Electrical Power and Energy Systems 133 (2021) 107230

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Home energy management system for smart buildings with inverter-based air conditioning system

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ARTICLE INFO

Keywords:
Demand response programs
Home energy management system
Self-scheduling
Air conditioner
Electrical energy storage
Smart buildings

ABSTRACT

This paper presents a new model for the self-scheduling problem using a home energy management system (HEMS), considering the presence of solar photovoltaic (PV) panels and an air conditioner (AC). The AC used in this study utilizes an inverter for controlling the temperature. The proposed model adopts the time-of-use (TOU) tariff for electricity, and minimization of the daily bill is the main objective of the proposed model. In the proposed model, there are some fixed and flexible loads, and optimal scheduling of the home appliances is modeled as a mixed-integer linear programming (MILP) problem to achieve the minimum daily bill. The HEMS in this paper incorporates a PV system, combined with the electrical energy storage (EES) system to deal with the uncertain solar power generation as well as optimally serving the loads during the peak hours, taking into account the charging and discharging control strategy of the installed EES. The indoor temperature can be held within a predefined margin and the settings of the AC system may be obtained according to the indoor-outdoor temperature model, which has been presented in this paper. During peak hours, the contribution of the AC in energy consumption to the daily bill is considerable. Therefore, optimal operation of the AC and other home appliances can effectively reduce the energy consumption and consequently, will result in reduced bills.

1. Introduction

1.1. Motivation

Emerging technological development in smart appliances and smart devices has provided new opportunities for end-users. The main feature of smart homes is the capability to program controllers for the optimal scheduling of plugging time of the appliances. In some cases, the consumers can benefit from the installation of smart controllers as well as smart meters to manage their usage. A home energy management system (HEMS) can schedule the optimum operation of home appliances and electrical kitchenware to minimize the daily bills of end-users. In addition, installing photovoltaic (PV) panels can provide some benefits for the consumers and they can benefit from local power generation at their private area. Since the PV power generation merely depends upon the solar irradiance, installing electrical energy storage (EES) devices can improve the flexibility of power generation for such prosumers. Moreover, by installing the EES devices, end-users can benefit from different energy tariffs during the day by optimally scheduling charge/discharge of the EES to reduce the daily bills. On the other hand, there are some appliances with considerable energy consumption, like the washing machine (WM), the spin dryer (SD), the electric vehicle (EV), and the air conditioner (AC), that can be scheduled in a way to reduce the energy bill. Some of the appliances have merit order, like WM and SD, while some others have not any priority. The operating points of some appliances depend upon the previous time interval, such as EES and AC. The AC, used in this paper, utilizes an inverter for controlling the temperature and it has multiple operating points. The indoor temperature can be controlled by the AC; therefore, the optimal setting of the AC can be determined in such a way that the indoor temperature is in the acceptable range and the electricity consumption and the corresponding electricity bill are reduced. This paper presents a mixed-integer linear programming (MILP) model for the HEMS scheduling, aimed at minimizing the daily energy bill. In this model, the self-generation by PV panel is done in line with the optimal operation of EES devices, considering different types of home appliances and time-of-use (TOU) pricing mechanism.

1.2. Literature review

The main purpose of designing a HEMS is to optimally schedule the

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https://doi.org/10.1016/j.ijepes.2021.107230
Received 18 August 2020; Received in revised form 6 March 2021; Accepted 20 May 2021
Available online 4 June 2021

Nomenclature

Indices/Sets

t Index for the time intervals of scheduling
i Index for home appliances
j Index for EES devices
ω Index for scenario
NT Scheduling period
NAN_g Set of shiftable home appliances
NSN_g Total number of EES devices
Ω Total number of scenarios

Variables

$\mathrm{P_s(g,t)}S_{\omega,i,t}$ Binary variable indicating the status of operation of appliance i at time interval t
$\mathrm{P_s(g,t)}P^{G2H}_{\omega,t}$ Delivered power from grid to home at time interval t
$P^{H2G}_{\omega,t}$ Delivered power from home to grid at time interval t
$\overline{\mathrm{P_s}}(\mathrm{g,t}) : DI^{+}_{\omega,i}$ Discomfort index regarding usage of the appliance i before the scheduled time
$\mathrm{P_h(j,t)}DI^{-}_{\omega,i}$ Discomfort index regarding usage of the appliance i after the scheduled time
$STUP_{\omega,i,t}$ Binary variables, specifying the start-up
$SHDN_{\omega,i,t}$ Binary variables, specifying the shut-down
$\mathrm{P_s(g,t)}P^{Ch.}_{\omega,j,t}$ Charging power of EES j at time interval t
$\mathrm{P_s(g,t)}P^{Disch.}_{\omega,j,t}$ Discharging power of EES j at time interval t
$\mathrm{P_s(g,t)}E_{\omega,j,t}$ Energy stored at EES j at time interval t
$\mathrm{P_s(g,t)}I^{Ch.}_{\omega,j,t}$ Charging status of EES j at time interval t
$\mathrm{P_s(g,t)}I^{Disch.}_{\omega,j,t}$ Discharging status of EES j at time interval t
$DV^{+}_{\omega,t}$ Indoor temperature deviation from θ^{max}_t
$DV^{-}_{\omega,t}$ Indoor temperature deviation from θ^{min}_t
$D^{AC}_{\omega,t}$ The power, consumed by the inverter-based AC at time interval t
$\theta^{In}_{\omega,t}$ Indoor temperature at time interval t

Parameters

$\mathrm{a_s(g),b_s(g),c_s(g),d_s(g),e_s(g)} : \pi^{G2H}_t$ The price of energy, sold to grid by home at time interval t
π^{H2G}_t The price of energy, sold to home by grid at time interval t
C^{ST}_i The cost, imposed due to the start-up of switchable loads
C^{SD}_i The cost, imposed due to the shut-down of switchable loads
$\alpha_s(\mathrm{g}),\beta_s(\mathrm{g}),\gamma_s(\mathrm{g}),\omega_s(\mathrm{g}),\delta_s(\mathrm{g}) : P_i$ Rated power of appliance i
$\alpha_s(\mathrm{g}),\beta_s(\mathrm{g}),\gamma_s(\mathrm{g}),\omega_s(\mathrm{g}),\delta_s(\mathrm{g}) : D^{Fix}_{\omega,t}$ The amount of fixed load at time interval t
$\mathrm{C_1(j),C_2(j),C_3(j),C_4(j),C_5(j),C_6(j)}\Delta t$ Operation time interval
$\eta_g(\mathrm{i}) : \eta_p(\mathrm{i}) : B_{\omega,i,t}$ The end-user's preferred usage status of the appliance i at time interval t
$\eta_g(\mathrm{i}) : \eta_p(\mathrm{i}) : T_i$ Total number of time intervals of the operation
$\mathrm{P^{min}_{P-S}(i)} : LB_{i,b}$ The lower band of baseline operation time interval
$\mathrm{P^{max}_{P-S}(i)} : UB_{i,b}$ The upper band of baseline operation time interval
$\mathrm{P^{min}_{P-S}(i)} : LB_{i,s}$ The lower band of allowable operation time interval
$\mathrm{P^{max}_{P-S}(i)} : UB_{i,s}$ The upper band of allowable operation time interval
$\mathrm{P_s(g,t)}P^{Ch.max}_j$ The upper bound of charging power of EES j
$\mathrm{P_s(g,t)}P^{Disch.max}_j$ The upper bound of discharging power of EES j
$\mathrm{P_s(g,t)}\eta^{Ch.}_j$ The efficiency of EES j in the charging mode
$\mathrm{P_s(g,t)}\eta^{Disch.}_j$ The efficiency of EES j in the discharging mode
$\mathrm{P_s(g,t)}E^{min}_j$ The lower bound of energy stored at EES j
$\mathrm{P_s(g,t)}E^{max}_j$ The upper bound of energy stored at EES j
$\mathrm{P_s(g,t)}E^{1}_j$ Initial energy stored at EES j
$\mathrm{P_s(g,t)}E^{T}_j$ Final energy stored at EES j
ρ_ω The probability, associated with each scenario
σ Penalty factor for discomfort index
μ_t Monetary value, suggested to address the discomfort level due to violation from the comfort temperature bounds at each time interval
$\theta^{Out}_{\omega,t}$ Outside temperature at time t
θ^{min}_t The minimum acceptable temperature
θ^{max}_t The maximum acceptable temperature

