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Javadi Mohammad Sadegh, Esmaeelnezhad Ali, Nardelli Pedro H.J., Gough Matthew, Lotfi Mohamed, Santos Sérgio, Catalão João P.S.

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Self-Scheduling Model for Home Energy Management Systems considering the End-Users Discomfort Index within Price-Based Demand Response Programs

Mohammad Sadegh Javadi [*1], Ali Esmaeel Nezhad [2], Pedro H. J. Nardelli [3], Matthew Gough [1,4], Mohamed Lotfi [1,4], Sérgio Santos [1], João P. S. Catalão [1,4]

1 Institute for Systems and Computer Engineering, Technology and Science (INESC TEC), Porto, Portugal

2 Department of Electrical, Electronic, and Information Engineering, University of Bologna, Italy

3 Department of Electrical Engineering, School of Energy Systems, LUT University, 53850 Lappeenranta, Finland

4 Faculty of Engineering of the University of Porto, (FEUP), Porto, Portugal

Abstract–This paper presents a self-scheduling model for home energy management systems (HEMS) in which a novel formulation of a linear discomfort index (DI) is proposed, incorporating the preferences of end-users in the daily operation of home appliances. The HEMS self-scheduling problem is modelled as a mixed-integer linear programming (MILP) multi-objective problem, aimed at minimizing the energy bill and DI. In this framework, the proposed DI determines the optimal time slots for the operation of home appliances while minimizing end-users' bills. The resulting multi-objective optimization problem has then been solved by using the epsilon-constraint technique and the VIKOR decision maker has been employed to select the most desired Pareto solution. The proposed model is tested considering tariffs in the presence of various price-based demand response programs (DRP), namely time-of-use (TOU) and real-time pricing (RTP). In addition, different scenarios considering the presence of electrical energy storage (EES) are investigated to study their impact on the optimal operation of HEMS. The simulation results show that the self-scheduling approach proposed in this paper yields significant reductions in the electricity bills for different electricity tariffs.

Keywords: Home Energy Management System; Discomfort Index; Self-scheduling; MILP; Price-Based Demand Response.

Nomenclature

Acronyms

ABC	Artificial bee colony
BSA	Backtracking search algorithm
DA	Dragonfly algorithm
DER	Distributed energy resource
DI	Discomfort index
DR	Demand response
DSO	Distribution system operator
EES	Electrical energy storage
EH	Energy hub
ELPSO	Enhanced leader particle swarm optimization
GSA	Gravitational search algorithm
HEMS	Home energy management system
IBR	Inclining block rate
IoT	Internet of things
MILP	Mixed-integer linear programming
MINLP	Mixed-integer non-linear programming
P2P	Peer-to-peer
PSO	Particle swarm algorithm
PV	Photovoltaic
RTP	Real-time pricing
TOU	Time-of-use
VPP	Virtual power plant

Indices

t	Index for the time intervals of scheduling
i	Index for home appliances
j	Index for EES devices

Variables

$S_{i,t}$	Binary variable showing the status of operation of appliance i at time slot t
ω	Penalty factor for discomfort index
P_t^{G2H}	Delivered power from grid to home at time slot t
DI_i^+	Discomfort index regarding usage of the appliance i before the scheduled time
DI_i^-	Discomfort index regarding usage of the appliance i after the scheduled time

$P_{j,t}^{Ch.}$ Charging power of EES j at time slot t

$P_{j,t}^{Disch.}$ Discharging power of EES j at time slot t

$E_{j,t}$ Stored energy at EES j at time slot t

$I_{j,t}^{Ch.}$ Charging status of EES j at time slot t

$I_{j,t}^{Disch.}$ Discharging status of EES j at time slot t

Parameters

ρ_t^{Tariff} Electricity price at time slot t based on *Tariff*

P_i Rated power of appliance i

P_t^D Hourly demand of home appliances

Δt Operation time interval

$B_{i,t}$ The end-user's preferred usage status of the appliance i at time slot t

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

$P_j^{Ch.\max}$ Maximum charging power of EES j

$P_j^{Disch.\max}$ Maximum discharging power of EES j

$\eta_j^{Ch.}$ Charging efficiency of EES j

$\eta_j^{Disch.}$ Discharging efficiency of EES j

$E_j^{\min}$ Minimum acceptable energy stored at EES j

$E_j^{\max}$ Maximum acceptable energy stored at EES j

E_j^1 Initial energy stored at EES j

E_j^T Final energy stored at EES j

Sets

NT Scheduling period

NA Set of shiftable home appliances

NS Total number of EES devices

1. Introduction

A. Motivation

In recent years, there has been a proliferation in the use of smart meters in residential households (Martinez-Pabon, Eveleigh, & Tanju, 2018), providing highly granular data on their energy usage. These meters, being a vital element of smart grids, allow for new forms of communication, control, and automation of electrical power flow between the grid and the household. This unlocks the great potential for residential users to be active participants in smart grids. For instance, according to the Federal Energy Regulatory Commission (FERC), residential demand response (DR) offers the largest unused DR resource of all sectors (residential, commercial, and transport) (Albadi & El-Saadany, 2007).

To exploit this potential, home energy management systems (HEMS) have been developed to assist in the optimal scheduling of home appliances to lower the electricity cost, while keeping the user's comfort within an acceptable range (Al-Ali, Zualkernan, Rashid, Gupta, & Alikarar, 2017; Jordehi, 2019; Z Yahia & Pradhan, 2018). This paper builds upon this research and presents a novel self-scheduling model which uses a linear penalty function to mitigate customers' discomfort resulting from HEMS operation. According to (Siano, 2014), a smart grid is an electrical grid which can connect various sources of generation and consumers in a controllable manner, and it is "smart" in the sense that it allows the consumers to adjust their actions according to various signals received. A universal definition of a smart grid is not agreed-upon since the concept covers a wide scope and can mean different things to different people. One of the more general definitions of the smart grid is given by (Tuballa & Abundo, 2016), stating that the smart grid is an intelligent grid, which is capable of storing, communicating, and making decisions concerning energy and the smart grid increases the capability to cooperate and the capability to be responsive to fluctuations.

The smart grid concept provides the communication and flexibility required to enable improved management of the grid and through these aspects like DR and demand-side management (DSM) have become prevalent (Jalali & Kazemi, 2015). The U.S. Department of Energy defines DR as either a tariff or a program which aims to motivate changes in the usage of electricity by the end-use customers due to changes in the price of electricity or relevant incentives whose goal is to lower the electricity consumption at peak periods or periods when the grid is stressed. The Department of Energy also recognizes DR as a cost-effective and reliable technique for altering the customers' load profile (Balijepalli, Pradhan, Khaparde, & Shereef, 2011; Estahbanati, 2014). The residential sector consumes a significant portion of electrical energy while existing research has shown that up to 30% of overall electricity is used within the residential sector (Lokeshgupta & Sivasubramani, 2019). Thus, any means to manage or reduce this electricity consumption within the residential sector should be investigated (H. X. Li, Patel, Al-Hussein, Yu, & Gül, 2018).

One of the main techniques that have been used to manage residential (aside from commercial and industrial) electricity consumption has been DR. DR programs bring about a wide host of well-known benefits, including electricity bill reduction, reduction of the peak load demand, improving load profile of the system, and increased utilization of renewable energy sources (RES). In addition, there are also benefits to the electrical utility which can include improved power quality, reliability, and energy efficiency (Lokeshgupta & Sivasubramani, 2019). DR can be thought of as a flexibility mechanism as it enables load profiles to be modified according to various signals sent from the system operator (Celik, Roche, Suryanarayanan, Bouquain, & Miraoui, 2017). Traditionally, DR has generally been operated in a top-down manner where the consumption of numerous individual agents is aggregated into a single load which is then optimized. This approach has worked well up until recent years as it was simple enough to use the aggregate data. However, with the increased abundance of smart devices, there is a loss of information granularity when this approach is used, and the ability to precisely control the load of individual agents is lost (Celik et al., 2017).

In contrast with top-down strategies, bottom-up DR strategies are becoming more prevalent in their use. This type of DR program uses the consumption profile of each agent but, these models suffer from the inability to gather such granular data and then, should the data be available, the computing requirements to run these models are significant. Both DR models aim to modify the load profile of an agent through the use of incentives and signals from the electrical utility (Lotfi, Joao Catalao, Javadi, Nezhad, & Shafie-khah, 2019). This is in contrast with DSM programs which aim to increase the efficiency of electrical usage (Gelazanskas & Gamage, 2014). In this paper, the impacts of different price-based demand response regimes, time-of-use (TOU) and real-time pricing (RTP), have been evaluated.

B. Literature Review

The combination of smart grid and the incentives offered by DSM and DR has led to the development of HEMSs. The HEMS concept has been studied extensively in the existing literature. In (Setlhaolo, Xia, & Zhang, 2014), a mixed-integer non-linear programming (MINLP) case was formulated, including a penalty factor for inconveniencing customers. The paper took a set of 10 appliances, which could be controlled and allowed the customer to decide on the operational time frames and the power limits. The paper also included incentives to encourage electricity usage early in the morning and again after the evening peak period. The paper showed that the customers could save 25% of their electricity bill relative to a baseline scenario. Incentives were used again in (Wu et al., 2014), where the model was based on the conditional value-at-risk (CVaR) methodology.

Batteries and photovoltaic (PV) systems were included and uncertainty associated with prices, water usage, PV output, and load profiles were modelled stochastically. The incentives were used to increase the number of customers participating in DR programs and the results showed that the customers in such programs can save 18% of their baseline electricity bill.

A HEMS is developed in (Martinez-Pabon et al., 2018) using a novel limited memory algorithm and TOU pricing to optimize the scheduling of various residential appliances across 24 hours. The authors used clustering techniques to group 247 households and results show that customers could save approximately 33% of their daily electricity costs. A HEMS with battery energy storage systems and a PV system is presented in (Hemmati & Saboori, 2017). The model provides three flexible operating regimes, one which exports energy to the grid, one that imports energy from the grid, and the third one relates to an islanded state for standalone operation. The system uses a Gaussian probability density function to develop an MINLP problem, solved by the advanced adaptive particle swarm optimization (APSO) technique. Results from this paper show that the HEMS can reduce the annual electricity bill by 27.8%. Other metaheuristic approaches have been applied to the HEMS concept successfully, in particular, the authors of (Javaid et al., 2017) examine a host of heuristic approaches with significant cost savings and peak load reductions seen. A multi-objective mixed-integer linear programming (MILP) model to solve a HEMS model with an integrated battery energy storage system was developed in (Lokeshgupta & Sivasubramani, 2019). The TOU tariff was used to incentivize the customer's participation in the DSM program. The results indicate that across all of the six different scenarios studied, the HEMS mitigate the customer' bill while reducing the peak demand, benefiting the electric utility (Lokeshgupta & Sivasubramani, 2019). Another approach to model the HEMS by using the multi-objective optimization approach was proposed by (Yahia & Pradhan, 2020). The authors investigate three multi-objective approaches which were the Normalised Weighted Sum, Pre-emptive Optimisation, and Compromise Optimisation. Also, the TOU tariff was included as well as user preferences for the starting and ending operation time of various appliances. The obtained Results show a significant reduction in electricity costs as well as user's discomfort and also the reduction and flattening of the aggregated load from the various consumers. Another multi-objective model for self-scheduling of home appliances has been developed by (Mohammad, Lotfi, Osório, et al., 2020) addressing the demand response programs in the mentioned study. The model is investigated based on MILP optimization model with predefined time intervals for shiftable appliances. Another multi-objective optimization model based on standard MILP model has been investigated by (Zakaria Yahia & Pradhan, 2020) applying TOU to minimize the objectives, i.e. the electricity bills, peak load reduction as well as discomfort raised by changing the usage of the appliances in both coordinated and aggregated fashion. The obtained results confirmed that the peak load reduction is considerably lower in the coordinated mode rather than the aggregated one. A modified shuffled frog leaping algorithm for optimal day-ahead scheduling of microgrids has been studied by (H. Li, Rezvani, Hu, & Ohshima, 2021) in the presence of renewable power generation, electric vehicles, and storage systems providing superior solutions in scenario-based stochastic optimization.

A stochastic HEMS model is presented by (Shafie-Khah & Siano, 2018) taking into consideration the uncertainties caused by renewable energy production. The results obtained from this research study show a reduction of up to 42% in the monthly electricity bill faced by consumers, although the authors clearly pointed out that the results are highly case-sensitive and dependent upon the relevant information relating to the building and the specific individual. A study by (Yu, Jiang, & Zou, 2019) sought to minimise the electricity cost and thermal discomfort of users through a HEMS which also considered HVAC energy demand. This was done through stochastic programming which considered uncertainties associated with electricity price, outdoor temperature, RE generation output, load demand, and occupancy state of the home. The model was solved using a novel Lyapunov optimisation technique

A scheduling model has been presented in (Sharifi & Maghouli, 2019) to reduce the electricity bills as well as lower the peak-to-average (PAR) ratio while taking the comfort of the participants into account. This study makes use of a combination of RTP mechanism as well as the inclining block rate (IBR) tariff to limit the amount of high energy consumption during low-cost periods. Results reported in (Sharifi & Maghouli, 2019) show that the model helps lower the PAR so that the load profile is relatively flat assisting in keeping the electrical grid stable and reducing the need for expensive ramping resources. HEMSs are important as they can utilize and incentivize customer participation in the electricity market. Further research into the PAR was done by (Khalid et al., 2018) where a HEMS which uses a load shifting strategy to optimize the energy consumption of a home through demand-side management was proposed. Notably, the objective function sought to minimize the cost to the consumer as well as the Peak-to-Average ratio experienced by the system all the while maintaining the comfort of the user. The problem was formulated through a knapsack problem and solved using dynamic programming.

