A Multi-Objective Model for Home Energy Management System Self-Scheduling using the Epsilon-Constraint Method

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***Abstract*—Self-scheduling of Home Energy Management Systems (HEMS) is one of the most interesting problems for active end-users to reduce their electricity bills. The electricity bill reduction by adopting Demand Response Programs (DRP) considering the flexibility of the end-users is addressed in this paper. The problem is addressed as a multi-objective optimization problem. The first objective function is the minimization of the daily bill, while the second objective aims to minimize the Discomfort Index (DI) regarding shifting the home appliances plugging-in time. The Time-of-Use (ToU) tariff is adopted in this paper and therefore, the end-users can benefit from shifting their flexible loads from peak hours to the off-peak hours and this reduces their bills, accordingly. In this case, the end-users have to change their energy consumption which imposes a level of discomfort on the end-users. Therefore, a two-stage model is proposed in this paper to deal with the mentioned objective functions. The proposed model is represented as standard mixed-integer linear programming (MILP) and for solving this problem the epsilon-constraint method is adopted in this study. The obtained Pareto front from the epsilon-constraint multi-objective framework is fed to the fuzzy satisfying method for final plan selection. These results show that by providing the Pareto set of optimal solutions to the user, they are more informed and can make decisions that better suit their preferences.**

Keywords—Home Energy Management Systems, Epsilon-constraint Method, Multi-objective Optimization.

I. INTRODUCTION

A. Background and Motivation

Home Energy Management Systems (HEMS) are becoming an essential component of modern households, whose energy requirements are constantly increasing due to the shift towards modern, energy-dependent, lifestyles. Therefore, an automated system is undoubtedly needed to manage this electrical energy demand from modern households. Typically, HEMS have been a key component of Demand Side Management (DSM) strategies, mostly Demand Response (DR) programs [1], [2].

With this perspective, the main objective of HEMS was to shift consumer appliances' electricity usage from peak hours to off-peak hours, mainly to reduce overall energy costs (a shared benefit with participating consumers) and increasing power system reliability.

A major challenge in DR program implementation in general, and HEMS, in particular, has been the inconvenience caused by forcing consumers to shift their appliance usage, especially when the economic incentive is not large enough to compensate for the discomfort.

More recently, additional objectives for HEMS models have been introduced in the literature, such as consumer satisfaction and user behaviour, which have a major impact on the mass adoption of HEMS. This is because consumers normally like to control their own schedules, and thus Satisfaction-Oriented HEMS helps provide this by scheduling appliances into timeslots they would favour more than others.

B. Literature Review

Recent works on HEMS have considered a wide variety of objectives while solving the scheduling problem. In [3], a HEMS model was presented that also maintained the comfort of consumers by trying to minimize the total bill while achieving the consumer's electricity bill target and therefore relaxing the optimization problem.

Most studies in the literature focus on one objective function while modelling other objectives as problem constraints. Nonetheless, it's more reasonable to consider multiple objectives in order to satisfy both the consumer and the system's objectives.

In [4], the mathematical modelling of HEMS with the incorporation of small-scale renewable energy sources (RES) was addressed. The main objective of the proposed model was to manage the demand for household loads in a smart manner to simultaneously reduce both the energy bill of the customer and the peak demand of the network.

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A modern approach to HEMS was also introduced in multiple recent works [4], [5], connecting smart grids to appliances via Internet of Things (IoT) and using Radio Frequency Identification (RFID) technology to fully automate control over household appliances, and distributed energy resources (DER) such as RES or Electric Vehicles (EV). This concept of a smart home with IoT-enabled HEMS is shown in Fig. 1. In order to enhance energy efficiency while minimizing environmental pollution, local RES are incorporated into the HEMS problem In [5], the HEMS scheduling problem has been solved to minimize the cost of energy (CE) and time-based discomfort (TBD) with conflicting trade-offs, which was based on DR program participation with RES and energy storage system optimal dispatching.

There are some difficulties in the implementation phase of the HEMS scheduling problem dealing with the system uncertainties such as renewable energy as well as uncertainties about the actions of customers. There are some solutions proposed in literature, such as a stochastic approach which was suggested in [6], the model optimizes the expense of the consumer in various DRPs, thus maintaining the satisfaction of the consumers by implementing an index of fatigue response, different case studies done in [6] showed that implementing the proposed stochastic HEMS model can significantly reduce the cost and response fatigue of customers.

