Machine-Learning-Based Home Energy Management Framework Via Residents' Feedback

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***Abstract*—This study introduces a smart home energy management (SHEM) framework using an artificial neural network (ANN) approach that incorporates user feedback to gauge preferences regarding cost and comfort. The SHEM framework aims to minimize energy costs by adjusting the operation of home devices according to hourly electricity prices. However, deviations from user preferences can lead to varying levels of dissatisfaction. Residents provide feedback at the end of each day, rating their satisfaction with the energy management system on a scale from 0% (completely dissatisfied) to 100% (completely satisfied). The findings reveal how prioritizing dissatisfaction over cost affects energy management, overall cost, and total dissatisfaction. The ANN-based framework is then tested with two artificial users, demonstrating that the proposed SHEM framework can accurately learn to prioritize dissatisfaction over cost within a few days of operation.**

Keywords—Machine learning; Energy management; Residents satisfaction; smart home energy management (SHEM).

I. Introduction

The integration of emerging energy sources and the concurrent rise in energy demand, especially during climatic extremes, necessitate focused attention on energy optimization and the associated costs of procuring energy from the market for household consumption. Addressing these challenges can be effectively achieved by adopting smart home energy management (SHEM). Functioning as an intelligent control network, grounded in the principles of smart grids, smart homes (SH), and smart meters, SHEM is a viable solution capable of adeptly managing fluctuations in electricity price and consumption patterns [1]. In recent years, propelled by the swift technological progress of Artificial Intelligence (AI), SHEM has undergone significant advancements. This evolution enables local and remote control and autonomous operation, fostering heightened energy efficiency.

Numerous studies in the literature aim to present a management framework for SH. Ref [2] presented a SHEM system based on user experience, assigning profiles to assets considering Renewable Energy Sources (RES). Authors in ref [3], discussed a SH model balancing energy cost and user dissatisfaction with new comfort specifications. Ref [4] proposed a SHEM using time series-based load forecasting, showing effectiveness in predicting residents' behaviors. Ref [5] introduced a model based on Mixed Integer Linear Programming (MILP) for minimizing SH energy costs while considering electric vehicles and energy storage systems (ESS). Ref [6] proposed an energy management system to minimize the grid dependence of RES-integrated SHEM. Ref [7] presented an energy-sharing technique for SHEM of smart grid communities.

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Utilizing AI, these systems can assimilate and analyze extensive datasets to create models that establish control strategies, automatically adapting to optimal scenarios for energy consumption reduction. Nevertheless, it is necessary to fine-tune this AI model to prioritize energy reduction and consider maintaining resident comfort levels and responding to demand [8]. In [9], an ML-based method was introduced for a SHEM, integrating human feedback to prioritize low-cost electricity use in diverse homes. The study emphasized the impact of human activity patterns on AI system performance. Ref. [10] presented a hierarchical ML-based method for scheduling energy consumption in SHs, incorporating appliances and distributed energy resources. The approach utilized a two-level ML-based structure, demonstrating the programming of multiple devices and optimizing EV and ESS usage.

In [11] discussed an ML algorithm monitoring domestic appliances to reduce energy consumption, using a Q-Learning algorithm in a SHEM. The proposed method tried to reduce electricity costs without compromising user comfort. Flexible loads in this paper are controlled via the amount of their power consumption and Shiftable loads have not been studied. Ref [12] proposed an energy management strategy using ML for controllable loads in SHEM, achieving close-to-optimal results based on residents' lifestyle habits. Shiftable loads have not been studied in this work as well. Ref. [1] introduced an AI-based SHEM providing energy efficiency and user satisfaction. The heating system is considered as the main load in this work. Authors in [13] proposed an ML-based strategy for SHEM using the residents' historical data. Ref [14] introduced a Q-Learning algorithm for SHEM based on human-appliance interaction. Using historical data for understanding user behavior in [14] and [15] may not reflect the changes in their habit or preferences for cost reduction over discomfort.

The aim of the SH model of this study is like the SH frameworks presented in [14] and [15] through the incorporation of artificial intelligence. In [14] and [15], Q learning and reinforcement learning approaches are employed for energy management, while our work utilizes an ANN-based method.

Although many contributions in the literature presented different SHEM models [16], a straightforward SHEM framework that could understand user preferences on satisfaction over cost reduction via their feedback has not been efficiently addressed. By filling the mentioned research gap, this work develops a SHEM framework via an ANN-based approach based on the user's feedback to understand user preferences on cost and comfort in addition to the priority of each appliance for the user.

