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Abstract—Today, the fact that consumers are becoming more active in electrical power systems, along with the development in electronic and control devices, makes the design of Home Energy Management Systems (HEMSs) an expedient approach to mitigate their costs. The added costs incurred by consumers are mainly paying for the peak-load demand and the system’s operation and maintenance. Thus, developing and utilizing an efficient HEMS would provide an opportunity both to the end-users and system operators to reduce their costs. Accordingly, this paper proposes an effective HEMS design for the self-scheduling of assets of a residential end-user. The suggested model considers the existence of a dynamic pricing scheme such as Real-Time Pricing (RTP), Time-of-Use (TOU), and Inclining Block Rate (IBR), which are effective Demand Response Programs (DRPs) put in place to alleviate the energy bill of consumers and incentivize demand-side participation in power systems. In this respect, the self-scheduling problem is modeled using a stochastic Mixed-Integer Linear Programming (MILP) framework, which allows optimal determination of the status of the home appliances throughout the day, obtaining the global optimal solution with a fast convergence rate. It is noted that the consumer is equipped with self-generation assets through a Photovoltaic (PV) panel and a battery. This system would make the consumers have energy arbitrage and transact energy with the utility grid. Consequently, the proposed model is demonstrated by determining the best operation schedule for different case studies, highlighting the impact each different DRP has on designing and utilizing the HEMS system for best results.

Keywords: Demand Response Programs, Home Energy Management System, Self-scheduling, Incline Block Rate, Time of Use

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Nomenclature

Acronyms

- **BEES**: Battery electrical energy storage
- **DER**: Distributed energy resource
- **DI**: Discomfort index
- **DRP**: Demand response program
- **DSM**: Demand-side management
- **EV**: Electric Vehicle
- **HEMS**: Home energy management system
- **IBR**: Inclining block rate
- **MILP**: Mixed-integer linear programming
- **PV**: Photovoltaic
- **RTP**: Real-time pricing
- **TOU**: Time-of-use

Indices

- $i$: Index for home appliances
- $j$: Index for EES devices
- $k$: Index for energy consumption in IBR mechanism
- $t$: Index for the time intervals of scheduling
- $\omega$: Index for scenario

Variables

- $S_{\omega,i,t}$: The operation status of the shiftable appliances
- $P_{\omega,j}^{G2H}$: Delivered power from grid to home
- $P_{\omega,j}^{H2G}$: Delivered power home to grid
- $D_{\omega,j}^{\text{Shift}}$: Hourly demand of shiftable load
- $STUP_{\omega,i,t}$: Binary variables for start-up action
- $SHDN_{\omega,j}$: Binary variables for shut-down action
- $Energy_{\omega,k}^{\text{Tier}}$: Amount of energy for each tier in IBR mechanism
- $DI_{\omega,i}^{+}$: Discomfort index regarding usage of the appliance $i$ after the scheduled time
- $DI_{\omega,i}^{-}$: Discomfort index regarding usage of the appliance $i$ before the scheduled time
\( P_{\text{Ch}, j,t} \) Charging power of BEES

\( P_{\text{Disch.}, j,t} \) Discharging power of BEES

\( I_{\text{Ch.}, j,t} \) Charging status of BEES

\( I_{\text{Disch.}, j,t} \) Discharging status of BEES

\( I_{\text{Tier}, o,k} \) Status of activated tier in IBR mechanism

\( E_{o,k,j,t} \) Stored energy at BEES

### Parameters

\( \pi_t^{G2H} \) Hourly electricity price sold to home

\( \pi_t^{H2G} \) Hourly electricity price sold to grid

\( P_{o,j}^{PV} \) Hourly PV power generation

\( C_{sT}^i \) Start-up cost of switchable loads

\( C_{sD}^i \) Shut-down cost of switchable loads

\( IBR_k^{\text{Tariff}} \) Stepwise tariff for IBR mechanism

\( T_i \) Total number of time intervals of the operation

\( LB_{i,b} \) The lower band of baseline operation time slot

\( UB_{i,b} \) The upper band of baseline operation time slot

\( LB_{i,s} \) The lower band of allowable operation time slot

\( UB_{i,s} \) The upper band of allowable operation time slot

\( B_{o,k,i,t} \) The end-user’s preferred usage status of the appliance

\( D_{o,j}^{\text{Fix}} \) Hourly fixed demand

\( P_i \) Rated power of appliance \( i \)

\( P_j^{\text{Ch.\_max}} \) Maximum charging power of BEES

\( P_j^{\text{Disch.\_max}} \) Maximum discharging power of BEES

\( \eta_j^{\text{Ch.}} \) Charging efficiency of BEES

\( \eta_j^{\text{Disch.}} \) Discharging efficiency of BEES

\( E_j^{\text{min}} \) Minimum acceptable energy stored at BEES

\( E_j^{\text{max}} \) Maximum acceptable energy stored at BEES

\( E_{o,j,t} \) Initial energy stored at BEES
1. Introduction
   A. Motivation

In the near future, distribution companies will be facing new and unprecedented challenges to, and opportunities for, their business models. These challenges and opportunities are being brought about by the increasing rate of consumers’ ability to respond and participate in demand response programs (DRPs). Additionally, the increasing number of electric vehicles (EVs) within distribution networks will need to be accounted for and this can be done by optimizing the charging of these vehicles to minimize the resulting fluctuations on the load profile. From the prosumers’ perspective, ensuring that they receive a sufficient return on their investments in Photovoltaic (PV) panels, Battery Electrical Energy Storages (BEESs) and other Distributed Energy Resources (DERs) depends, to a large extent, on the market design, tariff structure, service costs, and the optimal scheduling of these devices.

Thus, in this paper, the impacts of various tariff structures on the optimal self-scheduling of prosumers’ devices are studied. The typical prosumer examined in this study has a PV panel installed on the rooftop and a stationary BEES. The effects of the various market designs on the amount of self-consumption of the prosumers are studied and how the optimal scheduling of
these devices can influence the amount of self-consumption is shown. The main motivation of this study is to determine the best strategy for a given household in terms of energy consumption scheduling, and how this optimal strategy can result in the reduction of the monthly electricity bill of the consumers. This goal can be achieved by shifting the consumption of electricity usage to the off-peak times as well as active participation in the market by selling the surplus energy to the grid.

