility and customers by shifting EV charging to the off-peak and low-cost periods. In addition, Chen et al. (2016), proposed a new scheduling approach for isolated microgrids (MGs) with renewable generations by incorporating the demand response of EVs. Khemakhem et al. (2019) proposed a rule-based double-layer supervision strategy for residential energy management systems. The first strategy aims to schedule the operation time of the household appliances using a demand response algorithm. The second strategy aims to ensure the bi-directional power flow from the home to the PEVs and vice versa. However, these strategies deal with exact values rather than approximate values compared to fuzzy reasoning which leads to a less accurate decision-making process.

Thus, the novel contributions of the proposed design can be summed up as follows: (I) An automated and independent HEMS assisted by the V2H technique is implemented without compromising the owner's driving needs and convenience. (II) The proposed

approach uses a fuzzy logic controller because of its flexibility in implementation and the capability of dealing with approximate values for more precise decisions. (III) This study also quantifies the potential cost savings of V2H operating mode. (IV) This paper also evaluates the impacts of PEVs participating in HEMS. It has the potential to achieve higher levels of self-consumption compared to using only stationary batteries.

This paper is organized as follows: In section “[Overview of HEMS and EV technologies](#)”, HEMS and EV technologies are briefly described. Section “[HEMS and PEV models](#)” demonstrates HEMS and the PEV models. Section “[Fuzzy logic controller and proposed strategies](#)” presents the FLC and discusses the proposed strategies. Section “[Simulation and result discussion](#)” presents the results and discussion. Finally, the conclusions of the paper are summarized in section “[Conclusion](#)”.

Overview of HEMS and EV technologies

Home energy management system (HEMS)

In the context of the SG, HEMS is a fundamental component that can achieve an effective DR. Based on the customer’s preferences, it is used to monitor, control and optimize the energy consumption in real-time. Therefore, customers are enabled to take part in DR programs to reduce electricity costs and achieve efficient energy utilization. Nowadays, HEMS is more flexible and able to manage different types of household resources such as RESs and home energy storage systems (HESS). Moreover, power consumption and electricity pricing are provided to the users in real-time which helps them to select their preferences to schedule the operation time of different appliances to improve their energy usage efficiency.

To design an effective HEMS model, adopted communication technologies and appliances classifications must be addressed. According to Serban et al. (2020), communication networks in smart grid applications based on their coverage classified as follow: Home Area Networks (HANs), Neighborhood Area Networks (NANs), and Wide Area Networks (WANs). These networks are the wired networks (optical fiber, twisted pair and power line), and wireless network (Wi-Fi, ZigBee, Bluetooth, LoRa, and different generations of cellular). Hylsberg et al. (2014), proposes implementing ZigBee IP and Smart Energy Profile 2.0 standards to a wide extend conforms with the Internet Protocol suite and state-of-the-art web services development enabling status monitoring and peak load shifting driven by distribution system operator (DSO) price policies as well as energy usage and energy bill reductions.

Moreover, the classification of home appliances is very important for the SG system as it provides a solution to understand the way of operation of each appliance. For example, the author in Xiao et al. (2019) has classified the household appliances into three categories: non-interruptible appliances and interruptible appliances and thermostatically controlled appliances while Pipattanasomporn et al. (2014) discusses high-resolution data at an appliance level intended to develop realistic load models, analyze various DR algorithms for home energy management, and thus ultimately gaining an insight into how individual appliance operation can be controlled for an emerging DR program. Furthermore, four types of household appliances discussed in Xu and Jiao (2020): core electrical appliances, electrical appliances capable of providing storing energy, electrical appliances of any use time, and load aggregators.

Overview of EVs battery and V2H technique

Unlike other types of batteries, EV batteries have a low self-discharge rate—which means they are less likely to lose their charge when they are not being used. Once an EV battery is no longer capable of powering a car, it can be reused for energy storage in the home, workplace, or electricity network. However, EV batteries are subjected to unavailability in some periods and different SOC constraints must be addressed (Storage et al. 2018; Bussar et al. 2013). Therefore, smart charging strategies and other energy management techniques like the V2H technique are addressing those challenges and benefiting from the EV battery as an auxiliary power supply.

According to battery university (Battery University 2020) comparison last updated on 2020-10-21, Table 1 compares the battery size and energy consumption of common EVs in the market.

Nowadays, Li-Ion batteries have the biggest market sale in fitting electric vehicles, thanks to their moderate energy consumption, increased cycle life, low weight, and high energy storage potential. Recently, Tesla has announced a new battery technology that lasts over 15,000 cycles makes it a suitable choice enabling V2G or/and V2H features. For EVs, a battery charger is a fundamental unit. Therefore, choosing the power converter topology is important for EV battery charging/discharging. An electric vehicle battery charger should be with bi-directional power flow to allow G2V, V2G, and/or V2H. for example, a bi-directional AC-DC converter with a flyback based regenerative clamp circuit can recycle the energy stored in the clamp capacitors twice in a switching cycle, thus the overall power conversion efficiency is improved (Nayak and Rajashekara 2019).

While wireless EV charging (both stationary and dynamic) has been proposed in different studies there is still some undergoing research investigating the dynamic charging and discharging strategies. With the increase in mobility-as-a-service and the eventual shift towards fully autonomous vehicles, these strategies need to be further adjusted, mainly in urban areas. EV battery has massive energy storage capacity which can be potentially utilized as a temporary energy source enabling V2H implementation. Hence transferring the power and relevant data between EVs and home and drive the

Table 1 Battery size and energy consumption of common EVs in the market

EV model	Battery size	Range km (mi)	Wh/km (mi)	Energy cost/km (mi)
BMW i3 (2019)	42 kWh	345 km (115)	165 (260)	\$0.033 (\$0.052)
GM Spark	21 kWh	120 km (75)	175 (280)	\$0.035 (\$0.056)
Fiat 500e	24 kWh	135 km (85)	180 (290)	\$0.036 (\$0.058)
Honda Fit	20 kWh	112 km (70)	180 (290)	\$0.036 (\$0.058)
Nissan Leaf	30 kWh	160 km (100)	190 (300)	\$0.038 (\$0.06)
Mitsubishi MiEV	16 kWh	85 km (55)	190 (300)	\$0.038 (\$0.06)
Ford Focus	23 kWh	110 km (75)	200 (320)	\$0.04 (\$0.066)
Smart ED	16.5 kWh	90 km (55)	200 (320)	\$0.04 (\$0.066)
Mercedes B	28 kWh	136 km (85)	205 (330)	\$0.04 (\$0.066)
Tesla S 60	60 kWh	275 km (170)	220 (350)	\$0.044 (\$0.07)
Tesla S 85	90 kWh	360 km (225)	240 (380)	\$0.048 (\$0.076)
Tesla 3	75 kw	496 (310)	151 (242)	\$0.030 (0.048)

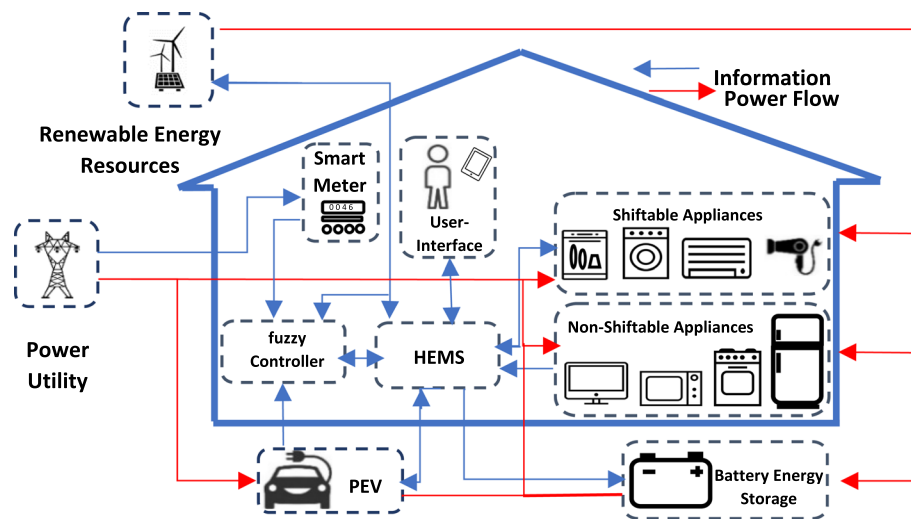


Fig. 1 HEMS Architecture

Table 2 Home appliances classification

None-shiftable appliance	Rated power (W)	Shiftable appliance	Rated power (W)
Iron	1000	Washing machine (WM)	800
Oven	2000	Dish washer (DW)	1100
Laptop	20	Clothes dryer (CD)	400
Microwave	600	Hair dryer (HD)	450
Television	200	Hair straightener (HS)	20
Lighting	100		
Refrigerator	200		
Water heater	2000		

development of new technologies such as wireless charging and move charging from home/office to hubs (Renewable, International Agency, Energy 2019).