Customers are evolving from passive elements to active ones that can play an important role in electricity markets (Iwafune, Mori, Kawai, & Yagita, 2017; Jia et al., 2019; Mehrjerdi & Hemmati, 2020). Research by (Paridari, Parisio, Sandberg, & Johansson, 2016) presented a robust approach for a HEMS considering smart appliances and ESSs to reduce the electricity bill as well as emissions taking user behaviour into account. This was done to ensure that the proposed solution is less sensitive to unexpected changes in user behaviour. The approach modelled user behaviour uncertainties as uncertainty in the coefficients of the cost functions and results showed that the proposed system helped to reduce both electricity costs and emissions. In (Li et al., 2018), a self-learning HEMS which considered DR, Demand-side management, as well as supply-side management was developed and tested in real-time in a smart home. Notable aspects of this study were the HEMS increased energy consumption awareness among its users and the system was customizable to take into account different types of smart homes. A Local HEMS was formulated by (Joo & Choi, 2017) to schedule the energy use of several homes which use DERs. The HEMS scheduling problem is decomposed into a distributed bi-level optimisation problem which at the Local HEMS at the base level and a Global HEMS as the upper level. Results from the study show that the distributed algorithm has an almost equivalent performance when compared to a centralised algorithm in terms of energy cost and user comfort. In (Mondal, Misra, & Obaidat, 2017), HEMS which considered storage was developed using a multiple-leader-multiple-follower Stackelberg game theory model. The leaders were the microgrids within the system and the customers acted as followers. The results have shown an increased profit for the microgrids as well as an increase in the utilisation of energy produced by the microgrids by the consumers. The price paid by the consumers for energy from the microgrid was lower than buying energy from the existing grid.

A HEMS is made up of many appliances, having different characteristics. Generally, electrical appliances within a household are classified into three categories as baseline loads, burst loads, and regular loads (Celik et al., 2017). Baseline loads are non-controllable and non-deferrable meaning that their operation cannot be affected and they are also called must-run appliances. Some examples of baseline loads are lighting, ovens, and televisions. Burst loads are also called deferrable, shiftable or schedulable loads as the HEMS can shift these loads across time to manage the household energy consumption. These loads may also be interrupted during their operation. This category includes washing machines and dryers. Regular loads are those whose load profile changes according to the environmental conditions and generally include thermal loads, such as water heaters, air-conditioners, and space heaters.

These loads have their operating limits set according to the user's preference (Choi & Xie, 2016). The load profile of each appliance, and thus, the load profile of the house, will depend on many factors, such as the size of the house, number of inhabitants, the climatic conditions of the surrounding area, and the income level of the inhabitants. This diversity of load profiles require bottom-up methods to ensure that each home is modelled as accurately as possible (Celik et al., 2017). The increasing use of distributed energy resources (DERs) in distribution grids can bring about issues for the distribution system operator (DSO). These problems can include power flow problems and voltage fluctuations.

Electrical energy storage devices can assist in rectifying these issues (Bucciarelli, Paoletti, & Vicino, 2018). These devices are becoming more popular and widespread and can have significant benefits to the HEMS operation (Marzband, Alavi, Ghazimirsaeid, Uppal, & Fernando, 2017). The adoption of EES devices in HEMS is the result of the increase in active energy consumers known as prosumers, in distribution networks. EES systems allow the prosumer to take advantage of low energy price period or increased self-generation to store the energy to use at higher-cost periods or when the amount of self-generation is low (Sharifi & Maghouli, 2019). A stochastic, dynamic optimal energy management strategy for a smart home is presented by (Wu et al., 2018). The objective function is to minimize electricity cost and uses time-varying electricity tariffs and used probability distributions to account for the uncertainty associated with Electric Vehicles. A HEMS which considered ESS and EVs was presented by (Hou, Wang, Huang, Wang, & Wang, 2019). The preferences of the users were considered and results show that costs are reduced and user comfort is maintained. Real-time pricing was used to provide incentives for the HEMS to optimally manage the ESS and EV to lower electricity cost and prolong the lifetime of the assets.

A HEMS may have different energy carriers in the input and output, known as energy hub (EH) (Javadi et al., 2019). Together with HEMS, the EH concept has captured research interest in recent years. A definition for an EH is given by (Papadimitriou, Anastasiadis, Psomopoulos, & Vokas, 2019) which classifies an EH as a unit which converts, conditions, and stores multiple energy carriers and an EH acts as an interface between different energy infrastructure and loads. The inputs for EHs are generally electricity and natural gas and the output of an EH are various energy types, such as heating and cooling. By using a number of energy carriers, the EH increases its flexibility and decreases the risk of its customers facing any discomfort caused by participating in DR programs. It should be noted that the concept of EH does not depend upon the type of input energy carriers, but rather there is some flexibility which allows the energy carriers to change over time. The EH can also be scaled according to the requirements of the customers using the energy output services (Mohammad, Lotfi, Nezhad, et al., 2020). The brief and detailed list of recent contributions in the field of HEMS is addressed in Table 1.

Table 1 A detailed listing of all reviewed recent scientific articles related to the modelling of HEMS

Ref.	User comfort	DR	Tariff	Type of loads	Type of optimisation	EV	Sequence
(Martinez-Pabon et al., 2018)	✓	✓	TOU	Interruptible, Fixed	MINLP	×	×
(Lokeshgupta & Sivasubramani, 2019)	×	×	TOU	Shiftable, Fixed	MO, MILP	×	×
(Setlhaolo et al., 2014)	✓	✓	TOU	Shiftable, Fixed	MINLP	×	×
(Wu et al., 2014)	×	✓	RTP	Fixed	MCS, CVaR	✓	×
(Hemmati & Saboori, 2017)	×	×	Fixed	Fixed	MCS, Metaheuristic	×	×
(Shafie-Khah & Siano, 2018)	✓	✓	RTP, TOU, CPP	Shiftable, Fixed	MILP	✓	×
(Sharifi & Maghouli, 2019)	✓	×	TOU, CPP, IBR	Interruptible, Fixed	NSGA II, Fuzzy	×	×
(Mehrjerdi & Hemmati, 2020)	×	✓	TOU	Interruptible, Fixed	MILP	✓	×
(Javadi et al., 2019)	×	×	Fixed	Fixed	MINLP	✓	×
(Khalid et al., 2018)	✓	✓	RTP, TOU, CPP	Interruptible, Fixed	Hybrid Metaheuristic	×	×
(Joo & Choi, 2017)	✓	✓	TOU	Interruptible, Fixed	MILP	×	×
(Li et al., 2018)	×	×	Peak, Off-Peak	Shiftable	Recurrent Neural Network	✓	×
(Yu et al., 2019)	✓	×	RTP	Shiftable, Fixed	Lyapunov	✓	×
(Paridari et al., 2016)	×	✓	Fixed	Shiftable, Fixed	MILP	✓	×
(Wu et al., 2018)	×	×	ToU	Fixed	Stochastic DP	✓	×
(Hou et al., 2019)	×	×	RTP	Interruptible, Fixed	MILP	✓	×
(Z Yahia & Pradhan, 2018)	✓	✓	TOU	Shiftable	MO	×	×
Proposed	✓	✓	RTP, TOU, CPP	Shiftable, Fixed	MILP	✓	✓

TOU, Time-of-Use; RTP, Real-Time Pricing; CPP, Critical Peak Pricing; IBR, Incline Block Rate; MO, Multi-objective; MCS, Monte Carlo Simulation; DP, Dynamic Programming; EV, Electric Vehicle; NSGA, Non-dominated Sorting Genetic Algorithm.

C. Novel Contributions

A novel approach is proposed in this paper to determine the optimal daily scheduling of home appliances, aiming at reducing the end-users' bills and DI, while sacrificing neither the comfort nor the computational efficiency. The proposed model is formulated as a single-objective MILP problem. The main contributions of this work can be listed as follows:

- Proposing a linear penalizing mechanism for shifted time slots (relative to ideal user preference) of scheduled appliances to calculate the discomfort index.
- Presenting a MILP multi-objective model for the HEMS self-scheduling problem. This is a novel framework to minimize the end-users' energy cost and DI.
- Evaluating different time-based DR programs in the self-scheduling problem. The results of this evaluation will be very useful for tariff designers since they need to be ensured that their chosen tariff is as efficient as possible.
- Assessing the impacts of the EES device on the self-scheduling problem. This is an important contribution as the penetration of EES devices is expected to grow rapidly and the effects of such devices need to be studied.

D. Paper Organization

This paper is laid out in the following manner: concepts relating to the HEMS are presented in Section 2. The problem formulation is presented in Section 3, while the descriptions of multi-objective optimization, epsilon-constraint technique, and VIKOR decision maker are given in Section 4. The simulation results are proposed and discussed in Section 5. Lastly, Section 6 comprises the relevant conclusions.

2. Home Energy Management System

HEMSs have increasingly become more common in recent years. A HEMS system was developed in the early 1980s (Shareef, Ahmed, Mohamed, & Al Hassan, 2018) and it has evolved into a growing field of study as consumer participation in the electricity market has increased. A HEMS system aims at optimizing the scheduling of various appliances in the home to manage the energy consumption of the household. Also, the management of the appliances is carried out with the idea of reducing the electricity bill for the homeowner.

The HEMS may assist in DR programs as the HEMS system can optimize the use of local resources, which can then participate in DR programs. With the rise of DERs, including battery energy storage systems, the scope for the HEMS has widened to include the management of such devices. The conceptual model of HEMS is addressed in Fig. 1.

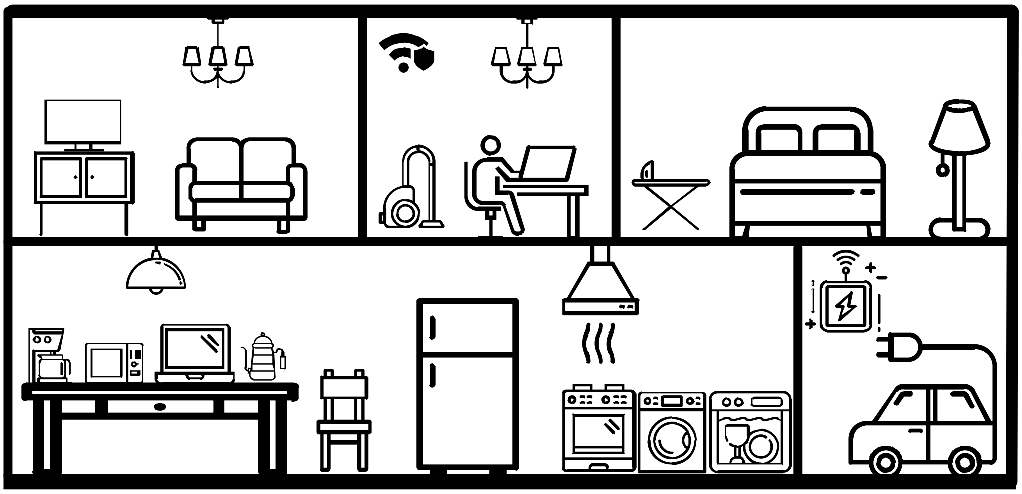

Fig. 1. Conceptual model of the HEMS.

In addition, HEMS may incorporate additional devices, such as internet of things (IoT) connected devices, which have captured significant attention in the recent years, as well as smart homes which have become more prevalent in the society (Iqbal et al., 2018). Recently, there have been various projects aimed at investigating the concept of peer-to-peer (P2P) energy trading and this may provide a path for future research. Virtual power plants (VPPs) may also provide interesting research opportunities as the major part of HEMS research studies has so far been devoted to individual systems (Al-Ali et al., 2017). By aggregating several HEMSs into a community VPP, it may help reap further benefits. There are also challenges that future HEMS must address, relating to the privacy and amount of data they may collect during the operation. The secure and efficient handling of data will be of the utmost importance to the HEMS in the future (Al-Ali et al., 2017).

There are already prominent examples of HEMSs or smart home systems being hacked (Baig et al., 2017) and with the number of smart devices expected to increase rapidly, it will be even more important that the HEMS is secure against any unauthorized access. With the number of HEMS and an ever-increasing number of appliances capable of interacting with the HEMS, the need for an efficient communication protocol is also extremely important and challenging

(Zhou et al., 2016), while the solution would be interoperability between the devices. Interoperability in this regard is defined as the capability of various systems to connect and exchange energy information, while still maintaining a suitable workflow concerning the existing constraints (Perumal, Ramli, & Leong, 2011).

Self-scheduling of the appliances within the HEMS allows owners to view the impact of each appliance on the electricity bill and thus, it can help owners modify their behaviour to optimize the bill, taking into account their preferences (Kong, Sun, Kong, & Li, 2020).

3. Problem Formulation

The HEMS self-scheduling problem in this paper aims to minimize the daily bill of the end-user. The representation of the objective functions can be stated as below:

Single Objective Optimization Weighted Sum Approach	**Multi Objective Optimization Epsilon Constraint Approach**
$Min\ Z = f_1 + \omega . f_2$	$Min\ f_1$ $Min\ f_2$

$$f_1 = \underbrace{\sum_{i=1}^{NA} \sum_{t=1}^{NT} \rho_t^{Tariff}\ S_{i,t}\ P_i\ \Delta t}_{Electricity\ Bill}$$
$$f_2 = \underbrace{\sum_{i=1}^{NA} \left[DI_i^+ + DI_i^- \right]}_{Discomfort\ Index} \tag{1}$$

The objective functions are minimization the daily bill and the discomfort cost of shifting the usage of home appliances. The daily bill, f_1, includes the total energy consumption by considering the tariffs of each time slot, ρ_t^{Tariff}. The tariff can be set as one of the price-based tariffs, i.e. RTP or TOU. The usage status of appliance i at time t is supposed to be a binary variable, $S_{i,t}$, and the rated power of the corresponding appliance is P_i. The time slot for the scheduling problem is considered to be Δt and the problem would be solved daily.