B. Literature Review

A home energy management system (HEMS) system aims to optimize the scheduling of various appliances within the home to manage the energy consumption of the household. Also, this management of the appliances has been done with the intent of reducing the electricity bill for the homeowner. Various energy pricing policies that change across time enable the prosumers to change their consumption behavior and the time they use electrical devices to reduce their electricity bills [1]. Such policies can also convince the consumers in the long-term to replace the existing low-efficiency devices with devices that are more energy efficient. HEMS may assist in demand response as the HEMS system can optimize the use of local resources which can then participate in DRPs. With the rise of DERs, including BEES, the scope for the HEMS has widened to include the management of these devices. Generally, these appliances can be grouped into three categories: baseline loads, burst loads, and regular loads [2]. Baseline loads are also often called must-run loads. They are non-controllable and non-deferrable which means that that the operation cannot be modified. Examples of this category include lighting services, ovens, and televisions. Burst loads can also be called deferrable-shiftable or schedulable loads as their operation can be shifted across time or paused during operation to better manage the current household electricity consumption. Examples of this type of load are washing machines or tumble dryers. The regular loads are those fluctuating according to the environmental conditions, such as space heaters and air-conditioners. These
loads are especially important in maintaining the user’s comfort. The household load comprised of several loads from appliances of different categories will also depend upon factors like the size of the house, the number of occupants and their schedule, the climate conditions as well as the income level of the occupants. These factors combine to ensure that household loads vary significantly and the best way to accurately model these profiles is to use bottom-up methodologies [2]. Fig. 1 depicts a typical smart HEMS aimed at operating different load demands, either non-shiftable or shiftable besides the PV and storage systems. Using such a model the decision-maker would be able to reduce the operating costs of the appliances according to the energy tariff and the available local generation. As it can be observed, this model mainly intends to consider home appliances. In this regard, the best consumption time and the best power transaction strategy between the smart home and the grid will be determined and possible to implement by the means of the proposed HEMS.

Fig. 1 The HEMS with self-generation and strategic conservation infrastructures.

The concept of HEMS is crucial to the idea of increased customer participation in electricity markets. The HEMS allows customers to evolve from being purely passive
consumers of electricity to being more proactive and having an influence on electricity markets. This active participation through HEMS has allowed consumers to optimize the size and shape of their residential load profile [3]. The contribution of end-users to their energy consumption management has been significantly increased over recent years. Most notably, the development in technology in the form of the Internet-of-Things (IoT) has provided the required infrastructure for implementing the Demand-Side Management (DSM) programs [4].

The HEMS concept has been studied thoroughly in the existing literature. A Mixed-Integer Nonlinear Programming (MINLP) was developed in [5] to include a penalty for causing the customers inconvenience in the final schedule. The problem took a set of 10 appliances and let the customers decide on their optimal operational schedules and the system was penalized for moving the operation of these appliances outside of the schedules. Results showed a decrease in the customers’ energy bill by 25%.

A novel Conditional Value at Risk (CVaR) formulation was used in [6] which included the uncertainty surrounding energy storage systems, PV arrays, price, and load profiles. Incentives were used to raise the participation of customers in such a program and the results show a saving of 18% on the bills should the customers choose to be part of the program. A limited memory algorithm and a Time-of-Use (TOU) tariff regime were used in [1] to determine the optimal operating schedule of several appliances in a residential setting over 24 hours. A total number of 267 households were studied and a clustering algorithm was used to group them. Results showed a reduction of 33% in the electricity costs for households [7].

Stationary energy storage was combined with a PV system in a HEMS in [8] to provide varying operational regimes using Gaussian probability distributions to create a MILP problem solved via the Advanced Adaptive Particle Swarm Optimization (AAPSO). Results from this model show a reduction of approximately 28% in annual electricity costs.
A Multi-Objective MILP HEMS model including stationary storage was formulated in [9]. The model also made use of a TOU tariff regime to increase the active participation of customers in the program. Six scenarios were studied and results revealed that the HEMS reduced the electricity costs in all six scenarios, as well as having the added benefit of reducing the peak load experienced by the system. A HEMS was developing by [10] which accounted for uncertainties associated with the power production of renewable energy sources in a building. The results were highly dependent on the various scenarios used, but the HEMS showed a saving of 42% of the electricity costs. Another multi-objective model based on MIP framework has been introduced in [11] addressing the discomfort index and electricity bills of the end-user using epsilon-constrained optimization method.

A HEMS for scheduling appliances in a smart home is proposed in [12]. The goal of the model is reducing electricity costs as well as reducing the peak load relative to the average load all the while maintaining the comfort of the customers. This model made use of two tariff regimes, Real-Time Pricing (RTP) and Inclining Block Rate (IBR), to reduce the energy consumption during periods of low prices. Results indicate a decrease in the peak-to-average ratio (the load profile was flattened compared to the case without the model).

A model to schedule appliances was developed in [13] which used a multi-stage stochastic non-linear mixed-integer program to account for weather-related uncertainties. Scenario groupwise decomposition was used to develop upper and lower bounds for the relevant scenarios. The results from the study show a reduction in both electricity costs and disutility for all types of consumer studied, especially when the combination of battery energy storage and renewable energy technologies are considered.

A two-stage stochastic mixed-integer model is developed in [14]. The model took the uncertainties surrounding solar PV production as well as electricity and heat demand into account. A further stochastic model that investigated the effects of the uncertainties around PV
production and critical load profiles is developed by [15]. The authors modeled deferrable appliances, energy storage systems, HVAC units, PV systems, and critical loads. Results show a decrease in the electricity bill of the consumer.

While the preceding sections of this paper focus on the benefits of HEMS (and by extension DERs) to customers and in some examples the wider distribution grid, it is important to note that the use of DERs can also bring about problematic issues to the distribution system operator [16–18]. Issues such as power flow problems and voltage fluctuations can be created by the use of DERs. One possible solution is to increase the penetration of stationary energy storage devices within the HEMS and distribution networks.

Having taken into consideration the positive impact of HEMS on the distribution network, there are also a few concerns that the HEMS system will need to address in the future if the potential is to be fully recognized. Concerns about data privacy and security are the most significant ones. There have already been examples of HEMS being compromised [2], and with the expectation that the number of smart devices that could be connected to the HEMS will increase this concern will become more important.

Connected to this idea is the challenge that a rapidly increasing number of smart devices, imposes the need to allow these devices to communicate with each other in a computationally efficient manner [19]. In addition to the need for an efficient communication system, it will be essential that the various smart devices can work together in a seamless manner. This aspect calls for greater interoperability between various device manufacturers. Over the recent past, the number of previously passive consumers who can now generate a portion of their consumption via self-generation has increased [6]. This has been caused by many factors such as increasing grid imported electricity prices, decreasing costs of DERs, and various governmental policies. Self-generation can contribute to policies aimed at achieving low carbon or other sustainability targets [2]. Countries and regions worldwide are now recognizing the
potential for customer generation and seek to increase the active participation of these customers, this is especially evident in Europe, where the European Commission’s ‘Clean Energy for All Europeans’ policy aims at adapting the rules around the energy markets too, explicitly, put the consumer at the heart of the energy system [16]. Research shows that 83% of households within the European Union have the potential to be active energy citizens while over 100 million households could produce renewable energy or provide flexibility services [20]. Key to this potential being realized will be the use of HEMSs to help schedule and manage the customer's electricity production and consumption.

C. Contribution

This paper presents the following novel contributions:

- Providing a stochastic MILP model for the HEMS self-scheduling problem. 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 devices.