HEMS and PEV models

Household appliances model

As shown in Fig. 1, the household power profile for each time-step can be fulfilled through (i) electricity generated by the PV system; (ii) electricity supplied from the stationary battery and/or from the EV battery if the vehicle is available; and (iii) electricity consumed from the power grid. Where charging/discharging of the stationery and EV batteries within the same time-step is not possible because the stationary battery can be used only during peak hours and if the EV is not available. As shown in Table 2, the household appliances in this paper are divided mainly into two categories; first, shiftable appliances that could reschedule their operating time based on load demand and electricity price such as washing machine, dishwasher, and clothes dryer. Then, non-shiftable appliances require a

permanent power supply during operating time regardless of electricity prices. Therefore, the total power consumption by the appliances can be calculated as follow:

$$P_A(t) = \sum_{j=1}^n P_j^{non-sh}(t)u_j(t) + \sum_{i=1}^m P_i^{sh}(t)u_i(t) - P_{PV}(t) \quad (1)$$

where P_j^{non-sh} and P_i^{sh} are the power of nonshiftable and shiftable appliances respectively, j and i represent the index of the appliances. n and m are the numbers of non-shiftable and shiftable appliances respectively. The status of the shiftable and non-shiftable appliances ($u_i(t)$, $u_j(t)$) are set as 0 if the appliance is off and 1 when the appliance is operating.

PEV system model and formulation

Some of Nissan Leaf 2017 model parameters are used in the simulations since it offers a capacity suitable for the designed case [the maximum battery capacity C_{PEV}^{max} (40 kWh), charging time empty to full (18 h)]. The maximum charging $P_{PEV}^{ch max}$ /discharging $P_{PEV}^{dis max}$ power rate is 2.3 kWh. All the PEV system components are viewed in terms of their input and output. Their internal behavior is out of the scope of this study. The charging P_{PEV}^{ch} /discharging P_{PEV}^{dis} power rates are dynamic with respect to the price and the demand respectively. Because PEV can act as a temporary source supplying the appliances during the peak hours, it can help maintain more cost reduction during the proposed charging slots, charging power rate depends on the real-time price is calculated as follow:

$$P_{PEV}^{ch}(t) = P_{PEV}^{ch max} - \left(((RTP(t) - Price_{min}) / Price_{min}) * P_{PEV}^{ch min} \right) \quad (2)$$

where $RTP(t)$ is the real-time price and $Price_{min}$ is the minimum price which is set as 0.08. $P_{PEV}^{ch min}$ is the minimum charging power rate of the PEV and set as 1150 kWh.

The discharging power rate set equal to the total demand power if the total demand power is less than the maximum discharging power rate:

$$P_{PEV}^{dis}(t) = P_A(t)P_A(t) < P_{PEV}^{dis max} \text{ otherwise } P_{PEV}^{dis}(t) = P_{PEV}^{dis max} \quad (3)$$

The total energy of the PEV is

$$E_{PEV}(t) = \int_{t_a}^{t_d} P_{PEV}^{ch}(t)u_{PEV}(t) + P_{PEV}^{dis}(t)(1 - u_{PEV}(t)) \quad (4)$$

u_{PEV} represent the status of PEV (1 charging state while 0 is discharging state).

The SOC of the PEV represented as follow:

$$SoC_{PEV}(t) = SoC_{PEV}(t - 1) + (P_{PEV}(t)) * \Delta t / C_{PEV}^{max} \quad (5)$$

To avoid deep charging and discharging, the upper and lower limits of the PEV battery SOC are

$$0.2SoC_{PEV}^{max} \leq SoC_{PEV}(t) \leq 0.8SoC_{PEV}^{max} \quad t \in [t_a, t_d - 1) \quad (6)$$

t_a and t_d represent the PEV arrival and departure time, respectively.

The designed charging/discharging strategy will ensure that the SOC of the PEV battery will be at least 40% before any trip. In case the user intends to take a long trip, he must define the target SOC SoC_{target} to calculate the required SOC as follow:

$$SoC_{req}(t) = SoC_{target} - SoC_{PEV}(t) \quad (7)$$

Therefore, the time duration needed to apply forced charging with the maximum power rate for this case can be calculated as follow:

$$T = (SoC_{req}(t) * C_{PEV}^{max}) / P_{PEV}^{ch max} \quad (8)$$

Fuzzy logic controller and proposed strategies

Smart scheduling

In this model, the appliances are controlled by an FLC in order to make an optimal scheduling decision. It provides a workspace for computation with words and offers a hand in managing uncertainty during the designing of expert systems. It has now become an unavoidable part of machine learning as it simplifies the overall implementation, leads to better performance, and lower time-consuming as compared to other techniques. Fuzzy logic-based implementation overcomes the limitation of rules-based techniques (crisp values) and can handle imprecise and uncertain situations.

Mamdani-type fuzzy inference system is used in this design because it offers a smooth output. A fuzzy inference system takes the electricity price signal and demand load as inputs. As shown in Fig. 2, the membership functions (MFs) for the input variable “power demand” are triangular and labeled as Low, Average, and High. The universe of discourse of power demand is chosen as [0 6300] (Watt) while the membership function for the input variables “electricity price” are gaussian and defined as “Low” and “High” and the universe discourse is [0 0.16] (€/kWh).

The outputs of the fuzzy inference system are: Shifting (switching the appliance off), Valley Filling (switching the appliance on) and Do-nothing (keep the operating status of the appliance without any change). As shown in Fig. 3, the fuzzy sets for each output are determined as Bad Action (BA), Good Action (GA) and Very Good Action (VGA). The universe of discourse of the membership functions is defined as [0 100] to evaluate all possible modes with values out of 100. While Table 3 shows the input and the output of the fuzzy logic controller (controller knowledge base rules).

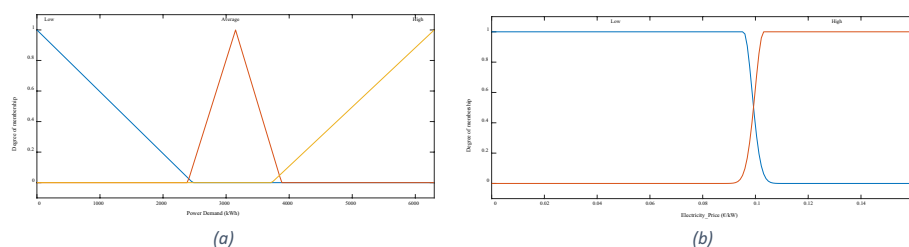


Fig. 2 **a** Fuzzy sets of power demand input variable, **b** fuzzy sets of electricity price input variable

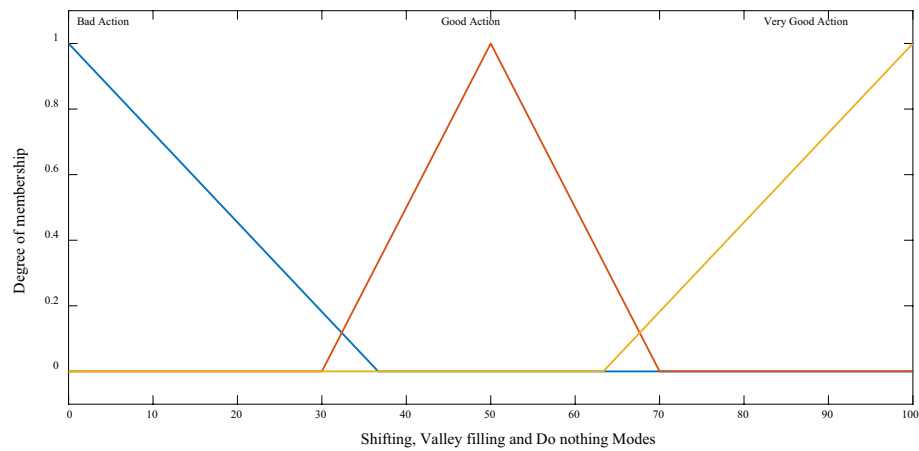


Fig. 3 Smart scheduling fuzzy sets of the output variables

Table 3 Smart scheduling fuzzy logic controller knowledge base rules

Power demand	Electricity price	Shifting	Valley filling	Do nothing
High	Expensive	VGA	BA	BA
High	Cheap	BA	BA	VGA
Average	Expensive	VGA	BA	GA
Average	Cheap	BA	VGA	GA
Low	Expensive	BA	BA	VGA
Low	Cheap	BA	VGA	BA

BA bad action, GA good action, VGA very good action

The pseudo-code listed in algorithm 1, illustrates the procedure of the main algorithm of the DR. The controller will receive the scheduling modes $m1$ (Shifting, Valley Filling and Do-nothing), then, the status of the shiftable appliances ($u_i(t)$) must be checked at each time step in order to update the status signal of all shiftable appliances $u_{all}^{new}(t)$ as follow:

Calculate the total power of shiftable appliances

$$P_{sh}(t) = \sum_{i=1}^n P_i^{sh}(t) u_i(t) \quad (9)$$

where n is the number of shiftable appliances, $u_i(t)$ is the appliances status (0—off, 1—on).