The second objective function, f_2, is the discomfort index related to the shifting the usage of home appliances. There is no difference between advancing and postponing usage. In the case of changing the time intervals of operation of appliances from the end-users' preferences, the discomfort index is non-zero. Therefore, the total discomfort index should be applied to minimize the user's convenience. In the weighted sum approach, the corresponding penalty is supposed to be ω. A larger penalty factor results in less shifting of operation. Therefore, the trade-off between the minimization of daily bills and discomfort cost should be considered based on the end-user's preferences. While, in the multi-objective framework, both objective functions should be minimized simultaneously, therefore, there is no need to considering the penalty factor for the DI.

The daily bill based on the end-user's preferences can be calculated by considering the baseline operation time intervals and corresponding hourly electricity price. The baseline operation time interval of the home appliances are subjected to the binary parameters, $B_{i,t}$, and the permissible bounds for each home appliance are available based on the end-user's preferences. Equation (2) confirms that during the baseline time intervals, the operation status of the corresponding appliance would be '1' and before the lower bound and after the upper bound of operation, this binary parameter would be '0'. The total operating time intervals for baseline operation must be equal to T_i.

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

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

In the self-scheduling problem of HEMS, the flexible loads can be shifted to before or after the scheduled time intervals to reduce the daily bills. Since the hourly tariffs affect the total cost of operation, the end-user can benefit from the optimal self-scheduling based on the predefined tariffs. The task scheduling for the flexible home appliances can be achieved by changing the time intervals of their operation and it yields a reduction in the daily bills. In this regard, for each home appliance, the end-user can set the allowable time intervals. Equation (4) deals with the allowable time intervals for plunging in the appliances to the grid (Javadi et al., 2020).

$$S_{i,t} \le \begin{cases} 0 & t < LB_{i,s} \\ 1 & LB_{i,s} \le t \le UB_{i,s} \\ 0 & t > UB_{i,s} \end{cases} \quad S_{i,t} \in \{0,1\} \tag{4}$$

It is noteworthy that for each home appliance, the operation duration should be the same T_i. It means that the end-user just changes the operation time intervals and the daily energy consumption should remain fixed after the scheduling implementation. Equation (5) shows this constraint.

$$\sum_{t=1}^{NT} S_{i,t} = T_i \quad \forall i = 1,2,...,NA \tag{5}$$

The main drawback of the DI calculation based on the absolute subtraction method is that there is no difference between the shifting of the appliances to the other time intervals. The DI calculation according to the absolute subtraction is provided in (Rezaee Jordehi, 2019):

$$DI_i = \sum_{t=1}^{NT} \left| B_{i,t} - S_{i,t} \right| \tag{6}$$

To properly address the DI for the 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 (Sadegh et al., 2020).

The corresponding DI for shifting each time slot can be easily calculated based on (7) and (8), 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 is no conflict between them if the right-hand side of these equations is negative.

$$DI_i^- \geq \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times B_{i,t} - \sum_{t=1}^{NT} t \times S_{i,t} \right] \tag{7}$$

$$DI_i^+ \geq \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times S_{i,t} - \sum_{t=1}^{NT} t \times B_{i,t} \right] \tag{8}$$

For the sake of illustration, a simple case of shifting the load of a typical appliance is addressed. Fig. 2 illustrates how the proposed model addresses the DI calculation for both absolute subtraction method according to (Rezaee Jordehi, 2019) and Euclidean distance method proposed in this paper. In this case, the operation time of the target appliance is defined to be between {15-33} and for the base case, the customer's preference is to use it for 2 hours as {19-22}. Therefore, in the case of baseline, the DI would be zero since the end-user decided to turn it on at the same time interval. In Case A, if the end-user defers the appliance usage to the time interval {22-25}, i.e. shifting three slots, the DI would be 6 and 3, according to the absolute subtraction and Euclidean distance, respectively. According to (Rezaee Jordehi, 2019), the DI will be calculated for different time slots. This means that for time slots {19-21} and {23-25} the binary variables are non-zero, therefore, the DI will be 6. However, in the Euclidean distance context, the DI is calculated according to |22-19|=|25-22|=3. In Case B, for changing the plugging in of the appliance to the grid at time interval {17-20}, the DI according to the absolute subtraction method is 4, {17-18} and {21-22}. Consequently, based on the Euclidean distance method, the DI will be 2, {21-22}. The main pitfall of the absolute subtraction can be found in Case C and Case D. In these two cases, the DI according to the absolute subtraction would be 8. However, these two cases have different representation and insight for changing the usage of the target appliance. According to the Euclidean distance model, the DI for Case C and Case D would be 6 and 10, respectively. In Case C, the DI is |25-19|=|28-22|=6 and in Case D, the DI is |29-19|=|32-22|=10. It is worth mentioning that the DI for these two cases are the same according to the absolute subtraction calculation.

Fig. 2 illustrates a graphical representation of the DI calculation. Table 2 represents the different DI values for the baseline case and Cases A to D addressed in Fig. 2.

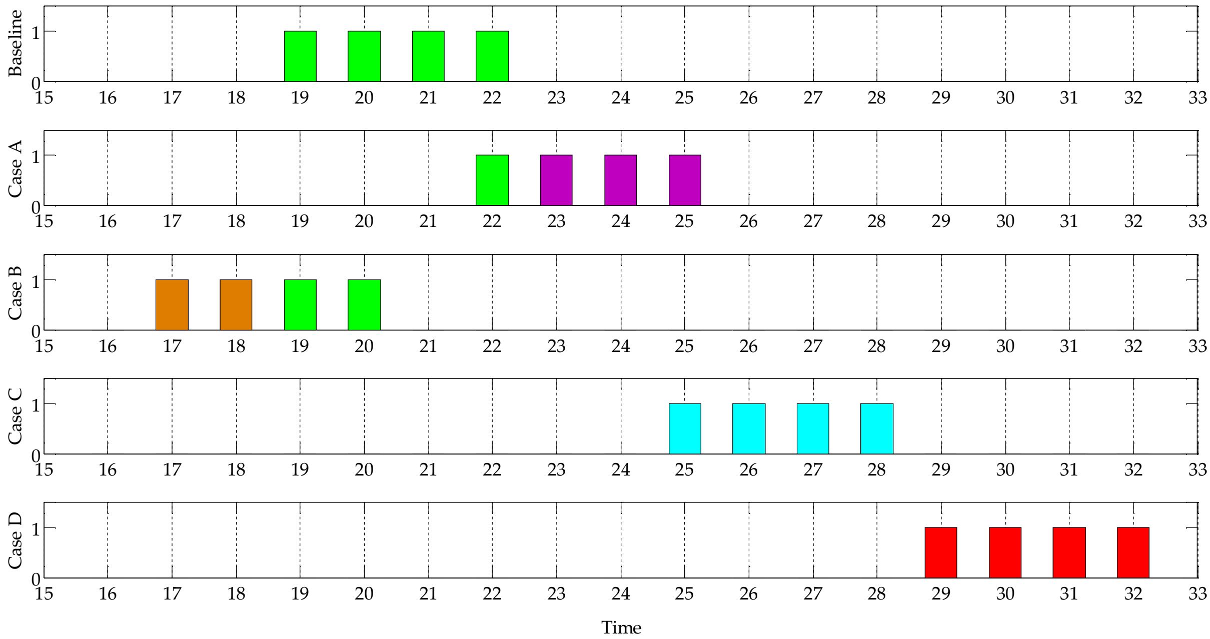

Fig. 2. Binary representation of HEMS for the baseline and four different cases

Table 2 The DI calculation based on Euclidean distance and absolute subtraction

Case	Duration	Start	End	Ref. (Rezaee Jordehi, 2019)	Proposed
Baseline	4	19	22	0	0
Case A	4	22	25	6	3
Case B	4	17	20	4	2
Case C	4	25	28	8	6
Case D	4	29	32	8	10

Since the usage status of appliance i at time t is supposed to be a binary variable, $S_{i,t}$ and the rated power of the corresponding appliance is P_i. Therefore, the total consumed energy for each time slot, P_t^D by the shifted operation of home appliances can be represented as:

$$\sum_{i=1}^{NA} S_{i,t}\, P_i = P_t^D \tag{9}$$

It is noteworthy that the total energy demand in each day has to equal before and after shifting the plugging in of the home appliances. Therefore, the total P_t^D for all cases should be the same without the implementation of EES. In the presence of EES, the energy flow from the grid side to the HEMS should be modelled to reflect the role of EES.

The power balance for each time slot is as follows:

$$P_t^{G2H} = P_t^D + \sum_{j=1}^{NS} P_{j,t}^{Ch.} - \sum_{j=1}^{NS} P_{j,t}^{Disch.} \tag{10}$$

The EES devices have their associated constraints in terms of operation in the planning horizon, i.e. daily operation in this study. The corresponding constraints for EES devices are as follows:

$$P_{j,t}^{Ch.} \le I_{j,t}^{Ch.} P_j^{Ch.,\max} \tag{11}$$

$$P_{j,t}^{Disch.} \le I_{j,t}^{Disch.} P_j^{Disch.,\max} \tag{12}$$

$$0 \le I_{j,t}^{Ch.} + I_{j,t}^{Disch.} \le 1 \tag{13}$$

$$E_{j,t} = E_{j,t-1} + \eta_j^{Ch.} P_{j,t}^{Ch.} - \frac{1}{\eta_j^{Disch.}} P_{j,t}^{Disch.} \tag{14}$$

$$E_{j,1} = E_{j,T} \tag{15}$$

$$E_j^{\min} \le E_{j,t} \le E_j^{\max} \tag{16}$$

Binary variables which represent each of the charging and discharging modes are introduced to ensure that the EES can only be in either the charging or discharging mode at any one time. These variables are shown in (11)-(13). The energy stored in the EES at a specific period is a function of the energy stored in the EES in the previous period plus the effects of any charging or discharging that occurred [10.1109/IECON.2019.8927263]. This is shown in (14) which also includes an efficiency factor for charging and discharging. It is assumed that the stored energy in the EES in the initial and final period of the day should be equal. This constraint is addressed in (15). The energy stored in the EES is constrained by the upper and lower limits and these limits are captured in (16).

4. Multi-Objective

A typical optimization problem of multi-objective form is stated as follows:

$$
\begin{aligned}
&Min \quad F = \left[f_1(\bar{x}), f_2(\bar{x}), \ldots, f_P(\bar{x})\right]^T \\
&subject\ to \\
&g_i(\bar{x}) < 0, \quad i = 1, 2, \ldots, N_{ueq} \\
&h_i(\bar{x}) = 0, \quad i = 1, 2, \ldots, N_{eq}
\end{aligned}
\tag{17}
$$

It is noteworthy that the number of inequality, equality and objective functions are indicated by N_{eq}, N_{ieq}, and *P*, respectively. Furthermore, $\bar{x}$ shows the vector of decision variables. The objective functions of the problem would be of any type, either minimization or maximization. In general, solving an optimization problem with more than one objective function gives a number of optimal solutions, each including *P* members, known as the Pareto optimal set. The Pareto front includes a set of solutions that are all non-dominated and it would not be possible to move from one solution to another one without losing the superiority in any of the objective's values (Collette & Siarry, 2004). There are too many approaches, thus far developed to tackle multi-objective optimization problems, among which the epsilon-constraint method has shown a rational performance, particularly when compared to the weighting sum method (WSM) (Sadegh Javadi, Saniei, Rajabi Mashhadi, & Gutiérrez-Alcaraz, 2013; Simab, Javadi, & Nezhad, 2018). By applying the WSM, the objective functions of the problem are all given a weighting factor and a unified objective function is constructed (Mavrotas, 2009; Roman & Rosehart, 2006). Nevertheless, there are some controversial issues with the epsilon-constraint method that need more attention. In case, the problem includes *P* objective functions, the range of the *P-1* objectives should be determined since they are added to the problem, but as constraints. In this respect, the lexicographic optimization has been deployed in this study to determine the range of every objective function. Another issue that should be taken into consideration is the efficiency of the derived solutions and if they are all non-dominated solutions. To this end, this paper employs the augmented version of epsilon-constraint method along with the lexicographic optimization to propose efficient, non-dominated Pareto optimal solutions. The explanations and mathematical model of the epsilon-constraint method have been given in the following (Javadi & Esmaeel Nezhad, 2019; Nezhad, Javadi, & Rahimi, 2014). This method assigns one of the objectives as the main objective function and assigns all others to the problem as constraints as below.

$$\begin{aligned}&Min \quad f_1(\bar{x})\\&subject\ to \quad f_2(\bar{x}) \le e_2, f_3(\bar{x}) \le e_3, \ldots, f_p(\bar{x}) \le e_p\end{aligned} \tag{18}$$

It should be noted that the objective functions are all set to be minimized and accordingly, the range of each of the *P-1* objectives are specified using the lexicographic optimization and pay-off table. A multi-stage procedure should be taken to obtain the pay-off table. In the first step, the ranges of all objective functions would be obtained by individually optimizing each objective function f_i. As a result, the optimal value of objective function *i*, i.e. $f_i^*(\bar{x}_i^*)$ and the associated decision variables vector, i.e. $\bar{x}_i^*$ are specified. In the second step, the single optimum, pertaining to other objectives, shown by $f_1(\bar{x}_i^*)$, $f_2(\bar{x}_i^*)$, … , $f_{i-1}^*(\bar{x}_i^*)$, $f_{i+1}(\bar{x}_i^*)$, … , $f_p(\bar{x}_i^*)$ should be computed by utilizing the optimal value of f_i. Subsequently, the desired pay-off table is derived as below (Aghaei, Amjady, & Shayanfar, 2011), in which the *i*th row includes $f_1(\bar{x}_i^*)$, $f_2(\bar{x}_i^*)$, … , $f_i^*(\bar{x}_i^*)$, … , $f_p(\bar{x}_i^*)$.

