A Fuzzy TOPSIS Approach for Home Energy Management in Smart Grid with Considering Householders' Preferences

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Abstract- **It is expected that demand response programs will be designed to decrease electricity consumption or shift it from on-peak to off-peak periods depending on consumers' preferences and lifestyles. This paper demonstrates a fuzzy TOPSIS decision-making approach to quantify and evaluate consumers' preferences at the micro-level when using electrical devices according to a real-time price scheme of demand response in order to best manage the use of appliances. This enables and supports householders to maximize their participation in demand response programs.**

***Index Terms*—** **Demand Response, Dynamic Real-Time Pricing, Fuzzy TOPSIS, Home Energy Management, Smart Grid, Smart Home, Scheduling Model**

I. Introduction

One of the main goals of the smart grid is to have end-users co-operate in order to consume electricity more efficiently [1]. When consumers receive information such as price signals, they try to monitor and limit their electricity consumption by making a real-time decision about their use of various electrical appliances [2]. The uncertainty in the householders' preferences increases the uncertainty of appliance prioritization and the difficulty of determining consistency of preferences. In this complex system, the preferences and judgments of householders are represented by linguistic and vague patterns. A much better representation of this linguistics can be developed and refined by using the evaluation methods of fuzzy set theory. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is an advanced analytical method developed from the traditional TOPSIS that the proposed approach will apply for achieving preferences.

The importance of the consumers' role in energy demand is demonstrated in approaches about demand response, home energy management system and consumers' behaviours.

A. Demand Response (DR) and Consumers' Behaviour

Demand response refers to the consumers' ability to modify their consumption pattern in response to time-varying electricity prices [3].

One of the main goals of smart grid is to achieve DR by increasing the end users' participation in decision-making and increasing the awareness that will help them to efficiently manage their energy consumption. The different forms of DR programs can be classified as energy efficiency and conservation programmes, static time of use pricing, critical day pricing, critical peak pricing, peak time rebates, real-time pricing, demand-side bidding and dynamic demand [4]. The underlying objective of these DR programmes is to actively engage consumers in modifying their consumption in response to pricing signals. In implementing dynamic energy pricing, the most difficult task is that of predicting people's reaction to various dynamic pricing schemes [5].

B. Home Energy Management Systems And Multiple Attribute Decision Making

A home energy management (HEM) system is an integral part of a smart grid that can potentially enable demand response applications for residential customers [6]. Several papers in the literature focus on controlling appliances by means of HEM during performing demand response and many approaches have developed the energy consumption scheduling for householders in a real-time pricing scheme [3, 7-16]. In the reviewed literature, it is demonstrated that the load profile, the load shifting and scheduling, demand response and power consumption are dependent on the consumer's preferences and lifestyle. Householders prioritize their use of electrical devices according to their lifestyle, and the imposition of a demand response program leads to the possibility of a comfort level violation or a high load compensation after finishing the period of DR [6]. In this scenario, giving consideration to the householders' preferences and priorities not only increases the level of customer satisfaction and comfort, but it could also produce significant benefits for the whole energy market. For example, in real-time pricing, the price of electricity may vary hourly and is tied to the real market cost of delivering electricity [17]. So, in this situation where the decision-making for adjusting energy demand and controlling the energy cost is difficult for end-users, Multiple Attribute Decision Making (MADM) is a suitable means of addressing such problems. Among numerous MADM methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has received interest from researchers as a means of evaluating and selecting the energy system performance [18]. For instance, Alami et al. [19] developed an extended responsive load economic model based on price elasticity and customer benefit function and a prioritization of DR programs has been realized by means of the TOPSIS method, or Xiaodong, et al. [20] evaluated the effectiveness of smart grid by Fuzzy TOPSIS methods.

This paper proposes a Fuzzy TOPSIS decision-making approach as a means of ascertaining the preferences of end-users for using groups of appliances located in different home areas in a real-time pricing scheme of demand response. Hence, in the next section, we illustrate how to capture the criteria for decision-making regarding home electrical energy management.