During the shifting mode process, the amount of power that needs to be curtailed during peak hours is calculated as:

$$P_{shifting_req}(t) = P_A(t) - P_{avg}^{lower} \quad (10)$$

where P_{avg}^{lower} is the lower limit of the average total demand power level.

During the valley filling mode process, the amount of shifted power that needs to be run during off-peak hours is calculated as:

$$P_{v_filling_req}(t) = P_{avg}^{upper} \quad (11)$$

where P_{avg}^{upper} is the lower limit of the average total demand power level.

If shifting mode is detected, there are two possible scenarios. Firstly, when the required power is higher than the total power demand of the shiftable appliances, then all shiftable appliances will be shifted. However, when the required power is lower than the demand of the shiftable appliances, there is no need to shift all appliances, some of them are enough to meet the average power demand. In this case, the system selects the appliances with the highest probability that calculated based on the rated power of the appliance as shown in Eq. (10)

$$\alpha_i^{shifting} = 1 - abs\left(\frac{P_i^{sh} - P_{shifting_req}(t)}{P_i^{sh} + P_{shifting_req}(t)}\right) \quad (12)$$

In case there is only a shiftable appliance is operating, If the value of the shifting power required is too small compared to the rated power of that shiftable appliance, then the appliance will not be shifted.

If valley filling mode is detected, to select which appliance needs to be switched on, the $P_{v_filling_req}(t)$ is compared to the $P_{sh}(t)$. Therefore, there are also two scenarios: when the required power is higher than the total rated power of shifted appliances, in this case, all shifted appliances will be switched on as the demand will not exceed the lower of the average power. However, when the required power is lower than the power rated of shifted appliances, it is not desired to run all shifted appliances. Therefore, selecting an appliance depends on the valley filling probability as presented in Eq. (11).

$$\alpha_i^{v_filling} = 1 - abs\left(\frac{P_i^{sh} - P_{v_filling_req}(t)}{P_i^{sh} + P_{v_filling_req}(t)}\right) \quad (13)$$

In case there is only one shifted appliance needs to be switched on, If the value of the valley filling power required is too small compared to the rated power of that shifted appliance, then the appliance will not be switched on.

In order to ensure that the shifted appliance will be switched on only for the calculated duration of the shifting mode for that appliance. The shifting counter (c_i) is used as shown in algorithm 1.

Finally, the updated status signal of all shiftable appliances is represented as follow:

$$u_{all}^{new}(t) = [u_{i=1}^{new}(t), u_{i=2}^{new}(t), \dots, u_{i=n}^{new}(t)] \quad (14)$$

Algorithm 1

Input: $P_{sh}(t)$, $P_{shifting_req}(t)$, $P_{v_filling_req}(t)$, $m1$, $P_A(t)$, $u_i(t)$, $P_i^{shifting}$, $\alpha_i^{v_filling}$, c_i , $\alpha_i^{sh}(t)$

Output: $u_{all}^{new}(t)$

1. **For** each time step
2. **If** $m1$ is shifting && $P_{shifting_req}(t) \geq P_{sh}(t)$
3. Then $u_{all}^{new}(t) = 0$ and increment c_i
4. **Elseif** $m1$ is v_filling && $P_{v_filling_req}(t) \geq P_{sh}(t)$ && $c_i > 0$
5. Then $u_{all}^{new}(t) = 1$ and decrement c_i
6. **Else**
7. **For** each shiftable appliance **do**
8. Use equations (12, 13) and check the max $\alpha_i^{shifting}$, $\alpha_i^{v_filling}$ to use in the following steps.
9. **if** $m1$ is shifting && $u_i(t) = 1$ && $P_{shifting_req}(t) < P_{sh}(t)$ && $|P_{shifting_req}(t) - P_i^{sh}(t)| > P_{avg}^{upper} \pm 50$
10. Then $u_i^{new}(t) = 0$ and increment c_i
11. **Elseif** $m1$ is v_filling && $u_i(t) = 0$ && $c_i > 0$ && $P_{v_filling_req}(t) < P_{sh}(t)$ && $|P_{v_filling_req}(t) - P_i^{sh}(t)| > P_{avg}^{lower} \pm 50$
12. Then $u_i^{new}(t) = 1$ and decrement c_i
13. **Else**
14. $u_i^{new}(t) = u_i(t)$
15. **End if**
16. Update $P_{shifting_req}(t)$ and $P_{v_filling_req}(t)$ (by subtracting $P_i^{sh}(t)$) and Update the max $\alpha_i^{shifting}$, $\alpha_i^{v_filling}$ (by removing the index of $P_i^{sh}(t)$)
17. **End inner loop**
18. update $u_{all}^{new}(t)$
19. **End outer loop**
20. **Return** $u_{all}^{new}(t)$

PEV charging/discharging strategy

The proposed PEV controller works based on the relationships between scheduled power demand, electricity price, availability of PEV and PV, and SOC of PEV. Due to the changes in the electricity price during a day, the DR program aims to inform customers about the prices on an hour ahead basis to shift the charging battery of the PEV from peak demand hours to off-peak and/or supply the household appliances during peak hours when the power demand and the electricity price are high which in return minimize the electricity bills for the consumer and reduce the stress on the power grid. The operational strategy of the proposed PEV system is categorized into three modes: Mode-I (discharging/supplying the household appliances during peak demand). Mode-II (Charging from the power grid during off-peak). Mode-III (Disable mode/Do-nothing).

As shown in Fig. 4, the input variables of the fuzzy controller are set as Scheduled Power Demand, Electricity Price, SOC of PEV, PEV Availability and PV Availability, where the output variables are; Charging, Discharging, and Do-nothing. The MFs for input variables “Scheduled Power Demand” are gaussian and are labeled as High, Average and Low.

The universe of discourse of the scheduled power demand is chosen as [0 6300] (Watt) and the fuzzy sets of electricity price are defined as “Cheap” and “Expensive”, the MFs are also gaussian and the universe discourse is [0 0.16] (€/kWh) as shown in Fig. 4a and b. In Fig. 4c, MFs of the PEV SOC is illustrated, the minimum SOC is set to 40% in order

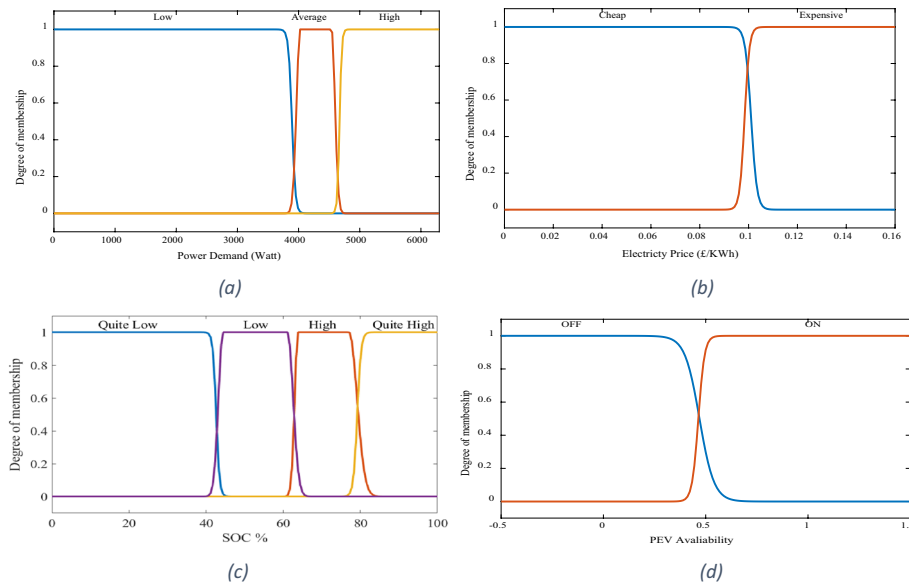


Fig. 4 PEV management fuzzy sets of the input variables **a** power demand, **b** electricity price, **c** SOC%, **d** PEV availability

to extend the battery life. The four fuzzy sets of SOC are labeled as; “Quite Low”: occurs when SOC less than 40% and then the battery has to be charged, “Low”: is the fuzzy set that can be detected when SOC is between 40 and 65%, however, it is not too low, “High”: SOC is lower than 80% and “Quite High”: the battery is almost full. The MFs for the input variable which refer to PEV availability depend on whether the PEV is connected to home “ON” or it is outside the home “OFF”. Therefore, the status of PEV set to “1” when it is available and connected to the home or “0” when it is outside as shown in Fig. 4d. The availability of PV is considered as a second auxiliary power supply for household appliances.