The proposed SHEM framework controls the operation of home assets based on the hourly electricity price to minimize energy costs. However, deviations from user preferences may lead to varying levels of dissatisfaction.

In this regard, residents at the end of consecutive days leave their feedback that presents to what extent they are satisfied with the performance of the energy management framework by submitting a number between 0% (indicative of complete dissatisfaction) to 100% (indicative of complete satisfaction).

Furthermore, various linearization methods are employed to alleviate the computational burden within the optimization framework facilitating the treatment of the problem as mixed-integer linear programming (MILP).

The remaining work is structured as follows: Section II provides the mathematical information related to the home energy management model, ANN-based approach, and users' comfort level index, while Section III provides the case study and the analysis results. Final remarks are addressed in Section IV as the conclusion.

II. Problem Formulation

A. Energy Management Framework

SH appliances have been categorized into two categories: permanent loads such as heating systems that permanently operate during the day (permanent loads do not refer to inelastic or uncontrollable loads. They are controllable loads via modifying the amount of their power consumption), and shiftable loads like washing machines and dishwashers that are required to operate a few hours a day.

The energy management problem consists of the objective function, the operational constraints of different assets, aiming at minimizing the energy cost and discomfort simultaneously, as represented in (1). The first term stands for the electricity cost of the SH and the second term represents the total discomfort. β defines the priority of comfort over cost reduction. λ_t, $D_{i,t}^c$, D_j^S stand for hourly electricity price, and discomfort related to the permanent and shiftable loads, respectively.

$$OF = \sum_{t=0}^{T} \lambda_t P_t + \beta \times \left(\sum_{i=0}^{N_i}\sum_{t=0}^{T} D_{i,t}^c + \sum_{i=0}^{N_j} D_j^S\right) \tag{1}$$

For the permanent loads, the discomfort criteria are calculated based on their operation point deviation from the residents' preferred operation point, and for the shiftable loads, it is calculated according to their operation time deviation from the residents' preferred time as represented in (*2*) and (3), respectively. $\theta_{i,t}$, T_i^{pr} , T_i^{min} , T_i^{max} are actual, preferred, minimum allowed, and maximum allowed temperature. f_j^{op} , f_j^{pr} , f_j^{min}, f_j^{max} are actual, preferred, minimum allowed, and maximum allowed operating hours.

$$D_{i,t}^c = \begin{cases} \dfrac{T_i^{pr} - \theta_{i,t}}{T_i^{pr} - T_i^{min}} & if \;\; \theta_{i,t} \leq T_i^{pr} \\ \dfrac{\theta_{i,t} - T_i^{pr}}{T_i^{max} - T_i^{pr}} & if \;\; \theta_{i,t} > T_i^{pr} \end{cases} \tag{2}$$

$$D_j^S = \begin{cases} \dfrac{f_j^{op} - f_j^{pr}}{f_j^{max} - f_j^{pr}} & if \;\; f_j^{op} > f_j^{pr} \\ \dfrac{f_i^{pr} - f_j^{op}}{f_j^{pr} - f_j^{min}} & if \; f_j^{op} \leq f_j^{pr} \end{cases} \tag{3}$$

Through the formulation of thermal modeling given by (4), the temperature of each room is calculated based on the heater consumption and outdoor temperature.

$$\theta_{i,t+1} = e^{\frac{-\Delta}{\tau}} \theta_{i,t} + \left(1 - e^{\frac{-\Delta}{\tau}}\right) R_i P_{i,t}^{heat} + \left(1 - e^{\frac{-\Delta}{\tau}}\right) \theta_t^{out} \tag{4}$$

As the discomfort formulation presented in (*2*) and (*3*) are nonlinear, a simplification method is used to provide linear discomfort formulation.

