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Multi-objective Scheduling of Smart Homes Integrated with Renewable Energy Sources and Energy Storage Systems

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ABSTRACT

A home energy management system optimizes the electrical demand of household appliances according to price-based demand response programs. In this paper, we proposed a price-based demand response for a smart home with different types of appliances according to customer satisfaction, which also used electric and thermal storage systems. In the proposed method, various appliances were considered in the smart home modeled by the energy hub system. A multi-objective daily management is proposed which considered electricity costs and customer satisfaction simultaneously to provide comprehensive management for smart homes. This paper presents a multi-objective optimization approach that not only minimizes operating costs and maximizes customer satisfaction but also reduces environmental impacts through emission reduction, creating a more sustainable energy management system. After solving the multi-objective problem, the technique for order preference by similarity to the ideal solution was used to brank the solutions considering the preference of the decision-maker. The proposed model investigates the response of the smart home energy system in different conditions. Also, stochastic optimization was applied to model the probabilistic nature of demands, PV, and wind energy. The simulation results demonstrate that the proposed method reduces the consumer dissatisfaction by 79.9% and reduces the range from 199 to 40.

NOMENCLATURE

Indices

t	Index of time periods.
i	Index of household appliances.
s	Index of Scenarios.
C_i	similarity index.

Parameters

A_{non}	Set of non-interruptible appliances.
$T_{C,i}$	The most comfortable temperature of the thermally controlled appliance i determined by the user.
A_{in}	Set of interruptible household appliances.
A_{ther}	Set of thermostatically controlled appliances.
$P_{R,i}^{APP}$	Rated power of the appliance i.
$T_{L,i}$	Time length of appliance i used from start to end.
Eb_{No_x}	No_x gas emissions for the boiler.
Eb_{co_2}	co_2 gas emissions for the boiler.
N_1	The maximum power that can be purchased from the grid.
N_2	The maximum power that can be sold to the grid.
Eb_{so_2}	so_2 gas emissions for the boiler.
E_{so_2}	Amount of so_2 purchased.
C_{No_x}	The cost of purchased No_x.
E_{No_x}	Amount of No_x purchased.
Lan_{NS}	Unsupplied energy costs.
C_{so_2}	The cost of purchased so_2.

Variables

J_1	Operation cost of HEMS (cents/kWh).
J_2	Objective function of the user's dissatisfaction level.

L_i	Allowed the beginning time of the task for the appliance i.	J_3	The cost of greenhouse gas emissions.
U_i	Allowed the deadline of the task for the appliance i	J_4	Unsupplied energy costs.
R_{ESS}^{c}	Maximum charging rate of the ESUs.	$T_{u,i}$	Temperature (air, water, etc) determined by the schedule plan and directly perceived by the user for the appliance i (◦C).
R_{ESS}^{d}	Maximum discharging rate of the ESUs.	Pns	Amount of energy not supplied.
S_{ESS}^{ini}	Initial state-of-energy of the ESUs (kWh).	Hb_{TES}	The heat that the boiler gives to the thermal storage.
S_{ESS}^{min}	Minimum allowed state-of-energy of the ESUs (kWh).	Hb_{WH}	The heat that the boiler consumes for heating water
S_{ESS}^{max}	Maximum allowed state-of-energy of the ESUs (kWh).	Hb_{TL}	The energy that the boiler provides for thermal loads.
ϖ_1	The weight corresponds to J_1 J_3 J_4 .	P_{TES}^{WH}	WH power used to heat water for storage.
ϖ_2	The weight corresponds to J_2.	P_{wh}^{WH}	WH power used to heat hot water.
ε_i	Coefficient representing the importance of appliances.	P_{TL}^{WH}	WH power used for thermal loads.
E_i^{APP}	The required total energy of the task of the appliance i.	H_{TES}^{TL}	The heat that the storage gives for thermal loads.
W_{out}	Outdoor temperature (◦C).	H_{TES}^{WH}	The stored energy is used for hot water consumption.
S_{TES}^{ini}	Initial state-of-energy of the TES (kWh).	P_T^{WH}	Thermal from WH, which is generally used for hot water.
S_{TES}^{min}	Minimum allowed state-of-energy of the TES (kWh).	X_{ij}	Decision matrix.
Ro	Probability.	R_{ij}	Normalized decision matrix.
λ	Constant (1/3600000) for unit conversion.	V_{ij}	Weighted normal matrix.
m	The mass of water consumed.	V_j^{+}	Positive ideal value.
C_w	Specific heat of water.	V_j^{-}	Negative ideal value.
P_{PV}	Forecasted power generation from PV system (kW).	S_j^{-}	The distance from the negative ideal value.
S_{TES}^{max}	Maximum allowed state-of-energy of the TES (kWh).	S_j^{+}	The distance from the positive ideal value.
Nb	Boiler efficiency.	S_{ESS}	State-of-energy of the ESUs (kWh).
T_{cold}	Temperature of inlet cold water (◦C).	S_{TES}	State-of-energy of the TES (kWh).
M	Mass of water in full storage (kg).	Gb	The amount of gas purchased for the boiler.
θ_i^{up}	Maximum desired temperature (◦C).	Hb	power generated by boiler.
θ_i^{dn}	Minimum desired temperature (◦C).	μ_{grid}	Binary variable: 1 if grid supplying power, 0 else.
$T0$	Initial water temperature in the water heater storage (◦C).	ρ_{wh}	Demand for hot water drawn (kg).
γ,η	Coefficient denoting the thermal condition surrounding the air conditioner.	ζ_i	Customer dissatisfaction associated with the appliance i.
C_{co_2}	The cost of purchased co_2.	u_i^{APP}	Binary variable: 1 if the appliance is on, 0 else.
E_{co_2}	Amount of co_2 purchased.	P_i^{APP}	Power consumption of the appliance i.
Lan_G	gas price.	$W_{k,i}$	Continuous and positive numbers to calculate the temperature distance to the desired temperature.
$P_{must_{run}}$	Power of the non-controllable household appliances must run (kW).	$Z_{k,i}$	Binary variable to determine the work area.
Dh	Thermal load.	μ_{ESS}	Binary variable: 1 if ESUs is charging, 0 else.

I. Introduction

A. MOTIVATION AND BACKGROUND

With the restructuring of power systems and the creation of modern communication infrastructures, more attention has been paid to the participation of consumers in energy management system. The demand side management program is able to reduce the costs of production, transmission and distribution by changing the load profile of the grid. With the implementation of the demand response (DR) program, the amount of consumption during peak hours has been reduced by consumers who are willing to reduce their consumption. As a result, it is avoided to spend extra money to create production capacity for a short period of time every year. The primary goal of a demand response program has always been to smooth the load profile. Creating incentive programs in order to increase the participation of consumers in demand-side management is essential. In order to increase the efficiency of the system, the consumers should take a greater role. Today, people's desire to use smart homes is expanding, while the capabilities of smart homes in the market are more based on comfort and amenities for the user than relying on energy management. Therefore, one should look for solutions to identify the needs and desires of the consumer and obtain consumer satisfaction. Analyzing customer information is necessary to provide differentiated services. Smart home users face lower electricity bills in the short term and lower electricity tariffs in the long term. Experience has shown that consumers are generally not interested in reducing their consumption, especially during peak hours because they prioritize their comfort and convenience. With the development of smart homes, customers have the opportunity to manage their electricity consumption to reduce their electricity costs [1]. Smart meters and home energy management systems (HEMS) play an important role in managing demand response activities in residential areas [2]. The main motivation of the consumer in using HEMS is cost reduction, which requires changing or reducing electricity consumption, which is associated with the disruption of daily comfort [3]. HEMS can enable demand response programs for residential customers [4]. Consumers implement demand response programs in order to achieve economic benefits and prevent blackouts. In fact, although the main reason for consumers' participation can be attributed to financial and economic benefits, but indirectly, they also help to improve the reliability of the grid.In addition to economic benefits and comfort considerations, environmental sustainability has become a critical factor in smart home energy management. The utilization of smart homes can significantly reduce the emission of greenhouse gases because it facilitates the integration of renewable energy in the system. This environmental aspect adds another dimension to the value proposition of HEMS, making them essential tools not only for cost reduction and comfort enhancement but also for building a more sustainable and environmentally friendly residential sector.