electricity consumption of the appliances and other household loads so as to mitigate the amount of the electricity bill of the consumer. Other functionalities can also be achieved using an efficiently-developed HEMS, such as implementing demand response (DR) programs. Recently, the end-users are equipped with distributed energy resources (DERs), such as batteries. In this respect, the HEMS is capable of optimally scheduling such DERs to make the most of their potential. Recently, the role of end-users has been changing with respect to the utility grid and the interaction with that system. Thus, the HEMS would efficiently modify the load profile of residential users [1]. HEMSs have been extensively investigated in the literature, among which Ref. [2] has proposed a mixed-integer non-linear programming (MINLP) framework to apply a penalty due to discomfort, occurring to the consumers. The mentioned model considers ten electrical devices and provides the consumer with the optimal schedule of such devices, where a penalty would be applied in case the assets operation would not be within the desired intervals. The mentioned HEMS has succeeded in alleviating the amount of the bill by 25%. Real-time bidirectional communications between the utility grid and several residential consumers have been provided in Ref. [3], where every consumer has been considered an HEMS. Ref. [4] carried out a risk assessment, using the conditional value-at-risk (CVaR) index, taking into account the uncertainties, caused by EES systems, solar PV system, market price, and load demand. An incentive-based DR program has also been utilized to motivate consumers to participate in the scheduling, leading to reducing the energy bills of the consumers by 18%. Ref. [5] used a TOU-based limited memory algorithm for optimally scheduling different residential appliances within a day-ahead time horizon. In this respect, 267 houses were taken into consideration and grouped, utilizing an effective clustering algorithm. The framework has led to 33% drop in the costs. An advanced adaptive particle swarm optimization (AAPSO) has been employed in Ref. [6] to efficiently determine the operational strategies of a HEMS, including a hybrid PV-battery system. It is noted that the problem was formulated as a MILP problem, solved using the AAPSO, leading to 28% decrease in the annual bills. Ref. [7] presented a TOU-based multi-objective linear model for a HEMS, operating with a stationary storage system. The suggested model could effectively mitigate the residential electricity bills and also shave the system's peak load demand. A HEMS model was designed in [8], taking into consideration the intermittent renewable power generation in a residential building. The simulation results were case-sensitive and mainly dependent upon the scenarios studied. However, the proposed framework resulted in 42% reduction the electricity bills. The problem of optimal scheduling of home appliances was modeled as a single-objective optimization problem, and solved in Ref. [9] by employing the binary particle swarm optimization with quadratic transfer function (QBPSO). A comprehensive HEMS has been developed in Ref. [10], aimed at alleviating the electricity bills and peak load demand, as well as retaining the consumers' comfort at the desired level. The framework was based on DR programs, i.e. real-time pricing (RTP), intended to mitigate the demand for energy over the hours with low prices. The presented framework has led to mitigating the peak-to-average ratio of the load demand and as a result, the load profile has been smoothed. The idea beyond introducing the HEMS lies in the increased involvement of users in the electricity markets. The HEMS would provide the customers with the opportunity to actively participate in the market and play a significant role rather than being strictly passive users. It is noteworthy that a HEMS includes several home appliances, which can be categorized into three main groups in terms of their type of load demand. These groups are baseline loads, burst loads, as well as regular loads [11]. The first category is also known as must-run loads, which in turn implies that they cannot be curtailed, controlled or deferred. The usual baseline loads are lighting system, oven, and television. The second group, i.e. burst loads are known as deferrable-flexible or schedulable loads as their operating period can be deferred to another time period of the day so that the energy demand of the house would be more appropriately handled. This group is generally comprised of WMs and SDs. The regular loads as the third group refer to the appliances that their energy consumption varies with climate conditions. Space heaters and ACs are categorized into this load type. The third load type is significant to the consumer as it directly impacts the comfort index of the user. The third load type includes the power demand, relating to the home appliances of various groups that are generally dependent upon the house area, the weather conditions, and the occupants residing in the house, both their number and their revenue. Taking into account all the items, mentioned above, shows that the amount of the household load demand changes considerably and the most appropriate solution would be employing bottom-up strategies [11]. A two-stage energy sharing mechanism was presented in Ref. [12] for the peer-to-peer (P2P) energy sharing between smart homes using a distributed energy transaction strategy. The total social energy cost is intended to be minimized in the first stage of the model while the second stage proposes a non-cooperative game to clear mutual energy sharing. A two-phase framework has been developed in Ref. [13] for the P2P energy sharing for several consumer communities. Moreover, a risk-averse energy sharing strategy has been proposed in Ref. [14] for community prosumers.

Although HEMSs and DERs can bring numerous advantages to current electric systems, DERs may inversely impact the operation of the distribution system [15–18]. These problems mainly relate to the issues, arisen in the power flow calculations and oscillations in the voltage. In this respect, storage systems have already been introduced and they can be effectively utilized to address such problems in the HEMS and distribution systems. There are also some controversial issues regarding the HEMS that require to be thoroughly considered in the future to make the most of the capabilities of such systems. These issues are mainly caused by cyber security and data privacy issues. Such concerns regarding the HEMSs have already been discussed in [11] and it has been emphasized that the data privacy problem would deteriorate with the increase in the number of smart appliances, connected to the HEMS. Another concern is the growing number of such appliances, connected to the HEMS to transact data, which in turn causes a huge amount of data [19]. Moreover, a stable connection is needed so that these devices can communicate with each other. This issue has led to a wider collaboration between different manufacturers. Recently, the prevalent passive users have been changing to active users, having the capability to produce power by using their installed generation assets [4]. This phenomenon is the result of relatively high market prices as well as reducing capital cost of DERs, besides the regulations executed by different countries to support local power generation. Local power generation in the context of self-generation by consumers can help some long-term targets, like low-carbon energy systems and sustainable power systems [11]. Some countries, particularly in Europe, have already started to provide the infrastructure and regulation to raise the self-generation level. One of these policies is 'Clean Energy for All Europeans' of the European Commission [10]. The research project, already conducted in Europe, revealed that almost 83% of the households in the European Union could be active users and around 100 million households are capable of generating clean energy or supplying the required flexibility, by using renewable power generation technologies [11]. All the above-mentioned items can be achieved by employing efficient HEMSs.

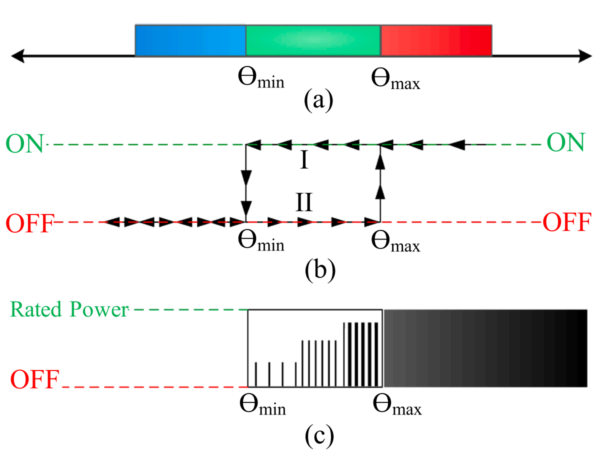

Fig. 1. Comfortable indoor temperature bounds (a), indoor temperature control mechanism by the AC system with thermostat technology (b), indoor temperature control by the AC system with the inverter technology (c).

1.3. Contribution

This paper presents four novel contributions as follows:

- Providing a stochastic MILP to represent the self-scheduling problem for HEMS. This is an effective strategy to reduce the computational burden of the self-scheduling problem and can be embedded in the current processors for HEMS purposes.
- Incorporating price-based DR programs in controlling the indoor temperature by an inverter-based AC system.
- Optimally scheduling interruptible and deferrable home appliances to reduce the daily bill, while maintaining the end-user's preferences for utilizing the appliances.
- Incorporating self-generation and strategic energy-saving to lower the bills and reducing the dependency of the HEMS on the public electrical grid.

1.4. Paper organization

The organization of the paper is as follows: Section 2 provides the key concepts of the HEMS, while the self-scheduling model of the HEMS with local power generation in the house is given in Section 3. The mathematical modeling of the studied problem is presented in Section 4 and Section 5 proposes the simulation results. Finally, the relevant conclusions have been drawn in Section 6.

2. Smart buildings and home energy management system

Active participation of end-users can be effectively attained by HEMS applications in smart buildings. The main infrastructure of HEMS in smart buildings is the smart metering system. Smart meters can record energy consumption, according to the prescheduled tariffs during the workdays and weekends. According to the electricity market rules, the electricity bill can be issued based on the hourly energy consumptions. From the end-user's side, an effective bill reduction can be achieved by optimally scheduling the plugging time of home appliances. In some cases, consumers tend to install PV panels and EES devices to partially serve their demands. During the peak hours, the PV panels produce considerable electricity and their production can be stored in the EES or even consumed by the HEMS's appliances. The presence of EES devices

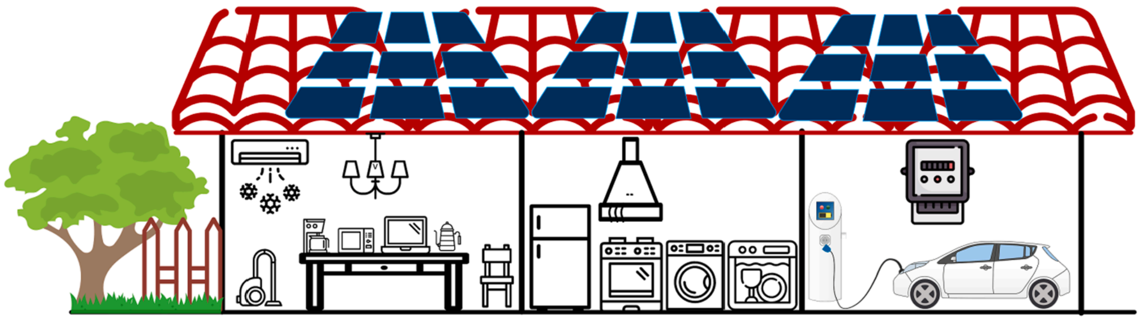

Fig. 2. The HEMS with fixed, deferrable, and interruptible loads.