Another approach used regarding the uncertainty related to solar energy generation is in [7] as a Chance-Constrained (CC) optimal scheduling which was used subject to the operational limitations of each HEMS. The proposed Distributional Robust Chance Constrained (DRCC) HEMS has proven to be optimally effective and computationally efficient while taking into account the uncertainties. A new heuristic optimization algorithm was introduced by the authors of [8] to solve an optimal Distributed Residential Energy Resources (DRERs) scheduling model which was proposed to minimize the cost of home operations while taking into account the needs of consumers.

Recently, real-time scheduling framework was introduced to HEMS, as shown in [9] a new DSM System where a real-time electricity scheduling model was used to operate the smart homes. The optimization problem was solved by using a genetic algorithm and in order to reduce the differences between predicted and real information, a real-time method for renewable generation prediction was introduced. Results confirm that the proposed solution could increase home electricity scheduling efficiency.

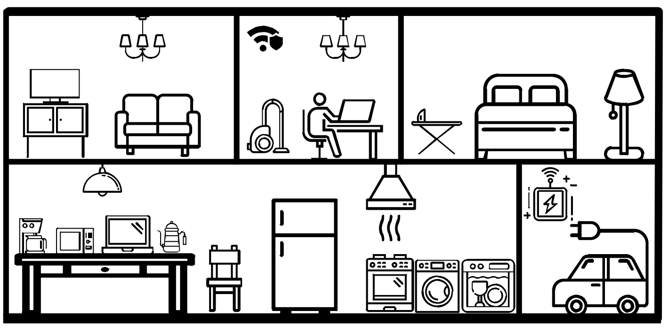

Fig. 1. Conceptual model of an IoT-enabled smart home with HEMS.

Making use of EV batteries has been acknowledged as a crucial issue in the realization of a sustainable system, but it has its difficulties, uncertainties and many unknown variables.

One of the most challenging issues is related to the timing of consumers plugging-in their EVs. In this regard, the authors in [10] presented a new solution for vehicle battery charging control which optimizes in-vehicle battery loading and discharge mode using predicted home power load data and potential vehicle state in the household. The prediction algorithm was developed based on semi-Markov model alongside a dynamic programming approach. User discomfort is one of the main concerns of HEMS, as consumers generally won’t adopt a technology that will disrupt their behaviour even if it will reduce their bill.

In [11], a flexibility analysis has been performed to help the HEMS run appliances effectively without causing excessive discomfort to users. Using smart plugs, the type of device connected could be deduced and the user behaviour could be patterned to dispatch appliances without disrupting these patterns. Thermal appliances have a considerable effect regarding users’ discomfort levels and the authors in [12] took an approach to address this issue by transforming the HEMS optimization problem from single-time scale to multi-time scale in order to decrease the computational time. A multi-objective model for HEMS has been proposed in [13] and two primary objectives have been considered, the consumer's energy bill and the peak load demand, and the problem was converted to a single-objective problem using weighted sum technique.

In [14] a three-stage HEMS was introduced, at the first stage, short-term forecasting to generate day-ahead predicted solar energy profiles, at the second stage a peak-to-average Home Energy Resource (HER) scheduling model is used to decrease the daily bill, in the last stage a model predictive control is introduced to correct HER actions with the use of real-time information, the proposed HEMS applies a reactive thermal comfort model to support decision-making on the scheduling of the household's heating, ventilation and air conditioning system.

C. Contributions

This paper presents two novel contributions. The first is the multi-objective optimization using both the electricity bill and the user’s Discomfort Index as objectives and taking into account ToU tariffs. The second contribution of this paper is to use the concept of fuzzy decision making, specifically the Epsilon-Constraint Method, to ensure that the chosen solutions adequately account for the trade-off between cost and comfort and thus the solution should lie on the Pareto front of various solutions.

D. Paper Organization

The rest of this paper is organized in the following manner, the methodology and problem formulation are described in the next section. Particular emphasis is placed on fuzzy decision-making approaches, especially the Epsilon-Constraint Method used to solve multi-objective models. Then in Section IV, the methodology is applied to a case study and the results of this are presented. In Section V, the conclusions drawn from these results are presented.