$$\Phi = \begin{bmatrix} f_1^*(\bar{x}_1^*) & \ldots & f_i(\bar{x}_1^*) & \ldots & f_p(\bar{x}_1^*) \\ \vdots & \ddots & & & \vdots \\ f_1(\bar{x}_i^*) & \ldots & f_i^*(\bar{x}_i^*) & \ldots & f_p(\bar{x}_i^*) \\ \vdots & & & \ddots & \vdots \\ f_1(\bar{x}_p^*) & \ldots & f_i(\bar{x}_p^*) & \ldots & f_p^*(\bar{x}_p^*) \end{bmatrix} \tag{19}$$

It is worth mentioning that the resulting pay-off table is a $P \times P$ matrix and the optimal value of every objective function f_n is included in the *n*th column while the difference between smallest and largest values gives the range of the related objective function. There are also some key concepts that need to be explained in detail. In case it is desirable to minimize all objective functions, the *Utopia* point illustrated by f^U represents a point outside the feasible region, where all objectives would take their weakest value as below:

$$f^U = \left[f_1^U, \ldots, f_i^U, \ldots, f_p^U\right] = \left[f_1^*(\bar{x}_1^*), \ldots, f_i^*(\bar{x}_i^*), \ldots, f_p^*(\bar{x}_p^*)\right] \tag{20}$$

Unlike the *Utopia* point, the *Nadir* point, i.e. f^N, shows a point in the feasible region, where all objective function have their most superior value.

$$f^N = \left[f_1^N, \ldots, f_i^N, \ldots, f_p^N\right] \tag{21}$$

where:

$$\begin{aligned} & f_i^N = \underset{\bar{x}}{Max}\ f_i(\bar{x}) \\ & subject\ to \quad \bar{x} \in \Omega \end{aligned} \tag{22}$$

The feasible space is addressed by Ω. A point, having almost the same concept as f^N, is the *Pseudo Nadir* point, i.e. f^{SN}, stated as follows:

$$f^{SN} = \left[f_1^{SN}, \ldots, f_i^{SN}, \ldots, f_p^{SN}\right] \tag{23}$$

where,

$$f_i^{SN} = Max\ \left\{f_i\ \left(\bar{x}_1^*\right), \ldots, f_i^*\left(\bar{x}_i^*\right), \ldots, f_i\ \left(\bar{x}_p^*\right)\right\} \tag{24}$$

According to the following relationship, f^{SN} and f^U determine the range of each objective function.

$$f_i^U \leq f_i(\bar{x}) \leq f_i^{SN} \tag{25}$$

The dimension of objective functions is used to show the objective space. Fig. 3 depicts a typical bi-objective Pareto front.

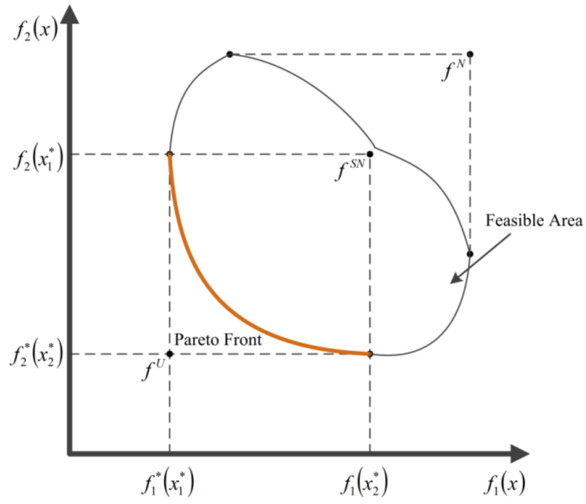

Fig. 3. A typical bi-objective Pareto front.

Afterwards, the range of the *P-1* objectives from the pay-off table is used and converted to equidistance intervals by employing the intermediate grid points, i.e. $(q_2 - 1),\ldots,(q_p - 1)$. By assuming the first objective as the main one to be optimized, $\prod_{i=2}^{p}(q_i + 1)$ sub-problems should be iteratively solved accordingly.

$$\begin{aligned} &Min \quad f_1(\bar{x}) \\ &S.T. \quad f_2(\bar{x}) \le e_{2,n2}, \ldots, f_p(\bar{x}) \le e_{p,np} \end{aligned} \tag{26}$$

$$e_{2,n2} = f_2^{SN} - \left(\frac{f_2^{SN} - f_2^{U}}{q_2}\right) \times n2, \quad n2 = 0,1,\ldots,q_2 \tag{27}$$

$$e_{2,np} = f_p^{SN} - \left(\frac{f_p^{SN} - f_p^{U}}{q_p}\right) \times np, \quad np = 0,1,\ldots,q_p \tag{28}$$

The above expressions imply that every single sub-problem is subject to the constraint (26) along with the constraints of the original problem. Tackling the mentioned sub-problems would lead to the desired Pareto set, including only efficient and non-dominated solutions. Any inefficiency that may occur would be avoided by converting the expression (26) to equalities by using the slack variable method (Bard, 1998; Javadi & Esmaeel Nezhad, 2019):

$$
\begin{cases}
Min \quad \left(f_1(\bar{x}) - r_1 \sum_{i=2}^{P} (\frac{s_i}{r_i}) \right) \\
subject\ to \\
f_i(\bar{x}) + s_{i,ni} = e_{i,ni}, \quad i = 2, \dots, p \quad \& \quad s_{i,ni} \in R^+ \\
\bar{x} \in \Omega
\end{cases} \tag{29}
$$

It is noteworthy that $s_2,...,s_p$ indicate the slack variables, added to the problem for the constraints in (26). In this respect, $r_1(s_i / r_i)$ has been taken into account in the second part of the objective function to prevent any issues due to the objectives' scale, where $r_i = f_i^{SN} - f_i^U$. By applying this technique, the slack variables would be scaled to the range of the main objective function. In this regard, expression (29) shows the augmented epsilon-constraint technique as a result of the improvement, made in the objective function f_1 by the second part. Fig. 4 depicts the conceptual flowchart of the proposed augmented epsilon-constraint technique.

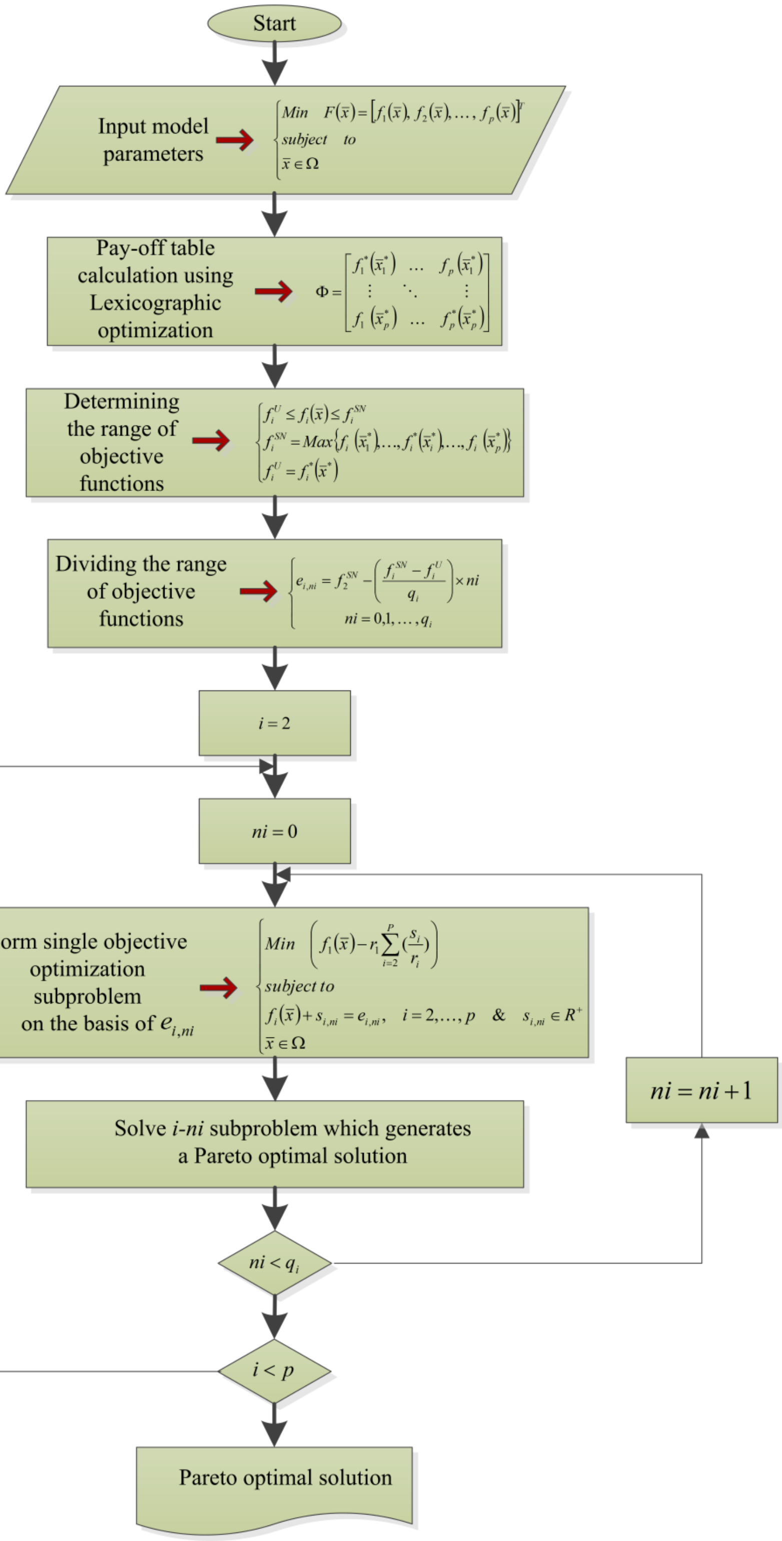

Fig. 4. The conceptual flowchart of the augmented epsilon-constraint method.

4-2 VIKOR

The VIKOR decision-making method as a promising technique was first developed in 1998 to tackle the multi-criteria decision making problems (Opricovic & Tzeng, 2004). The principle of this technique is on the basis of defining positive ideal and negative ideal values to properly determine the relative interval, existing between the solution and the Pareto optimal solution. The next step would be specifying the importance of the members of Pareto set by ranking the solutions, using x_j, while j denotes the members of the Pareto set and it continues to P (Tavana, Kiani Mavi, Santos-Arteaga, & Rasti Doust, 2016):

Step 1. Utilizing the rating function that are used to calculate the value of criterion i for the solution x_j. Subsequently, f_i^+ and f_i^-, which denote the best and worst values of the objective function would be specified through the following formulas:

$$f_i^+ = \max\left[(f_{ij}) \mid j = 1,2,...,m\right] \quad (30)$$

$$f_i^- = \min\left[(f_{ij}) \mid j = 1,2,...,m\right] \quad (31)$$

Step 2. Calculating R_j and S_j, which respectively indicate the individual regret measure and group utility measure by using the following relationships:

$$R_j = \max_i \left[w_i \frac{(f_i^+ - f_{ij})}{(f_i^+ - f_i^-)}\right] \quad (32)$$

$$S_j = \sum_{i=1}^{n} w_i \frac{(f_i^+ - f_{ij})}{(f_i^+ - f_i^-)} \quad (33)$$

It is noteworthy that the weighting factor of the objective functions has been shown by w_i and sum of the weighting factors should be strictly equal to 1. Accordingly, Q_j will be calculated by using (34), which uses the value of weighting factors, the individual regret measure along with its maximum and minimum values, determined by (35) and (36), respectively, and also the group utility measure along with its maximum and minimum values, determined by (37) and (38) respectively.

$$Q_j = w_j \left[\frac{S_j - S^+}{S^- - S^+}\right] + (1 - w_j)\left[\frac{R_j - R^+}{R^- - R^+}\right] \quad (34)$$

$$R^{+} = Min\left[(R_j) \mid j = 1,2,...,m\right] \quad (35)$$

$$R^{-} = Max\left[(R_j) \mid j = 1,2,...,m\right] \quad (36)$$

$$S^{+} = Min\left[(S_j) \mid j = 1,2,...,m\right] \quad (37)$$

$$S^{-} = Max\left[(S_j) \mid j = 1,2,...,m\right] \quad (38)$$

Step 3. Making a ranking list of the Pareto solutions based on the values of Q_j, where the solution with the minimum value of Q_j is the most desired one (Sayadi, Heydari, & Shahanaghi, 2009).

5. Simulation Results

To evaluate the proposed MILP framework for solving the self-scheduling problem of the HEMS, four scenarios have been considered in two categories in this paper. The first two scenarios have been considered to compare the obtained results by the MILP model with those reported in (Rezaee Jordehi, 2019). The next two scenarios are considered to address the effects of the EES in another benchmark considering both fixed and shiftable loads.

The specifications of shiftable home appliances for all case studies in this paper are listed in Table 3. In this study, the time slots are considered to be in the order of 30 minutes. Therefore, there are a total of 48 time slots in the daily operation. The baseline operating time slots for each appliance as well as the allowable operating ranges are shown in Table 3. In this study, the self-scheduling of 29.05 kWh energy consumption of 10 shiftable appliances are studied to show the effects of different price-based DR programs on the daily bill before and after implementation of the self-scheduling of HEMS. The hourly tariffs based on TOU and RTP tariffs are provided in Table 4.