in line with some other controlling apparatus can provide an effective energy resource with considerable flexibility to serve the demand during peak hours. In addition, there are some home appliances and kitchenware as well as the lighting system with smart controllers in smart buildings; hence, end-users can utilize such appliances to reduce the daily electricity expenditure. In such smart buildings, the smart AC is supposed to control the temperature at the convenience level. An AC with the thermostat works in a way to maintain the temperature within a predefined interval and the operating commands will be generated according to the minimum and maximum bounds of the interval. Therefore, the energy consumption is beyond the control of the user. The inverter technology can provide much more flexibility and can effectively maintain the room temperature by using an internal controller. In smart AC systems, the inverter technology can adjust the temperature, humidity, and air filtration as well. Thus, these systems have the flexibility to provide convenient conditions for consumers. An adjustable AC system with internal controllers is much more flexible to control the room temperature rather than the thermostat-based AC systems. Fig. 1 illustrates a conceptual model of the comfortable indoor temperature margin, the indoor temperature control by utilizing the AC with a thermostat system, as well as the control system of the inverter-based AC system. An AC system with a thermostat mechanism controls the indoor temperature. When the indoor temperature is greater than θ_{max}, the thermostat activates the AC system and it will work to reduce the temperature to reach θ_{min} (I). Then, the thermostat turns off the AC system. Since the indoor temperature is below θ_{max}, the thermostat will keep the AC system in the off mode (II). Afterward, the thermostat will activate the AC system again. The inverter-based AC system has a different controlling strategy. The inverter-based AC system adopts a variable frequency (V/F) strategy to adjust the power and, consequently, the indoor temperature. The mentioned strategy has been extensively used in the recent AC systems with both cooling and heating air conditioning systems. In this paper, the cooling mode of the inverter-based AC systems is studied.

In smart buildings with PV panels and EES devices, the flexibility of self-consumption will be effectively improved. Since the electricity price varies during the day, the monitoring system can provide sufficient information for the best decision making. In this paper, the self-generation and self-consumption strategies are considered in the problem formulation to cope with the load and price variations during the day. In this model, the AC system with inverter technology is also considered to control the indoor temperature. Besides, other home appliances with fixed, flexible and interruptible loads are considered in this paper. The HEMS controller aims to minimize the daily electricity bill, considering the discomfort index (DI) for deferrable loads and DI regarding the temperature margin violations during the operation. Recent advancements in the area of computer technology and internet of things (IoT) have resulted in increased participation of consumers in energy management. Such technologies have enabled the demand-side management (DSM) possibility [20]. Different pricing mechanisms over the day provide the opportunity for prosumers to make profit by changing their consumption pattern and their consumption time [21]. These strategies would motivate the prosumers in the long term to change their old devices with high-efficiency ones. Using the HEMS would ensure the comfort level, required by the end-user and simultaneously enable the daily load management. It is noteworthy that in case of self-generation capability, for example, by using a PV panel and a storage system, the design of HEMS will be complex; however, it assures the needed flexibility for the prosumer [22]. Besides, the prosumer would be able to have bidirectional power transaction with the distribution system by utilizing the signals, received from the electricity market.

Fig. 2 depicts a typical smart HEMS, aimed at supplying different load demands, taking into account fixed, flexible and interruptible loads, besides the PV and storage systems. By using such a model, the decision-maker would be able to reduce the operating costs of the appliances according to the TOU tariff and the available solar generation. As it can be observed, this model mainly intends to consider diverse types of home appliances. In this regard, the best consumption time will be scheduled to implement by means of the proposed HEMS.

3. HEMS Self-scheduling in smart buildings

In smart buildings, there are some sensors, and actuators for controlling the electrical and mechanical appliances. Some of the appliances have internal controllers and thus, the central controller coordinates these appliances for different purposes. In this study, the HEMS can be controlled by a centralized agent as well as clients. In this paper, it is supposed that the client manages the electrical appliances according to the predefined preferences. Therefore, the proposed methodology can be adopted by the centralized agent by means of the IoT infrastructure or P2P transactions between the smart appliances and the central coordinator. In the former structure, end-users are responsible for optimal scheduling of the home appliances while in the latter, the central controller communicates with smart appliances according to the smart decisions, made by the intelligent system. In this study, the indoor temperature control by the inverter-based AC system is addressed, maintaining the consumer's preferences regarding the room temperature while effectively reducing the daily bills. The electrical assets used in this paper for the self-scheduling are categorized into three main groups:

I Generation assets (rooftop PV panels)
II The EES system, which can be supplied by the PV system or by transacting power with the grid through AC-DC converters. It can also supply the appliances' demand using a DC-AC converter or even deliver power to the grid.
III Electrical devices, used at homes. These devices are divided into three groups as fixed, flexible and interruptible loads.

In this configuration, the control system receives the price signals, which can be predetermined TOU tariff, and decides on the optimal operation of the DC section. Moreover, the bill amount can be reduced by such a control scheme through determining the state-of-charge (SoC) of the EES system with respect to the load demand and system's requirements. This model utilizes a controllable converter, capable of controlling the optimal operating point and energy flow. The self-scheduling problem, proposed in this paper aims at deciding on the optimal operation of the flexible loads. Indeed, one of the decision variables in the self-scheduling problem is the determination of the best scheduling for the flexible loads that end-user is willing to utilize. Other electrical load demands include the ones that the prosumer does not tend to shift like the lighting system or TV. Furthermore, the refrigerator and the freezer are non-flexible loads. The amount of their consumption is constant, disregarding the electrical storage and the self-generation. By taking into consideration such required energy, the bill amount can be mitigated by following an optimal consumption pattern [10,23]. The time-based tariff depends upon the consumption time, which can help the self-scheduling result in reducing the bill amount [24]. The EES system significantly increases the flexibility of the self-scheduling model. Besides, different energy tariffs provide the opportunity to charge over the off-peak hours and discharge over peak hours [24]. The energy, stored in the battery can be used to supply the demand at hours with high energy tariffs or at the time the prosumer does not tend to shift the load demand. One of the merits of the EES system relates to its joint operation with renewable energies, which in turn minimizes the operational risks. Taking the best operational strategy in such systems is highly dependent upon the accuracy of the forecasts. In hybrid PV-EES systems, the PV power spillage can be stored in the battery. Moreover, in case there is a deficit in the renewable power generation with regard to the forecasted values, the EES system can compensate [25,26].

4. Problem formulation

The self-scheduling problem of HEMSs, considering the self-generation feature of renewable power generation, is aimed at minimizing the daily bills of the prosumers in this paper. A discomfort penalty is considered in the cases the prosumer's load is shifted to undesired time intervals. As a result, the comfort and the bill amount are two conflicting issues. In other words, the prosumer has to significantly change the consumption pattern to more decrease the cost. Consequently, the problem should be modeled and solved as a multi-objective optimization problem or a single-objective one, by assigning weights to the objectives. This paper presents a single-objective optimization model assigning weight to the load shifting. The main objective function can be stated as below:

$$\begin{aligned} &\quad Min \\ Z = &\underbrace{\sum_{\omega\in\Omega}\rho_\omega\left(\sum_{t=1}^{NT}\left(\pi_t^{G2H}P_{\omega,t}^{G2H}-\pi_t^{H2G}P_{\omega,t}^{H2G}\right)\Delta t\right)}_{Expected\ Energy\ Cost}+\underbrace{\sum_{\omega\in\Omega}\rho_\omega\left(\sum_{i=1}^{NA}\sigma_i\left[DI_{\omega,i}^{+}+DI_{\omega,i}^{-}\right]\right)}_{Expected\ Discomfort\ Cost\ of\ Shifting\ Loads} \\ &+\underbrace{\sum_{\omega\in\Omega}\rho_\omega\left(\sum_{t=1}^{NT}\mu_t\left[DV_{\omega,t}^{+}+DV_{\omega,t}^{-}\right]\right)}_{Expected\ Discomfort\ Cost\ of\ Tmeperature\ Deviation}+\underbrace{\sum_{\omega\in\Omega}\rho_\omega\left(\sum_{i=1}^{NA}\sum_{t=1}^{NT}\left[STUP_{\omega,i,t}C_i^{ST}+SHDN_{\omega,i,t}C_i^{SD}\right]\right)}_{Expected\ Cost\ of\ Multiple\ Power\ Interruption\,s\ for\ Shiftable\ Loads} \end{aligned} \tag{1}$$