C. *Consumption Behaviour and Decision Making Criteria for Energy Consumption*

Householders' decision-making in regards to energy consumption is dependent on factors that influence the end-user's energy consumption behavior; hence, several surveys have been conducted to investigate these factors [13, 16, 21, 22]. For instance, Stern [23] demonstrated that the contextual domain of this behavior comprises: attributes that an individual has at birth, the immediate situation, public policy and economic variables. Kowsari et al. [21] presented a conceptual framework as a basis for formulating the household consumption behavior strategy and he proposed an integrated approach for the economic characteristics of a household. On the other hand, in many load scheduling and planning approaches such as those of [11, 24, 25], the researchers have included the consumers' preferences and utility function in their optimization models. For instance, in the approaches suggested by Lampropoulos et al. [16] and Wang et al. [25], the importance of including the behavior of householders in power system planning is demonstrated but there is no methodology for obtaining and ranking these preferences.

The measurement and inclusion of these factors would be more complex when there is a conflict of preferences among several consumers in a home. This issue is demonstrated by [26] when there is "analysis talk" among household members to identify how energy saving might be made. Therefore, in the proposed approach, the aggregated fuzzy rating of criteria for more than one consumer is computed.

By doing a survey of the literature [12, 16, 21, 23, 25, 27-30], we identified that the householders with different culture background, gender, income, education and social status who are located in different geographic locations and climate change and dealing with different energy policy, subsidies and energy supply, will utilize appliances in accordance with different criteria that are demonstrated in Tables I and II. Criteria such as cost and budget are based on householders' income [21]; and energy demand urgency and comfort level are associated with the consumers' lifestyle [2, 13, 25].

As the concept of smart grid aims to support "green" sources [1], and the emission trading scheme and carbon tax policy are designed to impact on the energy demand [31], there are some criteria identified by consumer's attitudes and behaviour towards the green electricity market [32, 33] such as green gas emission, carbon tax and energy efficiency score. The criteria presented in Table II are two types. The criteria with higher values produce profit (positive) and the criteria that are higher in value produce more cost (negative). Therefore, we try to decrease cost and increase profit when making decisions.

TABLE I. CRITERIA FOR EVALUATION OF ENERGY CONSUMPTION IN HOME AREAS

	Criterion	Definition	Type
c_1	Energy Cost	Energy consumption cost of all electrical devices in area A_i in time slot t_1	-
c_2	Budget	The amount of budget that users are prepared to expend on utilizing the appliances in area A_i	-
c_3	Urgency	Energy demand urgency for each area in time slot t_1	-
c_4	Comfort level	The level of convenience and comfort for each area in time slot t_1	+
c_5	GHG emission	Greenhouse gas emissions that are produced by consumption in areas	-
c_6	Energy efficiency score	Energy efficiency rate provided for users that can be compared with data for neighbors and other households (in social network or in a region)	+
c_7	Carbon tax	The amount of carbon tax allocated to areas by consumed energy	-
c_8	Occupancy level	Amount of time that a dwelling is occupied.	+

TABLE II. CRITERIA FOR EVALUATION OF APPLIANCES LOCATED IN AN AREA

	Criterion	Definition	Type
c_1	Cost	Energy consumption cost of a electrical device in time slot t_1	-
c_2	Adjusting demand	Flexibiklity of shifting their demand to off-peak hours	+
c_3	Urgency	Urgency of running an appliance in time slot t_1	-
c_4	Enjoyment	The level of pleasure that will be obtained by usage in time slot t_1	+

II. TOPSIS: TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SOLUTION

A. *Methodology*

To arrive at an effective means of obtaining householders' preferences for utilizing appliances in a real-time pricing scheme of smart grid, and to better understand the energy distribution flow in a home energy management system, this paper focuses on different areas of a home where groups of electrical devices are likely to be located. These areas are the alternatives in our decision-making model when householders want to decide how to distribute energy consumption flow. Then, we ask householders to specify their preferred appliances in each area. Therefore, this approach proposes two sets of criteria for decision-making: the first criteria for evaluating energy distribution in specific areas and the second set for appliance ranking. In this paper, we have just demonstrated the home area ranking.