B. RELATED WORKS

In recent years, several researches works had been focused on the design and discussion of demand response programs. Ref. [4] studied the impact of satisfaction factors, such as the level of satisfaction with the use of smart home appliances. However, the authors were not considered the uncertainty of demands and renewable generation. In [5], the joint evaluation of dynamic pricing and DR strategies had been studied based on peak limitation and the possibility of bidirectional operation of Electrical Vehicles (EVs) and Energy storage units (ESUs). In [6], risk- constrained bidding strategy was suggested for smart grid considering the plug-in EV and DR applications. A multi-objective decision making operation was suggested in [7] for the simultaneous optimization of water extraction and daily costs. However, the impact of demand- response programs was not studied. Also, the authors in [8] presented a method for predicting household loads. The proposed model investigated the effect of price-based demand response programs on the load pattern of smart homes. In [9], an energy management system is proposed for energy management of distributed energy resources in order to reduce residential energy consumption and efficient use of batteries. The authors in [10] provided an optimal approach for home energy management in which the consumers responded to different drivers of the DR programs. The results showed that different levels of motivation affect consumers' comfort index differently. The authors in [11] proposed a stochastic programming model to optimize the performance of a smart microgrid in the short-term scheduling to minimize the operating costs and greenhouse gas emissions simultaneously. Ref. [12] developed a comprehensive optimization method for the use of different home appliances considering the preferences of customers. In addition, a separate system was designed for charging and discharging storage devices. In [2], the authors presented a smart home model that proposed a two-level algorithm for energy management of home appliances, which also considered reactive loads. [13] studied the role of artificial intelligence in smart homes. Ref [14] investigated a real-time energy scheduling framework for a smart home considering uncertainty. Authors in [15] developed an integrated home energy management system that participated in a demand-side management program and implemented smart home computing with the help of a smart home operation platform. In [3], the authors considered both costs and satisfaction for energy management of households to maximize the user's comfort. However, energy storage and distributed energy sources were not considered. [16] used different energy sources to supply and control the operation of the appliances. Also, the authors investigated the direction of the power flow on the proposed model. The authors of [17] studied the impact of smart thermostat with a home energy management system. Ref. [18] minimized the total energy cost and thermal dissatisfaction of a sustainable smart home with heating, and air conditioning loads for a long period of time. In [19], a MILP model of energy management system based on reducing the cost of electricity consumption is presented. The considered loads were divided into two groups controlled by thermostat and non-thermostat. Battery storage systems and distributed generation systems were also integrated in the proposed model. Ref. [20] examined the use of second life battery energy storage systems (SL-BESSs) to support the home energy management system. In [21], the energy planning of a house that included solar heating, air conditioning and water heating system was investigated in real-time pricing. However, the correlation between electricity price and ambient temperature were not considered. In [22], smart thermostats were used to provide flexibility in demand-side energy management aiming to combine the use of a smart thermostat with a home energy management system to bring more benefits. In [23], a comprehensive class of household appliances was presented. Nevertheless, energy storage devices and renewable energy sources were not used in the suggested model. A multi-objective scheduling framework was developed in [24] to determine the optimal performance of the smart homes. The

objectives of the suggested framework were to minimize the cost of electricity consumption, flatten the consumption profile, and increase the convenience of customers. An energy management system was proposed in [25] that integrated plug-in EV (PEV), solar PV panel, and battery electrical energy storage (BEES), and DR programs. The suggested model evaluated the efficiency of different DR programs on the performance of smart homes. In [26], an operation model of a single house with alternating DERs and comprehensive load types was studied. In order to model and correctly manage household appliances, an intelligent planning scheme based on model predictive control was presented. However, level consumer welfare was not considered. In [27], the authors tried to minimize the electricity cost and thermal discomfort of users through HEMS considering heating, ventilation, and air conditioning (HVAC). This was done through stochastic programming that took into account the uncertainty associated with electricity prices, outdoor temperatures, and the output of distributed energy sources. The authors in [28] presented a predictive home energy management system for a residential building by integrating a plug-in electric vehicle, a photovoltaic array, and a heat pump. In [29], the optimal production structure of a multi-energy system with zero net emissions was investigated by separating the optimization problem into a two-stage investment problem and exploitation sub-problem. In [30], the performance of a home energy management system under the export rate was compared with a home energy management system under TOU tariff. In this paper, the energy hub model was not considered. In [31], an advanced satisfaction-based home energy management system using deep reinforcement learning for planning controllable and removable appliances was presented. In this reference, the proposed model was not transformed into an energy hub model and the uncertainty of renewable resources was not considered. A joint scheduling model of electric and natural gas utilities for HEMS was proposed in [32].In [33], the authors proposed a smart charging approach for off-range electric vehicle chargers in home energy hub (HEH) applications with direct current sources such as photovoltaics and battery storage systems. In [34], an integrated approach for optimal planning and operation of energy hubs considering the effects of wind energy resources was presented. The stable uncertainties of electricity demand, heating, cooling, and also wind power generation was considered in this study. In order to check the uncertainty parameters in the model, various scenarios were created by the Monte Carlo simulation method and then the scenarios was reduced using the K-means method. In the proposed model, the emission reduction was not considered. In [35], a stochastic home energy management system was proposed that integrates renewable energy sources with demand response programs using an improved ABC algorithm, achieving significant cost reductions under various grid constraints. In [36], an energy hub optimization model was proposed using the IPSO algorithm that efficiently coordinates electricity, gas, and thermal grids, resulting in significant operational cost reductions. In [37], a method for power system stability analysis was proposed that identifies coherent generator groups and their oscillation patterns, which can be applied to optimize the integration of renewable energy sources and improve islanding detection in smart energy management systems with distributed generation. In [38], a risk-based decentralized model for peer-to-peer energy trading among smart homes was proposed, which integrates demand-side management, photovoltaic systems, and energy storage while addressing uncertainties in renewable generation and market prices through conditional value-at-risk optimization. In [39], a flexibility-constrained energy management framework for smart energy hubs was developed that incorporates peer-to-peer transactive energy and demand response programs, integrating multiple energy carriers and storage systems to minimize operational and environmental costs while enhancing system flexibility. A number of related research works are compared in Table 1.

C. CONTRIBUTIONS

According to the best of our knowledge, the main contributions of the proposed model are listed as follows:

- This study develops a demand response framework for smart homes featuring diverse categories of household appliances, incorporating an accurate pricing mechanism while accounting for customer satisfaction. Distinct from prior works such as [6], [7], [9], [10], [11], [15], [22], [26–30], and [33–34], the proposed model formulates a multi-objective optimization problem that simultaneously minimizes electricity costs and customer dissatisfaction.

TABLE 1. Taxonomy of the model used for designing DR-based HEMS.

References	Hub Energy	Wide variety of appliances	Customer Satisfaction	Uncertainty	Emission reduction	DER	ESUs
[30],[26],[28], [22],[27]	N	Y	N	Y	N	Y	Y
[13]	N	N	Y	N	Y	N	N
[23]	N	Y	N	N	N	N	N
[4],[20]	N	Y	Y	N	N	Y	Y
[14]	N	Y	Y	Y	N	N	Y
[12]	N	Y	Y	Y	N	Y	Y
[32],[25],[31]	N	Y	Y	N	N	N	Y
[3]	N	Y	Y	Y	N	N	N
[9],[2]	N	Y	N	N	N	Y	Y
[33]	Y	Y	N	Y	N	N	Y
[6],[11]	N	N	N	Y	N	Y	Y
[7]	Y	N	N	N	N	Y	N
[29]	Y	N	N	Y	Y	Y	Y
[34]	Y	N	N	Y	N	Y	Y
[10],[15]	N	Y	N	N	N	N	Y
Proposed model	Y	Y	Y	Y	Y	Y	Y

Y/N denotes that the subject is/is not considered.

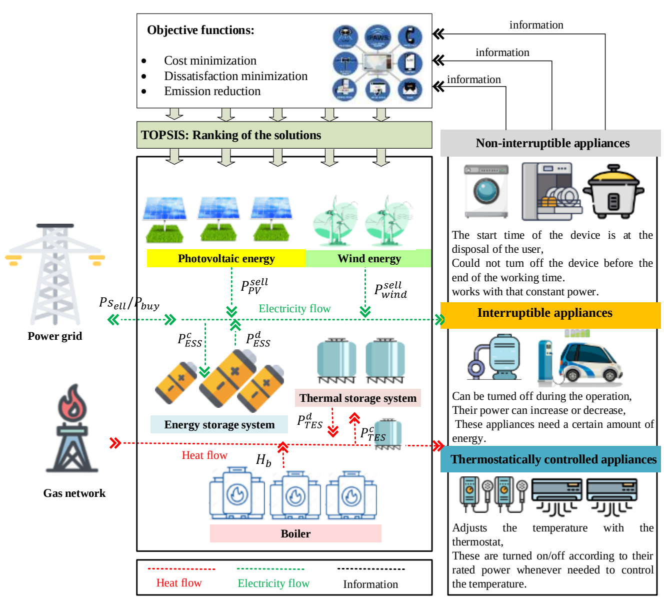

Fig. 1 Structure of the proposed smart home

- In contrast to [2–4], [6], [10–15], [20], [22, 23], [25–28], and [30–32], this study models smart homes as integrated energy systems that jointly manage electricity, heating, and cooling demands. This sectorial integration enhances the overall control efficiency, enabling more effective handling of renewable energy source (RES) uncertainties and reducing operational expenditures. Furthermore, the coupled system significantly improves the flexibility of smart homes in terms of both power and energy, thereby enhancing their ability to accommodate RES fluctuations.
- In contrast to [2–4], [6, 7], [9–12], [14, 15], [20], [22, 23], [25–28], and [30–34], this study proposes a hybrid environmental–techno-economic scheduling framework for smart homes. The proposed model aims to minimize greenhouse gas emissions alongside electricity costs and customer dissatisfaction, while ensuring compliance with all relevant technical operational constraints.