The objective function includes four parts. The first part states the expected value of the cost of power, purchased from the grid by the HEMS, considering the buying/selling power from/to the grid. The second part shows the discomfort cost due to shifting the load demand to another time interval. The third part is the discomfort cost due to temperature deviation from the convenient temperature bounds. The last section is the expected cost, related to the multiple turning on and turning off the flexible appliances during the operation interval. The net power, purchased from the grid is calculated based on the TOU tariff, which is predetermined and denoted byπ_t^{G2H}. The energy, purchased from the grid can be specified by knowing the number of hours at which the energy is imported from the grid [27]. The monetary value is addressed to model the DI due to shifting the appliances as σ_i in the second part of the objective function. The same monetary value is suggested to address the discomfort level due to violating from the comfort temperature bounds at each time interval, μ_t. It is supposed that this monetary value is time-dependent due to the change of the temperature during the day and the consumer's preferences. As mentioned above, the fourth part of the objective function shows the start-up and shut-down costs. Once a flexible device is turned on, it should stay turned on for a certain period. In theory and by using a MILP model, a device can turn off/on multiple times a day while in practice, it is not possible for some of the home appliances according to their functionalities. For such appliances, called uninterruptible appliances, the multiple turns on and turns off are not allowed. Thus, each of the assets can turn on and turn off just once over the scheduling period. Any extra turning on and turning off would cause amortization costs. Hence, the start-up and shut-down costs, i.e. C_i^{ST} and C_i^{SD}, have been considered high values to prevent any redundant start-up and shut-down. The net start-up and shut-down cost in the optimal state would be zero over the scheduling period. The optimization problem's constraints are as follows:

4.1. Fixed load's constraints

The interval of the plugging time of electrical devices with a fixed amount of energy consumption is characterized by utilizing a binary parameter, assigned to every time interval. The lighting system and refrigerator are of fixed-consumption devices over the scheduling period. Accordingly, a binary parameter $B_{\omega,i,t}$ would be used to model the consumption behavior of such devices, that is equal to "1″ once the device is connected and in case it is off with no consumption, $B_{\omega,i,t}$ would be equal to "0".

$$B_{\omega,i,t}=\begin{cases}0 & t<LB_{i,b}\\ 1 & LB_{i,b}\leqslant t\leqslant UB_{i,b}\\ 0 & t>UB_{i,b}\end{cases}\qquad B_{\omega,i,t}\in\{0,1\} \tag{2}$$

$$\sum_{t=1}^{NT}B_{\omega,i,t}=T_{\omega,i}\quad\forall i=1,2,\ldots,NA \tag{3}$$

Expression (2) states that the plugging time of the asset should be continuous during a certain period of operation time. Furthermore, Eq. (3) shows that the sum of the plugging time intervals of the devices with fixed consumption should meet the operation time of the device, $T_{\omega,i}$.

4.2. Flexible loads' constraints

The procedure is different for the flexible loads, as it is possible to predict or defer the plugging time of the devices based on the desired time windows of the prosumer. However, the sum of energy, demanded by the flexible loads should be unchanged for the scheduling period. Efficiently specifying the plugging time of the devices by using a binary variable would significantly mitigate the amount of energy bill in this case. The relationship (4) is used to show that the flexible load demand at every time slot, denoted by $D^{Shift}_{\omega,t}$, is a function of the rated power of the device, indicated by P_i, and its operation status would be specified by applying the binary variable $S_{\omega,i,t}$.

$$D^{Shift}_{\omega,t} = \sum_{i=1}^{NA} S_{\omega,i,t} P_i \tag{4}$$

$S_{\omega,i,t}$ would be "1″ in the time slots determined by the prosumer, while its value will be "0" for other slots. Again, the operation of the devices should be continuous to form an operation string for each device. Consequently, the appliance should be employed in the allowed time intervals as much as needed. The constraints of $S_{\omega,i,t}$ are stated in relationships (5) and (6).

$$S_{\omega,i,t} \leqslant \begin{cases} 0 & t < LB_{i,s} \\ 1 & LB_{i,s} \leqslant t \leqslant UB_{i,s} \\ 0 & t > UB_{i,s} \end{cases} \quad S_{\omega,i,t} \in \{0,1\} \tag{5}$$

$$\sum_{t=1}^{NT} S_{\omega,i,t} = T_{\omega,i} \quad \forall i = 1,2,\ldots,NA \tag{6}$$

It is worth mentioning that the constraints are similar to those used for fixed-consumption devices with the difference in the binary variable used in this case and binary parameter used for fixed loads. It should be noted that the right-hand side of constraint (6) includes a pre-given parameter, indicating the in-service time of the asset during the scheduling period. As described before, any redundant start-up and shut-down is avoided by using a penalty with regard to the binary variable, specifying the operation status of the device. In theory, these binary variables would be one or zero, but in reality, it is not applicable for some devices, such as the WM and SD. In this respect, only one start-up, as well as one shut-down is allowed and any more start-up/shut-down would be penalized. Moreover, two different time periods have been taken into account in this paper to utilize the appliance in two time intervals during the scheduling period. $STUP_{\omega,i,t}$ and $SHDN_{\omega,i,t}$denote the start-up and shut-down binary variables, respectively, specified by using constraint (7). As a result, the start-up cost and shut-down cost can be determined as the product of the related variables by C^{ST}_i and C^{SD}_i, respectively.

$$STUP_{\omega,i,t} - SHDN_{\omega,i,t} = S_{\omega,i,t} - S_{\omega,i,t-1} \quad \forall t > 1 \tag{7}$$

The DI for shifted loads is modeled by using a linear penalty in this study. In this regard, the shifted time slots are specified by employing the cumulative rolling mapping process in this model. Accordingly, the DI due to modifying the operation time slots before and after the baseline time intervals would be determined by (8) and (9), respectively, where DI^-_i and DI^+_i are variables with positive values. Thus, in case the right-hand side of constraints (8) and (9) is negative, the conflicts between these two variables will be eliminated.

$$DI^-_{\omega,i} \geqslant \frac{1}{T_{\omega,i}} \left[\sum_{t=1}^{NT} t \times B_{\omega,i,t} - \sum_{t=1}^{NT} t \times S_{\omega,i,t} \right] \tag{8}$$

$$DI^+_{\omega,i} \geqslant \frac{1}{T_{\omega,i}} \left[\sum_{t=1}^{NT} t \times S_{\omega,i,t} - \sum_{t=1}^{NT} t \times B_{\omega,i,t} \right] \tag{9}$$

4.3. Interruptible load constraints

It is worth noting that the AC is the only device which can be interrupted and it does not necessarily have continuous operation. In this respect, the control system of the device can be used to adjust the temperature, either in the heating or cooling modes. It should also be noted that the negative sign in (10) is used to characterize the cooling mode, while the positive sign is used to manage the heating mode. Relationships (11) and (12) are used to model these two modes of the AC operation. The power, consumed by the inverter-interfaced AC, $D^{AC}_{\omega,t}$, would be precisely calculated as a function of some discrete variables and derated power. Thus, $D^{AC}_{\omega,t}$ at every time interval can be modeled by using a set of binary decision variables, $\delta^{(j)}_{\omega,t}$, where only one binary variable is possible to be equal to one at a time. As the desired temperature interval is pre-given by the prosumer, any operating conditions beyond this interval would be penalized and applied to the objective function. The violations from the desired temperature have been modeled and applied to the problem using constraints (13) and (14). In case, the temperature exceeds θ^{max}_t, constraint (13) is applied to the model and in case the temperature is below θ^{min}_t, constraint (14) is applied, where $DV^+_{\omega,t}$ and $DV^-_{\omega,t}$ are positive variables.

$$\theta^{In}_{\omega,t} = \alpha\theta^{In}_{\omega,t-1} + \beta\theta^{Out}_{\omega,t-1} \pm \gamma D^{AC}_{\omega,t} \tag{10}$$

$$D^{AC}_{\omega,t} = \left[0.2\delta^{(1)}_{\omega,t} + 0.4\delta^{(2)}_{\omega,t} + 0.6\delta^{(3)}_{\omega,t} + 0.8\delta^{(4)}_{\omega,t} + \delta^{(5)}_{\omega,t}\right] P^{AC} \tag{11}$$

$$\sum_{j=1}^{5} \delta^{(j)}_{\omega,t} \leqslant 1 \tag{12}$$

$$DV^+_{\omega,t} \geqslant \theta^{In}_{\omega,t} - \theta^{max}_t \tag{13}$$

$$DV^-_{\omega,t} \geqslant \theta^{min}_t - \theta^{In}_{\omega,t} \tag{14}$$

4.4. Dispersed energy resources constraints

Modeling the power transaction between the HEMS and the utility grid is dependent upon the behavior of the battery EES system and self-generation using the PV panel. Accordingly, the power balance equation at each time slot can be stated as Eq. (15) [28]:

$$P^{G2H}_{\omega,t} + P^{PV}_{\omega,t} - P^{H2G}_{\omega,t} = D^{Fix}_{\omega,t} + D^{Shift}_{\omega,t} + D^{AC}_{\omega,t} + \left[\sum_{j=1}^{NS} P^{Ch.}_{\omega,j,t} - \sum_{j=1}^{NS} P^{Disch.}_{\omega,j,t} \right] \tag{15}$$

It is noteworthy that the power balance equation is comprised of different items. The first item in the left-hand side of (15) shows the power, bought from the grid, $P^{G2H}_{\omega,t}$, and $P^{PV}_{\omega,t}$ is the PV power generation. Besides, the power, delivered to the grid by the HEMS is denoted by $P^{H2G}_{\omega,t}$ in the left-hand side of Eq. (15). The first three items in the right-hand side of this equation, i.e. $D^{Fix}_{\omega,t}$, $D^{Shift}_{\omega,t}$, and $D^{AC}_{\omega,t}$, denote fixed loads, flexible loads, and interruptible loads, respectively. The two items in the bracket also show the charging power and discharging power of the battery EES system, denoted by $P^{Ch.}_{\omega,j,t}$ and $P^{Disch.}_{\omega,j,t}$ respectively. It should be noted that the value of the PV power generation and the value of the fixed-load demand have been previously determined and applied to the model. The other variables are all positive decision variables of the presented framework. The battery EES system operation is subject to different constraints, expressed through (16)-(21).

$$P^{Ch.}_{\omega,j,t} \leqslant I^{Ch.}_{\omega,j,t} P^{Ch.,max}_j \tag{16}$$

$$P^{Disch.}_{\omega,j,t} \leqslant I^{Disch.}_{\omega,j,t} P^{Disch.,max}_j \tag{17}$$

$$0 \leqslant I^{Ch.}_{\omega,j,t} + I^{Disch.}_{\omega,j,t} \leqslant 1 \tag{18}$$

$$E_{\omega,j,t} = E_{\omega,j,t-1} + \eta^{Ch.}_j P^{Ch.}_{\omega,j,t} - \frac{1}{\eta^{Disch.}_j} P^{Disch.}_{\omega,j,t} \tag{19}$$

$$E_{\omega,j,1} = E_{\omega,j,T} \tag{20}$$

Table 1
The specifications of fixed loads in the HEMS self-scheduling study.