Among many multiple criteria decision making (MCDM) methods, TOPSIS is a practical and useful technique for ranking and selecting a number of possible alternatives by measuring Euclidean distances. TOPSIS, developed by Hwang and Yoon [34], is a simple ranking method in conception and application [18]. The working principle of fuzzy TOPSIS is based on the fact that the selected alternative should have the shortest distance from the fuzzy positive ideal solution (FPIS) and the farthest from the fuzzy negative ideal solution (FNIS) for solving MCDM problems. As a result, the ideal solution is composed of all the best criteria, whereas the negative ideal solution is made up of all the worst attainable criteria [35].

The stepwise procedure of implementing fuzzy TOPSIS is presented in Fig1. By forming an initial decision matrix, normalizing procedure of the decision matrix will be started. This is followed by building the weighted normalized decision matrix in Step 5, compute the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) in Step 6, and calculating the separation measures for each alternative in Steps 7. The procedure ends with the computation of the relative closeness coefficient in step 8. The set of alternatives can be ranked according to the descending order of the closeness coefficient in step 9.

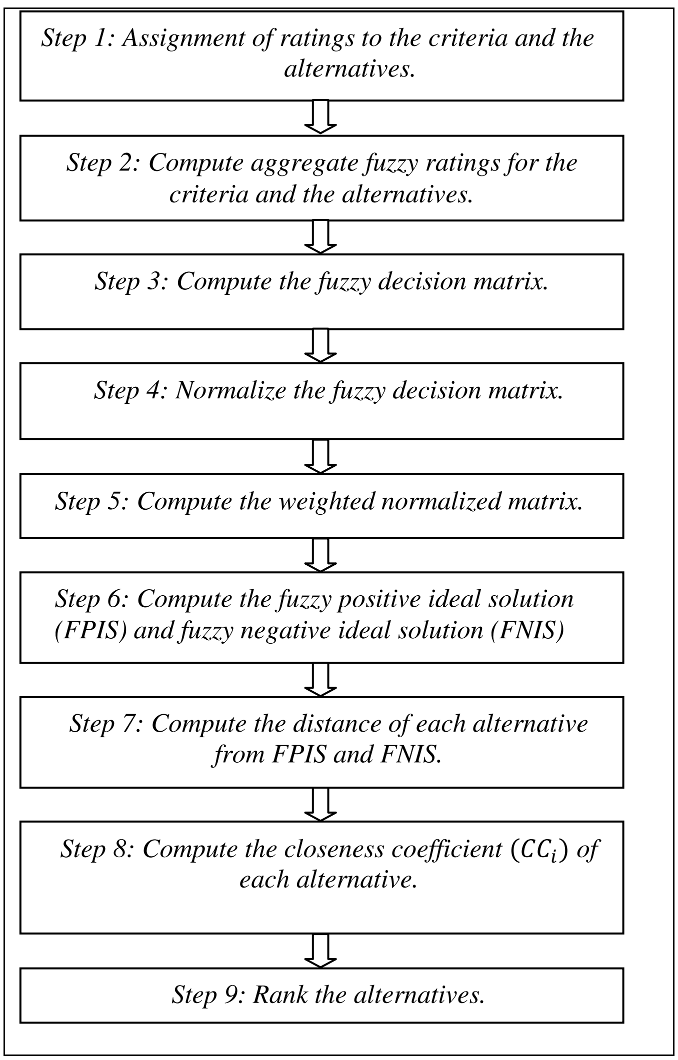

Figure1. TOPSIS method diagram

The aim of this paper is to demonstrate, when the price of energy unit is changed in a slot time, which part of a home is the area where appliances are most required and therefore the area where users want the least load curtailment.

The steps of the fuzzy TOPSIS algorithm can be described as follows:

Step 1*: Assignment of ratings to the criteria and the alternatives*

Let us assume there are j possible home areas called $A = \{A_1, A_2, .. A_j\}$ which are to evaluated against n criteria, $C = \{C_1 \ , C_2, \dots, , C_i\}$. The criteria weights are denoted by $w_i \ (i = 1, 2, \dots, m)$. The ratings of each consumer (family member) as a decision-maker $D_k = (k = 1, 2, \dots, k)$ for each alternative or home area $A_{kj} = (j = 1, 2, \dots, n)$ with respect to criteria $C_i \ (i = 1, 2, \dots, m)$ are denoted by $\tilde{R}_k = \tilde{x}_{ijk}$ with membership function $\mu_{\tilde{R}_k}(x)$.