This paper is organized as follows. Section II describes the methodology and mathematical formulation of the proposed model. Section III introduces the case studies and discussion. Finally, conclusion is presented in Section IV.

II. METHODOLOGY

According to Fig. 1, the home energy management system adjusts the performance of the smart home according to the signal prices and consumer satisfaction. In the proposed model, a smart home with various electrical, heating and cooling loads is considered. The structure of the optimization is presented in Fig. 2. First, loads and PV output are predicted according to weather forecast and historical data. Then, the DR problem is considered according to the forecasted PV output, loads, electricity price, along with the desired user input by the home owner. A home with different types of appliances connected to smart home is considered as case study. Before smart home scheduling, customers

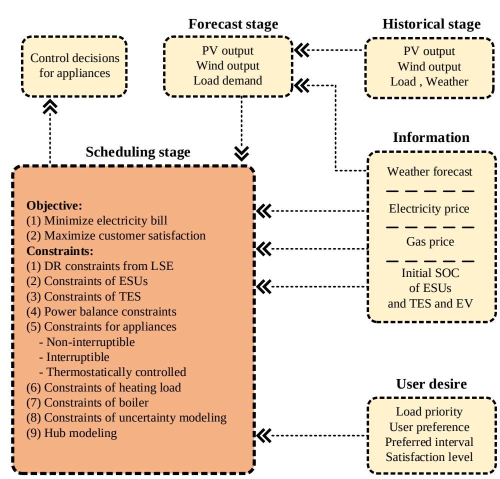

Fig. 2. The optimization framework of HEMS.

record information about the occupants' comfort and lifestyle preferences. Here, the goal is that the consumers participate in the demand response program and manage their energy systems. In this proposed model, the consumer will pays the lowest costs and has the most satisfaction in using their smart devices at the same time. The output of this work is a software tool that optimally schedules appliance usage and local energy generation based on objectives like reducing electricity costs and enhancing user comfort. It considers real-time pricing, user preferences, system limitations, and energy availability to create an efficient operation plan. This tool can be integrated into a home energy management system (HEMS) for smart and automated energy control.

A. MULTI-OBJECTIVE FUNCTION

The existing problem is a multi-objective problem where the first objective function is the house bill and the second objective function is the customer satisfaction level. Using the weighted sum approach, we convert different objective functions into one. The objective function is as Eq. (1):

$$Min\ \varpi_1(J_1 + J_3 + J_4) + \varpi_2 J_2 \qquad \varpi_1 + \varpi_2 = 1 \ , \ \varpi_1 \,\&\, \varpi_2 \in [0, 1] \tag{1}$$

The objective function creates this opportunity for the consumer to decide about optimal performance of their smart appliances. J_1, J_2, J_3, and J_4 in the above equation are respectively expressed as follows.

ϖ_1 is the weight related to J_1, J_3, and J_4 and also ϖ_2 is the weight related to J_2. Also, J_1 refers operating cost of HEMS (cents) and J_2 is the objective function of the participant's level of dissatisfaction. Also, J_3 is the cost of pollution and J_4 is load shading. Eq. (2) represents the operating cost (J_1), which includes electricity purchase costs, revenue from selling excess electricity, and natural gas consumption costs. Eq. (3) quantifies customer dissatisfaction (J_2) by summing the dissatisfaction levels across all appliances, ensuring user comfort preferences are considered. The emission cost (J_3) in Eq. (4) calculates the environmental impact from grid electricity consumption and natural gas combustion, accounting for CO_2, SO_2, and NO_x emissions[29]. Finally, Eq. (5) represents the cost of unsupplied energy (J_4), calculated as the product of unsupplied power and the penalty factor to ensure reliability.

$$J_1 = \sum_{s\in S} Ro(s) * \sum_{t\in T}\left[\lambda_{buy}(t) * P_{buy}(t,s) * \Delta t - \lambda_{sell}(t) * P_{sell}(t,s) * \Delta t\right] + \sum_{t\in T} Lan_G(t) * Gb(t) * \Delta t \qquad \forall t \in T, \forall s \in S \tag{2}$$

$$J_2 = \sum_{i\in A} \zeta i \tag{3}$$

$$J_3 = \sum_{s\in S} Ro(s) * \sum_{t\in T}\left[P_{buy}(t,s) * \left(C_{CO_2} * E_{CO_2} + C_{SO_2} * E_{SO_2} + C_{NO_x} * E_{NO_x}\right)\right] + \sum_{t\in T} Hb(t) * \left(C_{CO_2} * Eb_{CO_2} + C_{SO_2} * Eb_{SO_2} + C_{NO_x} * Eb_{NO_x}\right) \qquad \forall t \in T, \forall s \in S \tag{4}$$

$$J_4 = \sum_{s\in S} Ro(s) * \sum_{t\in T} Pns(t,s) * Lan_{NS}(t) \qquad \forall t \in T, \forall s \in S \tag{5}$$

B. CONSTRAINTS OF HOUSEHOLD APPLIANCES

There are different types of devices that have several advantages and disadvantages in terms of HEMS-based operational strategy. According to the ability of control, household devices can be divided into controllable and uncontrollable appliances. Based on operational characteristics, controllable appliances are classified into:

- Non-interruptible appliances (NIA) such as rice cooker (RC), dishwasher (DW), washing machine (WM).
- Interruptible appliances (IA) such as pool pump (PP) and electric vehicle (EV).
- Thermostatically controlled appliances (TCA): such as water heaters (WH), air conditioners (AC).

1) Non-interruptible appliances (NIA) modeling:

In non-interruptible appliances, when a device is turned on, it must be operated for the same period of time as the device is supposed to work. Also, it should be turned off after finishing the work. The start time of the device is at the disposal of the user, but the user cannot turn off the device before the end of the working time. In NIA, the power is constant, which means that when the device is turned on, it works with that constant power for the number of hours specified by the user. In this paper, three NIAs are considered such as a washing machine and two dishwashers. The constraints related to NIA during the planning horizon are defined as Eq. (6) to (9):

$$u_i^{APP}(t) = 0 \quad \forall t \in [1, L_i) \cup (U_i, N_T] \ , \forall i \in A_{non} \tag{6}$$

$$P_i^{APP}(t) = u_i^{APP}(t) * P_{R,i}^{APP} \quad \forall t \in [L_i, U_i] \ , \ \forall i \in A_{non} \tag{7}$$

$$\sum_{t=j}^{j+T_{L,i}-1} u_i^{APP}(t) \geq T_{L,i} * \left(u_i^{APP}(j) - u_i^{APP}(j-1)\right) \quad \forall j \in \left(L_i, U_i - T_{L,i} + 1\right) \ \forall i \in A_{non} \tag{8}$$

$$\zeta i = \sum_{t=L_i}^{U_i} (1 + \varepsilon_i * t) * u_i^{APP}(t) \quad \forall i \in A_{non} \tag{9}$$

Equation (6) shows the time when the devices are off. u_i^{APP} is a binary variable for equipment, if it is 1, it means that the device is on, and if it is zero, it means that it is off. Equation (7) shows the power consumption of the device during operation. Equation (8) shows the minimum time the device stays on, while Eq. (9) shows the satisfaction level of consumers during interval L_i to U_i . This equation shows that the earlier the equipment is turned on, the smaller the level of consumer dissatisfaction is, and it is better for the user because he seeks to minimize the level of dissatisfaction and maximize his level of comfort in using the equipment. Index *R* refers to the rated (nominal) value of the corresponding parameter. For instance, $P_{R,i}^{APP}$ denotes the rated power consumption of the appliance *i*.