Appliance	P_i	T_i	LB_b	UB_b	LB_s	UB_s
Refrigerator (W)	350	48	1	48	1	48
TV (W)	100	12	35	46	35	46
Lighting 1 (W)	150	2	11	12	11	12
Lighting 2 (W)	100	2	13	14	13	14
Lighting 3 (W)	50	2	15	16	15	16
Lighting 4 (W)	50	2	37	38	37	38
Lighting 5 (W)	100	2	39	40	39	40
Lighting 6 (W)	150	2	41	42	41	42
Lighting 7 (W)	180	4	43	46	43	46

Table 2
The specifications of flexible home appliances in the HEMS self-scheduling study [10].

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

Table 3
Daily tariffs for different price-based demand response programs.

Hour	TOU	Hour	TOU
00:00–01:00	0.01	12:00–13:00	0.04
01:00–02:00	0.01	13:00–14:00	0.04
02:00–03:00	0.01	14:00–15:00	0.04
03:00–04:00	0.01	15:00–16:00	0.04
04:00–05:00	0.01	16:00–17:00	0.04
05:00–06:00	0.01	17:00–18:00	0.04
06:00–07:00	0.01	18:00–19:00	0.04
07:00–08:00	0.02	19:00–20:00	0.04
08:00–09:00	0.02	20:00–21:00	0.02
09:00–10:00	0.04	21:00–22:00	0.02
10:00–11:00	0.04	22:00–23:00	0.01
11:00–12:00	0.04	23:00–00:00	0.01

$$E_j^{min} \leqslant E_{\omega,j,t} \leqslant E_j^{max} \tag{21}$$

Table 4
Technical parameters of the battery EES system.

E^{max}	E^{min}	$P^{Ch.,max}$	$P^{Disch.,max}$	$\eta^{Ch.}$	$\eta^{Disch.}$	$E_1 = E_T$
(kWh)	(kWh)	(kW)	(kW)	%	%	(kWh)
4.00	0.200	0.500	0.500	0.90	0.85	0.2

Table 5
Technical parameters of the AC system and building characteristics.

P^{AC}	α	β	γ	θ^{min}	θ^{max}	θ^{max}
(kW)			(°C/kW)	(°C)	(°C)	(°C)
4.80	0.70	0.30	0.25	10.0	22.0*	25.0**

* for t∈ {[0:00–8:00] ∪ [21:00–0:00]}.

** for t∈ {[8:00–21:00]}.

The battery EES system operation should be in either charging or discharging modes, characterized by binary variables at each time slot of the scheduling period as (16)-(18). Furthermore, the energy available at each time of the scheduling is a function of the energy, stored in the previous slot and the charging and discharging power of the battery at the present time slot, while applying the charging and discharging modes efficiencies, as indicated in Eq. (19). In order to meet the following day's operation requirements, it is assumed that at the end of the scheduling period, the battery should have energy equal to the initial amount at the beginning of the scheduling period, as applied in Eq. (20). The energy that can be stored in the storage system is limited within the permitted range, determined by the capacity of the battery and the minimum permitted energy level as stated in (21). The energy, bought from the utility grid at every scenario can be easily determined. Accordingly, the energy bill would be easily calculated and it can be reduced by effectively lowering the reliance of the HEMS on the utility grid [29]. Moreover, the final amount of the energy bill can be further mitigated by shifting the demand to the off-peak load time slots, where the higher adaptability of the prosumer's consumption to the more economical time intervals would result in the more reduced energy bill.

5. Simulation results

This section presents the results, obtained from simulating the proposed self-scheduling model with a rooftop PV panel and a battery EES system. The main target of this simulation is to show the effectiveness of the proposed model for solving the self-scheduling problem of the

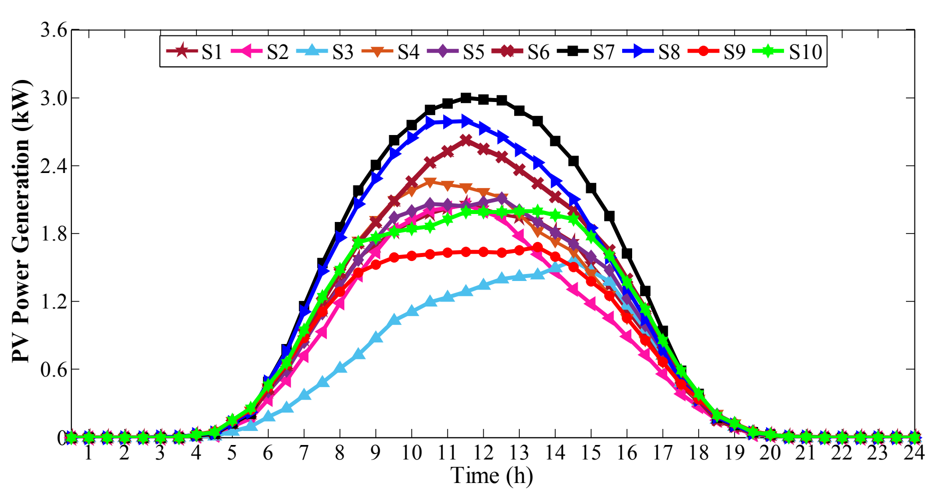

Fig. 3. Solar power generation scenarios for the target day.

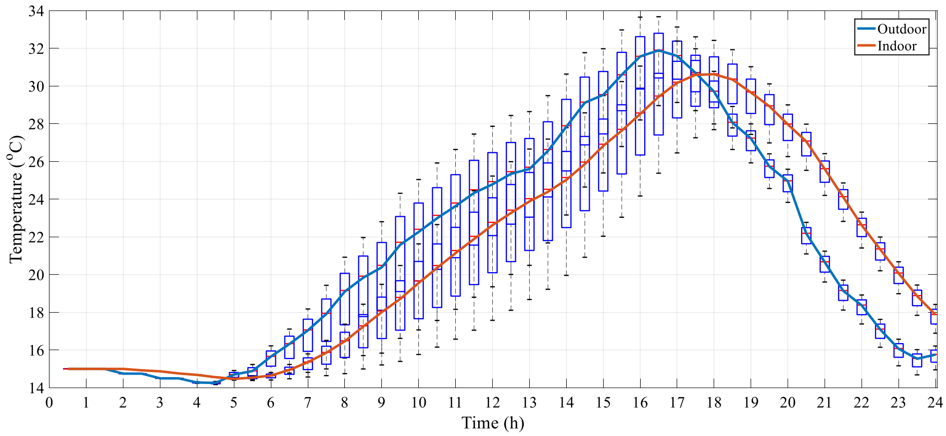

Fig. 4. Outdoor and indoor temperature scenarios.

HEMS. In this case, the home appliances are categorized into fixed, flexible, and interruptible loads. The fixed loads must be exactly supplied at the specified time. Thus, the permitted time interval, denoted by subscript b and the acceptable time interval, denoted by subscript s are the same for such loads. Tables 1 and 2 represent the data of fixed and flexible loads respectively.

It is worth noting that each time interval lasts for 30 min in this study. Different capacities and intervals have been considered for the lighting system with respect to the prosumer's preferences and also before the sunrise and after the sunset. The hourly tariffs for the time-based DR program are provided in Table 3 [30]. In the TOU, there are three different tariffs considered for peak, mid-peak and off-peak hours.

It should be noted that the energy tariffs are on an hourly basis and they are applied for each 30-min interval according to this table. The installed capacity of the rooftop PV panel is 3 kW and Fig. 3 shows the power generation scenarios over the day [31,32]. The scenarios, depicted in Fig. 3 are generated using the historical data and also the day-ahead solar irradiance forecast. The number of scenarios has been shrunk to 10. The capacity of the battery is 4 kWh with 200 Wh minimum energy. Besides, the energy stored in the battery at the initial interval and the final interval of the scheduling period is set to the minimum energy of the battery. Table 4 includes the data of the battery EES system. As mentioned above, the operating costs of the battery EES system and the rooftop PV panel are neglected. Fig. 3 illustrates the PV power generation of most probable scenarios, adopted in this study.