This way the binary variable u^1 is introduced which takes the value 1 if $\theta_{i,t} > T_i^{pr}$ and 0 otherwise. This way, if conditions are removed, and (5) is added to the constraints, therefore, formula (2) is replaced by (6).

$$(2u_{i,t}^1 - 1)(\; \theta_{i,t} - T_i^{pr}\;) > 0 \tag{5}$$

$$D_{i,t}^c = \frac{u_{i,t}^1(\theta_{i,t} - T_i^{pr}) + (1 - u_{i,t}^1)(T_i^{pr} - \theta_{i,t})}{u_{i,t}^1(T_i^{max} - T_i^{pr}) + (1 - u_{i,t}^1)(T_i^{pr} - T_i^{min})} \tag{6}$$

Although the nonlinearity from the if condition is removed, there exists the nonlinear term $u_{i,t}^1\theta_{i,t}$ in (5) and (6) which is the multiplication of two variables. In this regard, a new variable is introduced where $z_{i,t}^1 = u_{i,t}^1\theta_{i,t}$. So, (7)-(10) are added to the problem as constraints to present a linear formulation for $u_{i,t}^1\theta_{i,t}$. It should be noted that $M_1$is a big enough value.

$$z_{i,t}^1 \leq M_1 u_{i,t}^1 \tag{7}$$

$$z_{i,t}^1 \leq \theta_{i,t} \tag{8}$$

$$z_{i,t}^1 \geq 0 \tag{9}$$

$$z_{i,t}^1 \geq \theta_{i,t} - M_1(1 - u_{i,t}^1) \tag{10}$$

Considering (7)-(10), it is guaranteed that $z_{i,t}^1$ is equal to $u_{i,t}^1\theta_{i,t}$. Therefore, $u_{i,t}^1\theta_{i,t}$ is replaced by $z_{i,t}^1$ in (5) and (6). This way, the nonlinearity from the multiplication of two variables is removed. So, (5) and (6) are replaced by (11) and (12).

$$2z_{i,t}^1 - 2u_{i,t}^1 T_i^{pr} - \theta_{i,t} + T_i^{pr} > 0 \tag{11}$$

$$D_{i,t}^c = \frac{2z_{i,t}^1 - 2u_{i,t}^1 T_i^{pr} - \theta_{i,t} + T_i^{pr}}{u_{i,t}^1(T_i^{max} - T_i^{pr}) + (1 - u_{i,t}^1)(T_i^{pr} - T_i^{min})} \tag{12}$$

With the same process and introducing of binary variables u_j^2 as well as z_j^2 that is equal to $u_j^2 f_j$, the nonlinear discomfort formulation for temporary services (3) is replaced by (18) where (13) – (17) are added to the constraints of the problem.

$$z_j^2 \leq M_2 u_j^2 \tag{13}$$

$$z_j^2 \leq f_j^{op} \tag{14}$$

$$z_j^2 \geq 0 \tag{15}$$

$$z_j^2 \geq f_j^{op} - M_2(1 - u_j^2) \tag{16}$$

$$2z_j^2 - 2u_j^2 f_j^{pr} - f_j^{op} + f_j^{pr} > 0 \tag{17}$$

$$D_j^S = \frac{2z_j^2 - 2u_j^2 f_j^{pr} - f_j^{op} + f_j^{pr}}{u_j^2(f_j^{max} - f_j^{pr}) + (1 - u_j^2)(f_j^{pr} - f_j^{min})} \tag{18}$$

B. Artificial Neural Network

ANN are computational models inspired by the human brain consisting of artificial neurons interconnected in layers, which process input information, pass through hidden layers, and produce output results. ANN is trained by adjusting the weights of connections between neurons, to minimize errors, with gradient descent being the fundamental optimization algorithm for training ANNs, and error backpropagation being a crucial component of this process [17].

The overall scheme of an ANN is depicted in Fig. 1. This way, ANN is trained via sets of input data and their corresponding output data for defining the weights of connections between neurons.

In this work, a single-input/single-output ANN is used, where the input is the feedback submitted by the user on different days, and the output is their corresponding β with which the energy management was performed on that day.

C. Process for Understanding the β Related to the User

As mentioned beforehand, β reflects the priority of comfort over the cost reduction for the residents. However, since different users have diverse priorities about cost and comfort, a process is required to understand the value of the β for each user. In this proposed approach, the user's experience with the performance of the SHEM is used to understand the value of β for the user. Indeed, the β_{real} of a user is for when the submitted feedback by the user is 100%.

In this regard, a few days are considered the evaluation days d_e. The evaluation days are considered for trial and error to provide an efficient dataset for β. This way, firstly, an initial value for β is considered and the energy management is done on the first day. At the end of the day, the user reflects their satisfaction with the performance of the SHEM by submitting a number between 0% and 100%.

This process is repeated for the second day via a random β. For the rest of the evaluation days, β is calculated based on the user's feedback on previous days as represented in Fig. 1. It should be noted that after the calculation of β for each day, the energy management is done based on the obtained β and the user will submit feedback on the performance of the SHEM at the end of the day.