Step 2*: Compute aggregate fuzzy ratings for the criteria and the alternatives.*

If the fuzzy rating of all consumers or family members is represented as a triangular fuzzy number $\tilde{R}_k = (a_k, b_k, c_k), k = 1, 2, \dots, K$ then the aggregated fuzzy rating is given by $\tilde{R} = (a, b, c), k = 1, 2, \dots, K$ where;

$$a = min_k\{a_k\} \quad b = \frac{1}{k}\sum_{k=1}^{k} b_k \quad c = max_k \{c_k\}$$

If the fuzzy rating and importance weight of the kth consumer are $\tilde{x}_{ijk} = (a_{ijk}\,, b_{ijk}\,, c_{ijk}\,)$ and $\widetilde{w}_{ijk} = \left(w_{jk1}\,, w_{jk2}\,, w_{jk3}\,\right), \mathrm{i} = \ 1, 2, \dots, \mathrm{m} \ , \ \mathrm{j} = \ 1, 2, \dots \ , \mathrm{n}$ respectively, then the aggregated fuzzy ratings $\tilde{x}_{ijk}$ of home area with respect to each criteria are given by $\tilde{x}_{ij} = \left(a_{ij}\,, b_{ij}\,, c_{ij}\,\right)$ where

$$a_{ij} = min_k\{a_{ijk}\}; b_{ij} = \tfrac{1}{k}\textstyle\sum_{k=1}^{k} b_{ijk}$$
$$c_{ij} = max_k \{c_{ijk}\} \tag{1}$$

The aggregated fuzzy weights $(\widetilde{w}_{ij})$ of each criterion are calculated as $\widetilde{w}_{ij} = \left(w_{j1}\,, w_{j2}\,, w_{j3}\,\right)$ where

$$w_{j1} = min_k\{w_{jk1}\}\,; \ w_{j2} = \frac{1}{k}\sum_{k=1}^{k} w_{jk2}$$
$$w_{j3} = max_k \{w_{jk3}\} \tag{2}$$

Step 3*: Compute the fuzzy decision matrix.*

The fuzzy decision matrix for the alternatives (home areas) $\left(\widetilde{D}\right)$ and the criteria $\left(\widetilde{W}\right)$ is constructed as follows:

$$\widetilde{D} = \begin{array}{c} A_1 \\ A_{..} \\ A_m \end{array} \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{3}$$

$$\widetilde{W} = (\widetilde{w}_1, \widetilde{w}_2, \dots, \widetilde{w}_n\,) \tag{4}$$

Step 4*: Normalize the fuzzy decision matrix.*

The raw data are normalized to bring the various criteria scales into a comparable scale. The normalized fuzzy decision matrix is $\tilde{R}$ given by:

$$\tilde{R} = [\tilde{r}_{ij}]_{m\times n}, \; i = 1,2,\dots,m; j = 1,2,\dots,n \tag{5}$$

Where

$$\tilde{r}_{ij} = \left(\frac{a_{ij,}}{c_j^+}, \frac{b}{c_j^+}, \frac{c_{ij,}}{c_j^+}\right) \tag{6}$$

and $c_j^+ = max_i \, c_{ij}$ (benefit criteria)

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \tag{7}$$

and $a_j^- = maxmin_i \, a_{ij}$ (cost criteria)

***Step 5**: Compute the weighted normalized matrix.*

The weighted normalized matrix $\tilde{V}$ for criteria is computed by multiplying the weights $(\tilde{w}_j)$ of evaluation criteria with the normalized fuzzy decision matrix normalization of the decision matrix $\tilde{r}_{ij}$

$\tilde{V} = [\tilde{v}_{ij}]_{m\times n} \; i = 1,2,\dots,m; j = 1,2,\dots,n$ where