Table 5 addresses the AC system and building temperature-related characteristics [33]. According to this table, the rated power of the AC is 4.8 kW and as it was mentioned in the problem formulation, the internal inverter can appropriately control the effective consumption power of this appliance; therefore, it can consume 0.96, 1.92, 2.88, 3.84 and 4.8 kW based on the requirements. Furthermore, the AC system has the functionality to be interrupted if it is needed. Fig. 4 illustrates the outdoor temperature and the indoor temperature scenarios without utilizing the AC system. The outdoor, and indoor temperature scenarios without the HVAC system, have been shown in Fig. 4. According to this figure, the indoor temperature should be reduced to be convenient for the consumer in the evening.

In this study, the HEMS self-scheduling problem is solved for the TOU tariff. According to Table 3, the hourly electricity tariff is provided. The TOU tariff in this study includes three steps according to the peak, shoulder and off-peak periods. This kind of pricing provides incentives for active consumers to save money by shifting their consumption of peak periods to less expensive shoulder and off-peak periods. This static pricing mechanism brings some incentives for the end-users to reshape their consumption patterns. In this case, the self-scheduling problem is carried out for three different scenarios. The first scenario includes the self-scheduling problem for fixed and flexible demands, excluding the AC system, PV power generation, and battery EES. This case study is

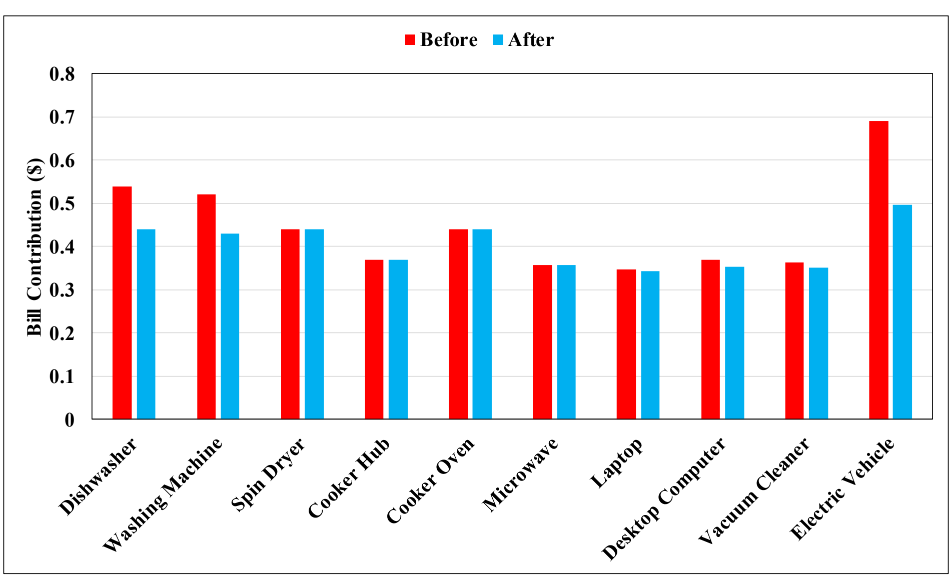

Fig. 5. The contribution of flexible appliances in the daily electricity bill.

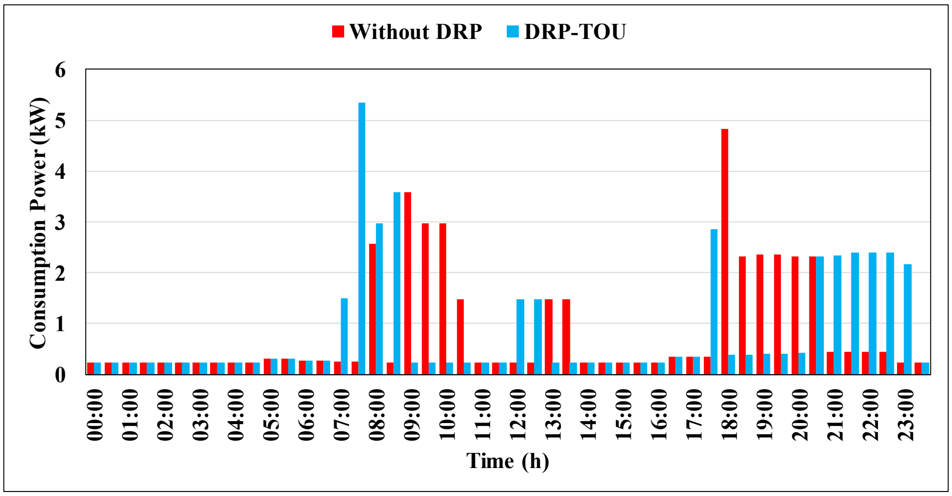

Fig. 6. The power consumption without implementing DRP and fully dedicated consumer (DRP-TOU).

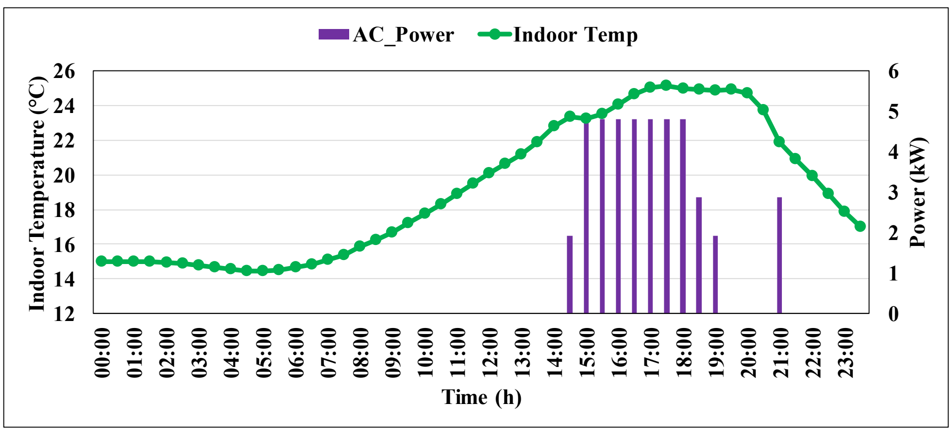

Fig. 7. The indoor temperature controlled by the AC system and its associated consumed power.

presented to approve the functionality of the proposed model and compare the results with the previously published works. In the second scenario, the inverter-based AC system is also added and in the last scenario, all types of appliances in line with PV and battery EES are considered.

5.1. Self-scheduling problem - base case

In this case, the self-scheduling problem is solved according to Table 1 and Table 2 to find the optimal scheduling of fixed and flexible appliances. It is evident that the fixed loads have a constant contribution

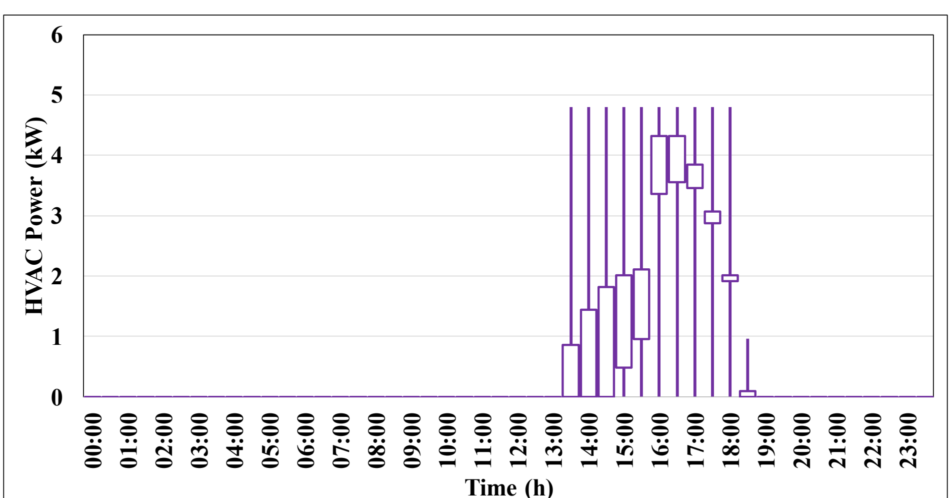

Fig. 8. Power consumption of the HVAC system.