- Incentivizing self-generation and strategic energy-saving to lower the bills. This is an important contribution as the penetration of BEES devices in the presence of PV panels is expected to grow rapidly and the potential effectiveness of such hybrid systems needs to be evaluated.

D. Paper Organization

This paper has the following structure: In Section 2, the main idea of the HEMS self-scheduling considering the possibility of self-generation at the household level is provided. Section 3 contains the problem formulation and the results are presented and discussed in Section 4. Conclusions are then addressed in Section 5.
2. **Self-generation and Self-scheduling**

The electrical assets of the consumers considered in the proposed model for the self-scheduling with self-generation are categorized into three main groups:

i) **PV panels:** installed on rooftops are the local generation assets of the consumers.

ii) **BEES:** can be directly charged by the PV panels or supply the appliances’ demand or inject power to the grid (using a DC-AC inverter). It can also be charged/discharged by transacting power with the grid through AC-DC converters. It can also

iii) **Electrical appliances:** owned by consumers. These devices are divided into two groups with shiftable and non-shiftable loads.

Fig. 2 depicts the conceptual configuration for integrating the PV panel and BEES to supply the home demand.

![Smart energy management system for self-generation purposes.](image)

In this configuration, the control system receives the price signals, which can be either the predetermined TOU tariff or RTP tariffs, and decides on the optimal operation of the DC section. Moreover, the bill amount can be reduced using such a control scheme by determining the State-of-Charge (SoC) of the BEES with respect to the load demand and considering the
IBR mechanism and system requirements. This model utilizes a bidirectional controllable converter capable of controlling the optimal operating point and energy flow. Today, such converters are commercially available for different voltage levels.

The self-scheduling problem proposed in this paper aims at deciding on the optimal operation of the shiftable loads. One of the decision variables in the self-scheduling problem is the determination of the best scheduling for the shiftable loads that the end-user is willing to utilize. Other electrical load demands include the ones that the consumer does not tend to shift like the lighting system or TV. Furthermore, the refrigerator and the freezer are non-shiftable loads. The amount of their consumption is constant disregarding the electrical storage and the self-generation. Taking into consideration such required energy, the bill amount can be mitigated by following an optimal consumption pattern [12]. The time-based tariff depends upon the consumption time which can help the self-scheduling result in reducing the bill amount [21]. The BEES significantly increases the flexibility of the self-scheduling model. Because different energy tariffs provide the opportunity to charge over the off-peak hours and discharge over peak off-peak hours [21]. The energy stored in the BEES can be used to supply the demand at hours with high energy tariffs or when the prosumer cannot shift the load demand. One of the merits of the BEES 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 RES-BEES systems, the RES spillage power can be stored in the BEES. Besides, in case there is a deficit in the renewable power generation with regard to the forecasted values, the BEES can compensate [22].

3. Problem Formulation

The self-scheduling problem of HEMSs considering the self-generation feature of renewable power generation in this paper aims to minimize the daily electricity bills of the prosumers. 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 further decrease the cost. Consequently, the problem should be modeled and solved as a multi-objective optimization problem or a single-objective one 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:

\[
\text{Min } Z = \sum_{o \in \Omega} \rho_o \left( \sum_{t=1}^{N_T} \left( \pi_t^{G2H} P_{o,t}^{G2H} \Delta t - \pi_t^{H2G} P_{o,t}^{H2G} \Delta t \right) + \sum_{o \in \Omega} \sum_{i=1}^{N_A} \sigma \left[ DI_{o,j}^+ + DI_{o,j}^- \right] + \right)
\]

\[
\sum_{o \in \Omega} \left( \sum_{i=1}^{N_A} \left[ \text{STUP}_{o,i} C_{i}^{ST} + \text{SHDN}_{o,i} C_{i}^{SD} \right] \right) - \sum_{i=1}^{N_A} \left[ C_{i}^{ST} + C_{i}^{SD} \right] + \sum_{o \in \Omega} \sum_{k=1}^{N_K} \text{IBR}_{T_{o,k}} \cdot \text{Energy}_{T_{o,k}} \right)
\]

The objective function includes four terms. The first term states the expected value of the cost of power transaction between the grid and the HEMS. The second term shows the discomfort cost due to shifting the load demand. The third term is comprised of the start-up and the shut-down costs of the assets. Finally, the expected cost of applying the IBR tariff to the load demand over the scheduling horizon is included in the fourth term. The net power purchase from the grid is calculated based on the ToU tariff, which is predetermined and denoted by \( \pi_t^{G2H} \).

The energy purchased from the grid can be specified by knowing the number of hours at which the energy is imported from the grid. Likewise, the energy sold to the grid is determined [23]. It is noted that the price of the energy sold to the grid can be equal to or even greater or smaller than the TOU tariff. \( \sigma \) in the second part of the objective function denotes the discomfort penalty factor and it is applied for shifting the load to previous or next hours. As mentioned above, the third part of the objective function shows the start-up and shut-down costs. Once a device is turned on, it should stay turned on for a certain time period. In theory and using a MILP model, a device can turn off/on multiple times a day while in practice it is not possible. 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. \( C^{ST}_i \) and \( C^{SD}_i \), 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 fourth term of the objective function indicates the expected value of the additional cost due to purchasing energy from the grid according to the IBR tariff. It should be noted that the energy purchase cost increases exponentially with the increase in consumption. Thus, the self-scheduling problem seeks to find a solution to generate power and store it so that the energy can be sold to the grid. This strategy would reduce the dependency on the grid and help manage the energy self-purchase costs. In addition, the investment in the rooftop PV panel and BEES would be economically justified by utilizing such a market mechanism. The constraints of the problem relate to the technical and economic constraints of load shifting, the power transaction of the HEMS with the electrical grid, and also the BEES. Constraint (2) shows that the amount of shiftable load at each time interval, \( D^{\text{Shift}}_{a,i,t} \), is a function of the nominal power of the asset, \( P_i \), and its operating status determined by the binary variable \( S_{a,i,t} \).

\[
D^{\text{Shift}}_{a,i,t} = \sum_{i=1}^{N_A} S_{a,i,t} P_i
\]  

The value of the binary variable can be equal to “1” only over the time intervals specified by the prosumer and its value will be zero before and after that. Generally, the permitted time to use the electrical device is greater than the required time to use it, which is in line with the load shiftability. As a result, the device must be used in the permitted time as much as required. The limitations of the binary variable \( S_{a,i,t} \) are stated through (3)-(4).
\[
S_{\omega,i,t} = \begin{cases} 
0 & t < LB_{\omega,i} \\
1 & LB_{\omega,i} \leq t \leq UB_{\omega,i} \\
0 & t > UB_{\omega,i}
\end{cases} \quad S_{\omega,i,t} \in \{0,1\} \quad (3)
\]

\[
\sum_{t=1}^{NT} S_{\omega,i,t} = T_i \quad \forall i = 1,2,...,NA \quad (4)
\]