When the evaluation days are finished, the ANN is trained by the set of feedback values submitted by the users and their corresponding β. It should be noted that the set of feedback is the input of the ANN and the corresponding β is the output. The goal here is to develop an ANN that can estimate the user's feedback for each β.

However, the ANN is developed in such a way that could provide an estimation of the β that will result in 100% feedback. This is why the feedback set is the input of the ANN and the β set is the output. It is noteworthy that the β selection process in the evaluation days is designed to sooner reach closer feedback to 100%. This way, the accuracy of the ANN in the higher ranges of the feedback for estimating the equivalent β is higher.

For the next day, the output β of the ANN called β_{v} for input feedback equal to 1 is obtained to provide a preliminary estimation of the β that results in 100 feedback. However, β_v is not accurate as the ANN has not been trained with a large data set. Therefore, β for that day is calculated based on β_v as well as β and feedback of the last two days as represented in Fig. 2. The formula is designed to utilize the obtained β in the previous days to better estimate the real β. The energy management is done based on the obtained β and the user submits feedback on the performance of the SHEM at the end of each day.

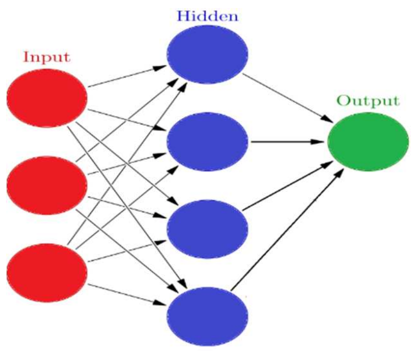

Fig. 1. The simplified scheme of an ANN.

The new β and feedback are added to the existing database and the ANN is trained again with the new database to repeat the same process for the next day.

The process will be repeated until reaching to 99% feedback as the desired feedback. Through several simulations, the activation function of the neural network chosen for this case was "Elu". This ANN is a 3-layer Feed Forward ANN.

In this work, it is considered that the user submits the feedback based on their feeling about the performance of the energy management framework. Considering the real behavior, in the long term, the user preference may vary, however, in a short time each user has a unique preference.

III. Results and Discussion

A. Case Study

The SH consists of three rooms each having a separate heating system. The maximum, minimum, and preferred temperatures for each room are presented in TABLE. *I*.

Moreover, the maximum, minimum, and preferred operation times for the dishwasher and laundry are presented in TABLE. *II*. Regarding laundry appliances: a Samsung Add Wash WW90T554DAW washing machine, energy class A, consumption of 49 kWh/100 cycles [18]; and a Samsung DW60M6040FS dishwasher, energy class E, consumption of 262 kWh/year (considering 100 washes per year) [19].

The operating times of both machines were 1h and their operating times are presented in TABLE. *II*. Furthermore, hourly electricity price and outdoor temperature are depicted in Fig. 3.

B. Operational Results

In this section, the operation of the home energy management system is investigated given that the priority of the cost over dissatisfaction is known. In this regard, the results for different βs and seasons are presented in TABLE. III. It is observed that for higher β the dissatisfaction is lower, and cost is higher as expected because the priority of dissatisfaction over cost is higher.

As expected, in winter, the energy cost is higher than in summer, especially for β with 100% feedback. Moreover, the dissatisfaction with using the washing machine is 0 in all cases. This shows that the preference of the user is completely in line with the economical scheduling of the washing machine. Furthermore, both the dissatisfaction and energy costs are higher in winter in comparison with summer due to lower outdoor temperatures for β equal to 0.01 and 0.1. However, for β with 100% feedback, total dissatisfaction is equal to 0 owing to the very high importance of dissatisfaction over cost.

The indoor temperature is depicted in Fig. 4 (a) and (b) in summer and winter. In this regard, it is shown that for the consumer with β with 100% feedback, the indoor temperature is equal to the preferred temperature at all hours. However, for β equal to 0.1 and 0.01 the temperature deviates from the preferred temperature, which results in dissatisfaction, and the deviation for $\beta = 0.01$ is higher than when $\beta = 0.1$ due to lower priority of dissatisfaction over cost.