2) Interruptible appliances (IA) modeling:

In interruptible appliances, when the equipment are turned on, they can be turned off during operation, or even their power can increase or decrease. The important thing about this type of appliances is that these appliances must consume a certain amount of energy during the day and need a certain amount of energy. In this paper, A pool pump and two electric vehicles are considered. Constraints related to interruptible appliances are defined as Eq. (10) to (13):

$$P_i^{APP}(t) = 0 \quad \forall t \in [1, Li) \cup (Ui, N_T] \qquad \forall i \in A_{in} \tag{10}$$

$$\sum_{t=Li}^{Ui} P_i^{APP}(t) * \Delta t \ \geq \ E_i^{APP} \qquad \forall i \in A_{in}, \forall t \in T \tag{11}$$

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP} \qquad \forall t \in T, \forall i \in A_{in} \tag{12}$$

$$\zeta i = \sum_{t=L_i}^{U_i} (1 + \varepsilon_i * t) * u_i^{APP}(t) \qquad \forall i \in A_{in} \tag{13}$$

Equation (10) shows that if the interruptible appliances are outside of the operating range, the device must be turned off. Equation (11) states that the total power consumption of the interruptible appliances must be at least equal to the energy that the user specifies, in other words, the amount of energy required for the appliances. Eq. (12) specifies the power consumption limits. Eq. (13) shows the satisfaction level of consumers using interruptible appliances in the time interval L_i to U_i. Similar, index *R* refers to the rated value of the corresponding parameter.

3) Thermostatically controlled appliances (TCA) modeling: Thermostat-controlled appliances include air conditioners, electric water heaters, etc., where electrical energy is consumed to adjust the temperature. In this study, WH and AC, which are the most important thermostat-controlled appliances in a smart home, are used. These appliances adjust the temperature with the thermostat that is available in their system. For example, the electric water heater tries to keep the temperature of the heated tank constant or control it within the desired range of the user. These devices are turned on or off according to their rated power whenever needed to control the temperature. Constraints related to water heater is defined as Eqs. (14)- (18):

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP} \quad \forall t \in T, \forall i \in WH \tag{14}$$

$$\sum_{k=1}^{t} P_T^{WH}(k,s) * \Delta t \geq \sum_{k=1}^{t} \rho_{wh}(t) \qquad \forall t \in T, \forall i \in WH \tag{15}$$

$$\rho_{wh}(t) = \lambda * m(t) * C_w * \left(T_{u,i}(t) - T_{cold}\right) \qquad \forall t \in T, \forall i \in WH \tag{16}$$

$$\sum_{k=1}^{t} P_T^{WH}(k,s) * \Delta t \leq \lambda * M * C_w * \left(\theta_i^{up} - T0\right) + \sum_{k=1}^{t} \rho_{wh}(k) \quad \forall t \in T, \forall i \in WH \tag{17}$$

$$\theta_i^{dn} \leq T_{u,i}(t) \leq \theta_i^{up} \qquad \forall t \in T, \forall i \in WH \tag{18}$$

Equation (14) shows the power consumption limits. It is clear from Eq. (15) that the power consumption of water heater from hour 1 to t must be at least equal to the power required to heat water from hour 1 to t time. Equation (16) shows the amount of required energy for heating. Equation (17) states that the power consumption by the water heater from the first hour to t must be at most equal to the energy that remains in the water heater in addition to the energy needed to heat the water, Also, it is clear from Eq. (18) that the temperature of hot water should always be between the range determined by the user. Constraints related to air conditioner is defined as Eqs. (19) to (21):

$$0 \leq P_i^{APP}(t) \leq P_{R,i}^{APP} \qquad \forall t \in T, \forall i \in AC \tag{19}$$

$$T_{u,i}(t) = T_{u,i}(t-1) + \eta\left[W_{out}(t) - T_{u,i}(t-1)\right] + \gamma * P_i^{APP}(t) * \Delta t \quad \forall t > 1, t \in T, \forall i \in AC \tag{20}$$

$$\theta_i^{dn} \leq T_{u,i}(t) \leq \theta_i^{up} \qquad \forall t \in T, \forall i \in AC \tag{21}$$

Equation (19) shows the power consumption limit of air conditioning. Equation (20) shows the relationship between indoor temperature and AC energy consumption. Equation (21) presents that the temperature inside the building should always remain within the range determined by the user. To measure users' satisfaction with TCA, the piecewise linear function shown in Fig. 3 is used. It can be seen that the deviation from $T_{C,i}$ results in a penalty for the objective function.

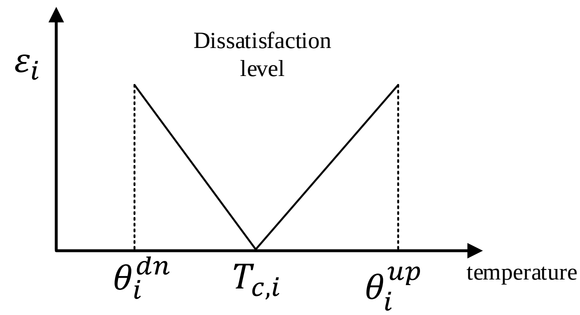

Fig. 3. Dissatisfaction function for thermostatically controlled appliances.

Satisfaction coefficients for TCAs are defined that the operating temperature of these appliances must be between the minimum and maximum temperature set by the user. An optimal temperature for the appliances, which is $T_{c.i}$, is considered as the distance from this temperature and $T_{c.i}$. Move to higher or lower temperature, the level of well-being of the residents will decrease. Now by linearizing this curve, Eqs. (22) to (24) are obtained:

$$\begin{gathered} W_{1,i} \leq Z_{1,i} \quad , W_{2,i} \leq Z_{1,i} + Z_{2,i} \quad , W_{3,i} \leq Z_{2,i} \\ W_{1,i} + W_{2,i} + W_{3,i} = 1 \quad , W_{k,i} \geq 0 \quad (k = 1,2,3) \\ Z_{1,i} + Z_{2,i} = 1 \, , Z_{k,i} = 0 \; OR \; 1 \quad (k = 1,2) \end{gathered} \tag{22}$$

Three coefficientsW_1, W_2, and W_3 are continuous and positive numbers. These coefficients calculate the temperature distance from $T_{c.i}$. Two binary variable Z_1 and Z_2 are also taken into account, which determines the working area of the device in the curve. Based on this, the temperature inside the building is modeled according to Eq. (23) based on W_1, W_2, and W_3 which depends on the desired temperature and the minimum and maximum temperature.

$$T_{u,i}(t) = \theta_i^{dn} * W_{1,i} + T_{c,i} * W_{2,i} + \theta_i^{up} * W_{3,i} \qquad \forall i \in A_{ther} \tag{23}$$

According to Eq. (24), the temperature is equal to $T_{c.i}$, the dissatisfaction is equal to zero. Accordingly, dissatisfaction is calculated only in terms of W_1 and W_3.

$$\zeta i = W_{1,i} * \varepsilon_i + W_{3,i} * \varepsilon_i \qquad \forall i \in A_{ther} \tag{24}$$

All these three categories of mentioned appliances have a series of importance coefficients that are determined by the user, that is, when the well-being of the residents of the house is measured, the effect of using these appliances on the well-being of the residents is not the same.

C. CONSTRAINTS OF ENERGY STORAGE SYSTEM

Here the storage system refers to a set of batteries that can store electrical energy and deliver it to other devices or even to the main grid when needed. Constraints related to the electric energy storage systems are as Eqs. (25)- (30):

$$P_{ESS}^{use}(t,s) + P_{ESS}^{sold}(t,s) = \eta_{ESS}^{d} * P_{ESS}^{d}(t,s) \qquad \forall t \in T \,, \forall s \in S \tag{25}$$

$$0 \leq P_{ESS}^{c}(t,s) \leq R_{ESS}^{c} * \mu_{ESS}(t) \qquad \forall t \in T \,, \forall s \in S \tag{26}$$

$$0 \leq P_{ESS}^{d}(t,s) \leq R_{ESS}^{d} * (1 - \mu_{ESS}(t)) \qquad \forall t \in T \,, \forall s \in S \tag{27}$$

$$S_{ESS}(t,s) = S_{ESS}(t-1,s) + \eta_{ESS}^{c} * P_{ESS}^{c}(t,s) * \Delta t - \frac{1}{\eta_{ESS}^{d} * P_{ESS}^{d}(t,s) * \Delta t} \quad \forall t > 1, \in T \,, \forall s \in S \tag{28}$$

$$S_{ESS}(t,s) = S_{ESS}^{ini} + \eta_{ESS}^{c} * P_{ESS}^{c}(t,s) * \Delta t - \frac{1}{\eta_{ESS}^{d} * P_{ESS}^{d}(t,s) * \Delta t} \forall s \in S, if\ t = 1 \tag{29}$$

$$S_{ESS}^{min} \leq S_{ESS}(t,s) \leq S_{ESS}^{max} \qquad \forall t \in T \,, \forall s \in S \tag{30}$$

It is clear from Eq. (25) that if the storage system is discharged, the total discharged power should either be used at home or sold to the grid. Equations (26) and (27) show the charging power and discharging power limits, respectively. Eq (28) shows the storage energy level in each hour and scenario. Eq (29) shows the energy level at each time. Finally, Eq. (30) presents the limit of stored energy in the storage system.