It is noteworthy that the right-hand side of Eq. (4) is a predetermined parameter showing the in-service time of the device over the scheduling horizon. Similar constraints can be considered for electrical devices with shiftable loads to calculate the bill amount in the base case. The difference lies in the fact that a binary parameter is used instead of a binary variable to model the operation of the asset in the desired time of the prosumer. Consequently, the optimal value of this parameter will be equal to “1” over the operating period; otherwise “0”.

\[
B_{\omega,i,t} = \begin{cases} 
0 & t < LB_{\omega,i} \\
1 & LB_{\omega,i} \leq t \leq UB_{\omega,i} \\
0 & t > UB_{\omega,i}
\end{cases} \quad B_{\omega,i,t} \in \{0,1\} \quad (5)
\]

\[
\sum_{t=1}^{NT} B_{\omega,i,t} = T_i \quad \forall i = 1,2,...,NA \quad (6)
\]

As it has been previously mentioned, a penalty is applied to prevent any redundant start-up and shut-down with respect to the binary variable determining the operating status of the asset. This binary variable of the assets can be theoretically “0” or “1”, but in practice such a schedule is not realistic for appliances like the washing machine and the spin dryer. It should be noted that one start-up and one shut-down is permitted and any more start-ups and shut-downs will be penalized. Furthermore, two separate time intervals are considered to use a device in two intervals over the day in this study. The start-up and shut-down binary variables are determined using the following equation:

\[
STU P_{\omega,i,t} - SHDN_{\omega,i,t} = S_{\omega,i,t} - S_{\omega,i,t-1} \quad \forall t > 1
\]
$STUP_{ao, i, t}$ and $SHDN_{ao, i, t}$ are the binary variables showing the start-up and shut-down of the assets. Accordingly, the start-up and shut-down costs of each asset would be calculated by multiplying the corresponding variables by $C_i^{ST}$ and $C_i^{SD}$, respectively [24].

In order to address the DI for shifted loads, a linear penalty has been considered in this paper. This model adopts the cumulative rolling mapping procedure for calculating the shifted time intervals. The corresponding DI for shifting of each time slot can be easily calculated based on (8) and (9), respectively for changing the operation time intervals before and after the baseline time intervals. It is noted that both $DI_i^-$ and $DI_i^+$ are positive variables. Therefore, there are no conflicts between them if the right-hand side of these equations is negative.

\[
DI_i^- \geq \frac{1}{T_i} \left[ \sum_{t=1}^{NT} t \times B_{ao, i, t} - \sum_{t=1}^{NT} t \times S_{ao, i, t} \right] \quad (8)
\]

\[
DI_i^+ \geq \frac{1}{T_i} \left[ \sum_{t=1}^{NT} t \times S_{ao, i, t} - \sum_{t=1}^{NT} t \times B_{ao, i, t} \right] \quad (9)
\]

In the presence of BEES system and PV generation, the energy flow from the grid side to the HEMS should be modeled in a way to reflect the role of BEES and self-generation. The power balance for each time interval is as follows [11,25]:

\[
P_{G, j, t}^{2H} + P_{PV, j, t} - P_{H, j, t}^{2G} = D_{PV, j, t}^{Shift} + D_{Ch, j, t}^{Shift} + \left[ \sum_{j=1}^{NS} P_{Ch, j, t}^{Ch.} - \sum_{j=1}^{NS} P_{Disch, j, t}^{Disch.} \right] \quad (10)
\]

where the left-hand side of the equation includes the power purchased from the grid and power generated by the roof-top PV, both with a positive sign. Moreover, the left-hand side includes the net power sold to the grid with a negative sign. The power consumed by shiftable and non-shiftable loads and the charging power of the BEES are represented in the right-hand-side with a positive sign and the discharging power is shown with a negative sign. It is worth mentioning that the power generated by the rooftop PV system and non-shiftable load demand are of parameter type and their values are predetermined, while others are the variables of the
stochastic self-scheduling problem. The BEES has its associated constraints in terms of operation in the planning horizon, i.e. daily operation in this study. The corresponding constraints for the BEES are as follows:

\[ P_{\text{Ch},j,t}^{\text{max}} \leq P_{\text{Ch},j,t} \]  \hspace{1cm} (11)

\[ P_{\text{Disch},j,t}^{\text{max}} \leq P_{\text{Disch},j,t} \]  \hspace{1cm} (12)

\[ 0 \leq I_{\text{Ch},j,t} + I_{\text{Disch},j,t} \leq 1 \]  \hspace{1cm} (13)

\[ E_{\text{Ch},j,t} = E_{\text{Ch},j,t-1} + \eta_j^{\text{Ch}} P_{\text{Ch},j,t} - \frac{1}{\eta_j^{\text{Disch}}} P_{\text{Disch},j,t} \]  \hspace{1cm} (14)

\[ E_{\text{Ch},j,1} = E_{\text{Ch},j,T} \]  \hspace{1cm} (15)

\[ E_{\text{min},j} \leq E_{\text{Ch},j,t} \leq E_{\text{max},j} \]  \hspace{1cm} (16)

Binary variables which represent each of the charging and discharging modes are introduced to restrict the BEES to be in either a charging or discharging mode at a time. These variables are shown in (11)-(13). The energy stored in the BEES at a specific period is a function of the energy stored in the BEES in the previous period plus the effects of any charging or discharging that occurred. This is shown in (14) which also includes an efficiency factor for charging and discharging. It is assumed that the initial energy stored in the BEES system should be remained fixed at the end of the operation horizon. This constraint is addressed in (15). The energy within the BEES is constrained by upper and lower limits as shown in (16). The energy purchased from the grid can be obtained for each scenario. The cost of energy purchased is calculated in a stepwise manner according to the IBR tariff. Generally, the energy bill is calculated for one month considering the IBR tariff. Thus, for a short-term horizon, e.g. 24 hours, the IBR tariff must be determined proportionally to the amount of energy over the day and applied to the objective function. Each energy tier is equal to \( \text{Energy}_{\text{Tier},j} \). Therefore, the sum of these tiers shows the total energy over the scheduling horizon as shown in (17). The number of energy tiers to be purchased from the grid is stated in (18). These tiers can be either
identical or different. It is noteworthy that the energy price is determined exponentially while the energy tiers would be selected according to a priority list from the cheapest to the most expensive. It should be noted that $Energy_{\omega,k}^{Tier}$ must be less than the maximum energy of each tier denoted by $E_{k}^{Tier,max}$. The binary variable $I_{\omega,k}^{Tier}$ models these energy tiers.

$$\sum_{t=1}^{NT} P_{GCH,t}^{CH} \Delta t = \sum_{\omega=1}^{NK} Energy_{\omega,k}^{Tier} \text{ } \forall \omega \in \Omega$$  \hspace{1cm} (17)$$

$$Energy_{\omega,k}^{Tier} \leq E_{k}^{Tier,max} I_{\omega,k}^{Tier} \text{ } I_{\omega,k}^{Tier} \in \{0,1\}$$  \hspace{1cm} (18)

Consequently, the energy bill of the prosumer would reduce by decreasing the HEMS dependency on the electrical grid [26]. In addition, the energy bill will be more reduced by shifting the load to off-peak hours. The more the end-user will be able to adapt the patterns of his own consumption to the off-peak intervals; the better will be his bill at the end of the month.