II. Methodology and Problem Formulation

A. HEMS Self Scheduling Problem

The self-scheduling problem for optimal operation of HEMS appliances is subjected to determining the time intervals for each flexible load. The HEMS consists of some smart controllers connected to the smart meters and it can provide some signals for activating the plugging-in of the devices to the grid. In a simple model of the HEMS, the end-user is responsible for the optimal operation of the home appliances.

In such a structure, the self-scheduling problem can be defined as the optimal scheduling of each flexible appliance during the target horizon. For some appliances, the end-user can shift the plugging-in time to the nearest time intervals and for some others, the end-user can effectively defer the usage to reduce the bill when considering different time-based tariffs. Fig.1 illustrates the general home appliances considered in this paper.

These appliances generally can be decomposed to the fixed and shiftable loads. The refrigerator is one of the fixed loads connected all the time to the grid. Some other appliances like lighting and television are assumed to be non-flexible loads. Therefore, these loads can be addressed as fixed loads as well. On the other hand, the washing machine, vacuum cleaner, dishwasher, spine dryer, iron, etc. can be assumed as flexible loads. In this context, the end-user can handle the plugging time of such appliances to reduce the electricity bills. In this paper, the self-scheduling problem of HEMS is proposed.

The main target of the end-users in this paper is a reduction in the daily bill. The main signal sent to the end-user is the hourly tariffs and then, the end-user has this ability to manage the energy consumption. The ToU tariffs can be provided for the weekdays and weekends and holidays for each season.

The ToU tariffs used in this study are shown in Fig 2. Such tariffs are fixed during the specific months and the end-user knows about the peak and off-peak hours. Therefore, the tariff wouldn't be changed and it hasn't any fluctuations in the target day for implementing the self-scheduling of HEMS.

The optimal scheduling of HEMS in this paper is modelled as a multi-objective optimization problem. In this model, the first objective is related to the minimization of daily bills, while the second objective function aims to minimize the discomfort index. It is evident that the discomfort index can be defined just for the shiftable loads.

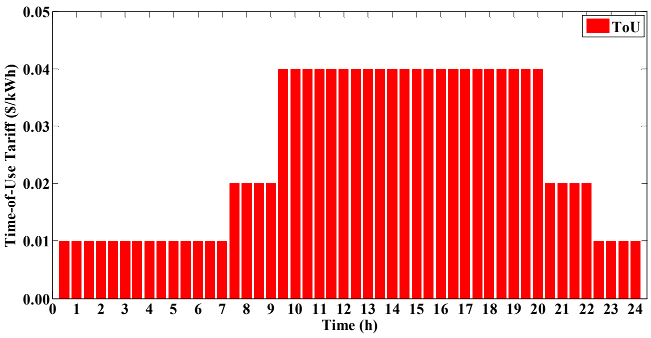

Fig. 2. Typical Time-of-Use tariff

The mathematical formulation of the mentioned cost functions are as follows:

$$\begin{aligned} &Min\\ &f_1 = \underbrace{\sum_{t=1}^{NT}\left[\pi_t^{Tariff} P_t^{G2H} \Delta t\right]}_{Electricity\ Bill} + \\ &\underbrace{\left(\sum_{i=1}^{NA}\sum_{t=1}^{NT}\left[ST_{i,t}C_i^{ST} + SH_{i,t}C_i^{SD}\right] - \sum_{i=1}^{NA}\left[C_i^{ST} + C_i^{SD}\right]\right)}_{Start-up\ and\ Shut-down\ Cost} \end{aligned} \tag{1}$$

$$\begin{aligned} &Min\\ &f_2 = \underbrace{\left(\sum_{i=1}^{NA}\left[DI_i^+ + DI_i^-\right]\right)}_{Discomfort\ Index} \end{aligned} \tag{2}$$