D. CONSTRAINTS OF THERMAL ENERGY STORAGE

A thermal energy storage can be used in a smart home. There is a tank in this home where hot water is stored and its loss can be reduced by isolating it. Constraints related to the thermal energy storage unit are in equations 31 to 33:

$$S_{TES}(t,s) = S_{TES}(t-1,s) + \eta_{TES}^{c} * P_{TES}^{c}(t,s) * \Delta t - \frac{1}{\eta_{TES}^{d} * P_{TES}^{d}(t,s) * \Delta t} \forall t > 1, \in T, \forall s \in S \tag{31}$$

$$S_{TES}(t,s) = S_{TES}^{ini} + \eta_{TES}^{c} * P_{TES}^{c}(t,s) * \Delta t - \frac{1}{\eta_{TES}^{d} * P_{TES}^{d}(t,s) * \Delta t} \quad \forall s \in S, if\ t = 1 \tag{32}$$

$$S_{TES}^{min} \leq S_{TES}(t,s) \leq S_{TES}^{max} \qquad \forall t \in T \,, \forall s \in S \tag{33}$$

Equation (31) shows the energy level of thermal storage in every hour and every scenario. It is clear that Eq. (32) presents the energy level of thermal storage in the first hour. Equation (33) limits the stored energy between minimum and maximum values.

E. PV MODELLING

A small Photovoltaic panel with a 1 kW capacity is also used in this smart home. Equation (34) states that the generating power of PV unit can be used by indoor appliances or injected into the grid.

$$P_{PV}^{use}(t,s) + P_{PV}^{sell}(t.s) = P_{PV}\,(t,s) \qquad \forall t \in T\,, \forall s \in S \qquad (34)$$

F. WIND MODELLING

A small wind turbine with a 1 kW capacity is also used in this smart home. It is clear from Eq. (35) that the actual production power of the wind turbine can be used for two purposes. It can be injected into the grid or consumed by the appliances inside the home:

$$P_{wind}^{use}(t,s) + P_{wind}^{sell}(t,s) = P_{wind}\,(t,s) \qquad \forall t \in T\,, \forall s \in S \qquad (35)$$

G. POWER BALANCE CONTRAINT

Equation (36) expresses the power balance that ensures the generated energy must be equal to the consumption for each hour[7].

$$P_{buy}(t,s) + P_{PV}^{use}(t,s) + P_{wind}^{use}(t,s) + P_{ESS}^{use}(t,s) + Pns(t,s) = P_{ESS}^{c}(t,s) + \sum_{i \in A} P_i^{APP}(t) + P_{must_{run}}(t) \qquad \forall t \in T\,, \forall s \in S \qquad (36)$$

H. POWER EXCHANGED WITH THE GRID

Equation (37) shows the total amount of power sold to the grid:

$$P_{sell}(t,s) = P_{PV}^{sell}(t,s) + P_{ESS}^{sell}(t,s) + P_{wind}^{sell}(t,s) \qquad \forall t \in T\,, \forall s \in S \qquad (37)$$

Equations (38) and (39) ensure that power purchased from the grid and power injected into the grid cannot occur simultaneously:

$$P_{buy}(t,s) \leq N_1 * \mu_{grid}\,(t) \qquad \forall t \in T\,, \forall s \in S \qquad (38)$$

$$P_{sell}(t,s) \leq N_2 * \left(1 - \mu_{grid}\,(t)\right) \qquad \forall t \in T\,, \forall s \in S \qquad (39)$$

N_1 and N_2 are the maximum power that can be bought from the grid and the maximum power that can be sold to the grid, respectively.

I. UNCERTAINTY MODELING

In this paper, wind and solar production sources are used as renewable sources, whose output power is a function of wind speed and solar radiation, respectively. In this study, the uncertainties caused by these sources have been modeled using scenario generation and using the Weibull and Beta distribution functions.

1) Uncertainty model of PV power:

In this simulation, to check the uncertainty related to solar energy, Beta distribution function is used, which is defined by two parameters α and β. For each solar power, these two parameters are adjusted based on the distribution of the series of numbers we have and produce a scenario. In this method, the predicted value of PV power is considered as the average value. In the Beta distribution, we need two parameters, the average predicted power per hour and its standard deviation. In this method, the probability of occurrence of each scenario should be calculated as follows. After calculating the probability of occurrence of the scenario, it should be normalized[11].

$$f(x;\alpha,\beta) = f_{p_{pv}} = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\times\Gamma(\beta)}\,(p_{pv})^{\,\alpha-1}\,(1-p_{pv})^{\,\beta-1} & if\; p_{pv} \in [0,p_{pv}(si)] \\ 0 & other\; wise \end{cases} \qquad (40)$$

For the Beta distribution, in order to reduce the volatility of different scenarios, the value of the standard deviation should be reduced.

2) Uncertainty model of wind power:

It is essential to use a suitable model in predicting wind turbine production. The Weibull distribution function is defined by two parameters, which are the scale parameter and the shape parameter. For each wind power, these two parameters are set based on the distribution of the series of numbers and produce a scenario. In the Weibull distribution, the probability of occurrence is calculated as follows. After calculating the probability of the scenario, it must be normalized. If the random variable X has support with non-negative and continuous values, so that its density function is written as follows, then this random variable has a Weibull distribution with parameters k and λ[11]:

$$f(x,\lambda,\mathrm{k}) = RO_{WIND} = \begin{cases} \frac{\mathrm{k}}{\lambda}\left(\frac{x}{\lambda}\right)^{\mathrm{k}-1} e^{-(x/\lambda)^{\mathrm{k}}} & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad (41)$$

In the above relation, λ is the scale parameter and k is the shape parameter. Also, x refers to p_{wind}. In this case, it is displayed as $x \sim w(\lambda, \mathrm{k})$ where x has a Weibull distribution with parameters λ and k. Both these parameters have positive values. If the dispersion of the scenarios is required to be further apart, the shape parameter or k should be reduced.

J. HUB MODELING

An energy hub represents an interface between different energy sub structures. In this paper, smart home appliances are considered such as dishwashers, washing machines, pool pumps, electric vehicles, uncontrollable loads, heat pumps, water heaters, boilers, thermal loads, electric storage, thermal storage, gas network, electricity grid, and renewable sources to model the smart home by an energy hub system. Constraints related to boiler and hub energy are in the form of Eqs. (42)-(49) [34]:

$$P_{TES}^{c}(t,s) = Hb_{TES}(t,s) + P_{TES}^{WH}(t,s) \quad \forall t \in T, \forall s \in S \tag{42}$$

$$P_{TES}^{d}(t,s) = H_{TES}^{TL}(t,s) + H_{TES}^{WH}(t,s) \quad \forall t \in T, \forall s \in S \tag{43}$$

$$Hb(t) = Gb(t) * Nb \quad \forall t \in T \tag{44}$$

$$0 \leq Hb(t) \leq Hb^{max} \quad \forall t \in T \tag{45}$$

$$Hb(t) = Hb_{WH}(t,s) + Hb_{TL}(t,s) + Hb_{TES}(t,s) \quad \forall t \in T, \forall s \in S \tag{46}$$

$$P_{i}^{APP}(t) = P_{TES}^{WH}(t,s) + P_{wh}^{WH}(t,s) + P_{TL}^{WH}(t,s) \quad \forall t \in T, \forall s \in S, \forall i \in WH \tag{47}$$

$$Dh(t) = H_{TES}^{TL}(t,s) + Hb_{TL}(t,s) + P_{TL}^{WH}(t,s) \quad \forall t \in T, \forall s \in S \tag{48}$$

$$P_{T}^{WH}(t,s) = H_{TES}^{WH}(t,s) + Hb_{WH}(t,s) + P_{wh}^{WH}(t,s) \quad \forall t \in T, \forall s \in S \tag{49}$$

It is clear from Eq. (42) that the charging power of the thermal storage must either be supplied by the boiler or WH. Equation (43) states that the power discharged by the thermal storage is consumed by the thermal loads or heats water. Equation (44) shows the production power of the boiler. Equation (45) presents the production limit of the boiler. It is clear from Eq. (46) that the generated heat of the boiler is used for heating water, thermal loads stored in the storage tank. From Eq. (47) it is understood that the power produced by WH can be stored in a storage tank, used for heat water or thermal loads. Also, Eq. (48) states that the thermal loads must either be supplied by the storage device, supplied by the boiler, or supplied by WH. Finally, Eq. (49) determines the total power consumption of heat water.