4. Simulation Results

This section presents the results obtained from simulating the proposed self-scheduling model with a rooftop PV panel and a BEES system. The home appliances are categorized into shiftable and non-shiftable loads. The non-shiftable load demand 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 shiftable and non-shiftable loads, respectively. It is worth noting that each time interval lasts for 30 minutes in this study. Different capacities and intervals have been considered for the lighting system with respect to the prosumer’s preference and also before the sunrise and after the sunset. The hourly tariffs for each time-based DRPs are provided in Table 3. In the TOU, there are three different tariffs considered for peak, mid-peak and off-peak hours. The daily RTP are extracted from Commonwealth Edison Company on May 14, 2018 and reported in Ref. [12], as well.
Table 1 The specifications of shiftable home appliances in the HEMS self-scheduling study [12]

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

Table 2 The specifications of non-shiftable loads in the HEMS self-scheduling study

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

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

<table>
<thead>
<tr>
<th>Hour</th>
<th>TOU</th>
<th>RTP</th>
<th>Hour</th>
<th>TOU</th>
<th>RTP</th>
</tr>
</thead>
<tbody>
<tr>
<td>00:00-01:00</td>
<td>0.01</td>
<td>0.014</td>
<td>12:00-13:00</td>
<td>0.04</td>
<td>0.034</td>
</tr>
<tr>
<td>01:00-02:00</td>
<td>0.01</td>
<td>0.015</td>
<td>13:00-14:00</td>
<td>0.04</td>
<td>0.033</td>
</tr>
<tr>
<td>02:00-03:00</td>
<td>0.01</td>
<td>0.015</td>
<td>14:00-15:00</td>
<td>0.04</td>
<td>0.040</td>
</tr>
<tr>
<td>03:00-04:00</td>
<td>0.01</td>
<td>0.013</td>
<td>15:00-16:00</td>
<td>0.04</td>
<td>0.047</td>
</tr>
<tr>
<td>04:00-05:00</td>
<td>0.01</td>
<td>0.010</td>
<td>16:00-17:00</td>
<td>0.04</td>
<td>0.047</td>
</tr>
<tr>
<td>05:00-06:00</td>
<td>0.01</td>
<td>0.014</td>
<td>17:00-18:00</td>
<td>0.04</td>
<td>0.047</td>
</tr>
<tr>
<td>06:00-07:00</td>
<td>0.01</td>
<td>0.017</td>
<td>18:00-19:00</td>
<td>0.04</td>
<td>0.043</td>
</tr>
<tr>
<td>07:00-08:00</td>
<td>0.02</td>
<td>0.019</td>
<td>19:00-20:00</td>
<td>0.04</td>
<td>0.034</td>
</tr>
<tr>
<td>08:00-09:00</td>
<td>0.02</td>
<td>0.024</td>
<td>20:00-21:00</td>
<td>0.02</td>
<td>0.038</td>
</tr>
<tr>
<td>09:00-10:00</td>
<td>0.04</td>
<td>0.024</td>
<td>21:00-22:00</td>
<td>0.02</td>
<td>0.037</td>
</tr>
<tr>
<td>10:00-11:00</td>
<td>0.04</td>
<td>0.025</td>
<td>22:00-23:00</td>
<td>0.01</td>
<td>0.024</td>
</tr>
<tr>
<td>11:00-12:00</td>
<td>0.04</td>
<td>0.037</td>
<td>23:00-00:00</td>
<td>0.01</td>
<td>0.018</td>
</tr>
</tbody>
</table>

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 [26]. 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 BEES system. As mentioned above, the operating costs of the BEES system and the rooftop PV panel are neglected.

![Solar power generation scenarios for the target day](image)

**Fig. 3.** Solar power generation scenarios for the target day [27]

![IBR tariff proportional to the daily energy consumption](image)

**Fig. 4.** Applying the IBR tariff proportional to the daily energy consumption

<table>
<thead>
<tr>
<th>Table 4 Technical parameters of the BEES.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_{\text{max}}$</td>
</tr>
<tr>
<td>(kWh)</td>
</tr>
<tr>
<td>4.00</td>
</tr>
</tbody>
</table>
Different case studies have been investigated in this paper for the self-scheduling problem. The simulation results for all scenarios are obtained by CPLEX solver formulated by IBM and activated through the General Algebraic Modeling System (GAMS). Using the CPLEX solver in GAMS allows large and difficult problems formulated in the high-level modeling system to be solved by the powerful CPLEX solver. The mentioned scenarios are as follows:

4.1. Energy bill evaluation based on the TOU tariff disregarding the self-generation

This case study studies the impact of load shifting on the energy bill reduction in a given day. In this case, the prosumer pays only for the energy purchased from the grid to supply the load demand. The energy tariffs represented in Table 3 are used to calculate the energy bill which is only due to purchasing energy in kWh from the grid. In this regard, the total energy demand over the day is 39.01 kWh from which 9.96 kWh relates to non-shiftable loads including the refrigerator, lighting system, and TV [27]. The remaining load demand relates to the shiftable loads. The total cost disregarding the load shifting is $1.2874 from which $0.2484 relates to supplying the non-shiftable loads and $1.039 relates to the shiftable loads. Having taken into account the load shifting policy, the total cost is $0.8709 comprised of $0.6225 due to supplying non-shiftable loads and $0.2484 due to supplying the shiftable load. It should be noted that this value is obtained, while the prosumer seeks only to reduce the energy bill. Thus, the DI impact is equal to zero, i.e. $\rho=0$. However, the value of the DI is equal to 25 in this state. In other words, the number of time intervals over which the load shifting occurs is equal to 25. The optimal consumption pattern shows that the load should be shifted for 4 time intervals for the dishwasher, 3 time intervals for the washing machine, and 1 time interval for the vacuum cleaner to the intervals before the desired time. The load shifting for the spin dryer and laptop occurs for 7 intervals while for the desktop computer and the EV, it occurs for 5 intervals after
the prosumer’s desired time. It is worth mentioning that shifting the demand of the vacuum
cleaner to one interval before the prosumer’s desired time results in 50% saving in the cost by
$0.1925. Fig. 5 depicts the share of each shiftable and non-shiftable load in the energy bill in
Case 1.

![Fig. 5. The share of each load to the cost due to load shifting \( \rho=0 \) _Case 1._]

As it can be observed, the cost of supplying the non-shiftable load, i.e. microwave, cooker
oven, cooker hob, and spin dryer is the same before and after applying the self-scheduling.
Furthermore, a sensitivity analysis has been carried out to specify the impact of the penalty due
to the DI. Table 5 represents the obtained results for the sensitivity analysis. This analysis
reveals the threshold for motivating the prosumer to act on load shifting.