The simulation results for all scenarios are obtained by CPLEX solver formulated by IBM and activated using the General Algebraic Modelling System (GAMS). Using the CPLEX solver in GAMS allows large and difficult problems to be formulated and solved in a high-level modelling system.

Table 3 The specifications of home appliances in the HEMS self-scheduling study (Rezaee Jordehi, 2019)

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
Spine 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 4 Daily tariffs for different price-based demand response programs (Rezaee Jordehi, 2019)

Hour	TOU	RTP	Hour	TOU	RTP
00:00-01:00	0.02	0.014	12:00-13:00	0.02	0.034
01:00-02:00	0.02	0.015	13:00-14:00	0.02	0.033
02:00-03:00	0.02	0.015	14:00-15:00	0.02	0.040
03:00-04:00	0.02	0.013	15:00-16:00	0.02	0.047
04:00-05:00	0.02	0.010	16:00-17:00	0.02	0.047
05:00-06:00	0.02	0.014	17:00-18:00	0.02	0.047
06:00-07:00	0.02	0.017	18:00-19:00	0.08	0.043
07:00-08:00	0.02	0.019	19:00-20:00	0.08	0.034
08:00-09:00	0.02	0.024	20:00-21:00	0.02	0.038
09:00-10:00	0.08	0.024	21:00-22:00	0.02	0.037
10:00-11:00	0.08	0.025	22:00-23:00	0.02	0.024
11:00-12:00	0.02	0.037	23:00-00:00	0.02	0.018

5.1 Self-scheduling of HEMS for shiftable loads

In this subsection, the self-scheduling problem is studied to show the effectiveness of the proposed MILP model to find the optimal operation of the HEMS under three different price-based DR programs. The following scenarios are considered during validation of the proposed model, considering the effects of different penalty factors as the monetizing coefficient factor in the objective function. It is noteworthy that in the subsequent scenarios, there is no EES device available for storing energy during off-peak hours. In such scenarios, the global optimum can be assessed for the corresponding tariffs.

The hourly tariffs for each time-based DRPs are provided in Table 4. In the TOU, four hours, two hours in the morning (9:00-11:00) and two hours in the evening (18:00-20:00), are the peak hours. The daily RTP are extracted from Commonwealth Edison Company on 14 May 2018 and reported in the (Rezaee Jordehi, 2019), as well. The total energy demand of the shiftable loads in this paper for the three studied scenarios is 29.05 kWh. Since this paper seeks to optimally shift loads to off-peak hours, the total amount of the energy demand is the same for the three scenarios, i.e. TOU and RTP. The EV with a demand of 10.5 kWh, i.e. 36.14% of the total demand has the highest contribution to the energy demand while shifting its load demand can significantly reduce the cost. This section excludes the EES system, so its impacts have been neglected and only those relating to shiftable loads are taken into account. It is noteworthy that the EES system is different from the EV, but its functionality is similar to Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) capabilities of EVs. The next subsection discusses the performance of the EES system.

5.1.1 Self-scheduling problem for shiftable loads considering TOU tariff

This section investigates the self-scheduling problem with shiftable loads based on the TOU tariff. The load procurement cost before applying the TOU mechanism is 1.805 \$/day. It is noted that 20.4 kWh of the total energy demand which is 29.05 kWh relates to the peak hours and the remaining demand, i.e. 8.65 kWh occurs at off-peak hours. In this regard, the total cost drops to 0.5810 \$/day by optimally shifting the energy demand to off-peak hours. Consequently, the global optimal solution(s) can be obtained. The optimal solution in this paper has converged to 0.581 \$/day. It is noted that the stated problem has more than one global optimal solution where the costs derived using the heuristic algorithms and the CPLEX solver are all the same at 0.581 \$/day. Table 5 represents the simulation results while neglecting the penalty factor. As it can be observed, the load procurement cost is the same using all methods with small differences in the operating hours leading to different DIs obtained from the CPLEX solver and other algorithms. For example, the DI calculated using the Euclidean distance of the TOU in this paper is 21, while the one calculated based on the absolute subtraction of the binary variable (Rezaee Jordehi, 2019) is 42.

Table 5 The optimal results for shiftable home appliances self-scheduling based on TOU tariff.

		Meta-heuristic (Rezaee Jordehi, 2019)						MILP
Appliance	**Base**	DA	GSA	BSA	ABC	PSO	ELPSO	CPLEX
Dishwasher	**19-22**	30-33	28-31	15-18	23-26	29-32	24-27	15-18
Washing Machine	**19-21**	16-18	16-18	16-18	16-18	16-18	16-18	16-18
Spine Dryer	**27-28**	34-35	29-30	31-32	33-34	26-27	32-33	27-28
Cooker Hub	**17**	17	16	16	17	16	17	17
Cooker Oven	**37**	36	36	36	36	36	36	36
Microwave	**17**	17	16	17	17	17	17	17
Laptop	**37-40**	42-45	41-44	42-45	41-44	43-46	41-44	33-36
Desktop Computer	**37-42**	42-47	41-46	42-47	42-47	41-46	41-46	41-46
Vacuum Cleaner	**19**	33	28	18	23	28	28	18
Electric Vehicle	**37-42**	41-46	41-46	41-46	41-46	31-36	41-46	41-46
Daily Bill ($)	**1.805**	0.5810	0.5810	0.5810	0.5810	0.5810	0.5810	0.5810
DI-Calculated *	**0**	48	50	50	48	50	46	42
DI-Proposed	**0**	50	38	28	31	41	35	21

* According to the approach presented in (Rezaee Jordehi, 2019)

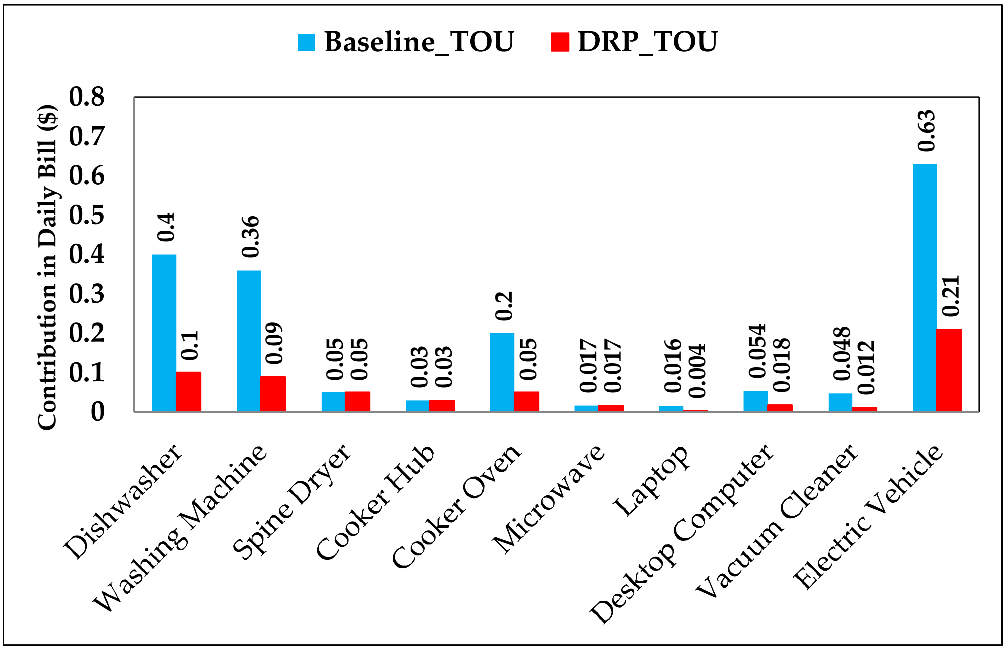

Fig. 5 The contribution of each shiftable appliance for baseline and self-scheduling based on TOU.

Fig. 5 depicts the contribution of each shiftable load to the daily energy bill. As it is expected, by shifting the load demand relating to the EV, the dishwasher, and the dryer to off-peak hours, the cost reduces from \$0.63, \$0.4, and \$0.36 to \$0.21, \$0.1, and \$0.09, respectively. Fig. 5 shows the energy cost of each load before and after applying the self-scheduling.

Table 6 represents the results of a sensitivity analysis carried out to assess the impact of the penalty factor on the consumer's DI when facing the load shifting. The reduction in the energy bill would be associated with the increase in the DI due to the load shifting. This relationship holds until the objective function and the base cost are equal at 1.805 $/day. The DI is calculated in this paper and (Rezaee Jordehi, 2019) by penalty factors 0.15 and 0.08 to the base case, respectively. In other words, the level of discomfort tolerated by the consumer has increased in the proposed method. It is noted that the mentioned results are obtained using weighted sum approach.

Table 6 The effects of different monetizing coefficient factors of the penalty associated with the DI –TOU tariff.

Absolute Subtraction			Euclidean Distance		Absolute Subtraction			Euclidean Distance	
ω	Optimal Bill	DI	Optimal Bill	DI	ω	Optimal Bill	DI	Optimal Bill	DI
0.000	0.5810	50	0.5810	21	0.040	0.9650	16	0.6650	12
0.001	0.5810	42	0.5810	21	0.045	1.2350	10	0.6650	12
0.002	0.5930	34	0.5810	21	0.050	1.2350	10	0.6650	12
0.003	0.5930	34	0.5900	18	0.060	1.6550	2	0.6650	12
0.004	0.5930	34	0.5930	17	0.070	1.6550	2	0.6650	12
0.005	0.6290	26	0.5930	17	0.080	**1.8050**	**0**	0.9650	8
0.010	0.6290	26	0.6290	13	0.090	**1.8050**	**0**	1.2350	5
0.015	0.6290	26	0.6290	13	0.100	**1.8050**	**0**	1.2350	5
0.020	0.6650	24	0.6290	13	0.110	**1.8050**	**0**	1.6550	1
0.025	0.6650	24	0.6290	13	0.120	**1.8050**	**0**	1.6550	1
0.030	0.6650	24	0.6290	13	0.140	**1.8050**	**0**	1.6550	1
0.035	0.6650	24	0.6290	13	0.150	**1.8050**	**0**	**1.8050**	**0**

Table 7 represents the results, obtained by using the epsilon-constraint technique and VIKOR decision-maker. Each Pareto solution of the derived Pareto set includes a pair of solutions including the DI and bill. The values of individual regret measure and group utility measure along with the associated value of Q have been shown in the last columns of this table, respectively.

Table 7 The Pareto optimal front and VIKOR results_ shiftable loads and considering TOU tariff.

Plan	DI	Bill ($)	R		S		Q	
Plan 1	0	1.805	Plan 1	0.800000	Plan 1	0.800000	Plan 1	1.000000
Plan 2	1	1.655	Plan 2	0.701961	Plan 2	0.711485	Plan 2	0.860856
Plan 3	2	1.550	Plan 3	0.633333	Plan 3	0.652381	Plan 3	0.765671
Plan 4	3	1.445	Plan 4	0.564706	Plan 4	0.593277	Plan 4	0.670486
Plan 5	4	1.340	Plan 5	0.496078	Plan 5	0.534174	Plan 5	0.575301
Plan 6	5	1.235	Plan 6	0.427451	Plan 6	0.475070	Plan 6	0.480116
Plan 7	6	1.145	Plan 7	0.368627	Plan 7	0.425770	Plan 7	0.399584
Plan 8	7	1.055	Plan 8	0.309804	Plan 8	0.376471	Plan 8	0.319052
Plan 9	8	0.965	Plan 9	0.250980	Plan 9	0.327171	Plan 9	0.238519
Plan 10	9	0.890	Plan 10	0.201961	Plan 10	0.287675	Plan 10	0.172640
Plan 11	10	0.815	Plan 22	0.200000	Plan 11	0.248179	Plan 11	0.106761
Plan 12	11	0.740	Plan 21	0.190480	Plan 12	0.208683	Plan 22	0.103250
Plan 13	12	0.665	Plan 20	0.180950	Plan 22	0.200000	Plan 21	0.090532
Plan 14	**13**	**0.629**	Plan 19	0.171430	Plan 21	0.192440	Plan 20	0.077818
Plan 15	14	0.620	Plan 18	0.161900	Plan 20	0.184870	Plan 19	0.065104
Plan 16	15	0.611	Plan 11	0.152940	Plan 19	0.177310	Plan 18	0.052390
Plan 17	16	0.602	Plan 17	0.152380	Plan 18	0.169750	Plan 17	0.042717
Plan 18	17	0.593	Plan 16	0.142860	Plan 13	0.169190	Plan 12	0.041486
Plan 19	18	0.590	Plan 15	0.133330	Plan 17	0.166110	Plan 16	0.033045
Plan 20	19	0.587	Plan 14	0.123810	Plan 16	0.162460	Plan 15	0.023372
Plan 21	20	0.584	Plan 13	0.114290	Plan 15	0.158820	Plan 13	0.017709
Plan 22	21	0.581	Plan 12	0.104760	Plan 14	0.155180	**Plan 14**	**0.013699**

5.1.2. Self-scheduling problem for shiftable loads considering RTP tariff

This section includes the results obtained from applying the RTP tariff to study the load shifting in the HEMS. In this scenario, the energy price changes over the hours of the day. Thus, the signals required for the self-scheduling of shiftable loads must be determined based on the hourly price variations. The base case cost without applying the self-scheduling of shiftable loads is equal to $0.9375. The cost disregarding the DI is calculated as $0.8004.