For each possible decision that the system can make in order to manage the status of the PEV (charging/discharging/do nothing), the fuzzy sets are determined as Bad Action (BA), Good Action (GA) and Very Good Action (VGA). The universe of discourse of MFs is set to [0 1] to evaluate all possible decisions with values out of 1 as shown in Fig. 5. The list of fuzzy rules fed to the controller are shown in Table 4. The total applicable rules are 24 since we have eliminated all the rules when the EV availability input is off which is not applicable.

In the pseudo-code below of algorithm 2, the first five steps are to ensure the availability of the PEV to apply the proposed strategy and to ensure that the battery has enough SOC % for the next trip by setting the mode *m2* to charging with the maximum charging power rate, one hour prior to the departing time if the SOC% is less than 40%. Then the algorithm checks if the driver has requested a SOC for a long trip in order to start the forced charging scenario when the time left for the trip ($t_d - t$) is exactly equal to the duration need to meet the required SOC with the maximum charging power *T*. Other than that, algorithm 2 will calculate the charging and discharging power rates according to the real-time price and the power demand respectively described in Eqs. (2) and (3). PEV availability depends on the existence of the

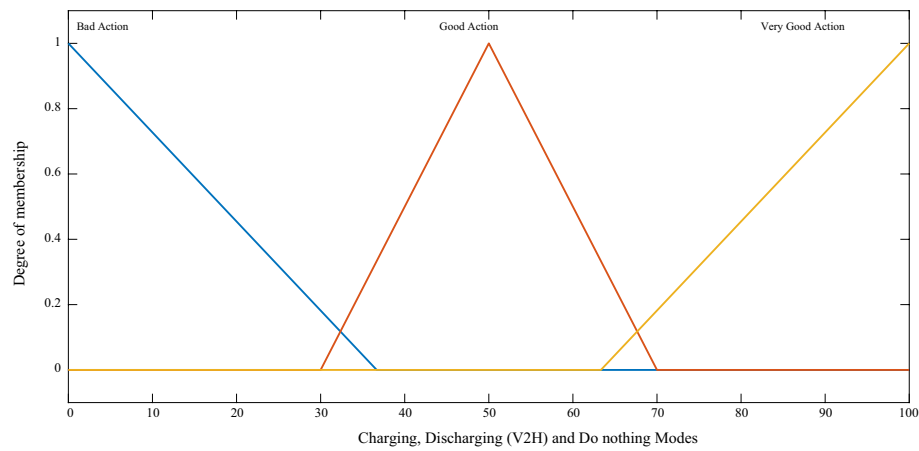


Fig. 5 PEV management fuzzy sets of the output variables

Table 4 PEV management fuzzy logic controller knowledge base rules

Power demand	Electricity price	EV availability	SOC	Discharging	Do nothing	Charging
High	Expensive	ON	Quite Low	BA	VGA	BA
High	Expensive	ON	Low	VGA	GA	BA
High	Expensive	ON	High	VGA	GA	BA
High	Expensive	ON	Quite high	VGA	GA	BA
High	Cheap	ON	Quite low	BA	GA	VGA
High	Cheap	ON	Low	BA	VGA	BA
High	Cheap	ON	High	VGA	GA	BA
High	Cheap	ON	Quite high	VGA	GA	BA
Average	Expensive	ON	Quite low	BA	VGA	BA
Average	Expensive	ON	Low	VGA	GA	BA
Average	Expensive	ON	High	VGA	GA	BA
Average	Expensive	ON	Quite high	VGA	GA	BA
Average	Cheap	ON	Quite low	BA	GA	VGA
Average	Cheap	ON	Low	BA	VGA	BA
Average	Cheap	ON	High	VGA	BA	BA
Average	Cheap	ON	Quite high	VGA	BA	BA
Low	Expensive	ON	Quite low	BA	BA	VGA
Low	Expensive	ON	Low	BA	VGA	BA
Low	Expensive	ON	High	VGA	BA	BA
Low	Expensive	ON	Quite high	VGA	BA	BA
Low	Cheap	ON	Quite low	BA	BA	VGA
Low	Cheap	ON	Low	BA	BA	VGA
Low	Cheap	ON	High	BA	BA	VGA
Low	Cheap	ON	Quite high	BA	VGA	BA

BA bad action, GA good action, VGA very good action

PEV at home, where the availability is set to 1 when EV is existing and connected to the home, and 0 when the EV is outside the home.

Algorithm 2

Input: $P_A(t)$, $RTP(t)$, $m2$, t_d , t_d , $P_{PEV}^{ch\ min}$, C_{PEV}^{max} , t , T

Output: $P_{PEV}^{ch}(t)$, $P_{PEV}^{dis}(t)$, $m2$

```

1.  If  $t > t_d$  &&  $t < t_d$ ,
2.     $P_{PEV}^{ch}(t)$ ,  $P_{PEV}^{dis}(t) = 0$ 
3.  Else if  $t = t_d - 1$  &&  $SoC_{PEV}(t) < 0.4 SoC_{PEV}^{max}$ 
4.     $m2 = \text{charging}$ 
5.    and  $P_{PEV}^{ch}(t) = P_{PEV}^{ch\ max}$ 
6.  Else if  $(t_d - t) = T$  &&  $T > 0$ 
7.     $m2 = \text{charging}$ 
8.    and  $P_{PEV}^{ch}(t) = P_{PEV}^{ch\ max}$ 
9.  Else
10.   For each time step
11.    If  $m2$  is discharging
12.      If  $P_A(t) \geq P_{PEV}^{dis\ max}(t)$ 
13.         $P_{PEV}^{dis}(t) = P_{PEV}^{dis\ max}(t)$ 
14.      Else
15.         $P_{PEV}^{dis}(t) = P_A(t)$ ,
16.      End if
17.    Elseif  $m2$  is charging
18.       $P_{PEV}^{ch}(t) = P_{PEV}^{ch\ max} - ((RTP(t) - 0.08)/0.08) * P_{PEV}^{ch\ min}$ 
19.    Else
20.       $P_{PEV}^{ch}(t)$ ,  $P_{PEV}^{dis}(t) = 0$ 
21.    End if
22.  End for
23. End if
24. Return  $P_{PEV}^{ch}(t)$ ,  $P_{PEV}^{dis}(t)$ ,  $m2$ 

```

Simulation and result discussion

Scenario 1: Implementing smart scheduling strategy without V2H technique

The proposed scheduling strategy works based on real-time pricing (RTP), which is considered dynamic pricing. Using the DR program, the customers receive price signals on an hour-ahead basis as the electricity price varies at different time intervals of a day. Therefore, smart meters are used to receive the RTP signal from a utility and record the current power consumption data of all household appliances and PEV charging during their operation times, and then send them to the HEMS to manages and schedule the shiftable appliances. The simulation time is set at one day (24 h) with 1 s time step.

In order to evaluate the proposed scheduling strategy without implementing the V2H technique, two cases are considered based on equipping the PV into the home due to its impact on the total household demand.