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_{ij} \tag{8}$$

***Step 6**: Compute the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)*

The FPIS and FNIS of the alternatives is computed as follows:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+) \tag{9}$$

Where

$\tilde{v}_j^+ = max_i \{v_{ij3}\}, \mathrm{i} = 1,2,\dots,\mathrm{m}, \quad \mathrm{j} = 1,2,\dots,\mathrm{n}$

and

$$A^- = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+) \tag{10}$$

Where

$\tilde{v}_j^- = min_i \{v_{ij1}\}, \mathrm{i} = 1,2,\dots,\mathrm{m}, \quad \mathrm{j} = 1,2,\dots,\mathrm{n}$

***Step 7**: Compute the distance of each alternative from FPIS and FNIS.*

The distance(d_i^+, d_i^-) of each weighted alternative $i = 1,2,\dots,m$ from the FPIS and the FNIS is computed as follows:

$$d_i^+ = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_{ij}^+), \; i = 1,2,\dots,m \tag{11}$$

$$d_i^- = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_{ij}^-), \; i = 1,2,\dots,m \tag{12}$$

Where $d_v(\tilde{a}, \tilde{b})$ is the distance measurement between two fuzzy numbers $\tilde{a}$ and $\tilde{b}$.

***Step 8**: Compute the closeness coefficient (CC_i) of each alternative.*

The closeness coefficient CC_i represents the distances to the fuzzy positive ideal solution (A^+) and the fuzzy negative ideal solution(A^-) simultaneously. The closeness coefficient of each alternative is calculated by:

$$(CC_i) = \frac{d_i^-}{d_i^- + d_i^+} \quad \mathrm{i} = 1,2,\dots,\mathrm{m} \tag{13}$$

***Step 9**: Rank the alternatives or home areas.*

In step 9, the different alternatives (home areas) are ranked according to the closeness coefficient (CC_i) in decreasing order. The best alternative is closest to the FPIS and farthest from the FNIS.

III. SIMULATION RESULTS

According to the above analysis, this paper defines a scenario to demonstrate the fuzzy TOPSIS methodology. In this scenario, the conversion scale is applied to transform the linguistic terms for determining the rating of alternatives and criteria into fuzzy numbers as shown by the fuzzy triangular membership function in Fig 2.

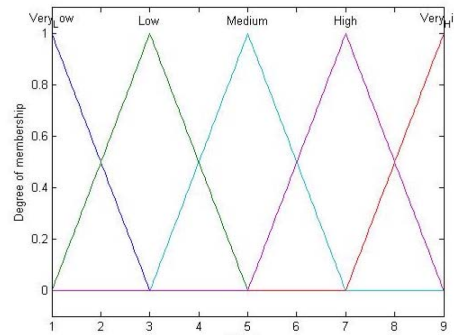

Figure 2. Fuzzy triangular membership function

In this scenario, there are two users in a house with different income and cultural background: user 1 who does not care about cost and wants a high level of comfort by energy utilization and user 2 who is concerned about environmental issues and is a green consumer. Both have received energy consumption information via a home energy management system. This information includes the cost of energy, carbon tax and GHG emission in the home areas of A_1 = Kitchen, A_2 = Bedrooms, A_3 = Living room and A_4 = Laundry and the information is used to compare the efficiency of their consumption with that of their neighbors. So, a decision on energy allocation should be made when the unit price of electrical energy increases from the slot time of t_i to t_{i+1}. The users use linguistic assessment to rate the criteria (Table III). For example, user 1 believes that the importance of energy cost is high but user 2 believes that it is very high or the importance of carbon tax for user 1 is at medium but it is high for user 2 and so forth. To construct the fuzzy TOPSIS model, the first step is the linguistic assessment of criteria and alternatives and the computation of the aggregated fuzzy value using (1) and (2) the results of which are presented in Tables III, IV and V. For example, in Table III for criteria c_2 ,"budget", user 1 is satisfied to allocate a medium amount of budget for energy for fuzzy triangular number that is (3, 5, 7), but user 2 likes to spend a high amount of budget for energy for the fuzzy triangular number of (5, 7, 9), so the aggregated fuzzy weight is given by $\tilde{w}_2 = (w_{21}, w_{22}, w_{23})$ where: $\mathrm{W}_{21} = \mathrm{MIN}_2(3,5) = 3$; $\mathrm{W}_{22} = \frac{1}{2}(5+7) = 6$; $w_{23} = max_2(7,9) = 9$; $\tilde{w}_2 = (3,6,9)$

In step 4, we normalize the fuzzy decision matrix of alternative using (8) and the result is shown in Table VI.