Table 8 indicates the comparative results while assigning the penalty factor to the model as zero. It is noted that only the enhanced leader particle swarm optimization (ELPSO) algorithm results in the same solution as the obtained cost. The DI has been derived 27 in this paper while it has been reported 48 in (Rezaee Jordehi, 2019). Besides, the operational schedules using both the CPLEX solver and ELPSO algorithm are the same with a difference in the operating hour of the vacuum cleaner in hour 9:30-10:00 (time slot 18) and then, hour 10:30-11:00 (time slot 20). The price of energy purchased from the grid is 0.024 $/kWh in both methods. Consequently, both solutions are global optimal and valid. It should be noted that the time shift of this asset's usage is exactly one slot, i.e. one slot before and one slot after the baseline. Hence, the DI is calculated as 26 and 46 using the Euclidean distance and absolute subtraction methods, respectively. As it is expected, shifting the energy demand of the EV has the highest contribution to the cost reduction so that the cost decreases from \$0.403 to \$0.312 for the EV charging.

Table 8 The best results for shiftable home appliances self-scheduling based on RTP tariff

		Meta-heuristic (Rezaee Jordehi, 2019)						MILP
Appliance	**Base**	DA	GSA	BSA	ABC	PSO	ELPSO	CPLEX
Dishwasher	**19-22**	15-18	15-18	15-18	15-18	15-18	15-18	15-18
Washing Machine	**19-21**	16-18	16-18	16-18	16-18	16-18	16-18	16-18
Spine Dryer	**27-28**	27-28	27-28	25-26	26-27	27-28	27-28	27-28
Cooker Hub	**17**	16	16	16	16	16	16	16
Cooker Oven	**37**	37	37	37	37	37	37	37
Microwave	**17**	16	16	16	16	16	16	16
Laptop	**37-40**	39-42	40-43	34-37	44-47	39-42	44-47	44-47
Desktop Computer	**37-42**	42-47	39-44	42-47	42-47	42-47	42-47	42-47
Vacuum Cleaner	**19**	19	25	18	19	18	18	19
Electric Vehicle	**37-42**	42-47	42-47	42-47	42-47	42-47	42-47	42-47
Daily Bill (\$)	**0.9375**	0.8025	0.8146	0.8069	0.8016	0.8025	0.8004	0.8004
DI-Calculated*	**0**	42	40	50	48	44	48	46
DI-Proposed	**0**	21	25	25	27	22	27	26

* According to the approach presented in (Rezaee Jordehi, 2019)

Table 9 represents the simulation results relating to the load shifting based on different penalty factors using the RTP tariff. The consumer's discomfort tolerance using the Euclidean distance method is double than that of the absolute subtraction method. In other words, when the penalty factor equals 0.02 in the proposed method, the consumer's tendency to change his usage pattern would be zero. While using the absolute subtraction method the tendency to shift usage is zero when the penalty factor equals 0.01. Consequently, the consumer tends to act according to his preferences. Table 10 represents the Pareto optimal front along with the results, obtained from the VIKOR decision maker.

Table 9 The effects of different monetizing coefficient factors of the penalty associated with the DI –RTP tariff.

Absolute Subtraction			Euclidean Distance		Absolute Subtraction			Euclidean Distance	
ω	Optimal Bill	DI	Optimal Bill	DI	ω	Optimal Bill	DI	Optimal Bill	DI
0.000	0.8004	48	0.8004	26	0.006	0.8465	10	0.8390	6
0.001	0.8107	28	0.8029	19	0.007	0.8465	10	0.8390	6
0.002	0.8347	14	0.8107	14	0.008	0.8465	10	0.8465	5
0.003	0.8390	12	0.8197	11	0.009	0.8465	10	0.8465	5
0.004	0.8465	10	0.8347	7	0.010	**0.9375**	**0**	0.8465	5
0.005	0.8465	10	0.8390	6	0.020	**0.9375**	**0**	**0.9375**	**0**

Table 10 The Pareto optimal front and VIKOR results_ shiftable loads considering RTP tariff.

Plan	DI	Bill ($)	R		S		Q	
Plan 1	0	0.9375	Plan 1	0.800000	Plan 1	0.800000	Plan 1	1.000000
Plan 2	1	0.9270	Plan 2	0.738731	Plan 2	0.746423	Plan 2	0.914312
Plan 3	2	0.9165	Plan 3	0.677462	Plan 3	0.692846	Plan 3	0.828623
Plan 4	3	0.8990	Plan 4	0.575346	Plan 4	0.598423	Plan 4	0.681797
Plan 5	4	0.8815	Plan 5	0.473231	Plan 5	0.504000	Plan 5	0.534970
Plan 6	5	0.8465	Plan 6	0.269001	Plan 6	0.307462	Plan 6	0.235297
Plan 7	6	0.8390	Plan 7	0.225237	Plan 7	0.271391	Plan 7	0.175811
Plan 8	7	0.8347	Plan 8	0.200438	Plan 8	0.254284	Plan 8	0.144711
Plan 9	8	0.8333	Plan 25	0.200000	Plan 9	0.253223	Plan 9	0.137629
Plan 10	9	0.8300	Plan 24	0.192310	Plan 10	0.241951	Plan 10	0.115263
Plan 11	10	0.8240	Plan 9	0.191680	Plan 11	0.214633	Plan 25	0.101920
Plan 12	11	0.8197	Plan 23	0.184620	Plan 25	0.200000	Plan 24	0.094744
Plan 13	12	0.8183	Plan 10	0.172720	Plan 24	0.197850	Plan 23	0.086427
Plan 14	13	0.8150	Plan 22	0.161540	Plan 12	0.197530	Plan 11	0.068878
Plan 15	**14**	**0.8107**	Plan 21	0.153850	Plan 13	0.196470	Plan 22	0.053712
Plan 16	15	0.8099	Plan 20	0.146150	Plan 23	0.194240	Plan 21	0.043339
Plan 17	16	0.8089	Plan 19	0.138460	Plan 14	0.185190	Plan 12	0.037777
Plan 18	17	0.8074	Plan 11	0.137710	Plan 22	0.173500	Plan 19	0.035151
Plan 19	18	0.8060	Plan 18	0.130770	Plan 17	0.172970	Plan 20	0.032967
Plan 20	19	0.8029	Plan 17	0.123080	Plan 18	0.171910	Plan 13	0.030696
Plan 21	20	0.8027	Plan 16	0.115380	Plan 19	0.170850	Plan 18	0.030487
Plan 22	21	0.8024	Plan 12	0.112910	Plan 16	0.170530	Plan 17	0.025822
Plan 23	24	0.8020	Plan 15	0.107690	Plan 15	0.168090	Plan 14	0.018905
Plan 24	25	0.8013	Plan 13	0.104160	Plan 21	0.167270	Plan 16	0.018418
Plan 25	26	0.8004	Plan 14	0.100000	Plan 20	0.161030	**Plan 15**	**0.011013**

5.2 Self-scheduling of HEMS in the presence of EES

This scenario discusses a case study with both shiftable and non-shiftable loads, such as the lighting system in the presence of an EES system with a capacity of 3 kWh. Tables 13 and 14 show the data of the EES system and the fixed loads of the consumer, respectively. As the

EES system can supply a fraction of the load demand, both shiftable and non-shiftable loads have been taken into consideration in this case. The energy purchased from the grid can be directly consumed by the home appliances and the EV or to used charge the EES system. Moreover, the EES system can supply a fraction of the load over peak hours and it is not necessary to purchase electricity from the grid. It is noteworthy that the refrigerator with 0.35 kW for the entire day and the TV with 0.1 kW demand over hours 18:00-23:00 are the non-shiftable loads besides the lighting system. The load demand for the lighting system varies over the hours of the day. It is worth mentioning that due to the constant demand of the above mentioned loads, the base and the permitted intervals are the same.

Table 13 Technical parameters of the EES.

E^{max} (kWh)	E^{min} (kWh)	$P^{Ch.,max}$ (kW)	$P^{Disch.,max}$ (kW)	$\eta^{Ch.}$ %	$\eta^{Disch.}$ %	$E^1=E^T$ (kWh)
3.00	0.200	0.500	0.500	0.95	0.95	0.5

Fig.6 shows the total daily load demand of the studied system, including both shiftable and non-shiftable loads in scenario 2. The refrigerator with a demand of 0.35 kW has the highest consumption. It should be noted that the performance of the compressor of the refrigerator over different hours has been neglected and this appliance has been considered a fixed load.

Table 14 The specifications of non-shiftable 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

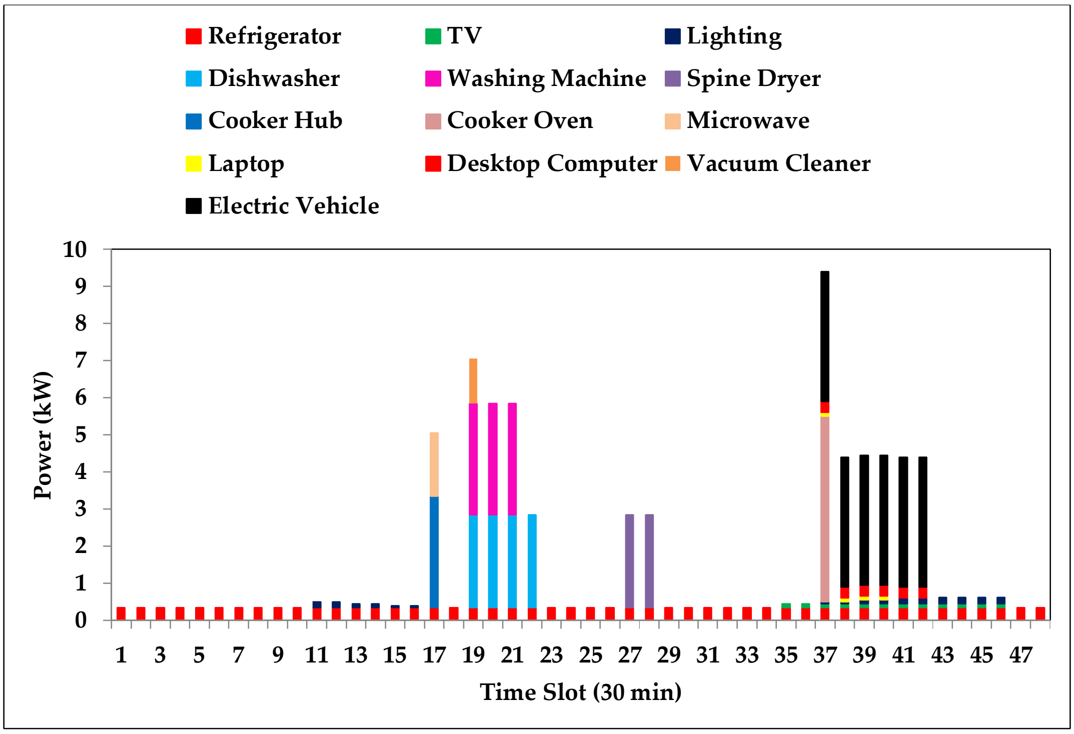

Fig. 6. The total daily load demand in scenario 2.

Fig. 7 depicts the tariffs used in this study applied using a 30-minute resolution. Utilizing the TOU tariff, three price levels as 0.01 \$/kWh, 0.02 \$/kWh, and 0.04 \$/kWh have been applied. During time slots 19-40, the energy price is 0.04 \$/kWh, during the slots 15-18 and 41-44 the price is 0.02 \$/kWh, and for the remaining hours, the price is 0.01 \$/kWh. For the RTP case, the energy price at each time slot is the same as the previous scenario.

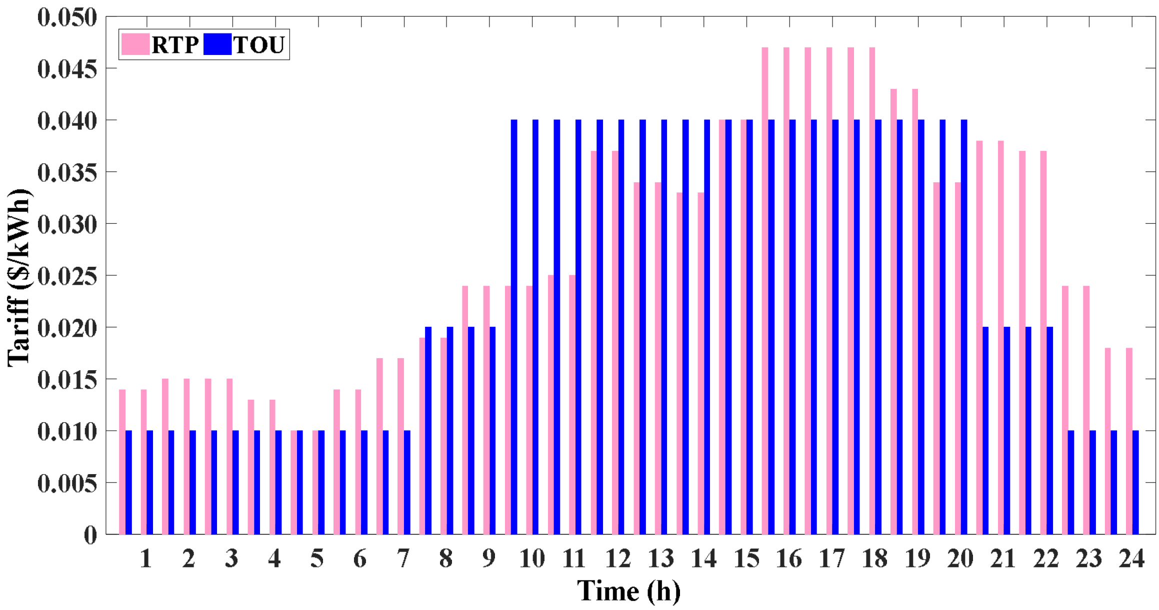

Fig. 7. Different time tariffs based on TOU and RTP

5.2.1 Self-scheduling problem for fixed and shiftable loads considering TOU tariff

This scenario implements the self-scheduling problem to determine the best schedule for using shiftable-load assets based on the TOU tariff. The simulation results show that the total load demand procurement cost is equal to \$1.287. In this regard, applying the load shifting capability would reduce the cost to \$0.871 and employing the EES system beside the load shifting can help lower the cost to \$0.832. It is noteworthy that the EES system is not ideal; thus, charging/discharging would occur only if it tangibly reduces the cost. As this system can supply a fraction of the load over some hours of the day, it is not required to purchase energy from the grid. The amount of the energy purchased from the grid is 39.01 kWh in the absence of the EES system and in the presence of the EES system it increases to 39.15 kWh. Due to the difference in the energy tariff over the day and the efficiency of the EES which is 95%, the amount of the energy purchased from the grid is almost the same, but the bill would be different. It can be observed that the battery system operates according to the energy tariff and load demand variations.