The daily bill cost includes the amount of consumed energy by the household for both fixed and shiftable loads. Therefore, for the fixed loads, the end-user has to pay for the energy consumption billed at the hourly tariff, π_t^{Tariff}. The total energy consumption can be represented by the amount of injected power from the grid to the house, P_t^{G2H} considering the time interval, Δt. Since the shiftable loads can be deferred in the predefined bands, it is necessary to avoid the interruptions during their operations. Therefore, in this paper, one start-up and one shut-down is assumed for each shiftable appliance. In order to penalize the frequent start-up and shut-down actions in the operational horizon, the number of start-up and shut-down actions are added to the cost function. So, if an appliance has more than one start-up and one shut-down action in the predefined band, it will be penalized. The associated binary variables for start-up, $ST_{i,t}$, and shut-down, $SD_{i,t}$, are considered to address these costs. Regardless of the real costs of the start-up and shut-down costs, C_i^{ST} and C_i^{SD}, respectively, the optimization problem should avoid multiple these actions. Therefore, for the sake of simplicity, the aforementioned costs can be selected as a big positive parameter to attain the target. Moreover, the multi-objective problem has some constraints as follows:

$$B_{i,t} = \begin{cases} 0 & t < LB_{i,b} \\ 1 & LB_{i,b} \le t \le UB_{i,b} \\ 0 & t > UB_{i,b} \end{cases} \quad B_{i,t} \in \{0,1\} \tag{3}$$

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

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

$$\sum_{t=1}^{NT} S_{i,t} = T_i \quad \forall i = 1,2,...,NA \tag{6}$$

$$\sum_{i=1}^{NA} S_{i,t}\, P_i = P_t^{D,Shift} \tag{7}$$

$$P_t^{G2H} = P_t^{D,Fix} + P_t^{D,Shitf} \tag{8}$$

$$ST_{i,t} - SH_{i,t} = S_{i,t} - S_{i,t-1} \quad \forall t > 1 \tag{9}$$

$$DI_i^- \geq \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times B_{i,t} - \sum_{t=1}^{NT} t \times S_{i,t}\right] \tag{10}$$

$$DI_i^+ \geq \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times S_{i,t} - \sum_{t=1}^{NT} t \times B_{i,t}\right] \tag{11}$$

The baseline and shifted operating intervals are addressed as binary parameters and binary variables, respectively. For the baseline, the binary string must represent the same interval as the end-user prefers. Therefore binary parameters, $B_{i,t}$ are supposed to be "1" for the predefined intervals and must be "0" for the other time intervals, (3). However, the identical binary variables, $S_{i,t}$, in the case of shiftable loads can be "1" in the acceptable range of operation (4). Equations (5) and (6) are introduced to address the plug-in duration of each shiftable appliance. It is evident the total number of non-zero binary parameters and binary variables must be equal with the usage duration of the appliances, T_i. Equation (7) deals with the shiftable demand representation considering the total plugged-in status of the shiftable appliances, while the load balance constraint is addressed in (8). In order to address the start-up and shut-down actions, for each shiftable appliance, a simple equality constraint as suggested in (9). By addressing the operation string of the binary variables, the transition states from "0" to "1" and "1" to "0" can provide the start-up and shut-down actions, respectively. Equation (10) and (11) represent the shifting the operation duration for the shiftable loads to before and after the baseline intervals, respectively. These equations are provided according to the Euclidian distance index.

B. Fuzzy Decision Making Approach

In multi-objective optimization, fuzzy decision making is employed to make a selection of a feasible solution set in order to provide the best compromise. Membership functions are assigned to fuzzy sets, in which each solution in the set is assigned a membership value ranging from 0 to 1, corresponding to completely incompatible to fully compatible, respectively [15]. I.e., for a given objective function f, a candidate solution X fully satisfies the objective if its membership function value, $\mu f(X)$, is equal to one, and completely discarded if it is equal to zero. In this study, linear membership functions are assigned.

Once membership functions are assigned to all candidate solutions in the feasible space, the most compatible solutions are selected according to their membership functions. This is done by minimizing the total deviation from the ideal value for $\mu f(X)$ for the selected subset. This selection is performed repetitively until the ideal trade-off between the different objective functions is determined according to the decision maker's priorities.

In this study, those are the user's discomfort index, and the total electricity bill and the selection were based on the second norm of the deviation of $\mu f(X)$ from the desired value. More details regarding the fuzzy decision-making approach used can be found in [16]–[18]. To employ fuzzy decision making, a set of candidate solutions that satisfy the multiple objective functions must first be calculated. In this study, the Epsilon-Constraint method is used, as described in the next section.