K. TOPSIS METHOD

After solving the multi-objective problem for the residential hub, a set of optimal Pareto solutions is recommended, which must be chosen from the user's point of view. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a widely used and practical multi-criteria decision-making (MCDM) method. This method provides different advantages. It ranks alternatives based on their proximity to the ideal and negative-ideal solutions, making it intuitive and easy to implement. TOPSIS can simultaneously handle both beneficial and non-beneficial criteria without requiring assumptions about data distribution or utility functions. It also allows for flexible weighting of criteria and produces interpretable results. In this study, TOPSIS is employed to select the optimal demand response strategy considering multiple conflicting technical, economic, and operational criteria. In this method, *m* options are evaluated by *n* indicators. It is assumed that the desirability of each index is uniformly increasing or decreasing, which is defined for positive ideal (A^{+}) and negative ideal (A^{-}) options. The value of the indicators is between 0 and 1 and is mostly based on mathematical calculations. The biggest value shows the higher priority, which means that it is a suitable option. The best option has the minimum distance from the positive ideal solution and the furthest distance from the negative ideal solution. This TOPSIS model is implemented in eight steps according to the following steps:

1) Creating a decision matrix from the collected information and creating a data matrix based on n indicators and m options in Eq. (50) where i options and j represent indicators. X_{ij} is the i-th index value for the j-th option.

$$X_{ij} = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix} \quad (i = 1, \dots, n), \quad (j = 1, \dots, n) \tag{50}$$

2) The decision-making matrix must be normalized by Eq. (51) so that its data is descaled. Then, by standardizing the indices, the domain of X_{ij} values is converted into a standard domain and the standardized values of R_{ij} indices are obtained as the standard matrix of Eq. (52).

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} {X_{ij}}^{2}}} \tag{51}$$

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{52}$$

3) Determining the weight of each index based on Eq. (53). Indices with more weight are more important, and the sum of the weights must be equal to 1, where W_j is the weight of the i-th index. It should be noted that the weights of the objectives are assigned according to the decision-maker’s

priorities and can vary depending on the specific requirements and preferences of the system under study.

$$\sum_{j=1}^{n} W_j = 1 \tag{53}$$

4) Converting the step 2 decision matrix into a weighted unscaled matrix. V_{ij} is the weighted normalized matrix elements which is created based on Eqs. (54) and (55):

$$v_{ij} = r_{ij} \times w_j \tag{54}$$

$$V_{ij} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \tag{55}$$

5) Finding the positive ideal solution (A^+) by determining the maximum value based on equation (56) and the negative ideal solution (A^-) by determining the minimum value based on equation (57). V_j^+ is the positive ideal value for the jth index and V_j^- is the negative ideal value for the jth index.

$$A^+ = (V_1^+, V_2^+, V_3^+, \ldots, V_n^+) \quad \{(max_i\, v_{ij} | j \in J), (min_i v_{ij} | j \in J')\} = v_j^+ \tag{56}$$

$$A^- = (V_1^-, V_2^-, V_3^-, \ldots, V_n^-) \quad \{(min_i\, v_{ij} | j \in J), (max_i v_{ij} | j \in J')\} = v_j^- \tag{57}$$

6) Calculation of the distance between the positive ideal and the negative ideal based on the Euclidean method. S_i^+ is the distance of the i-th option from the positive ideal that is calculated based on Eq. (58). S_i^- is the distance of the i-th option from the negative ideal that is calculated based on Eq. (59).

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{58}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{59}$$

7) Calculation of the relative closeness of the ideal solution based on the index C_i based on Eq. (60) which is defined to combine the values of S_i^+ and S_i^- and compare the options:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{60}$$

8) Ranking options based on their relative proximity to the ideal solution and the similarity index C_i .This value varies between 0 and 1. The closer the similarity index value to one, the more superior the option is which means that the option is ranked better.

III. CASE STUDY

A. DESCRIPTION OF DESIGNED TEST SYSTEM

A home with various appliances connected to HEMS is considered as a test system. The costumers register their information that reflects their preferences for comfort and desired lifestyle. Some of the registered information which makes the user comfortable and other information about the equipment are given in Table 2. Other specifications related to thermostat-controlled appliances, which include water heaters and air conditioners, are listed in Tables 3 and 4, respectively. The specifications related to the electrical storage are given in Table 5 and the specifications related to the thermal storage are given in Table 6.The price of energy exchanged with the grid is shown in figure (4). The outside temperature is shown in Fig. 5. The amount of hot water consumption of the smart home is demonstrated in Fig. 6. Also, there are uncontrollable loads in the smart home, such as lighting loads, as shown in Fig. 7.

B. RESULT

In order to evaluate the effect of the proposed method on the operation cost and customer's welfare, three case studies have been designed. The designed case studies are as follows:

- Case Study 1: In this case, $\varpi_1 = 1$ and $\varpi_2 = 0$ are considered, which means that the objective function is to reduce the operation cost without considering customer satisfaction. In this case, the well-being of consumers is not important in using smart home devices, and the only goal is to optimize the cost of payment. This case is considered as a base case in this study.
- Case study 2: In this case, $\varpi_1 = 0.5$ and $\varpi_2 = 0.5$ are considered. In this case, the proposed model simultaneously considers both cost payment and customer satisfaction. Also, both objectives have the same preferences from the smart home point of view.
- Case Study 3: In this case, weight coefficients are changed from 0 to 1 and the best solution is selected by TOPSIS. Actually, this case study considers different preferences between objective functions.

Table 2. User of desired comfort preferences.

Type	Appliances	Preferred temperature	Duration (h)	Preferred interval $[L_i,U_i]$	Rated power(kW)	Required energy(kW)	Coefficient resenting importance
NIA	WM	-	2	[8,23]	1.8	-	0.1
	DW1	-	1	[13,16]	1.2	-	0.2
	DW2	-	1	[17,23]	1.2	-	0.3
IA	PP	-	-	[2,15]	0.8	1.6	0.1
	EV1	-	-	[6,24]	2.2	6.5	0.2
	EV2	-	-	[11,23]	1.7	5	0.3
TCA	AC	27	-	-	2	-	1
	WH	55	-	-	3	-	2
HA	Boiler	-	-	-	2	-	-

Table 3. Specifications related to the water heater model

$T_{c,i}$ (°C)	$T_{0_{WH}}$ (°C)	M (kg)	θ_i^{dn} (°C)	θ_i^{up} (°C)	T_{cold} (°C)	C_w (J/kg/C)	λ (kWh/J)
55	49	140	45	68	30	4200	1/3600000

Table 4. Specifications related to the Air conditioning model

$T_{0_{AC}}$(°C)	$T_{c,i}$(°C)	θ_i^{dn} (°C)	θ_i^{up} (°C)	γ	η
23	27	23	29	-9.5	0.9

Table 5. Specifications related to the electric storage model

S_{ESS}^{max} (kWh)	S_{ESS}^{min} (kWh)	S_{ESS}^{ini} (kWh)	S_{ESS} (kWh)	R_{ESS}^{c} (kWh)	R_{ESS}^{d} (kW)	η_{ESS}^{c}	η_{ESS}^{d}
7.20	0.80	2.80	8	1.80	1.80	0.95	0.95

Table 6. Specifications related to the Thermal storage model

S_{TES}^{max} (kWh)	S_{TES}^{min} (kWh)	S_{TES}^{ini} (kWh)	S_{TES} (kWh)	R_{TES}^{c} (kWh)	R_{TES}^{d} (kW)	η_{TES}^{c}	η_{TES}^{d}
10	0	2.50	11	1	1	0.95	0.95

(1) Case study 1:

The main goal of this case study is payment cost minimization. The simulation results show that the consumer payment cost is 79 cents and the dissatisfaction value is 199. Smaller dissatisfaction shows the higher the residents' welfare level. For the proposed model, 10 scenarios have been considered due to uncertainty in power generation by renewable sources. The energy transactions with the grid, encompassing both import and export, are depicted in Fig. 8.

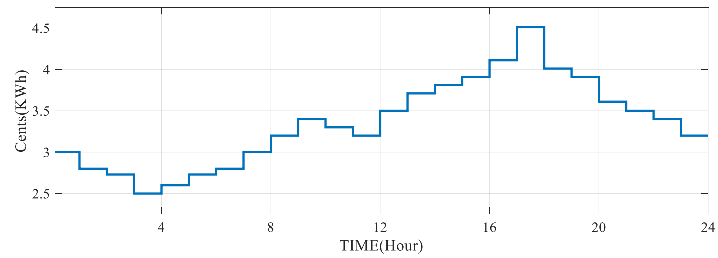

Fig 4. Information on the price of buying and selling electricity from the grid.