Since there is no real data from users, we tried to proceed with artificial data. In this regard, for data generation, it is assumed that there is a logical relation between β and user feedback as represented in Eq. (19) . This way, it is assumed that the artificial user will leave feedback based on (19). In this regard if $\beta = \beta_{real}$, the feedback is equal to 100%. Otherwise, there exists feedback less than 100% for other values of β.

$$Feedback = 1 - |\beta - \beta_{real}| \tag{19}$$

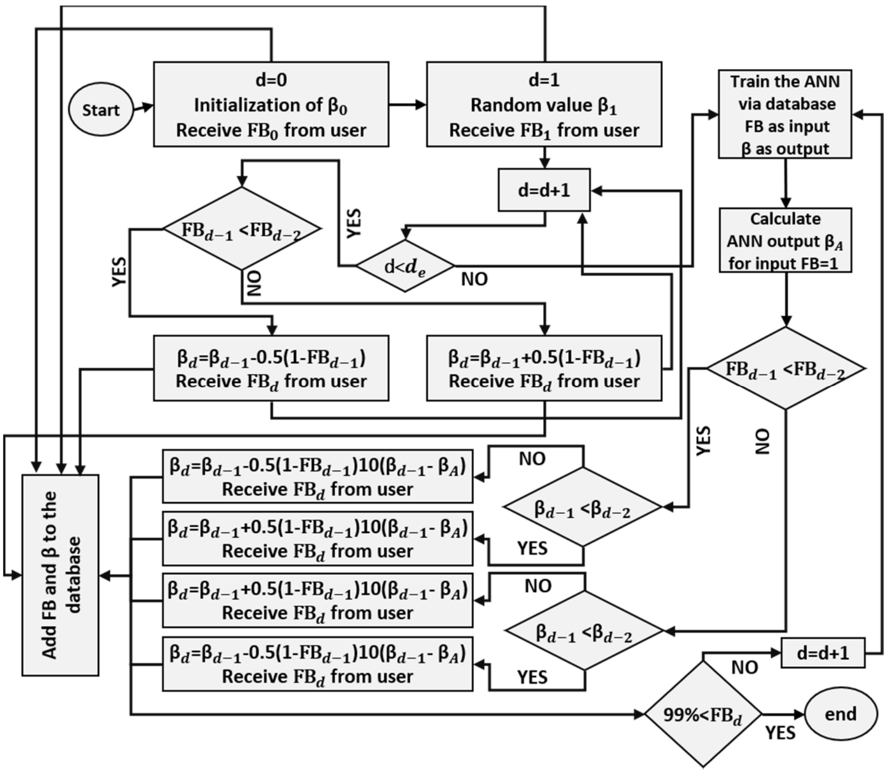

Fig. 2. Flowchart of the proposed ANN-based framework.

TABLE. I TEMPERATURE DATA

	Winter	Summer
T^{min}	15	18
T^{max}	24	26
T^{pr}	21	24

TABLE. II APPLIANCE DATA

	Dishwasher	Laundry
f^{min}	9	17
f^{max}	16	23
f^{pr}	12	21

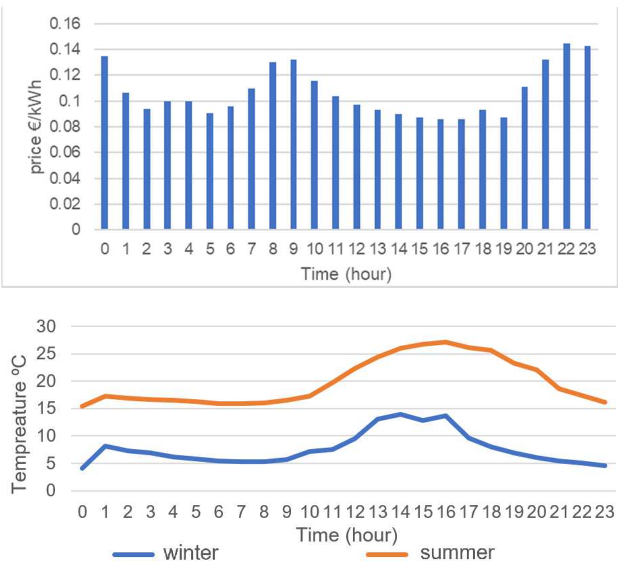

Fig. 3. Hourly electricity price (up) and outdoor temperature (down).

Now, it is necessary to investigate if the proposed framework could understand the $Beta_{Real}$ of the user. Here it is considered two different cases for validating the proposed approach to analyze data from two different users.; case A where the β_{real} for the residents is 0.05 and for case B where the β_{real} for the residents is 0.7. The β_{real} values are selected in such a way as to provide an evaluation of our proposed approach for two cases with completely different priorities.