The weighted decision matrix in step 5 is obtained by (8). The result is shown in Table VII below.

TABLE III. LINGUISTIC ASSESSMENT FOR CRITERIA

Criteria		**Users**		*Aggregated fuzzy weight*
		User 1	*User 2*	
c_1	Energy Cost	H	VH	(5,8,9)
c_2	Budget	M	H	(3,6,9)
c_3	Urgency	H	M	(3,6,9)
c_4	Comfort level	VH	M	(3,7,9)
c_5	GHG emission	VL	VH	(1,5,9)
c_6	Energy efficiency score	L	VH	(1,6,9)
c_7	Carbon tax	M	H	(3,6,9)
c_8	Occupancy level	H	H	(5,7,9)

TABLE IV. LINGUISTIC ASSESSMENT FOR ALTERNATIVES

Criteria	**Home Areas**							
	A1		*A2*		*A3*		*A4*	
	U1	*U2*	*U1*	*U2*	*U1*	*U2*	*U1*	*U2*
c_1	H	M	M	H	M	VH	L	H
c_2	L	VH	M	L	H	L	H	L
c_3	M	H	M	L	M	L	VH	M
c_4	VH	M	VH	M	VH	H	L	VL
c_5	L	H	M	H	L	VH	VL	VH
c_6	L	M	H	H	L	VH	VL	H
c_7	M	M	M	VH	L	VL	M	H
c_8	VH	M	L	VL	VL	M	L	M

TABLE V. AGGREGATE FUZZY DECISION MATRIX

Criteria	*A1*	*A2*	*A3*	*A4*
c_1	(3,6,9)	(3,6,9)	(3,7,9)	(1,5,9)
c_2	(1,6,9)	(1,4,7)	(1,4,7)	(1,4,7)
c_3	(3,6,9)	(1,4,7)	(1,4,7)	(3,7,9)
c_4	(3,7,9)	(3,7,9)	(3,7,9)	(1,2,5)
c_5	(1,5,9)	(3,6,9)	(1,6,9)	(1,5,9)
c_6	(1,4,7)	(7,9,9)	(1,6,9)	(1,4,9)
c_7	(3,5,7)	(3,7,9)	(1,2,5)	(3,6,9)
c_8	(3,7,9)	(1,2,5)	(1,3,7)	(1,4,7)

TABLE VI. NORMALIZED FUZZY DECISION MATRIX FOR ALTERNATIVES

Criteria	*A1*	*A2*	*A3*	*A4*
c_1	(0.11,0.17,033)	(0.11,0.17,033)	(0.11,0.14,0.33)	(0.11,0.2,1.00)
c_2	(0.11,0.17,1.00)	(0.14,0.25,1.00)	(0.14,0.25,1.00)	(0.14,0.25,1.00)
c_3	(0.11,0.17,033)	(0.14,0.25,1.00)	(0.14,0.25,1.00)	(0.11,0.14,0.33)
c_4	(0.33,0.78,1.00)	(0.33,0.78,1.00)	(0.33,0.78,1.00)	(0.11,0.22,0.56)
c_5	(0.11,0.20,1.00)	(0.11,0.17,033)	(0.11,0.17,1.00)	(0.11,0.20,1.00)
c_6	(0.11,0.44,0.78)	(0.78,1.00,1.00)	(0.11,0.67,1.00)	(0.11,0.44,0.100)
c_7	(0.14,0.20,0.33)	(0.11,0.14,0.33)	(0.20,0.50,1.00)	(0.11,0.17,033)
c_8	(0.33,0.78,1.00)	(0.11,0.22,0.56)	(0.11,0.33,0.78)	(0.11,0.44,0.78)

The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) are obtained by (9) and (10) and then the distance of each alternative from FPIS and FNIS are obtained by using (11) and (12) as shown in Table VIII.