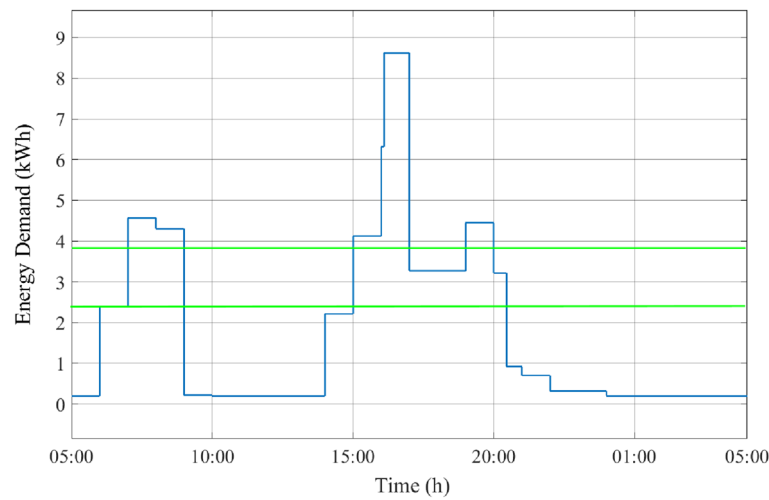


Fig. 6 Energy demand profile (average limits in green lines)

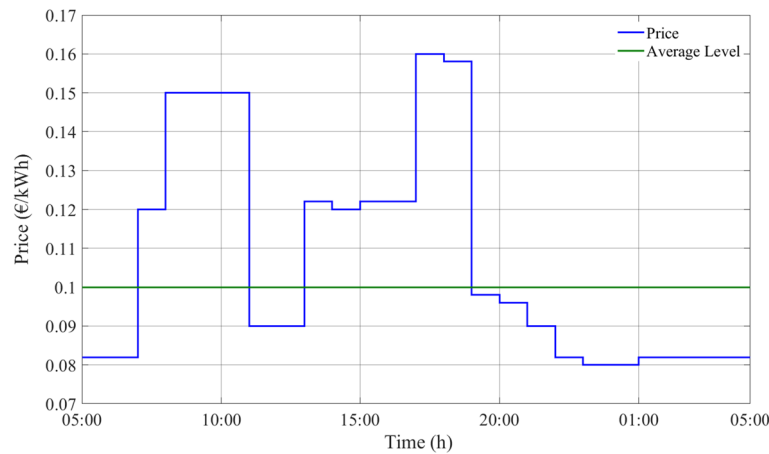


Fig. 7 Electricity price

Case 1: Demand + PEV

In this case, there are some assumptions to be considered; (I) The total household demand is the sum of all household appliances consumption and random PEV charging. (II) The PEV works under G2V mode only without implementing PEV charging strategy in which the PEV battery charge from the power grid and it does not supply power to the home. (III) The user leaves the home by 09:00 and returns at 16:00. (IV) Once the PEV is available, it starts charging with the maximum power rate until the SOC reaches the maximum limit which is set to 80% in order to avoid overcharging.

The daily energy consumption profile including all appliances' consumption and PEV charging shown in Fig. 6, and the electricity price signal received from the power utility is shown in Fig. 7. Two critical peak demand periods can be distinguished, which usually occur during morning and evening times when the electricity prices are higher. Due to a

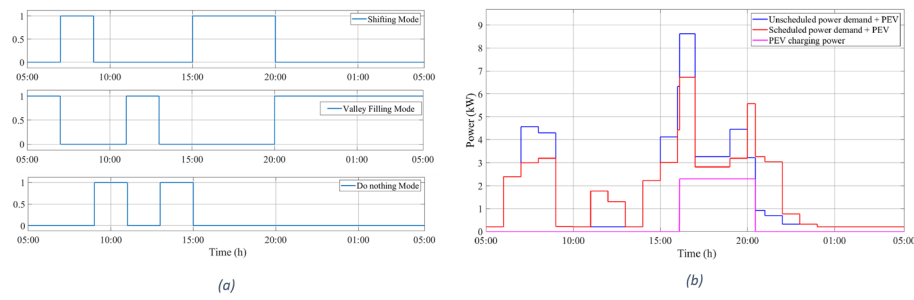


Fig. 8 a Scheduling output, b power profile

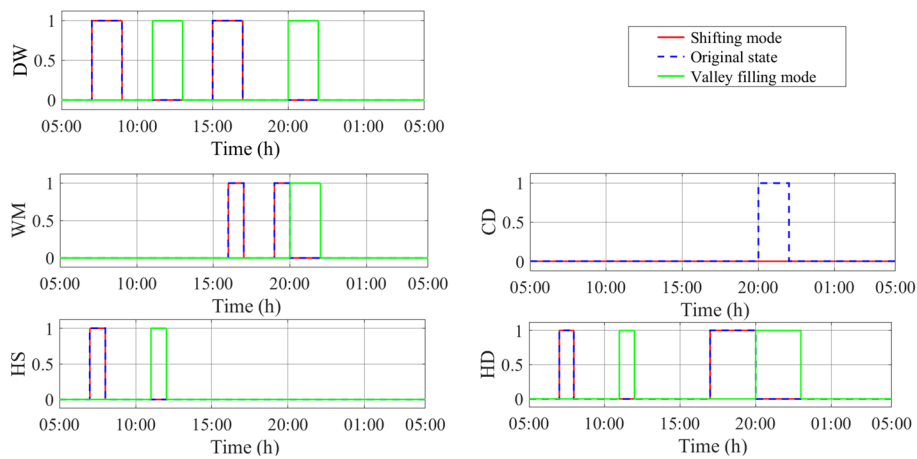


Fig. 9 Operating status of shiftable appliances case 1

decrease in user's activities such as cooking, washing, cleaning, and watching TV, there is also off-peak demand corresponding to a lower energy price.

Based on the proposed approach discussed in section "Scenario 1: Implementing smart scheduling strategy without V2H technique.", HEMS detects *Shifting*, *Valley filling* and *Do-nothing* modes. For example, the morning peak demand occurs during [07:00–09:00], where the total household demand is *High* and the electricity price is *Expensive*, hence the *Shifting* mode should be applied according to the fuzzy rules shown in Table 3. Based on algorithm 1, the total rated power of the operating times of all shiftable appliances is less than the shifting required power. As a result, Dish Washer, Hair straightener and Hair Dryer appliances have been shifted as shown in Fig. 9. During the period [9:00–14:00], the proposed control algorithm detects *Do-nothing* mode as shown in Fig. 8a, since the total household demand is *Low* and the electricity price is *Expensive*. Consequently, the operating time of the shiftable appliances maintains as it is. During the time [11:00–13:00], *Valley Filling* mode is detected because the load profile is *Low* and the electricity price is *Cheap*. According to algorithm 1, the total rated power of shifted appliances is more than the valley filling required power. As a result of this, HEMS switches on all the shiftable appliances

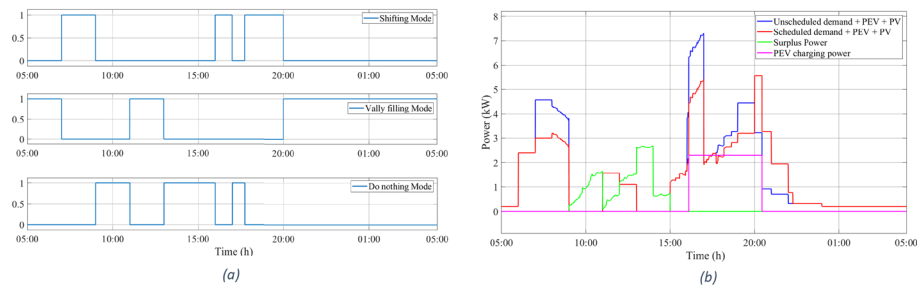


Fig. 10 **a** Scheduling output, **b** power profile

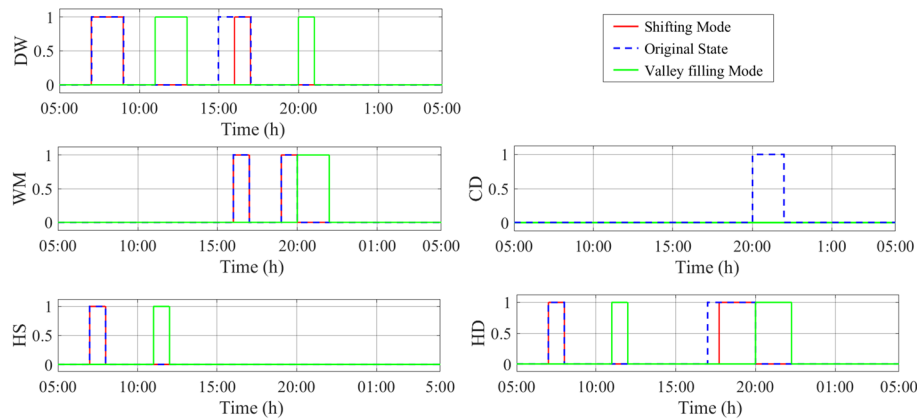


Fig. 11 Operating status of shiftable appliances case 2

which have been shifted before. Based on this technique, Fig. 8b shows the final power consumption profile of the household appliances over 24 h (Fig. 9).

Case 2: Demand + PEV + PV

In this case, it is assumed that the studied home is equipped with PEV, and PV. The same assumptions regarding the PEV data mentioned in the previous case are applied here too. The PV produces power during the period [08:00–19:00] as shown in Fig. 10b and supply to the home appliances when needed and store the surplus power in a stationary battery. According to the proposed scheduling strategy, all scheduling actions are shown in Fig. 10a.