Fig. 5 (a) shows the β training values for Case A where the β for different days (and their corresponding feedback) are used for training the ANN (the first 15 days for training and the last for days for testing). Fig. 5 (b) depicts the output of ANN for different feedback as input reflecting the performance of the developed ANN in predicting the β corresponding to each day (based on the feedback on that day). It is observed that the developed ANN can predict the β for both the training and test data with high accuracy.

Fig. 6 depicts the values of β obtained by our proposed approach on different days and their corresponding feedback. It is observed that after 8 days, the output β of the ANN-based framework is 0.051 which is close to the β_{real} of the user (0.05) which results in feedback equal to 99%. After day 8 when β is understood precisely, the cost and dissatisfaction of the energy management for the user of case A in winter and summer are obtained as presented in Table IV.

Similar to Fig. 5 in Fig. 7 the training and prediction data for Case B is depicted. Although the accuracy of the ANN for this case is less than Case A, the ANN can predict the user preference with acceptable accuracy. It is observed that after 20 days, the output β of the ANN-based framework is 0.689 which is close to the β_{real} of the user (0.7) which results in feedback equal to 99%. After day 20 when β is understood precisely, the cost and dissatisfaction of the energy management for the user of case A in winter and summer are obtained as presented in TABLE. V.

TABLE. III OPERATION RESULTS

Season	*Summer*			*Winter*		
β	0.01	0.1	100	0.01	0.1	100
Total D	14.16	1.75	0	18.97	2.91	0
D^c	13.66	1.25	0	18.47	2.41	0
D^S_{DW}	0.5	0.5	0	0.5	0.5	0
D^S_{WM}	0	0	0	0	0	0
f^{op}_{DW}	19	19	21	19	19	21
f^{op}_{WM}	12	12	12	12	12	12
Energy Cost	0.27	0.85	1.19	1.05	1.80	2.43

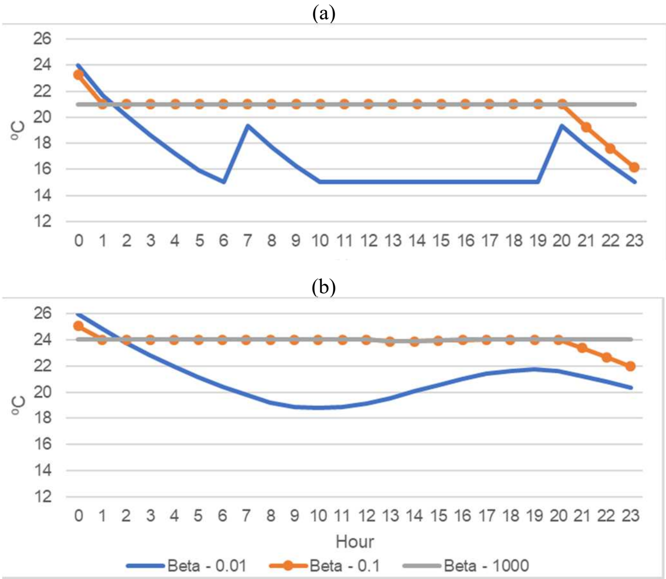

Fig. 4. The indoor temperature in summer (a) and winter (b).

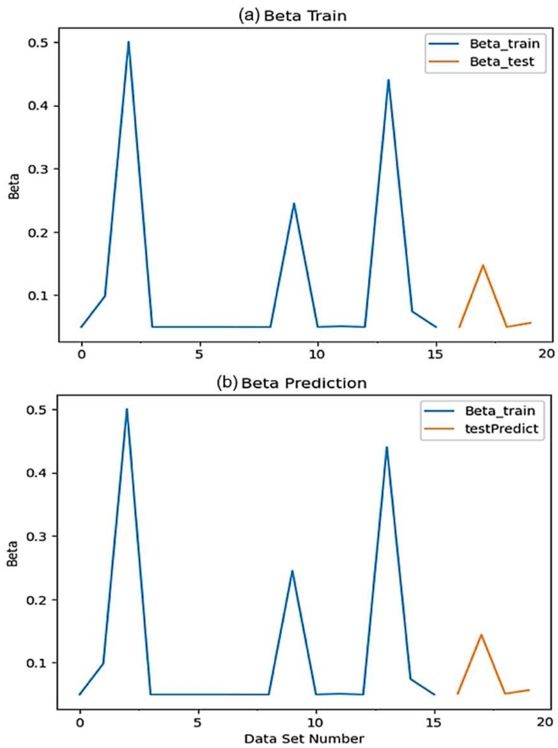

Fig. 5. Training (a) and prediction values of β (b) for Case A.