The EES system charges to its maximum capacity, i.e. 3kWh over the light load hours with low energy prices to supply the load during peak hours and reduce the energy purchased from the grid. However, simulation results show that smart load shifting would be much more effective compared to installing an EES system. A non-ideal EES system cuts the total cost by 4.4%. Fig. 8 illustrates the contribution of each of the shiftable loads to the energy bill both in the base case and after self-scheduling. Table 15 represents a sensitivity analysis to highlight the impact of the penalty factor on HEMS scheduling. The Pareto optimal front along with the decision making result by using the VIKOR in this case with the TOU tariff, without and with the EES system have been represented in Table 16 and Table 17, respectively.

Table 15 The sensitivity analysis based on TOU tariff considering the effects of EES on the DI.

	With ESS		Without ESS			With ESS		Without ESS	
ω	Cost	DI	Cost	DI	ω	Cost	DI	Cost	DI
0.000	0.8324	25	0.8709	25	0.015	1.0464	12	1.0849	12
0.001	0.8559	21	0.8944	22	0.020	1.1039	11	1.1424	11
0.002	0.8734	17	0.9119	17	0.025	1.1589	10	1.1974	11
0.003	0.8904	17	0.9289	17	0.030	1.1939	5	1.2324	7
0.004	0.9064	13	0.9449	13	0.035	1.2139	4	1.2524	4
0.005	0.9194	13	0.9579	13	0.040	1.2339	4	1.2724	4
0.010	0.9844	13	1.0229	13	0.045	1.2489	0	1.2874	0

Cost=Electricity Bill + DI* ω

As this figure shows, the EV, the dishwasher, and the washing machine have the highest contributions in the daily bill. The energy stored in the EES system has been indicated in Fig. 9 when ω=0. It is noted that there is a strict constraint on the initial and final energy storage at 0.5 kWh.

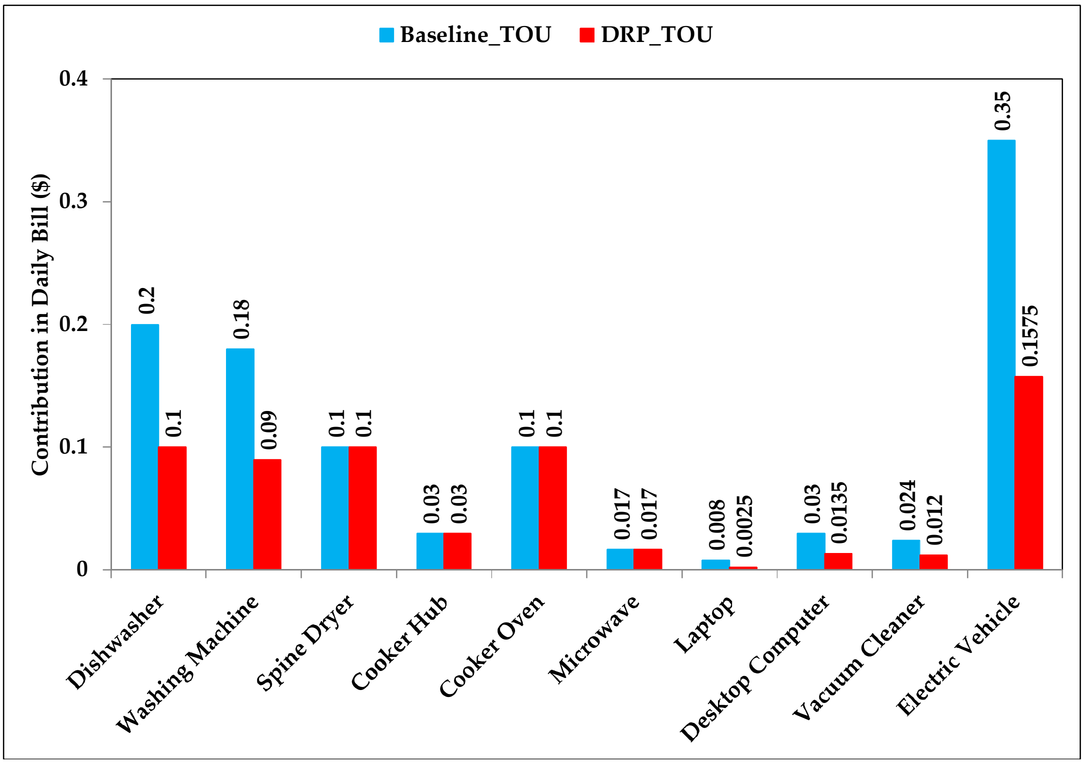

Fig. 8. The contribution of each shiftable load using the TOU tariff.

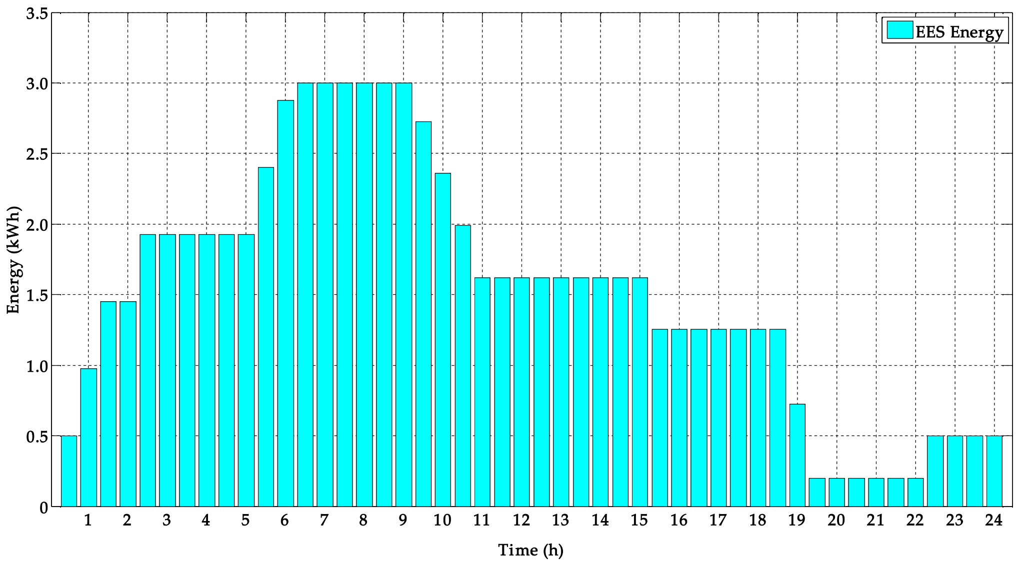

Fig. 9. The energy stored in the EES system using the TOU tariff when ω=0.

Table 16 The Pareto optimal front and VIKOR results_ without EES and considering TOU tariff.

Plan	DI	Bill ($)	R		S		Q	
Plan 1	0	1.2874	Plan 1	0.800000	Plan 1	0.800000	Plan 1	1.000000
Plan 2	1	1.2524	Plan 2	0.732773	Plan 2	0.740773	Plan 2	0.906955
Plan 3	2	1.2174	Plan 3	0.665546	Plan 3	0.681546	Plan 3	0.813911
Plan 4	3	1.1649	Plan 4	0.564706	Plan 4	0.588706	Plan 4	0.671284
Plan 5	4	1.1124	Plan 5	0.463866	Plan 5	0.495866	Plan 5	0.528658
Plan 6	5	1.0824	Plan 6	0.406242	Plan 6	0.446242	Plan 6	0.449780
Plan 7	6	1.0524	Plan 7	0.348619	Plan 7	0.396619	Plan 7	0.370901
Plan 8	7	1.0224	Plan 8	0.290996	Plan 8	0.346996	Plan 8	0.292023
Plan 9	8	0.9974	Plan 9	0.242977	Plan 9	0.306977	Plan 9	0.227310
Plan 10	9	0.9724	Plan 26	0.200000	Plan 10	0.266958	Plan 10	0.162600
Plan 11	10	0.9474	Plan 10	0.194960	Plan 11	0.226939	Plan 26	0.114970
Plan 12	11	0.9224	Plan 25	0.192000	Plan 26	0.200000	Plan 25	0.103900
Plan 13	12	0.9049	Plan 24	0.184000	Plan 25	0.192960	Plan 11	0.097886
Plan 14	**13**	**0.8929**	Plan 23	0.176000	Plan 12	0.186920	Plan 24	0.092836
Plan 15	14	0.8899	Plan 22	0.168000	Plan 24	0.185920	Plan 23	0.081770
Plan 16	15	0.8869	Plan 21	0.160000	Plan 23	0.178880	Plan 22	0.071439
Plan 17	16	0.8824	Plan 20	0.152000	Plan 22	0.172800	Plan 21	0.061107
Plan 18	17	0.8779	Plan 11	0.146940	Plan 21	0.166720	Plan 20	0.050776
Plan 19	18	0.8764	Plan 19	0.144000	Plan 13	0.161310	Plan 19	0.040445
Plan 20	19	0.8754	Plan 18	0.136000	Plan 20	0.160640	Plan 12	0.033173
Plan 21	20	0.8744	Plan 17	0.128000	Plan 19	0.154560	Plan 18	0.030848
Plan 22	21	0.8734	Plan 16	0.120000	Plan 16	0.150730	Plan 17	0.025658
Plan 23	22	0.8724	Plan 15	0.112000	Plan 17	0.150090	Plan 16	0.020468
Plan 24	23	0.8719	Plan 14	0.104000	Plan 18	0.149450	Plan 15	0.013075
Plan 25	24	0.8714	Plan 12	0.098920	Plan 15	0.148490	Plan 13	0.011510
Plan 26	25	0.8709	Plan 13	0.096000	Plan 14	0.146260	**Plan 14**	**0.005682**

Table 17 The Pareto optimal front and VIKOR results_ with EES and considering TOU tariff.

Plan	DI	Bill ($)	R		S		Q	
Plan 1	0	1.2489	Plan 1	0.800000	Plan 1	0.800000	Plan 1	1.000000
Plan 2	1	1.2139	Plan 2	0.732773	Plan 2	0.740773	Plan 2	0.906955
Plan 3	2	1.1789	Plan 3	0.665546	Plan 3	0.681546	Plan 3	0.813911
Plan 4	3	1.1264	Plan 4	0.564706	Plan 4	0.588706	Plan 4	0.671284
Plan 5	4	1.0739	Plan 5	0.463866	Plan 5	0.495866	Plan 5	0.528658
Plan 6	5	1.0439	Plan 6	0.406242	Plan 6	0.446242	Plan 6	0.449780
Plan 7	6	1.0139	Plan 7	0.348619	Plan 7	0.396619	Plan 7	0.370901
Plan 8	7	0.9839	Plan 8	0.290996	Plan 8	0.346996	Plan 8	0.292023
Plan 9	8	0.9589	Plan 9	0.242977	Plan 9	0.306977	Plan 9	0.227310
Plan 10	9	0.9339	Plan 26	0.200000	Plan 10	0.266958	Plan 10	0.162598
Plan 11	10	0.9089	Plan 10	0.194960	Plan 11	0.226939	Plan 26	0.114970
Plan 12	11	0.8839	Plan 25	0.192000	Plan 26	0.200000	Plan 25	0.103900
Plan 13	12	0.8664	Plan 24	0.184000	Plan 25	0.192960	Plan 11	0.097886

Plan 14	**13**	**0.8544**	Plan 23	0.176000	Plan 12	0.186920	Plan 24	0.092836
Plan 15	14	0.8514	Plan 22	0.168000	Plan 24	0.185920	Plan 23	0.081770
Plan 16	15	0.8484	Plan 21	0.160000	Plan 23	0.178880	Plan 22	0.071439
Plan 17	16	0.8439	Plan 20	0.152000	Plan 22	0.172800	Plan 21	0.061107
Plan 18	17	0.8394	Plan 11	0.146940	Plan 21	0.166720	Plan 20	0.050776
Plan 19	18	0.8379	Plan 19	0.144000	Plan 13	0.161310	Plan 19	0.040445
Plan 20	19	0.8369	Plan 18	0.136000	Plan 20	0.160640	Plan 12	0.033173
Plan 21	20	0.8359	Plan 17	0.128000	Plan 19	0.154560	Plan 18	0.030848
Plan 22	21	0.8349	Plan 16	0.120000	Plan 16	0.150730	Plan 17	0.025658
Plan 23	22	0.8339	Plan 15	0.112000	Plan 17	0.150090	Plan 16	0.020468
Plan 24	23	0.8334	Plan 14	0.104000	Plan 18	0.149450	Plan 15	0.013075
Plan 25	24	0.8329	Plan 12	0.098920	Plan 15	0.148490	Plan 13	0.011510
Plan 26	25	0.8324	Plan 13	0.096000	Plan 14	0.146260	**Plan 14**	**0.005682**

5.2.2 Self-scheduling problem for fixed and shiftable loads considering RTP tariff

This section investigates the self-scheduling problem of fixed and shiftable loads, taking into account the RTP mechanism. As this case depends strongly on the real-time prices, there should be smart communication infrastructure for the HEMS to receive the price signals. The compatibility with the real-time prices mainly relates to the existence of such infrastructure. Simulation results show that the daily energy bill would be $1.2209 in case the consumer tends to use energy according to his preferences. In the case of applying self-scheduling, this cost will drop significantly. The cost of energy purchased from the grid in the absence of the EES system is $1.0838 and it will reduce further to $1.0404 when the EES system is added.