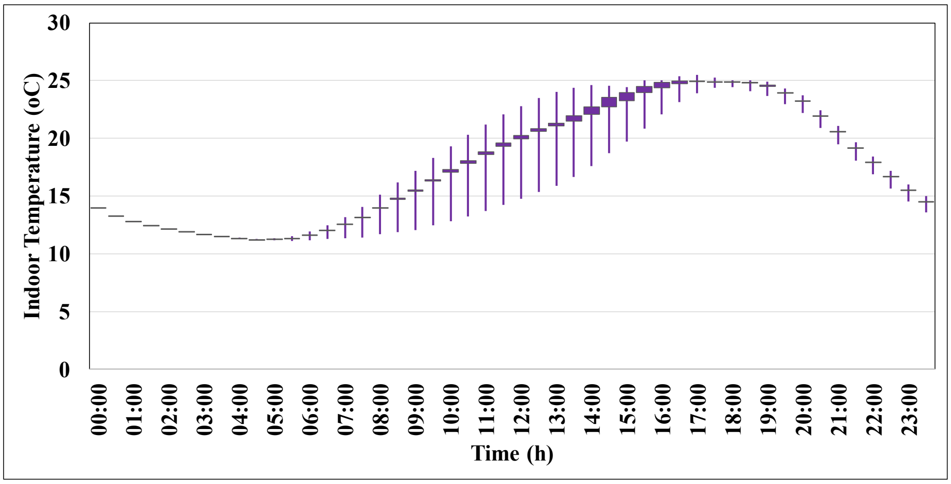

Fig. 9. Indoor temperature in different scenarios.

in the total cost of the smart home and the impacts of such loads could not change the scheduling of the flexible loads. Since the fixed loads result in a constant cost in the bill, it is easy to compare the overall cost of the flexible loads in the daily bill. According to Table 1 and Table 3, the total cost of fixed loads is 0.3399 $. It is noteworthy that the time steps in this study are supposed to last 30 min each, and the TOU tariff is presented on an hourly basis. For the given TOU and the flexible loads' characteristics, presented in Table 2, the corresponding cost is obtained as $1.039 without changing the initial preferences of the consumer. Therefore, the total daily cost for electricity in this case is $1.3789. According to the simulation results, by considering a high value for the DI, the scheduling of the flexible appliances would be the same as the preferences of the end-user, i.e. columns 4 and 5 of Table 2. It means that when the preferences of the end-user have higher merit of order rather than the electricity bill, the HEMS suggests the exact predefined time intervals for the utilization. On the other hand, whenever the total electricity cost is important for the consumer, the HEMS will rearrange the scheduling of utilization; however, the violation of the predefined time interval, i.e. columns 6 and 7 of Table 2, is not allowed. Therefore, the total cost reduction due to the fully dedicated consumer in the cost reduction is $0.9624. It means that the self-scheduling with the HEMS can reduce the cost by 40% for the flexible loads and 30% in the overall cost. Fig. 5 illustrates the contribution of the flexible loads in the daily bill, while the values of consumed power by the consumer with and without DRP are depicted in Fig. 6. According to Fig. 6, it is evident that the TOU can provide enough incentives for the dedicated consumer to shift the flexible appliances to off-peak and shoulder periods and therefore, the total daily electricity bill will be drastically decreased.

5.2. Self-scheduling problem – Impacts of interruptible load

In this case, the impacts of the interruptible loads have been studied. The only interruptible load in this study is the inverter-based AC system. In the presence of the AC system, the indoor temperature would be controlled according to the end-user's preferences and the hourly electricity tariff. The controlled temperature by the optimal utilization of the inverter-based AC system is shown in Fig. 7. Since the outdoor temperature is increasing during the daytime, the indoor temperature is accordingly following up the outdoor temperature as well. To achieve a convenient ambient, the AC will be utilized so as to reduce the indoor temperature. As it is expected, the AC system as an interruptible load works with different operating modes to alleviate the indoor temperature to a value less than 25 °C, during the evening time. In this scenario, the temperature deviation penalty is supposed to be 0.5, and it has resulted in some small deviations between (17:00–17:30). The exact

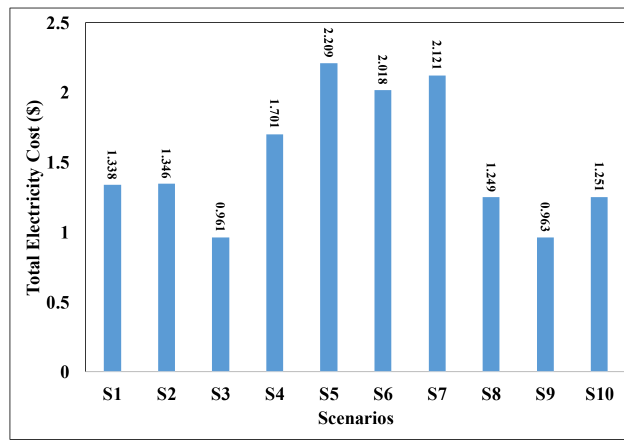

Fig. 10. The daily energy cost in different scenarios.

values of temperature in these two time slots are 25.05 °C and 25.16 °C, respectively, and it is acceptable for the consumer. The total electricity bill for the dedicated consumer is $1.327 and it is noteworthy that the contribution of the AC system in the daily cost is $0.3648. The base bill without changing the utilization of the flexible loads would be $1.744. It means that the AC system contributes to the daily bills by a considerable share. However, the daily electricity bill can be effectively reduced by means of self-generation and self-scheduling, using the HEMS.

Fig. 8 shows that the HVAC system has been used over hours 18:30–13:30. Besides, it has been used at its nominal capacity in some scenarios. It is also noted that this asset has been utilized at hours 16 and 17 to adjust the indoor temperature in an effective way. Moreover, there is no need to use the cooling system over other hours of the day.

The indoor temperature in different scenarios can be observed in Fig. 9. As it is expected, the indoor temperature has been kept within the permitted range, while during hours 00:00–15:30 and 18:30–23:30, the temperature is below 25 °C. The HVAC system has been used during hours 16:00–18:00 at its maximum capacity to reduce the indoor temperature. The energy cost in different scenarios has also been represented in Fig. 10.

5.3. Self-scheduling problem with self-generation capability

In the previous scenarios, the electricity bill assessment has been carried out in the deterministic representation, considering the impacts of fixed, flexible and interruptible loads. The cost assessment for the

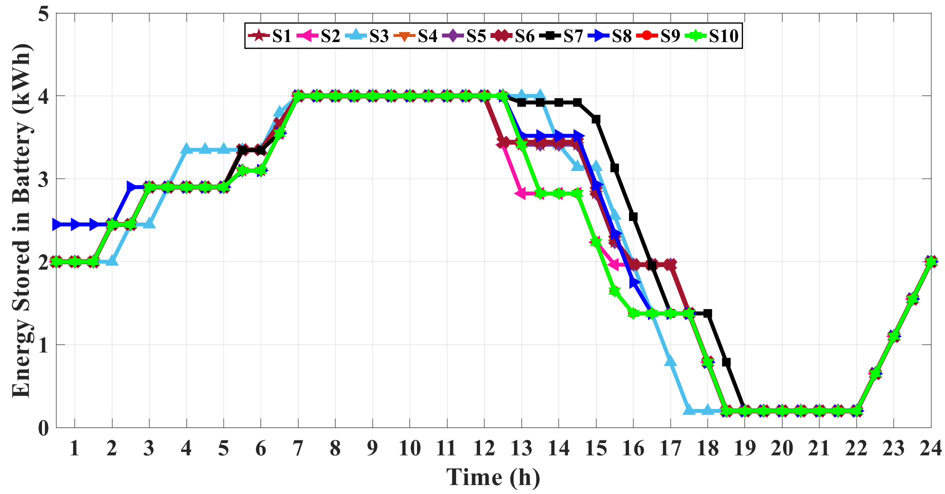

Fig. 11. The energy stored in the energy storage system for the given PV generation scenarios.

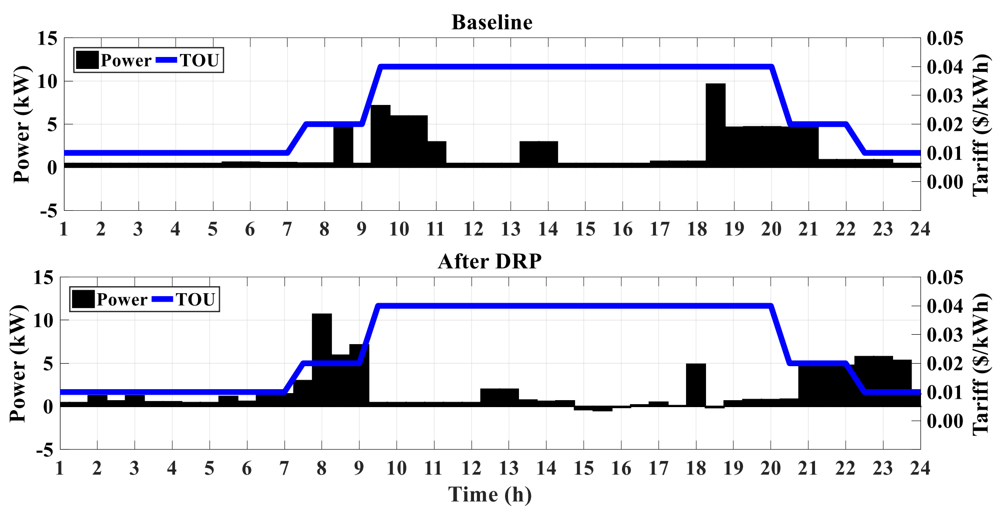

Fig. 12. Grid-to-HEMS power transactions for the baseline and after DRP considering the self-generation.

aforementioned scenarios shows that the daily electricity bill is considerable, specifically in the presence of the inverter-based AC system and PV. In this scenario, the impacts of PV and battery EES as the installed DERs have been evaluated. The problem is tackled considering all types of loads in this scenario. The expected electricity cost in this case is $1.173, while taking into account the possibility of selling the surplus energy to the upstream grid at a rate equal to 90% of the purchase price at each hour. The energy, stored in battery is depicted for 10 different scenarios in Fig. 11. As it is expected, the energy is stored in the battery in the morning time since the electricity price is low and during the daytime, the PV power generation meets the electricity demand. The stored energy will be discharged to serve the loads, particularly the AC, as a device with considerable consumption. During the nighttime, the battery will be charged again to achieve the initial SoC.