Fig. 6 illustrates the daily consumption in the base case with load shifting. As can be
observed, a substantial load has been successfully shifted from peak intervals to off-peak
intervals.
### Table 5: The sensitivity analysis based on TOU tariff considering the penalty factor the effects on the DI

<table>
<thead>
<tr>
<th>( \rho )</th>
<th>Optimal Bill</th>
<th>DI</th>
<th>( \rho )</th>
<th>Optimal Bill</th>
<th>DI</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>0.8709</td>
<td>25</td>
<td>0.015</td>
<td>1.0849</td>
<td>12</td>
</tr>
<tr>
<td>0.001</td>
<td>0.8944</td>
<td>19</td>
<td>0.020</td>
<td>1.1424</td>
<td>11</td>
</tr>
<tr>
<td>0.002</td>
<td>0.9119</td>
<td>17</td>
<td>0.025</td>
<td>1.1974</td>
<td>8</td>
</tr>
<tr>
<td>0.003</td>
<td>0.9289</td>
<td>17</td>
<td>0.030</td>
<td>1.2324</td>
<td>4</td>
</tr>
<tr>
<td>0.004</td>
<td>0.9449</td>
<td>13</td>
<td>0.035</td>
<td>1.2524</td>
<td>4</td>
</tr>
<tr>
<td>0.005</td>
<td>0.9579</td>
<td>13</td>
<td>0.040</td>
<td>1.2724</td>
<td>4</td>
</tr>
<tr>
<td>0.010</td>
<td>1.0229</td>
<td>13</td>
<td>0.045</td>
<td>1.2874</td>
<td>0</td>
</tr>
</tbody>
</table>

![Baseline](image1.png)

![After DRP](image2.png)

**Fig. 6.** Comparative illustration of the power consumption of the prosumer before and after applying the TOU tariff-based self-scheduling.

### 4.2. Energy bill Evaluation based on the TOU tariff considering the self-generation

This scenario seeks to investigate the impact of self-generation on the self-scheduling problem. The prosumer is equipped with a rooftop PV panel in addition to a 4-kWh battery. The hybrid system including the PV panel and the BEES would provide the opportunity to store the solar energy over the off-peak intervals. As a result, the required energy will be available over the peak hours. The expected value of the available solar energy is 18.887 kWh in this case. Moreover, the expected values of the energy purchased from the grid and the energy sold to the grid over the day are 30.309 kWh and 9.690 kWh, respectively. Considering the total load demand, 39.01 kWh, the residual of the sum of the energy transacted with the grid, the
energy generated by the PV panel, and the load demand of the system, i.e. 0.496 kWh is the
BEES system’s energy losses. The charging and discharging efficiencies of the BEES system
are 90% and 85%, respectively. Consequently, the sum of the generation and the sum of the
load demand are not equal. However, the simulation is also done taking into consideration an
ideal BEES system to verify the solution and the obtained results are indicated in Table 6.

Table 6. The simulation results of the energy flow with real and ideal BEES.

<table>
<thead>
<tr>
<th>BEES</th>
<th>Grid to HEMS</th>
<th>HEMS to Grid</th>
<th>PV</th>
<th>Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal</td>
<td>30.095 kWh</td>
<td>9.973 kWh</td>
<td>18.887 kWh</td>
<td>0.000 kWh</td>
</tr>
<tr>
<td>Real</td>
<td>30.309 kWh</td>
<td>9.690 kWh</td>
<td>18.887 kWh</td>
<td>0.496 kWh</td>
</tr>
</tbody>
</table>

The derived results show that employing a hybrid PV-battery system would lead to
reducing the energy bill amount. Besides, by applying the TOU tariff, the prosumer would be
able to more mitigate the energy bill. Meanwhile, the solar power generation is over the
intervals with substantial energy tariffs, enabling the prosumer to sell the surplus energy. The
expected value of total cost is equal to 0.203989 $/day in this case which has been tangibly
reduced compared to the case without the self-generation. If the prosumer does not tend to shift
the load demand, the total cost will be 0.610618 $/day with the self-generation. Fig. 6 indicates
the expected value of the energy stored in the BEES system for the two mentioned modes. As
expected, the BEES system stores power over the first hours of the day when the energy price
is low. It reaches the maximum amount when the PV panel starts to generate power over the
first hours at which the load demand is relatively low. The BEES system discharges at the time
intervals with high energy prices. It should be noted that the BEES system and the energy sold
to the grid must be controlled more conservatively in case the prosumer does not tend to shift
the load demand. On the contrary, when the load demand can be shifted, the HEMS takes an
optimal strategy with respect to the market conditions to more mitigate the amount of the energy
bill. The net power sold to the grid in the two mentioned modes is shown in Fig. 7. As expected,
the HEMS sells energy after supplying its load demand over the hours with high energy prices.
Besides, the BEES system injects power to get more profit. Fig. 7 also shows the TOU tariff to highlight the different flexibility of the system in response to the energy tariff. It can be observed that in the base case, if the surplus energy is not consumed in the HEMS, i.e. in the household load and the BEES system, it must be injected to the grid and there is no control.

![Graph showing energy stored in battery vs. time]  
**Fig. 6.** The comparison between the energy stored in the battery in the base case and in the case with the TOU tariff.

![Graph showing injected power vs. time]  
**Fig. 7.** The expected value of the energy injected to the grid in Case 2.
4.3. Energy bill Evaluation based on the RTP tariff disregarding the self-generation

Similar to Case 1, the reduction in the energy bill amount will be achieved only based on the RTP tariff and by load shifting in this case. The load shifting would be different from the case based on the TOU tariff with predetermined values due to the different energy price at each hour. The RTP mechanism provides a proper approximation of the real market prices. It should be noted that a considerable number of prosumers with the HEMS may result in influencing the real-time prices. However, the prosumer with the HEMS is a price-taker in this paper. The simulation results show that the daily total cost of the prosumer without load shifting is $1.22093 from which $0.28343 relates to supplying the fixed loads and $0.9375 relates to supplying the shiftable loads. Having taken into account the self-generation capability, the prosumer’s cost decreases to $1.08383 achieved by load shifting of the dishwasher, washing machine, cooker hob, microwave, laptop, desktop computer, and the EV. The non-shiftable loads in addition to the vacuum cleaner, spin dryer, and cooker oven do not contribute to the cost reduction. Fig. 8 indicates the share of each load in the prosumer’s cost before and after applying the DSM programs, while the EV has the highest impact, similarly to Case 1 due to its considerable load demand. The EV charging cost is $0.4025 in the base case while after applying the DSM program; it is reduced to $0.3115. The sensitivity analysis results revealed that for the penalty factor equal to zero, i.e. $\rho = 0$, the minimum cost is achieved while the DI reaches 26. As expected, the DI approaches zero by increasing the penalty factor and for $\rho = 0.02$, the cost would be the same as Case 1.