Moreover, the total amount of energy purchased from the grid in the absence of the EES system is 39.01 kWh, including 9.96 kWh fixed load and 29.05 kWh shiftable load. In the presence of the EES system, the total energy demand is 39.24 kWh, while this increase is due to the non-ideal EES system. However, installing the EES system decreases the cost by 4%. Fig. 10 indicates the impact of the self-scheduling of HEMS on the optimal operation of the home appliances and the EV. As this figure shows, the load shifting from the peak hours to off-peak hours has been optimally done. It is noteworthy that the total energy demand without the EES system is the same as the base case and the consumption pattern is following the self-scheduling.

The net load demand in the HEMS is zero over some hours in the presence of the EES system. This means that the EES system alone supplies the entire load demand, independently from the grid which is under the optimal operation of such a device.

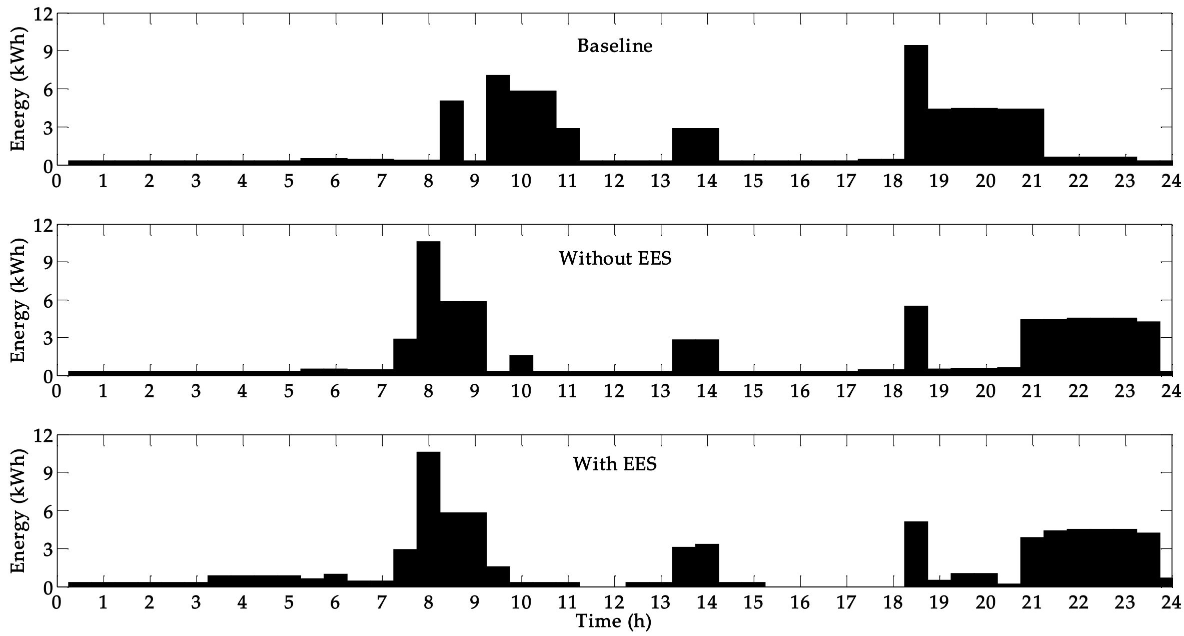

Fig. 10. The daily energy consumption before/after the self-scheduling with RTP tariff.

The sensitivity analysis in this scenario, shown in Table 18, has revealed that the consumer would not tend to shift his load for ω equal to or greater than 0.02. Consequently, the load procurement cost in the absence of the EES system for ω=0.02 is the same as the base case, i.e. \$1.2209. Moreover, the total cost with only the EES system is \$1.1776 showing a 3.55% reduction in the cost. The Pareto optimal front along with the decision making result by using the VIKOR in this case with the RTP mechanism, without and with the EES system have been represented in Table 19 and Table 20, respectively.

Table 18 The sensitivity analysis based on RTP tariff considering the effects of EES on the DI.

	With ESS		Without ESS			With ESS		Without ESS	
ω	Cost	DI	Cost	DI	*ω*	Cost	DI	Cost	DI
0.000	1.0405	**26**	1.0838	**26**	0.006	1.1151	6	1.1584	6
0.001	1.0621	19	1.1054	19	0.007	1.1211	6	1.1644	6
0.002	1.0789	14	1.1222	14	0.008	1.1266	5	1.1699	5
0.003	1.0929	11	1.1362	14	0.009	1.1316	5	1.1749	5
0.004	1.1029	7	1.1462	7	0.010	1.1366	5	1.1799	5
0.005	1.1091	6	1.1524	6	0.020	1.1776	0	1.2209	0

Table 19 The Pareto optimal front and VIKOR results_ without EES and considering RTP tariff.

Plan	DI	Bill ($)	R		S		Q	
Plan 1	0	1.1776	Plan 1	0.800000	Plan 1	0.800000	Plan 1	1.000000
Plan 2	1	1.1671	Plan 2	0.738731	Plan 2	0.746423	Plan 2	0.914312
Plan 3	2	1.1566	Plan 3	0.677462	Plan 3	0.692846	Plan 3	0.828623
Plan 4	3	1.1391	Plan 4	0.575346	Plan 4	0.598423	Plan 4	0.681797
Plan 5	4	1.1216	Plan 5	0.473231	Plan 5	0.504000	Plan 5	0.534970
Plan 6	5	1.0866	Plan 6	0.269001	Plan 6	0.307462	Plan 6	0.235297
Plan 7	6	1.0791	Plan 7	0.225237	Plan 7	0.271391	Plan 7	0.175811
Plan 8	7	1.0749	Plan 8	0.200438	Plan 8	0.254284	Plan 8	0.144711
Plan 9	8	1.0734	Plan 25	0.200000	Plan 9	0.253223	Plan 9	0.137629
Plan 10	9	1.0701	Plan 24	0.192310	Plan 10	0.241951	Plan 10	0.115263
Plan 11	10	1.0641	Plan 9	0.191680	Plan 11	0.214633	Plan 25	0.101920
Plan 12	11	1.0599	Plan 23	0.184620	Plan 25	0.200000	Plan 24	0.094744
Plan 13	12	1.0584	Plan 10	0.172720	Plan 24	0.197850	Plan 23	0.086427
Plan 14	13	1.0551	Plan 22	0.161540	Plan 12	0.197530	Plan 11	0.068878
Plan 15	**14**	**1.0509**	Plan 21	0.153850	Plan 13	0.196470	Plan 22	0.053712
Plan 16	15	1.0500	Plan 20	0.146150	Plan 23	0.194240	Plan 21	0.043339
Plan 17	16	1.0491	Plan 19	0.138460	Plan 14	0.185190	Plan 12	0.037777
Plan 18	17	1.0476	Plan 11	0.137710	Plan 22	0.173500	Plan 19	0.035151
Plan 19	18	1.0461	Plan 18	0.130770	Plan 17	0.172970	Plan 20	0.032967
Plan 20	19	1.0431	Plan 17	0.123080	Plan 18	0.171910	Plan 13	0.030696
Plan 21	20	1.0428	Plan 16	0.115380	Plan 19	0.170850	Plan 18	0.030487
Plan 22	21	1.0426	Plan 12	0.112910	Plan 16	0.170530	Plan 17	0.025822
Plan 23	24	1.0422	Plan 15	0.107690	Plan 15	0.168090	Plan 14	0.018905
Plan 24	25	1.0415	Plan 13	0.104160	Plan 21	0.16727	Plan 16	0.018418
Plan 25	26	1.0405	Plan 14	0.100000	Plan 20	0.16103	**Plan 15**	**0.011013**

Table 20 The Pareto optimal front and VIKOR results_ with EES and considering RTP tariff.

Plan	DI	Bill ($)	R		S		Q	
Plan 1	0	0.9375	Plan 1	0.800000	Plan 1	0.800000	Plan 1	1.000000
Plan 2	1	0.9270	Plan 2	0.738731	Plan 2	0.746423	Plan 2	0.914312
Plan 3	2	0.9165	Plan 3	0.677462	Plan 3	0.692846	Plan 3	0.828623
Plan 4	3	0.8990	Plan 4	0.575346	Plan 4	0.598423	Plan 4	0.681797
Plan 5	4	0.8815	Plan 5	0.473231	Plan 5	0.504000	Plan 5	0.534970
Plan 6	5	0.8465	Plan 6	0.269001	Plan 6	0.307462	Plan 6	0.235297
Plan 7	6	0.8390	Plan 7	0.225237	Plan 7	0.271391	Plan 7	0.175811
Plan 8	7	0.8347	Plan 8	0.200438	Plan 8	0.254284	Plan 8	0.144711
Plan 9	8	0.8333	Plan 25	0.200000	Plan 9	0.253223	Plan 9	0.137629
Plan 10	9	0.8300	Plan 24	0.192310	Plan 10	0.241951	Plan 10	0.115263
Plan 11	10	0.8240	Plan 9	0.191680	Plan 11	0.214633	Plan 25	0.101920
Plan 12	11	0.8197	Plan 23	0.184620	Plan 25	0.200000	Plan 24	0.094744
Plan 13	12	0.8183	Plan 10	0.172720	Plan 24	0.197850	Plan 23	0.086427
Plan 14	13	0.8150	Plan 22	0.161540	Plan 12	0.197530	Plan 11	0.068878

Plan 15	**14**	**0.8107**	Plan 21	0.153850	Plan 13	0.196470	Plan 22	0.053712
Plan 16	15	0.8099	Plan 20	0.146150	Plan 23	0.194240	Plan 21	0.043339
Plan 17	16	0.8089	Plan 19	0.138460	Plan 14	0.185190	Plan 12	0.037777
Plan 18	17	0.8074	Plan 11	0.137710	Plan 22	0.173500	Plan 19	0.035151
Plan 19	18	0.8060	Plan 18	0.130770	Plan 17	0.172970	Plan 20	0.032967
Plan 20	19	0.8029	Plan 17	0.123080	Plan 18	0.171910	Plan 13	0.030696
Plan 21	20	0.8027	Plan 16	0.115380	Plan 19	0.170850	Plan 18	0.030487
Plan 22	21	0.8024	Plan 12	0.112910	Plan 16	0.170530	Plan 17	0.025822
Plan 23	24	0.8020	Plan 15	0.107690	Plan 15	0.168090	Plan 14	0.018905
Plan 24	25	0.8013	Plan 13	0.104160	Plan 21	0.167270	Plan 16	0.018418
Plan 25	26	0.8004	Plan 14	0.100000	Plan 20	0.161030	**Plan 15**	**0.011013**

Regarding the computational burden, the self-scheduling problem is solved for the mentioned case studies and the comparative results are reported in Table 21. For the non-linear representation of DI, the problem has been solved by the standard branch and bound (SBB) solver, while the proposed linear model has been solved by CPLEX solver. For the sake of comparison, the results reported in the corresponding tables mentioned in this paper are organized in Table 21.

Table 21. Computational burden analysis for studied cases

Case Study	DI-TOU (Table 6)		DI-RTP (Table 9)		TOU-EES (Table 15)		RTP-EES (Table 18)	
Model	MILP	MINLP	MILP	MINLP	MILP	MINLP	MILP	MINLP
Number of Cases	24	24	12	12	28**	28**	24**	24**
Average Time (Sec)	0.220	14.175	0.215	13.575	0.292	18.354	0.311	19.875
Maximum Time (Sec)	0.233	15.169	0.232	15.227	0.411	21.375	0.423	22.341
Minimum Time (Sec)	0.201	0.738*	0.205	0.725*	0.203	0.875*	0.222	0.915*

* The results are obtained for the case with ω=0, i.e. excluding the nonlinear DI

** The simulations have been performed for both cases (with and without EES)

As can be seen from the simulation results, the computational burden for the non-linear DI function is considerably high. In the case of excluding the non-linear function (ω=0), the convergence time is less than one second.

6. Conclusion

This paper investigated a home energy management system (HEMS) with shiftable loads. This problem was studied in the context of a self-scheduling problem with different tariffs and an electrical energy storage (EES) system. The proposed model was formulated in a mixed-integer linear programming (MILP) multi-objective framework. In this respect, the discomfort index (DI) of the consumer was introduced as a linear function proportional to the amount of load shifted to before or after the consumer's desired time. The proposed DI can smoothly shift the operation time of home appliances close to the desired intervals. Therefore, the proposed index works precisely and efficiently in shifting the consumption of energy considering different energy tariffs. The most desired Pareto solution among the Pareto set was also selected using the VIKOR decision maker as a promising method.

In this study, the effectiveness of the HEMS on the daily bill reduction is confirmed. Moreover, a sensitivity analysis was carried out in each scenario to show to what extent the consumer tolerates the load shifting and to show the total discomfort reduction. By implementing the proposed Euclidean distance framework in the DI calculation, the total discomfort index is less than the absolute subtraction strategy in all case studies. The simulation results revealed that deferring the shiftable loads to off-peak hours can considerably decrease the consumer's bill in both scenarios. The simulation results in the second scenario, in the presence of EES devices, confirm that the effectiveness of using demand response programs to reduce the energy bill is much more than the installation of EES devices. In the presence of energy storage devices, smart homes can effectively benefit from the optimal operation of such storage devices. In such a way, the self-scheduling can be optimally achieved by utilizing the storage devices. Moreover, to achieve the best results from an economic point of view, it is necessary to assess the capital cost of such storage devices as well as their variable costs associated with their charging and discharging operating modes.

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