The closeness coefficient of each alternative is calculated by (13) and is represented in Table VIIII. The alternative that has a higher value is preferred. Hence, the ranking of alternatives is 1- Laundry, 2-Bedrooms, 3- Kitchen, 4- Living room. This ranking shows the users' preferences for energy distribution flow to the home areas or group of appliances in accordance with rising of energy unit price.

TABLE VII. WEIGHTED NORMALIZED FUZZY DECISION MATRIX

Criteria	*A1*	*A2*	*A3*	*A4*
c_1	(0.56,1.33,3)	(0.56,1.33,3)	(0.56,1.14,3)	(0.56,1.6,9.00)
c_2	(0.33,1.00,9.00)	(0.43,1.5,9.00)	(0.43,0.15,9.0)	(0.43,1.6,9.00)
c_3	(0.33,1.00,3.00)	(0.43,1.5,9.00)	(0.43,0.15,9.00)	(0.33,0.86,3.00)
c_4	(1.00,5.44,9.00)	(1.00,5.44,9.00)	(1.00,5.44,9.00)	(0.33, 1.56, 5.00)
c_5	(0.11,1.00,9.00)	(0.11,0.83,3.00)	(0.11,0.83,9.00)	(0.11,1.00,9.00)
c_6	(0.11,2.67,7.00)	(0.78,6.00,9.00)	(0.11,4.00,9.00)	(0.11,2.67,9.00)
c_7	(0.43,1.20,3.00)	(0.33,0.86,3.00)	(0.60,3.00,9.00)	(0.33,1.00,3.00)
c_8	(1.67,5.44,9.00)	(0.56,1.56,5.00)	(0.56,2.33,7.00)	(0.56,3.11,7.00)

TABLE VIII. DISTANCE OF EACH ALTERNATIVE FROM FPIS AND FNIS

	d_i^-				d_i^+			
	A1	*A2*	*A3*	*A4*	*A1*	*A2*	*A3*	*A4*
c_1	1.48	1.64	1.45	4.91	7.44	7.44	7.50	6.48
c_2	5.01	5.04	5.04	5.04	6.81	6.57	6.57	6.57
c_3	1.58	5.04	5.04	1.56	7.64	6.57	6.57	7.69
c_4	5.82	6.00	5.82	2.78	5.05	5.04	5.05	6.98
c_5	5.15	1.71	5.14	5.15	6.90	7.78	6.96	6.90
c_6	4.24	5.98	5.60	5.34	6.40	5.05	5.88	6.30
c_7	1.62	1.42	5.23	1.58	7.53	7.69	5.96	7.64
c_8	5.67	3.04	3.86	4.00	4.70	6.89	6.31	6.05
Σ	30.59	29.92	37.21	30.40	52.49	53.07	50.85	54.64

TABLE VIIII. RANKING ACCORDING TO THE CLOSENESS COEFFICIENT

	A1 Kitchen	*A2 Bedrooms*	*A3 Living room*	*A4 Laundry*
CC_i	0.3587	0.3602	0.3539	0.3742
Ranking	3	2	4	1

IV. CONCLUSION

The main purpose of this paper is to present a methodology to achieve the preferences of householders in order to prioritize the utilization of the groups of appliances when the function of users' utility is significant in load curtailment in demand response programs. There are economic, social, cultural and environmental factors that are effective in users' consumptional behavior and users with different backgrounds choose different linguistic terms to evaluate and to judge about their consumption. Hence, a fuzzy TOPSIS methodology proposed in this paper is a tool to support a group of household members to assess their consumption and to make decision about the energy flow distribution. This methodology can be applied for ranking the appliances in a home area by using the criteria presented in table II. Note that in this approach, we assumed that the information like price signal and consumption profile in details are provided for users so for the future approach, implementing the fuzzy rules for analyzing and predicting the users' consumption behavior is recommended.

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