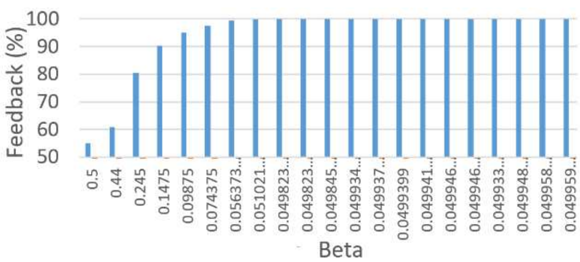

Fig. 6. β on different days and their corresponding feedback in case A.

TABLE. IV COST AND DISSATISFACTION IN CASE A

$\beta = 0.05$	Summer	Winter
Cost	3.432 €	5.729 €
Dissatisfaction	3.706	7.813

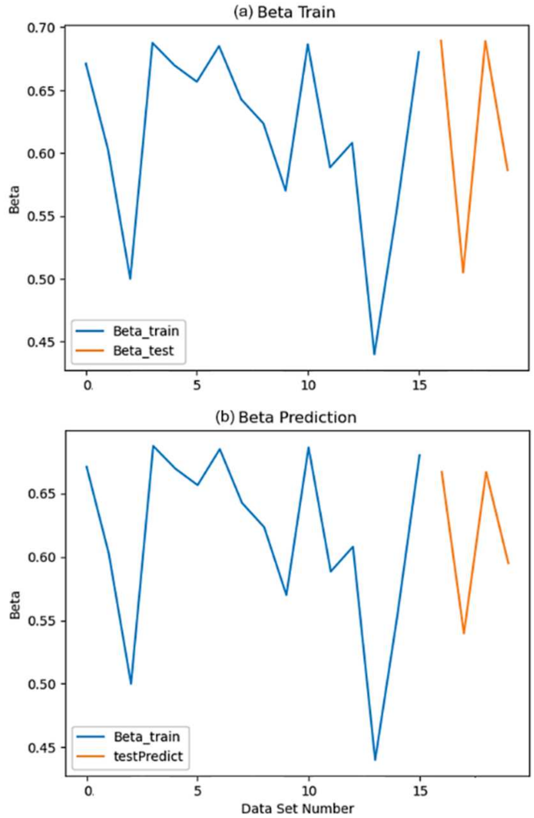

Fig. 7. Training (a) and prediction values of β (b) for Case B.

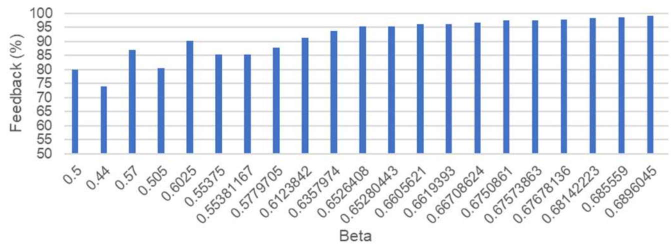

Fig. 8. β in different days and their corresponding feedback in case B.

TABLE. V COST AND DISSATISFACTION IN CASE B

$\beta = 0.7$	Summer	Winter
Cost	3.9€	6.699 €
Dissatisfaction	0.251	0.199

IV. CONCLUSION

In this work, an ANN-based SHEM framework is proposed to understand the propriety of cost over for the user based on the submitted feedback by the user at the end of consecutive days. The proposed SHEM framework manages the operation of the assets to minimize energy costs and dissatisfaction. In this regard, energy management was conducted for users with different preferences, and it was shown how the priority of dissatisfaction over cost impacts energy management, total cost, and total dissatisfaction. Then, the proposed ANN-based framework was validated for two artificial users. It was observed that our proposed framework could understand the priority of dissatisfaction over cost after a few days of running based on the users' feedback with high accuracy.

In future research, the studies will be conducted considering an ML-based approach to understand the priority of different assets and services for the users in smart homes, considering as well further comparison and analysis considering scalability of the problem and the problem facing user's random behavior.

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