The grid-to-HEMS power transactions for the baseline, i.e. according to the user's preferences and after implementing the DR program, are indicated in Fig. 12. In this figure, the average power transactions between the grid and the HEMS are depicted. According to the results, it can be stated that the HEMS effectively moves the power consumption from peak hours to off-peak and shoulder periods. The results also confirm that during the peak hours, the HEMS can sell the surplus power to the grid. Since the selling tariff during the peak hours is 0.036 $/kWh, i.e. 90% of the peak tariff, the consumer can sell the power to the grid and reduce the overall bill in this case.

6. Conclusion

This paper proposed a self-scheduling strategy for a HEMS application, with emphasis on the DRPs and self-generation capability. The suggested model was formulated as a stochastic MILP problem. Different types of loads were modelled in this study, such as fixed, flexible, and interruptible loads. The problem formulation was investigated to model different kinds of loads and a study was conducted for different scenarios while implementing the TOU tariff. The simulation results confirm that the TOU tariff can effectively motivate the active consumer to modify their consumption pattern. Consequently, in the presence of small DERs such as PV and battery EES systems, the overall daily bill can be effectively reduced by self-scheduling, performed by the HEMS. Furthermore, the effectiveness of the inverter-based AC in controlling the indoor temperature as an interruptible load was illustrated. The simulation results confirm that the indoor temperature may be controlled according to the preferences of the end-user. Since the AC system has a considerable contribution to the daily bill, and the power consumption is proportionally related to the outdoor temperature, the PV panels can serve such loads. The presence of the battery EES can increase the flexibility of the HEMS operation and reduce the overall cost accordingly. In addition, the impact of the penalty factors on changing the prosumer's load demand was discussed in this study. The simulation results revealed that the prosumer may be able to make a trade-off between reducing the energy bill with relative discomfort. If the prosumer intends only to reduce the amount of energy bill, the load shifting may be substantial. However, if shifting the load demand is not sufficiently motivating, the prosumer will likely tolerate a higher cost.

CRediT authorship contribution statement

Ali Esmaeel Nezhad: Conceptualization, Data curation, Formal analysis, Methodology, Writing - original draft. **Abolfazl Rahimnejad:** Validation, Software. **S. Andrew Gadsden:** Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Goncalves I, Gomes A, Henggeler AC. Optimizing the management of smart home energy resources under different power cost scenarios. Appl Energy 2019;242:351–63.
[2] Merei G, Moshovel J, Magnor D, Sauer DU. Optimization of self-consumption and techno-economic analysis of PV-battery systems in commercial applications. Appl Energy 2016;168:171–8.
[3] Hu M, Xiao J-W, Cui S-C, Wang Y-W. Distributed real-time demand response for energy management scheduling in smart grid. Int J Electr Power Energy Syst 2018;99:233–45.
[4] Mokgonyana L, Zhang J, Li H, Hu Y. Optimal location and capacity planning for distributed generation with independent power production and self-generation. Appl Energy 2017;188:140–50.
[5] Faruqui A, Hanser P, Lessem N. Best Practices in Tariff Design (Cost of Service and Tariff Design Workshop). The Brattle and Lantau Group; 2016. p. 1–47.
[6] European U. Clean energy for all Europeans. Brussels, Belgium: European Commission.
[7] Ohrlund I, Schultzberg M, Bartusch C. Identifying and estimating the effects of a mandatory billing demand charge. Appl Energy 2019;237:885–95.
[8] Kampman B, Blommerde J, Afman M. The potential of energy citizens in the European Union. Delft: CE Delft; 2016.
[9] Jordehi AR. Binary particle swarm optimisation with quadratic transfer function: A new binary optimisation algorithm for optimal scheduling of appliances in smart homes. Appl Soft Comput 2019;78:465–80.
[10] Rezaee JA. Enhanced leader particle swarm optimisation (ELPSO): a new algorithm for optimal scheduling of home appliances in demand response programs. Artif Intell Rev 2019.
[11] Nan S, Zhou M, Li G. Optimal residential community demand response scheduling in smart grid. Appl Energy 2018;210:1280–9.
[12] Cui S, Wang Y, Xiao J. Peer-to-peer energy sharing among smart energy buildings by distributed transaction. IEEE Trans Smart Grid 2019;10(6):6491–501.
[13] Cui S, Wang YW, Shi Y, Xiao JW. An efficient peer-to-peer energy-sharing framework for numerous community prosumers. IEEE Trans Ind Inf 2020;16(12):7402–12.
[14] Cui S, Wang Y, Li C, Xiao J. Prosumer community: A risk aversion energy sharing model. IEEE Trans Sustainable Energy 2020;11(2):828–38.
[15] Marzband M, Fouladfar MH, Akorede MF, Lightbody G, Pouresmaeil E. Framework for smart transactive energy in home-microgrids considering coalition formation and demand side management. Sustainable Cities and Society. 2018;40:136–54.
[16] Rastegar M, Fotuhi-Firuzabad M, Lehtonen M. Home load management in a residential energy hub. Electr Power Syst Res 2015;119:322–8.
[17] Pinto R, Bessa RJ, Matos MA. Multi-period flexibility forecast for low voltage prosumers. Energy. 2017;141:2251–63.
[18] Estahbanati MJ. Hybrid probabilistic-harmony search algorithm methodology in generation scheduling problem. J Exp Theor Artif Intell 2014;26(2):283–96.
[19] Setlhaolo D, Xia X, Zhang J. Optimal scheduling of household appliances for demand response. Electr Power Syst Res 2014;116:24–8.
[20] Reyna A, Martin C, Chen J, Soler E, Diaz M. On blockchain and its integration with IoT. Challenges and opportunities. Future Generat Comput Syst 2018;88:173–90.
[21] Shirazi E, Jadid S. Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS. Energy Build 2015;93:40–9.
[22] Ellabban O, Abu-Rub H, Blaabjerg F. Renewable energy resources: Current status, future prospects and their enabling technology. Renew Sustain Energy Rev 2019;39:748–64.
[23] Javadi MS, Nezhad AE, Nardelli PHJ, Gough M, Lotfi M, Santos S, et al. Self-scheduling model for home energy management systems considering the end-users discomfort index within price-based demand response programs. Sustainable Cities Soci 2021;68:102792.
[24] Javadi MS, Esmaeel Nezhad A, Shafie-khah M, Siano P, Catalao J. Assessing the benefits of capacity payment, feed-in-tariff and time-of-use programme on long-term renewable energy sources integration. IET Smart Grid. 2019;2(4):602–11.
[25] Javadi M, Lotfi M, Osório GJ, Ashraf A, Nezhad AE, Gough M, et al. A Multi-objective model for home energy management system self-scheduling using the epsilon-constraint method. In: Conference a multi-objective model for home energy management system self-scheduling using the epsilon-constraint method, vol. 1, 2020. p. 175–80.
[26] Li H, Rezvani A, Hu J, Ohshima K. Optimal day-ahead scheduling of microgrid with hybrid electric vehicles using MSFLA algorithm considering control strategies. Sustainable Cities Soc 2021;66:102681.
[27] Evins R, Orehounig K, Dorer V, Carmeliet J. New formulations of the energy hub model to address operational constraints. Energy 2014;73:387–98.
[28] Javadi MS, Firuzi K, Rezanezhad M, Lotfi M, Gough M, Catalao JPS. Optimal sizing and siting of electrical energy storage devices for smart grids considering time-of-use programs. In: 45th IEEE Annual Conference of the Industrial Electronics Society - IECON. Lisboa, Portugal, 2019. p. 1–6.
[29] Marzband M, Azarinejadian F, Savaghebi M, Pouresmaeil E, Guerrero JM, Lightbody G. Smart transactive energy framework in grid-connected multiple home microgrids under independent and coalition operations. Renewable Energy 2018;126:95–106.
[30] Javadi MS, Gough M, Lotfi M, Esmaeel Nezhad A, Santos SF, Catalão JPS. Optimal self-scheduling of home energy management system in the presence of photovoltaic power generation and batteries. Energy. 2020;210:118568.
[31] Javadi MS, Lotfi M, Nezhad AE, Anvari-Moghaddam A, Guerrero JM, Catalão JPS. Optimal operation of energy hubs considering uncertainties and different time resolutions. IEEE Trans Ind Appl 2020;56(5):5543–52.
[32] Javadi MS, Esmaeel Nezhad A, Anvari-Moghaddam A, Guerrero JM, Lotfi M, Catalao JPS. Optimal operation of an energy hub in the presence of uncertainties. In: 19th IEEE International Conference on Environment and Electrical Engineering - EEEIC 2019, Genoa, Italy, 2019. p. 1–6.
[33] Antunes CH, Rasouli V, Alves MJ, Gomes Á, Costa JJ, Gaspar A. A Discussion of mixed integer linear programming models of thermostatic loads in demand response. In: Bertsch V, Ardone A, Suriyah M, Fichtner W, Leibfried T, Heuveline V editors. Conference a discussion of mixed integer linear programming models of thermostatic loads in demand response, Cham. Springer International Publishing, 2018. p. 105–22.