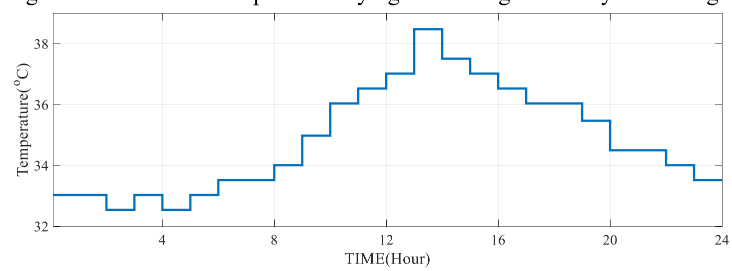

Fig. 5. Outdoor temperature over a day.

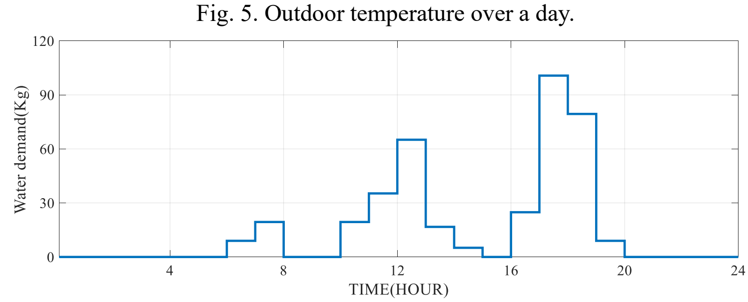

Fig. 6. Water demand over a day.

It can be observe that the purchasing electricity from the grid during off-peak hours is more than other hours because the electricity prices are low. Therefore, the customers prefer to purchase electricity from the grid. However, they reduce the purchasing electricity from peak hours because of high electricity prices. The charge and discharge power diagram of the electric storage and the charging level of the storage for case study 1 is shown in Fig. 9. Figure 9 shows that the electric storage is charged during off-peak times because the electricity prices are low. They discharged the stored energy during peak hours with high prices to reduce the total cost of the system. The charging and discharging capability of energy storage systems can effectively mitigate the uncertainty associated with renewable energy generation by balancing supply and demand in real time.The power consumption of home appliances is shown in Fig. 10 for case study 1. The types of equipment used in the smart home include washing machine, dishwasher 1 and 2, pool pump, electric vehicle 1 and 2, air conditioner, water heater, and boiler. The amount of energy consumption of each device is given along with the preset hour of its use. It can be observed that the proposed model attempts to achieve the lowest electricity bill by buying electricity from the grid during low

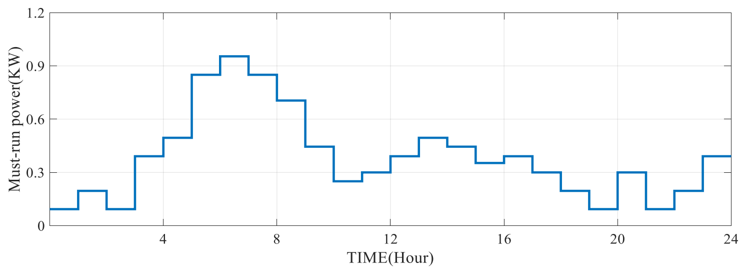

Fig. 7. Must-run power over a day.

price periods and charging the ESUs. The household appliances keep the lowest level of comfort in advance. According to Fig. 10, it can be observed that during the early hours of the day, the boiler is actively utilized due to the relatively low gas prices at that time. This operational strategy reflects the cost-effective use of available energy resources, whereby the system prioritizes gas-based heating when it is economically favorable. By doing so, the model minimizes energy expenses while ensuring that the thermal demands of the household are adequately met. This also allows the thermal storage unit to be charged in preparation for later hours when gas prices are higher. According to Fig. 11, during the same early hours when gas prices are relatively low, the thermal storage system is simultaneously charged while fulfilling the immediate thermal load requirements. This operational strategy reflects an effective energy management approach, wherein the boiler is utilized to generate heat at a lower cost, and the surplus thermal energy is stored for later use. As gas prices increase during subsequent periods, the stored thermal energy is discharged to meet the heating demand, thereby avoiding the need for expensive fuel consumption during peak price hours. This illustrates the model's capability to shift thermal energy usage from high-cost to low-cost periods, enhancing both economic efficiency and system flexibility. Such proactive utilization of thermal storage not only reduces operational costs but also contributes to the resilience and sustainability of the smart home energy system.

(2) Case study 2:

In this case, both the consumer's welfare and payment costs are considered with the same importance. The simulation results show that the payment cost by the consumer is 93 cents, and the amount of dissatisfaction is 38. Compared to case study 1, the level of consumer dissatisfaction has been significantly reduced. In this case study dissatisfaction as the objective function, the proposed model decreases it from 199 cents to 93 cents. The energy trading to the electricity grid in case study 2 is shown by Fig. 12. During off-peak periods, characterized by lower electricity prices, consumers are more likely to increase their energy usage or shift flexible loads to these hours in order to minimize their overall electricity costs. In contrast, during peak periods with higher prices, consumption is reduced or deferred. The proposed model effectively captures this behavior by optimizing the load scheduling to align with dynamic pricing signals, thereby improving economic efficiency while maintaining user satisfaction.

The consumed power of home appliances in case study 2 is shown in Fig. 13. Compared to case study 1, it is clear that some items such as DW2 and PP have been transferred to the previous times. The charging and discharging power diagram of the electric storage unit for case study 2 is shown in Fig. 14. Energy storage units are charged during off-peak hours when electricity prices are low, and subsequently discharged during peak demand periods to support the household's energy needs. This strategic operation not only enhances load flexibility but also contributes to cost reduction by leveraging the price differential between off-peak and peak hours. As shown in Fig. 15, the thermal storage unit is simultaneously charged when the boiler is in operation to meet the thermal loads. When the gas prices increase, the stored thermal energy is discharged to supply heating needs, thereby reducing the overall operational cost of the smart home.

(3) Case study 3:

In this case, we apply all of the available weight coefficients between zero and 1 and calculate 100 different solutions. This case shows the sensitivity of payment costs and dissatisfaction with the weight coefficients. Among these solutions, the best option is determined by the TOPSIS method. According to the TOPSIS ranking method, it can be seen that the optimal solution for ϖ_1 is $0.87-0.94$ and Also, for the weighting factorϖ_2 is $0.13-0.06$. In this case, the amount of consumer dissatisfaction is 40 and the payment cost is 80 cents. The TOPSIS method selected this solution because it offers an optimal balance between operation cost and consumer dissatisfaction. A slight increase in dissatisfaction can lead to substantial cost savings, making the trade-off efficient. Besides, system constraints tend to favor cost reduction without significantly compromising comfort. The chosen solution also ranks best by minimizing the distance to the ideal point and maximizing the distance from the worst, aligning with TOPSIS criteria.The amount of energy trading with the electricity grid in case study 3 is presented in Fig. 16. Due to the lower electricity prices during off-peak hours, consumers increase their energy transactions with the electricity grid. This increased activity is driven by the economic incentive to take advantage of cheaper electricity costs. Also, during peak hours 14-22, when electricity prices are substantially higher than at other times, substantially, the volume of energy transactions decreases to reduce the energy costs. The planning power of household appliances is shown in Fig. 17.

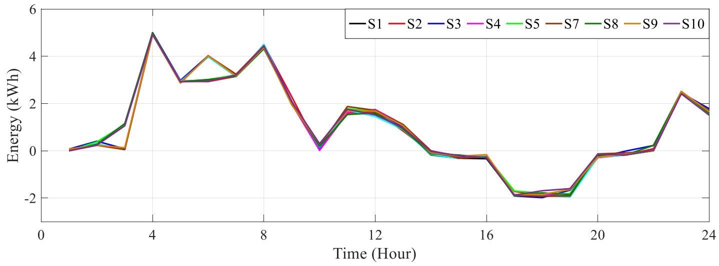

Fig. 8. Hourly purchase of energy from the grid or sale of energy to the grid for case 1.

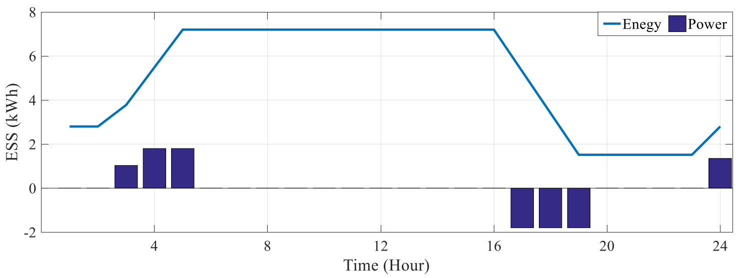

Fig. 9. Energy change of ESUs in one day for case 1.