For example, the total energy demand during [09:00–11:00] is *Low* and the electricity price is *Expensive*, hence the *Do-nothing* mode is detected but as shown in fig, the PV-generated power is increasing from 480 to 1900 Wh. Therefore, in this period the demand is covered by the PV, and the surplus power shown in the green line is transferred to the stationary battery for later use. During the period [11:00–13:00], valley filling mode is applied where shifted appliances are turned on and consume all its power from the PV. It is noted that at 15:00 Do nothing mode is operating due to the PV supplement which has changed the demand energy level from high to low as shown in fig, Therefore, DW did not shift all its operating period compared to the previous case. The same scenario is applied for the HD at 17:00. As shown below in Fig. 11

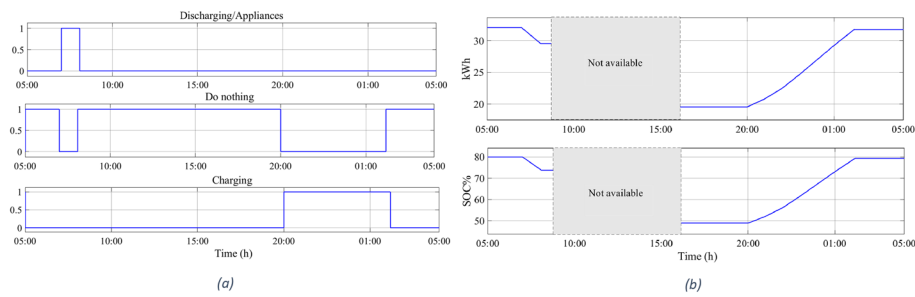


Fig. 12 **a** PEV management fuzzy controller output, **b** PEV power and SOC%

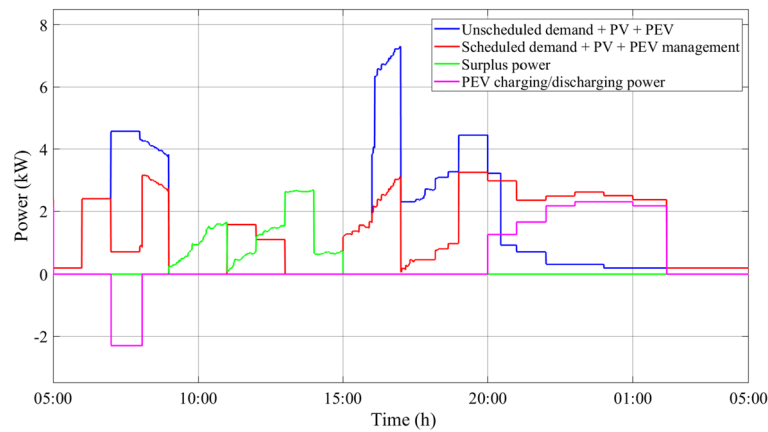


Fig. 13 Power profile

Scenario 2: Smart scheduling strategy with V2H technique

In this case, the electricity demand for each time-step in the household can be obtained from the home appliances, PV generated power and PEV charging/discharging power. The PEV works under G2V and V2H operating modes in which the PEV battery charge from the grid and supplies power to the home when needed according to the PEV management strategy discussed in section "Scenario 2: Smart scheduling strategy with V2H technique". To demonstrate the performance of the proposed design, the initial SOC of the PEV is set manually in different scenarios. Each scenario represents a critical limit of the SOC where the proposed strategies must perform as expected to satisfy user comfort and fulfill utility requirements. In the following cases, t_d set at 09:00 and t_a at 16:00.

Case 1: The initial SOC is 80%

According to the output of the PEV fuzzy control system, Fig. 12a shows the three possible actions; Discharging (V2H), Charging, and Do nothing. Figure 12b shows the SOC of PEV based on the action made while Fig. 13 shows the power demand profile before and after the proposed strategies. In this case, the initial SOC is set as 80%. The EV supplied power to the household appliances (Discharging) for one hour during the first peak period (high demand and expensive price) [07:00–08:00]. According to algorithm 2 lines 8–13, the discharging power rate depends on the total rated power of demand. For example, when the total rated power of the demand is less than the maximum discharging

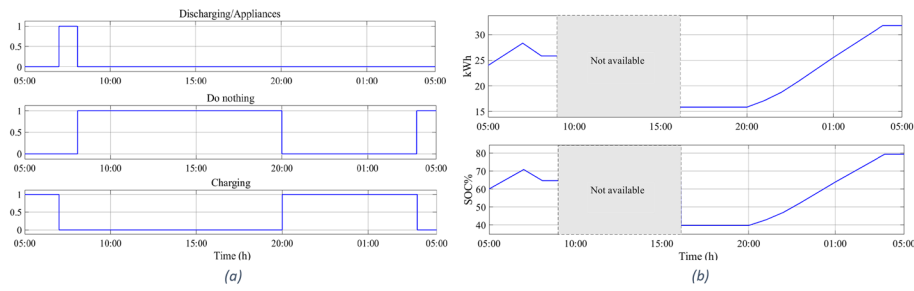


Fig. 14 a PEV management fuzzy controller output, b PEV power and SOC%

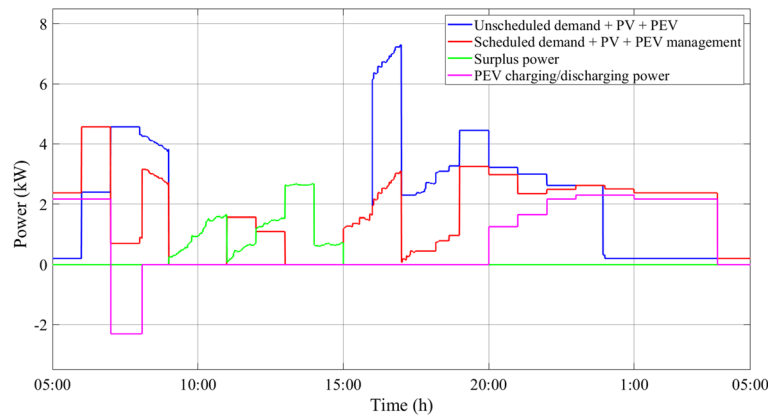


Fig. 15 Power profile

power the discharging power is set to the same value as the total rated power demand. Otherwise, the discharging rated power will be set to the maximum value. Therefore, the discharging power rate during [07:00–08:00] is set to maximum. The charging mode started during off-peak hours (low demand and cheap price) from [20:00] and ended at [02:00] when the SOC reached 80%. The remaining time of the day, the PEV was outside the home [09:00–16:00] or operated in *Do nothing* mode, where there was no need for *Charging* and *Discharging* modes to maintain the capacity limits set using the Eq. (6).

Case 2: The initial SOC is 60%

In this case, Fig. 15 shows the power demand profile before and after the proposed strategies under this case scenario. Moreover, as shown in Fig. 14b, the PEV started the day with 60% of SOC. During the first two hours [05:00–07:00] when the electricity price and power demand are low, PEV started *Charging* mode according to the fuzzy rules shown in Table 3. During the hours [07:00–09:00], the price is expensive, the SOC is high and the scheduled demand is high, which resulted in operating with *Discharging* mode to supply power to the appliances for only one hour [07:00–08:00]. Because the PV starts supplying power from 08:00, the total scheduled demand is decreased hence the *Do nothing* mode is operating leaving almost 65% SOC at [09:00] when the user left the home. At 16:00, the user arrived and plugged the vehicle in with 40% SOC while the total demand is low and the electricity price is cheap.

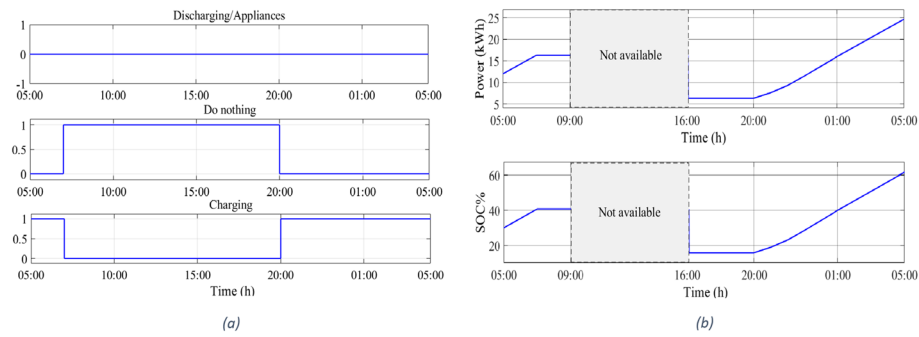


Fig. 16 a PEV management fuzzy controller output, b PEV power and SOC%

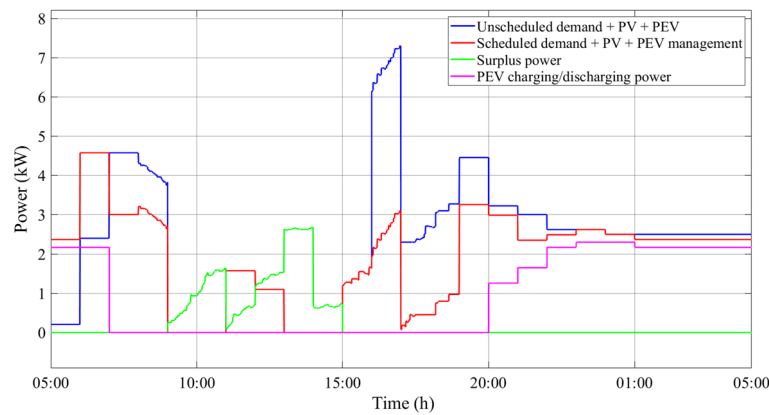


Fig. 17 Power profile

Therefore, *Do nothing* mode is activated avoiding charging with high cost. Then, the *Charging* mode started again at [20:00] when the total scheduled demand is low and the electricity price is cheap. By the end of the day, SOC was 80% to ensure that the user will start the next day with more stored energy in the PEV's battery. Compared to case 1, in Fig. 14a during the hour [06:00–07:00], the PEV is charging with low price in order to store enough power to supply the household appliances (Fig. 15).