C. Epsilon-Constraint Method for Solving MOPs

As opposed to single-objective optimization problems, MOPs have multiple objective functions which need to be satisfied. A set of decision variables improving the value of one function would lead to the worsening of another and vice versa. As such, rather than having a single optimal solution, a set of optimal candidate solutions is obtained. This set of candidate solutions forms what is known as the "Pareto front" (as shown for the current problem in Fig. 3). To obtain the Pareto front, the epsilon-constraint method was applied in this study [19]. The electricity bill is considered as the main objective function (f_1), while the discomfort index (f_2) is modelled as an inequality epsilon constraint:

$$\min f_1(x) \;\; subject\, to \;\; f_2(x) \leq \varepsilon \tag{12}$$

In this case, X is the solution vector containing the values of the decision variables for the current feasible solution. The value of ϵ is calculated as:

$$\varepsilon = f_2^{\min} + \frac{(f_2^{\max} - f_2^{\min})}{q} n, \qquad n = 1, 2, \ldots, q \tag{13}$$

The effects of the trade-off between the time of appliance use and the DI are shown in Fig 4.

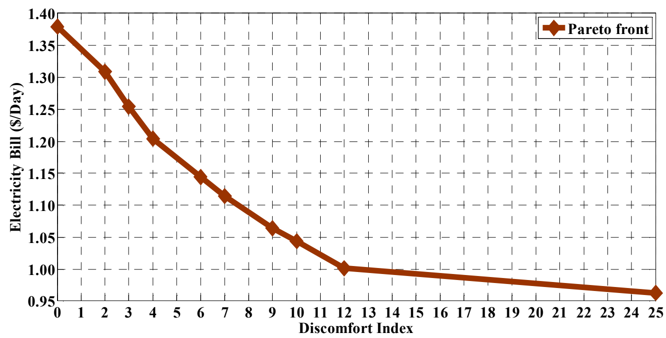

Fig. 3. Pareto front of Epsilon

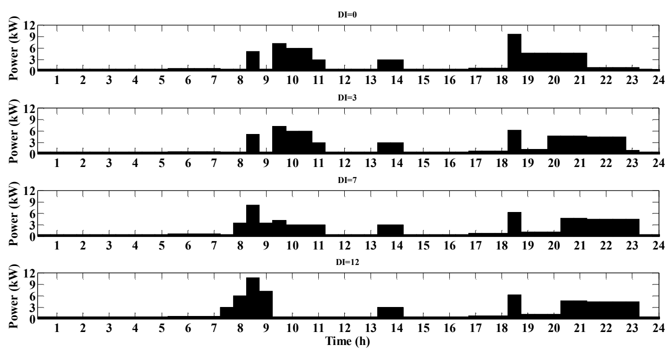

Fig. 4. Energy consumption pattern for varying Discomfort indices

In this figure, four levels of DI are shown along with the varying hourly bill. As the DI increases there is a notable shift for using the appliances in the later periods of the evening when the ToU tariff is lower. Also, there is less electricity used in the mid-morning (after 9:30 am) as the ToU tariff increases after this time. Being an iterative process, q is the number of iterations required for the generation of the Pareto set. The minimum and maximum values are iteratively calculated from the payoff table:

$$\Phi = \begin{bmatrix} f_1^*(x_1^*)\, f_2^*(x_1^*) \\ f_1^*(x_2^*)\, f_2^*(x_2^*) \end{bmatrix} \quad (14)$$

In each row, the optimal value of each objective function (f^*) is provided considering the constraints posed by the other objective functions. In other words, the diagonal elements form the edges of the Pareto front, and the epsilon-constraint method constructs the Pareto front by iteratively using Eq. 12 and 13, in which the minimum and maximum values of f are obtained from the corresponding row in the payoff table in Eq. 14. In this case, the diagonal elements would correspond to the optimal solution only considering the electricity bill, and the other optimal solution only considering the discomfort index, respectively. Once the Pareto front is obtained, the fuzzy decision-making process described earlier can be employed to determine the ideal trade-off between the objective functions according to the user's and/or operators' priorities.

III. Case Study and Simulation Results

In this section, the proposed MO model for the HEMS self-scheduling problem is evaluated. In this paper, it is supposed that household energy usage can be decomposed to the fixed and shiftable loads. It is evident that in such a case, the daily bills can also be decomposed into two different parts. The associated cost for fixed loads is constant while the terms related to the shiftable loads can be managed by considering the self-scheduling problem. In addition, the final strategy for shifting such loads depends upon the preference of the end-user according to the weighting factors of the fuzzy decision-making approach. Tables I and II represent the fixed and shiftable loads specifications for a typical day, respectively. In these tables, the home appliances, nominal power, baseline and acceptable bands of operation are provided.