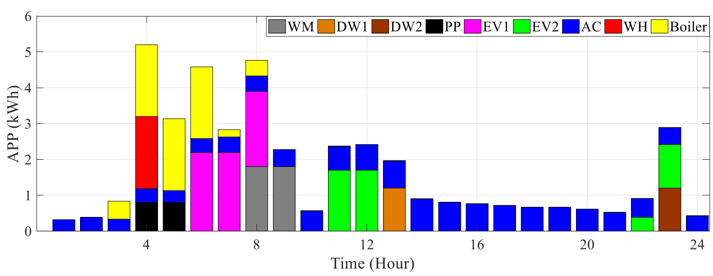

Fig. 10. Scheduling of household appliances for case 1.

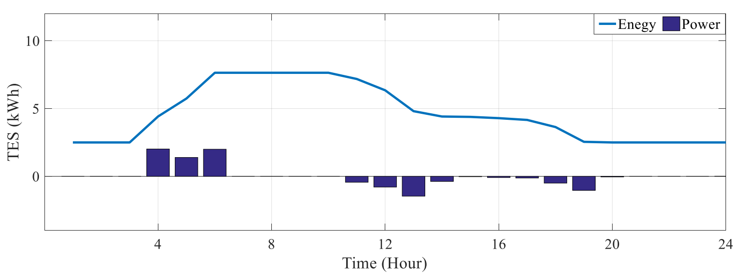

Fig. 11. Energy change of thermal storage in one day for case 1.

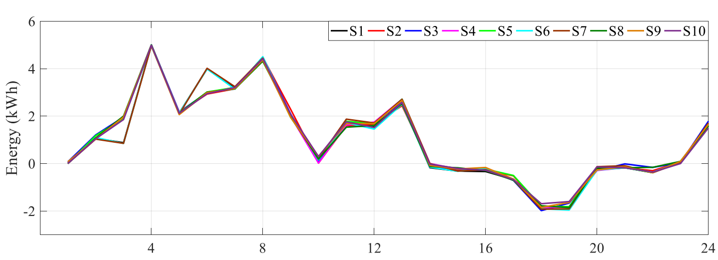

Fig. 12. Hourly purchase of energy from the grid or sale of energy to the grid for case 2.

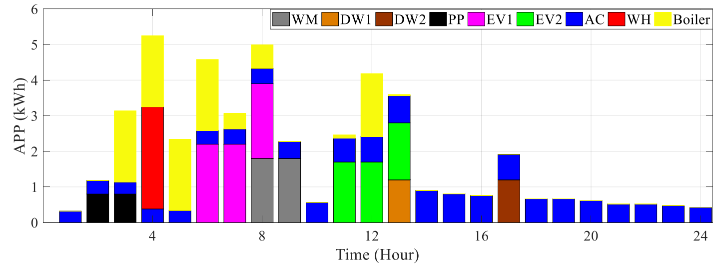

Fig. 13. Operation of smart home appliances for case 2.

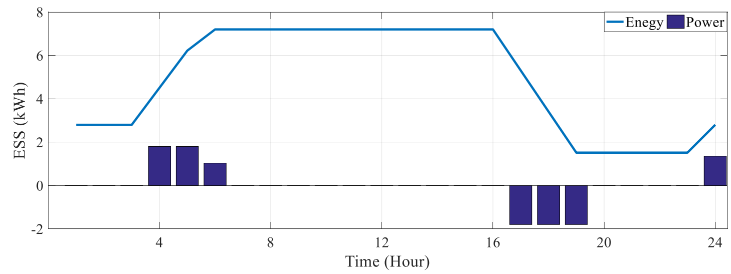

Fig. 14. Energy change of ESUs in one day for case 2.

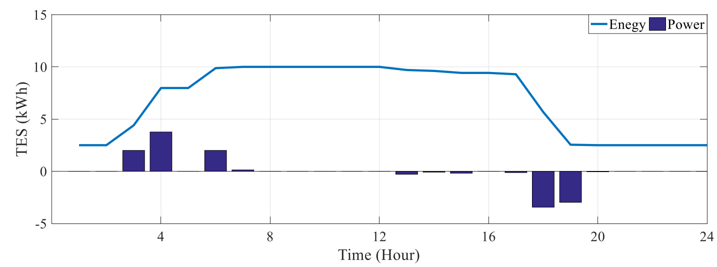

Fig. 15. Energy change of thermal storage in one day for case 2.

Electric vehicles are charged during off-peak periods to prevent increased operational costs associated with high electricity prices. Besides, dishwashers are scheduled to operate during low-price off-peak hours, reflecting a deliberate strategy to minimize energy expenses. Also, Figs. 18 and 19 demonstrate the charge and discharge power diagram of the electric and thermal storage devices, respectively. The results of Figs. 18 and 19 show that the energy storage devices are charged during low electricity prices and discharged during peak hours when prices are high. These charging and discharging performances enable the cost-saving opportunity for customers to reduce total cost.

IV. CONCLUSION

In this paper, a new price-based home energy management is proposed which tries to reduce costs and increase consumer satisfaction. In this model, several case studies have been discussed and all types of smart home appliances with various characteristics has been considered in the proposed

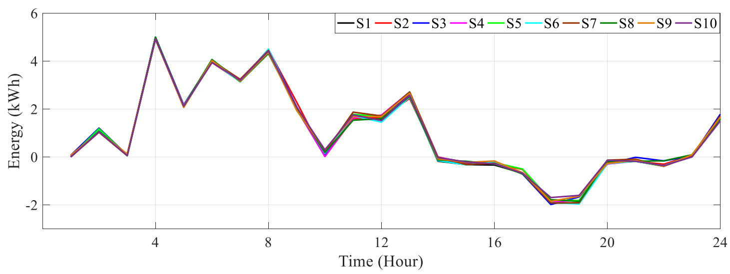

Fig. 16. Hourly purchase of energy from the grid or sale of energy to the grid for case 3.

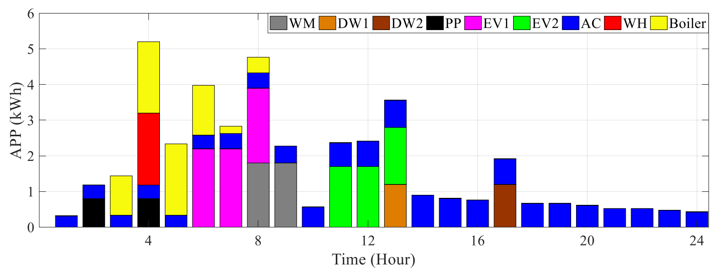

Fig. 17. Schedule of household appliances for case 3.

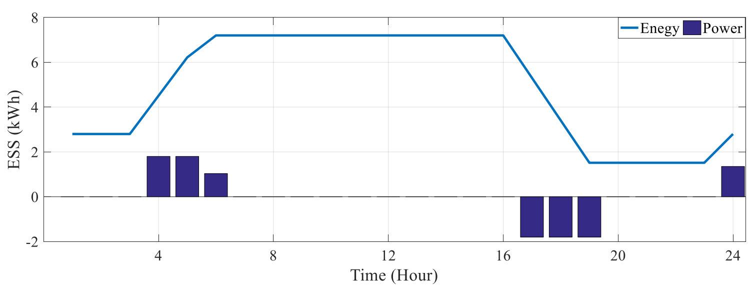

Fig. 18. Energy change of ESUs in one day for case 3.

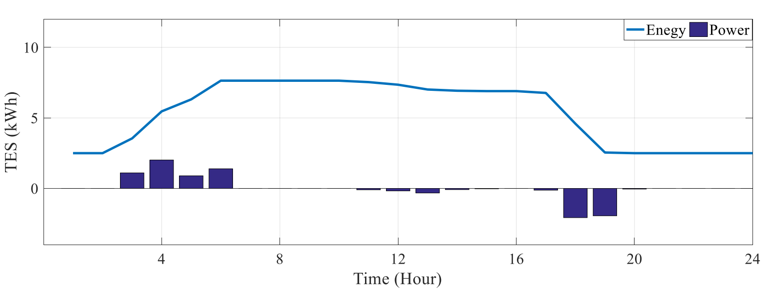

Fig. 19. Energy change of thermal storage in one day for case 3.

framework. Also, with a developed satisfaction model, the proposed HEMS can provide several flexible solutions with different levels of user satisfaction for residents. Different case studies have been considered to evaluate the impact of weight coefficients on smart home performance. To use the model, a balance must be found between the cost and the welfare level, which is expressed as the optimal response. In optimal response Compared to case study 1, by paying one cent more, the customer's well-being increases significantly, and also compared to case study 2, by paying 13 cents less, he can get the appropriate amount of well-being. In future work, the peer-to-peer energy trading among several HEMS will be studied.

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