Case 3: The initial SOC is 30%

In Fig. 16, with low initial SOC (30%), it can be noticed that there is no chance to supply power to the appliances whatever the observed states. PEV started to operate on the *Charging* mode at [05:00] during off-peak morning hours till [07:00]. This helped the user to leave the home with 40% of SOC and then he came back at [16:00] with quite low SOC (less than 20%). Hence, the “Charging” mode started again until SOC reached 60%. again, a new peak generated noticed in Fig. 17 during the hour [06:00–07:00] where the PEV is charging with low price but in this case, the PEV still has low SOC therefore it did not supply the household appliances. Finally, by the end of the day, the SOC reached more than 60% hence, case 2 will be the case for the next day.

Case 4: The initial SOC is 30% and the target SOC at the departure time is 50%

In this case, the same scenario of case 3 is applied with 50% SOC requested by the user at the departure time. Therefore, the controller has calculated the time duration needed for the forced charging process in order to maintain 50% SOC at 09:00 using Eq. (8). As shown in Fig. 18a although the do-nothing mode is operating, at 07:20 the forced charging process has been applied. As shown in Fig. 19, It can be noticed that before the forced charging processes the PEV battery was charging during the period 05:00–07:00 where the charging power was calculated using Eq. (2)

Table 5 summarizes the cost of all mentioned scenarios. Where the total cost can be calculated as follow:

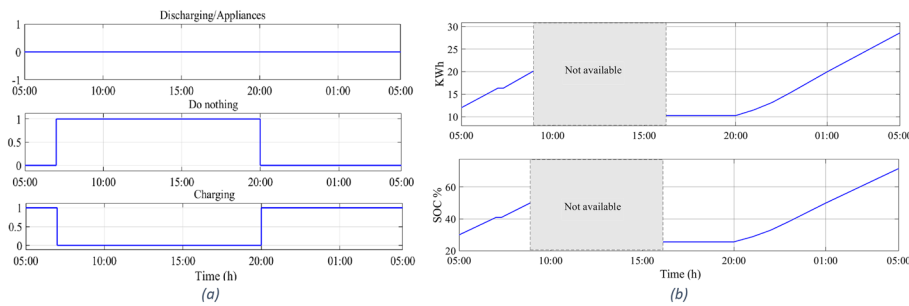


Fig. 18 a PEV management fuzzy controller output, b PEV power and SOC %

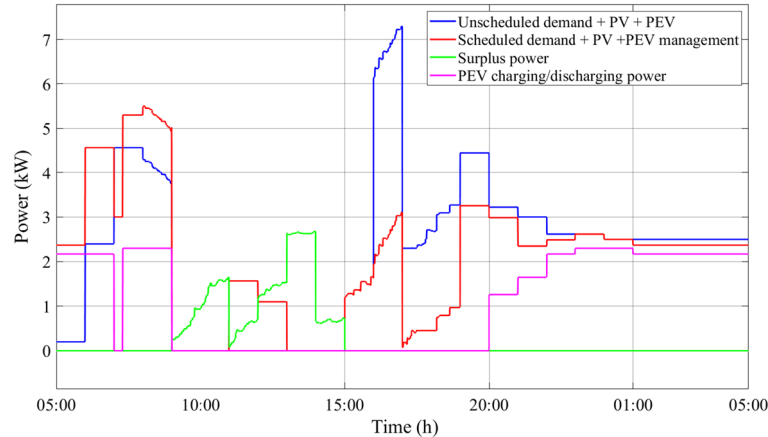


Fig. 19 Power profile

Table 5 Total cost and cost reduction of all simulation cases

Initial SOC%	Smart scheduling strategy						PEV charging strategy		
	Demand + PEV			Demand + PEV + PV			Before	After	Cost reduction rate (%)
	Before scheduling	After scheduling	Cost reduction rate (%)	Before scheduling	After scheduling	Cost reduction rate (%)			
30%	6.852	6.692	2.33	5.704	5.288	7.29	5.288	4.268	19.28
60%	5.899	5.739	2.71	4.751	4.335	8.75	4.335	3.762	13.21
80%	5.183	5.023	3.08	4.031	3.622	10.14	3.622	3.105	14.27

$$Cost(P_G) = \sum_{t=1}^T P_G(t) * RTP(t) \quad (15)$$

In the first scenario case 1, with 30% initial SOC of the PEV battery, the total cost before applying the smart scheduling strategy is 6.85. however, the total cost has been reduced by 2.33% with implementing the proposed scheduling strategy. Moreover, it can be observed that the total cost reduction is 3.08% when the initial SOC of the PEV battery is 80%. In addition, it is noted that the PV has contributed to more cost reduction compared to the 30% and 80% of SOC in the first scenario by 7.29% and 10.14% respectively. In the second scenario, the charging/discharging strategy contributes by 19.28% cost reduction when the initial SOC of the PEV is low (30%) while the cost reduction is 14.27% when the initial SOC of the PEV is 80%.

Conclusion

In this paper, a smart scheduling strategy for smart home appliances assisted with the PEV energy management strategy is presented. On one hand, the smart scheduling strategy aims to guarantee that the load profile does not violate the grid-related requirements such as peak generation and satisfy the household needs by maintaining the same amount of energy consumption with less cost by changing the operation period of shiftable appliances from peak hours when energy prices are high to off-peak hours when energy prices are low. On the other hand, the PEV energy management system is developed to coordinate the charging/discharging modes considering the travel needs of the PEV owner by maintaining enough SOC before each trip. Both proposed strategies are developed using the fuzzy logic system because it simplifies the overall implementation, leads to better performance, and lower time-consuming as compared to other techniques. The simulation results show that the overall demand profile was smoothed, user comfort has been satisfied and the cost of the total energy consumption was reduced by 19.28% and 14.27% in the case of 30% and 80% initial SOC of the PEV, respectively. For more reliability and independence in future work, further grid technical objectives will be considered, and reinforcement learning technique could be investigated considering the PEV mobility.

Abbreviations

V2H	Vehicle to home
G2V	Grid to vehicle
P_j^{non-sh}	Rated power of non-shiftable appliances
P_i^{sh}	Rated power of shiftable appliances
$u_j(t)$	Status of non-shiftable appliances
$u_i(t)$	Status of shiftable appliances
$P_A(t)$	Total power usage of household appliances
P_{avg}^{lower}	Lower limit of average total power demand
P_{avg}^{upper}	Upper limit of average total power demand
$P_{shifting_req}(t)$	Required shifting power
$P_{v_filling_req}(t)$	Required valley filling power
$\alpha_i^{shifting}$	Shifting probability of shiftable appliances
$\alpha_i^{v_filling}$	Valley filling probability
DR	Demand response

C_{PEV}^{max}	Rated capacity of PEV battery
p_{PEV}^{chmax}	Maximum PEV charging power
p_{PEV}^{dismax}	Maximum PEV discharging power
p_{PEV}^{ch}	PEV charging power
p_{PEV}^{dis}	PEV discharging power
$RTP(t)$	Real time electricity price
$E_{PEV}(t)$	Energy of PEV battery
u_{PEV}	Status of PEV
$SoC_{PEV}(t)$	State of charge of PEV battery
t_a	Arrival time of PEV
t_d	Departure time of PEV
$P_G(t)$	Consumed power from grid
SG	Smart grid
HEMS	Home energy management system
RESs	Renewable energy sources
DSM	Demand side management
MILP	Mixed integer linear programming
FLC	Fuzzy logic controller
HVAC	Heating, ventilation, and air conditioning
HANs	Home Area Networks
DSO	Distribution System Operator
PEVs	Plugged-in electric vehicles
EVs	Electric vehicles
ESSs	Energy storage systems
TOU	Time-of-use pricing
GA	Genetic algorithm
AFLM	Adaptive Fuzzy Logic Model
PV	Photovoltaic
WANs	Wide Area Networks
NANs	Neighbourhood Area Networks
SOC	State of charge

Author contributions

All authors read and approved the final manuscript. KA created the model and the computational framework, as well as the data analysis. The implementation was carried out by KA and FA. The computations were carried out by KA. The manuscript was written by KA and FA, with contributions from all authors KA, FA and LS. The study was supervised by LS, who was also in charge of overall direction and planning.