It is noteworthy that the main difference between the proposed model in this paper and the non-linear model developed in [12] is in the modelling of DI. In this paper, the ‘Euclidean Distance’ method is introduced for calculating the DI, while the ‘Absolute Subtraction’ has been addressed in [12]. Table 7 illustrates the optimal bill considering fixed and shiftable loads. Considering this fact that the contribution of the fixed load is $0.28343, the corresponding bills
are $0.8004 and $0.9375 respectively for shiftable loads in fully dedicated case ($\rho=0$), and the undedicated case (DI=0). It means that the obtained results for these cases are identical to those reported in [12].

Table 7 The sensitivity analysis based on RTP tariff considering the penalty factor the impacts on the DI.

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Optimal Bill</th>
<th>DI</th>
<th>$\rho$</th>
<th>Optimal Bill</th>
<th>DI</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>1.0838</td>
<td>26</td>
<td>0.006</td>
<td>1.1584</td>
<td>6</td>
</tr>
<tr>
<td>0.001</td>
<td>1.1054</td>
<td>19</td>
<td>0.007</td>
<td>1.1644</td>
<td>6</td>
</tr>
<tr>
<td>0.002</td>
<td>1.1222</td>
<td>14</td>
<td>0.008</td>
<td>1.1699</td>
<td>5</td>
</tr>
<tr>
<td>0.003</td>
<td>1.1362</td>
<td>11</td>
<td>0.009</td>
<td>1.1749</td>
<td>5</td>
</tr>
<tr>
<td>0.004</td>
<td>1.1462</td>
<td>7</td>
<td>0.010</td>
<td>1.1799</td>
<td>5</td>
</tr>
<tr>
<td>0.005</td>
<td>1.1524</td>
<td>6</td>
<td>0.020</td>
<td>1.2209</td>
<td>0</td>
</tr>
</tbody>
</table>

Fig. 8. The share of each load in the total cost with load shifting and for $\rho=0$ Case 3.

Fig. 9 shows the consumption of the prosumer before and after applying the DSM with the RTP mechanism. As can be observed, a substantial amount of the load demand has been shifted to the hours with load energy prices.
4.4. Energy bill evaluation based on the RTP tariff considering the self-generation

This case studies the RTP-based total cost of the prosumer equipped with the self-generation. Similar to Case 2, the prosumer owns a BEES system and a 3-kW rooftop PV panel contributing to lowering the total cost along with facilitating the load shifting. The expected value of the total cost is $0.477963. In case the prosumer prefers to use only the self-generation to actively participate in the market and not shift the load demand, the total cost increases to $0.611473. Utilizing the self-generation together with the BEES system and load shifting, the cost reduces from $1.08383 to $0.474963 and in case the prosumer does not tend to shift the load to off-peak time intervals, the cost reduces from $1.22093 to $0.611473. Fig. 10 shows the power injected to the grid by the prosumer in two modes; first, only with self-generation and second, both with self-generation and DRPs. This figure reveals that the prosumer will be able to more actively participate in the market if the demand is shifted to off-peak hours. It is noteworthy that the energy stored in the battery hits the top over the first hours of the day with low energy prices in both states. During time intervals 30-36 with the highest energy prices, the BEES system discharges. Fig. 11 depicts the energy stored in the battery over the 24-hour
period. As can be seen from the energy stored in the battery in the two states mentioned above, the maximum SoC occurs at time interval 12 and it stays constant by interval 30. The battery starts to discharge to deliver the maximum permitted power to the grid from time interval 30 in line with the increasing trend of the energy price. On the other hand, the power generation of the PV panel starts to reduce from interval 23 and it hits zero at time interval 40. As a consequence, the prosumer has to purchase energy from the grid from time interval 30 forth, by the decrease in the power output of the PV panel and the increasing demand over these hours.

Fig. 10. The expected value of the injected power to grid in Case4.

Fig. 11. Comparative results of the energy stored in the battery in the base case and after applying the RTP-based DRP.
4.5. Energy bill evaluation based on the TOU-IBR mechanisms disregarding the self-generation

This case investigates the simultaneous application of the IBR and TOU to the self-scheduling problem. Indeed, consumption management has been considered besides the load demand management. In case of aiming only at the consumption management, load shifting would lead to mitigating the amount of energy bill, but the total energy consumption remains constant. However, it is assumed that the prosumer is not willing to reduce the consumption and intends to alleviate the amount of energy bill, while the entire demand is supplied. When there is no opportunity to generate and store energy, the amount of power purchased from the grid is exactly the same as the load demand over the scheduling period. Consequently, the total energy imported from the grid is 39.01 kWh. By applying the IBR based model used in this case, the cost increases exponentially with the consumption. For instance, the energy is 0.02 $/kWh for the first tier of the consumption by 10 kWh and for the second tier the price increases to 0.024 $/kWh. The price for the next three tiers will be 0.036 $/kWh, 0.050 $/kWh, and 0.080 $/kWh, respectively. As a result, the prosumer pays more if consumes more. In case selling energy to the grid is not possible, the prosumer can only shift the load to save money. Accordingly, the total cost will be $2.114 comprised of $1.2505 relating to the IBR tariff and $0.8709 which is the supply cost due to shifting the load demand. It is noteworthy that the cost of applying the TOU tariff would be the same as Case 1.

4.6. Energy bill evaluation based on the TOU-IBR mechanisms considering the self-generation

As discussed in Case 5, when utilizing the IBR tariff along with the TOU tariff, a substantial part of the cost will be due to the amount of consumption. This is a logical reason to reduce the consumption and actively participate in the power generation using self-generation technologies and sell power to the grid. It is assumed that the prosumer is equipped with a 3-
31 kW rooftop solar panel and a 4-kWh battery aimed at reducing the total cost and selling the surplus power to the grid. The prosumer would be able to decrease the costs and get back the investment cost for the battery and PV panel. The expected value of the energy purchased is 23.316 kWh, while the expected value of the energy sold to the grid is 2.253 kWh. Besides, the expected value of the energy generated by the rooftop PV panel is 18.887 kWh. The overall loss of energy by the BEES is 0.941 kWh regarding charging and discharging efficiency. The battery has experienced two complete cycles over the day. In other words, the energy losses of the battery are doubled compared to Cases 2 and 4. The simulation results show that the prosumer prefers to use the available capacity of the appliances such that the total cost reduces. Hence, the HEMS decides on using the battery with two complete cycles. The expected value of the cost is $0.920654. Fig. 12 depicts the energy stored in the battery, the power purchased from the grid, and the expected value of the power generated by the PV system along with the TOU tariff. As Fig. 12 indicates, the HEMS decides on purchasing power from the grid, preferably not at peak hours and controlling the charge/discharge of the battery, such that the dependency on the grid becomes minimized or the total cost is minimized.