The time intervals supposed to be in 30 minutes intervals. The various plans derived from the Pareto front are shown in Table III. The simulation results show that in the base case without any change of plugging-in the shiftable appliances, the daily bill would be 1.3789 $, in which the share of fixed and shiftable loads are 0.3399 $ and 1.039 $, respectively. It is evident that the DI would be zero in this case. In the case of fully adopted policy for reducing the daily bill, the DI would be 25 and the daily bill would be 0.9624 $. It means that by ignoring the discomfort level of the end-user, a reduction in the bill reduction of 0.4165 $/day for both fixed and shiftable loads can be attained. The Pareto front has 10 optimal solutions in this case. Therefore, a fair decision-making framework is required to select one of these optimal solutions in the Pareto set. In this paper, the fuzzy satisfaction method has been adopted for the final plan selection.

TABLE I. The Specifications of Shiftable Loads [20]

Appliance	P_i(kW)	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 II. The Specifications of Fixed Loads

Appliance	P_i(kW)	T_i	LB_b	UB_b	LB_s	UB_s
Refrigerator	0.450	48	1	48	1	48
Television	0.250	12	35	46	35	46
Lighting 1	0.150	2	11	12	11	12
Lighting 2	0.100	2	13	14	13	14
Lighting 3	0.050	2	15	16	15	16
Lighting 4	0.050	2	37	38	37	38
Lighting 5	0.100	2	39	40	39	40
Lighting 6	0.150	2	41	42	41	42
Lighting 7	0.180	4	43	46	43	46

TABLE III. Pareto Set and Fuzzy Decision Making for Different Preferences

Plan	Objectives		Normalization		μ_{d1}=0.5	μ_{d2}=0.5	Decision S1	μ_{d1}=0.25	μ_{d2}=0.75	Decision S2	μ_{d1}=0.75	μ_{d2}=0.25	Decision S3
	DI	Bill	DI	Bill	DI	Bill		DI	Bill		DI	Bill	
1	0	1.3789	1.00	0.0000	0.2500	0.2500	0.5000	0.5625	0.5625	1.1250	0.0625	0.0625	0.1250
2	2	1.3089	0.92	0.1681	0.1764	0.1102	0.2866	0.4489	0.3386	0.7875	0.0289	0.0067	0.0356
3	3	1.2539	0.88	0.3001	0.1444	0.0400	0.1844	0.3969	0.2024	0.5993	**0.0169**	**0.0025**	**0.0194**
4	4	1.2039	0.84	0.4202	0.1156	0.0064	0.1220	0.3481	0.1088	0.4569	0.0081	0.0290	0.0371
5	6	1.1439	0.76	0.5642	0.0676	0.0041	0.0717	0.2601	0.0345	0.2946	0.0001	0.0987	0.0988
6	7	1.1139	0.72	0.6363	**0.0484**	**0.0186**	**0.0670**	0.2209	0.0129	0.2338	0.0009	0.1492	0.1501
7	9	1.0639	0.64	0.7563	0.0196	0.0657	0.0853	0.1521	0.0000	0.1521	0.0121	0.2563	0.2684
8	10	1.0439	0.60	0.8043	0.0100	0.0926	0.1026	0.1225	0.0029	0.1254	0.0225	0.3072	0.3297
9	12	1.0019	0.52	0.9052	0.0004	0.1642	0.1646	**0.0729**	**0.0241**	**0.0970**	0.0529	0.4293	0.4822
10	25	0.9624	0.00	1.0000	0.2500	0.2500	0.5000	0.0625	0.0625	0.1250	0.5625	0.5625	1.1250

These results show that by providing the Pareto set of optimal solutions to the user, they are more informed and can make decisions that better suit their preferences.

IV. Conclusions

The results of the case study show a clear trade-off between the daily electricity bill and the user's comfort. This trade-off is significantly affected by the user's choice of weights between the two objectives. This result provides a user to adjust the trade-off according to their own preferences and these preferences may change daily. By providing the Pareto front of optimal solutions to the user, the user has full information in terms of the trade-off that they can make and the effect of these trade-offs on their electricity bill and comfort. The use of the Epsilon-Constraint Method and fuzzy decision-making approaches allows for more informed participation by the user.

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