Funding

Open access funding provided by Budapest University of Technology and Economics.

Availability of data and materials

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Received: 29 December 2022 Accepted: 5 March 2023

Published online: 16 March 2023

References

- Ahmad A, Khan A, Javaid N, Hussain HM, Abdul W, Almogren A, Alamri A, Azim NI (2017) An optimized home energy management system with integrated renewable energy and storage resources. *Energies* 10(4):549. <https://doi.org/10.3390/en10040549>
- Antunes CH, Rasouli V, Alves MJ, Gomes Á (2018) A mixed-integer linear programming model for optimal management of residential electrical loads under dynamic tariffs
- Aslam S, Javaid N, Asif M, Iqbal U, Iqbal Z, Sarwar MA (2018) A mixed integer linear programming based optimal home energy management scheme considering grid-connected microgrids. In: 2018 14th Int. Wirel. Commun. Mob. Comput. Conf. pp 993–998. <https://doi.org/10.1109/WCMC.2018.8450462>

- B. University Electric Vehicle (EV). https://batteryuniversity.com/learn/article/electric_vehicle_ev accessed 22 Oct 2020
- Bussar R, et al (2013) Battery energy storage for smart grid applications. In: Assoc. Eur. Automot. Ind. Batter. Manuf.
- Chandran CV, Basu M, Sunderland K (2016) Comparative study between direct load control and fuzzy logic control based demand response. In: Proc. - 2016 51st Int. Univ. Power Eng. Conf. UPEC 2016, vol 2017-Janua, pp 1–6. <https://doi.org/10.1109/UPEC.2016.8114090>
- Chekired F, Mahrane A, Samara Z, Chikh M, Guenounou A, Meflah A (2017) Fuzzy logic energy management for a photo-voltaic solar home. *Energy Procedia* 134:723–730. <https://doi.org/10.1016/j.egypro.2017.09.566>
- Chen Y, Member S, Chang JM, Member S (2016) Fair demand response with electric vehicles for the cloud based energy management service. *IEEE Trans Smart Grid* 3053:1–11. <https://doi.org/10.1109/TSG.2016.2609738>
- Cui B, Wang S, Xue X (2014) Effects and performance of a demand response strategy for active and passive building cold storage. *Energy Procedia* 61:564–567. <https://doi.org/10.1016/j.egypro.2014.11.1171>
- Datta U, Kalam A, Shi J (2018) Electric vehicle (EV) in home energy management to reduce daily electricity costs of residential customer. *J Sci Ind Res* 77:559–565
- Denai M (2019) Enhanced electric vehicle integration in the UK low-voltage networks with distributed phase shifting control. *IEEE Access* 7:46796–46807. <https://doi.org/10.1109/ACCESS.2019.2909990>
- Durvasulu V, Hansen TM (2018) Benefits of a demand response exchange participating in existing bulk-power markets. *Energies*. <https://doi.org/10.3390/en1123361>
- Foroozandeh Z, Ramos S, Soares J, Lezama F, Vale Z, Gomes A, Joenck R (2020) A mixed binary linear programming model for optimal energy management of smart buildings. *Energies* 13(7):1719
- Fuzzy E, Controller L, Systems M (2018) Embedded fuzzy logic controller and wireless communication for home energy. *Electronics*. <https://doi.org/10.3390/electronics7090189>
- Hou X, Wang J, Huang T, Wang T, Wang P (2019) Smart home energy management optimization method considering energy storage and electric vehicle. *IEEE Access* 7:144010–144020. <https://doi.org/10.1109/ACCESS.2019.2944878>
- Hylsberg R, Søren J, Mikkelsen A (2014) Infrastructure for intelligent automation services in the smart grid. *Wirel Pers Commun*. <https://doi.org/10.1007/s11277-014-1682-6>
- Jabir HJ, Teh J, Ishak D, Abunima H (2018) Impacts of demand-side management on electrical power systems: a review. *Energies* 11(5):1–19. <https://doi.org/10.3390/en11051050>
- Khalid R, Javid N, Rahim MH, Aslam S, Sher A (2019) Sustainable computing: informatics and systems fuzzy energy management controller and scheduler for smart homes. *Sustain Comput Inform Syst* 21:103–118. <https://doi.org/10.1016/j.suscom.2018.11.010>
- Khan MSA, Kadir KM, Mahmood KS, Alam MII, Kamal A, AlBashir MM (2019) Technical investigation on V2G, S2V, and V2I for next generation smart city planning. *J Electron Sci Technol* 17:100010. <https://doi.org/10.1016/j.jnlest.2020.100010>
- Khemakhem S, Rekik M, Krichen L (2019) Double layer home energy supervision strategies based on demand response and plug-in electric vehicle control for flattening power load curves in a smart grid. *Energy* 167:312–324. <https://doi.org/10.1016/j.energy.2018.10.187>
- Lokeshgupta B, Sivasubramani S (2018) Cooperative game theory approach for multi- objective home energy management with renewable energy integration. *IET Smart Grid* 2:1–8. <https://doi.org/10.1049/iet-stg.2018.0094>
- Nayak P, Rajashekara K (2019) Single-stage bi-directional matrix converter with regenerative flyback clamp circuit for EV battery charging. pp 1–6
- Nour M, Said SM, Ali A, Farkas C (2019) Smart charging of electric vehicles according to electricity price. *Sustain Cities Soc*. <https://doi.org/10.1109/ITCE.2019.8646425>
- Paterakis NG, Erdinc O, Catalão JPS (2015) An overview of demand response: key-elements and international experience. *Renew Sustain Energy Rev* 69(871–891):2017. <https://doi.org/10.1016/j.rser.2016.11.167>
- Pipattanasomporn M, Kuzlu M, Rahman S, Teklu Y (2014) Load profiles of selected major household appliances and their. *IEEE Trans. Smart Grid* 5(2):742–750
- Radu AT, Eremia M, Toma L (2017) Promoting battery energy storage systems to support electric vehicle charging strategies in smart grids. In: 2017 Electr. Veh. Int. Conf. EV 2017, vol 2017-Janua, pp 1–6. <https://doi.org/10.1109/EV.2017.8242092>
- Rahman MM, Hettiwatte S, Gyamfi S (2014) An intelligent approach of achieving demand response by fuzzy logic based domestic load management. In: 2014 Australas. Univ. Power Eng. Conf. AUPEC 2014 - Proc., no. October, pp 1–6. <https://doi.org/10.1109/AUPEC.2014.6966610>
- Rajeswari N, Janet J (2018) Load scheduling using fuzzy logic in a home energy management system. *Int J Eng Technol* 10(5):1263–1272. <https://doi.org/10.21817/ijet/2018/v10i5/181005013>
- Renewable, International Agency, Energy (2019) Innovation Outlook Charging For Electric
- Sachan S, Deb S, Singh SN (2020) Different charging infrastructures along with smart charging strategies for electric vehicles. *Sustain Cities Soc* 60:102238. <https://doi.org/10.1016/j.scs.2020.102238>
- Serban I, Céspedes S, Member S (2020) Communication requirements in microgrids: a practical survey. *IEEE Access* 8:47694
- T. International, R. Energy, and A. Irena (2017) Electric vehicles: technology brief
- Verma A, Asadi A, Yang K, Tyagi S (2015) A data-driven approach to identify households with plug-in electrical vehicles (PEVs). *Appl Energy* 160:71–79. <https://doi.org/10.1016/j.apenergy.2015.09.013>
- Xiao L, Yao G, Bu S, Member S (2019) Pricing-based demand response for a smart home with various types of household appliances considering customer satisfaction. *IEEE Access* 7:86463–86472. <https://doi.org/10.1109/ACCESS.2019.2924110>
- Xu Q, Jiao X (2020) Research on a Demand Response Interactive Scheduling Model of Home Load Groups. *J. Electr Eng Technol* 15:1079. <https://doi.org/10.1007/s42835-020-00406-9>
- Zhou B et al (2016) Smart home energy management systems: concept, configurations, and scheduling strategies. *Renew Sustain Energy Rev* 61:30–40. <https://doi.org/10.1016/j.rser.2016.03.047>

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