![Fig. 12](image_url)
A sensitivity analysis has been carried out in this paper to assess the impact of self-generation on different items, such as the amount of energy purchase, the surplus energy that can be sold to the grid, the increased cost due to the IBR tariff, the electricity bill, and also the energy losses of the battery. The sensitivity analysis results are represented in Table 8. The independent variable in this study is the variation of the expected value of the 3-kW PV panel’s power output. In this regard, this variable has changed from 50% in the base case to 150%. The results, obtained for the base case, i.e. \( \psi = 100\% \), have been underlined in Table 8. The numerical results for the base case have been depicted in Fig. 12, showing that any reduction in the expected value of the PV power output would cause the power, purchased from the grid to include an increased cost due to the IBR tariff. For example, the prosumer has to purchase 30.788 kWh from the grid in the base case, i.e. the prosumer should buy 0.788 kWh for 0.05 $/kWh in the fourth price step. The 30 kWh energy should be purchased at 0.8 $/kWh. This amount can be transferred to the first two steps with lower prices, if the PV power generation increases. In case \( \psi \) is greater than 130%, the amount of energy, purchased is limited to the second step by 20 kWh, leading to mitigating the cost imposed by IBR tariff. The battery performance has also been evaluated in this study. The charging and discharging patterns of the battery would be in a way to manage the power output of the PV panel and minimize the power, purchased from the grid. The base case is associated with the largest battery utilization, as illustrated in Fig. 12. The battery is charged and discharged twice a day. It is fully charged by purchasing power over the off-peak time intervals and also by using the surplus power generation of the PV panel to supply the load demand over the final hours of the day.
Table 8. The sensitivity analysis for different self-generation of PV panels

<table>
<thead>
<tr>
<th>ψ</th>
<th>PV Energy* (kWh)</th>
<th>Energy Purchased* (kWh)</th>
<th>Energy Sold* (kWh)</th>
<th>IBR Cost* ($)</th>
<th>Bill* ($)</th>
<th>Battery Loss* (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.50</td>
<td>9.444</td>
<td>30.788</td>
<td>0.603</td>
<td>0.839411</td>
<td>1.418451</td>
<td>0.619</td>
</tr>
<tr>
<td>0.60</td>
<td>11.332</td>
<td>29.836</td>
<td>1.477</td>
<td>0.794100</td>
<td>1.318809</td>
<td>0.681</td>
</tr>
<tr>
<td>0.70</td>
<td>13.221</td>
<td>28.757</td>
<td>2.347</td>
<td>0.755238</td>
<td>1.229409</td>
<td>0.620</td>
</tr>
<tr>
<td>0.80</td>
<td>15.110</td>
<td>26.546</td>
<td>1.806</td>
<td>0.675644</td>
<td>1.129695</td>
<td>0.840</td>
</tr>
<tr>
<td>0.90</td>
<td>16.999</td>
<td>25.047</td>
<td>2.168</td>
<td>0.621694</td>
<td>1.025784</td>
<td>0.868</td>
</tr>
<tr>
<td>1.00</td>
<td>18.887</td>
<td>23.316</td>
<td>2.253</td>
<td>0.559387</td>
<td>0.950654</td>
<td>0.941</td>
</tr>
<tr>
<td>1.10</td>
<td>20.776</td>
<td>21.436</td>
<td>2.282</td>
<td>0.491685</td>
<td>0.813401</td>
<td>0.920</td>
</tr>
<tr>
<td>1.20</td>
<td>22.665</td>
<td>20.048</td>
<td>2.832</td>
<td>0.441727</td>
<td>0.710453</td>
<td>0.871</td>
</tr>
<tr>
<td>1.30</td>
<td>24.554</td>
<td>20.000</td>
<td>4.982</td>
<td>0.440000</td>
<td>0.627512</td>
<td>0.562</td>
</tr>
<tr>
<td>1.40</td>
<td>26.442</td>
<td>20.000</td>
<td>6.957</td>
<td>0.440000</td>
<td>0.549733</td>
<td>0.475</td>
</tr>
<tr>
<td>1.50</td>
<td>28.331</td>
<td>19.629</td>
<td>8.516</td>
<td>0.431089</td>
<td>0.477858</td>
<td>0.434</td>
</tr>
</tbody>
</table>

* Expected Value

5. Conclusion

This paper proposed a self-scheduling strategy for a Home Energy Management System (HEMS) application while investigating the impacts of different Demand Response Programs (DRPs). The main goal behind designing such a system was to mitigate the energy bill of the end-user. The problem was formulated as a single-objective stochastic optimization problem in a Mixed-Integer Linear Programming (MILP) framework so that the global optimal solution can be found at a high convergence rate. In this respect, the end-user was equipped with self-generation assets to make the energy transaction with the utility grid and cost mitigation possible. DRPs would provide the opportunity to end-users to be active in the system. Thus, several types of DRPs were evaluated in the paper. Accordingly, it was found that the Real-Time Pricing (RTP) mechanism was the best method as it reflexes the real conditions of the market. Besides, the cost of energy consumed by the prosumer will be desirably calculated. Moreover, by using the Time-of-Use (TOU) tariff, the prosumer would be able to decide on reducing the bill amount before. As there is no penalty for the over-consumption, this mechanism is effective only in cases with relatively low consumption. The Inclining Block Rate (IBR) along with the TOU tariff can also solve the over-consumption issue using the price signals. Besides, they would provide the prosumer with the opportunity to buy and install the
PV panels and storage devices. In other words, the saving on the energy bill will be considerable to reduce the dependency on the grid. This issue motivates the prosumer to invest in the self-generation. However, this paper can be further developed by proposing a robust optimization model to characterize the uncertainties and investigating the possibility of peer-to-peer energy transaction between multiple end-users.

The most important limitations of the presented model along with some suggestions to further extend and enhance the model can be briefly stated as follows:

- The proposed model utilized pre-determined operation intervals for the assets, while this situation can change in practical cases with real conditions. For example, the prosumer may decide to use the washing machine and dryer at times, different from the pre-given intervals. The solution would be employing model predictive control (MPC) techniques to tackle the problem over shorter time periods.

- The forecasted power output of the PV panel may be different from that, occurred in real conditions, which can substantially impact the obtained results and the electricity bill. One effective way to overcome this issue would be utilizing more effective forecasting tools or MPC techniques so as to modify and adapt the schedule according to the time-ahead PV power output forecasts.

- This paper considered a simple constant-power consumption pattern for the appliances with certain operation intervals. For instance, the washing machine operates with different time durations with different power consumptions. As a result, the power consumption for each time of the operation would be different. Meanwhile, smart meters record the energy consumption over each time of the operation. The solution would be applying determined power consumption patterns for such appliances and reducing the time intervals proportionally to the time intervals used by smart meters to record the
consumption, so that the scheduled consumed energy be close to the real consumption over that period.

- The assets, studied in this paper are of constant and programmable types, while for such kind of loads, interruption is not allowed. Nevertheless, some appliances, such as the air-conditioning systems can be interrupted. The solution would be adding new models for the interruptible assets and modelling the prosumers’ comfort index proportionally to the interruption duration and assets’ operation. For example, the comfort index of the prosumer for using the air-conditioning systems can be modelled and applied according to the indoor temperature.

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References


