MULTI-CRITERIA DECISION-MAKING APPROACH FOR FINDING OPTIMAL ENERGY EFFICIENT BUILDING MODEL

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ABSTRACT:

Building Sector is one of the most energy consumption sector that consume the biggest share of energy. As the population increasing continuously, it raises the demand for buildings which causes an increase in energy consumption in the building sector. Therefore energy-efficient buildings play a very important role to reduce the environmental effect. The selection of an appropriate model has a significant effect on the energy used by the buildings. In this paper, multiple criteria decision-making is used to find an optimum model among the different models of the building. The method Overall Proximity index value, determines the overall closeness of alternatives with the best feasible model among the different models. The AHP (Analytic Hierarchy Process) method is used for the evaluation of the weights of the Criteria. Five building models were selected as alternatives with the thirteen criteria. Using the overall proximity value method, the alternatives were ranked and the optimum building model was obtained.

Keywords: AHP, Building Parameters, Energy-Efficient, MCDM, PIV

1. Introduction:

Energy issues have become a hot topic among experts in recent years. Buildings are a major energy consumer, accounting for roughly 40% of global energy consumption and 33% of global greenhouse gas emissions [1-4]. By prioritising retrofitting in buildings, energy consumption in buildings can be reduced. According to many studies, variables such as building design issues, energy conservation issues, and faulty HVAC systems all affect a building's energy efficiency. It is important to use many retrofit strategies in existing buildings in order to increase their energy performance. Mills et al [5, 6] proposed that by enhancing the operation of an existing building in the United States, a median energy savings of 16 percent might be achieved.

According to Lam [7] and Reddy [8], Internal loads, temperature set-point, fenestration, and HVAC equipment efficiency are affects total energy usage in the building. In India, buildings are equipped with two types of HVAC systems: variable air volume (VAV) and traditional HVAC systems. Office buildings are more likely to have VAV systems. The parameters are separated into three groups to determine the impact of inputs on the building model: internal loads, building envelope, and HVAC systems. The selection of parameters is critical and plays an important role for energy-efficient structures. Different optimization techniques will be utilised to identify the ideal value of the parameters in order to reduce the building's energy usage. MCDM is used to select the optimum construction model for an energy-efficient structure from a variety of options. Both qualitative and quantitative aspects are included in the Multi-Criteria Decision Making technique. These methods are used to find the most likely best option.

Extensive variety of different modelling techniques provide possibilities to determine the cooling and heating load of the building and energy consumption in recent years. Such as simulation tools [9-11], ANN [12-15], and soft computing and Fuzzy Logic approaches [16-18]. Chibattoni et al. [19] calculate the energy consumption for the Italian residential building using fuzzy logic. They consider the domestic habits and occupancy activity in the model the model mean error was found as 0.52 percent. Kabak et al. [20] apply for the multi criteria decision making approach to investigate energy simulation tool BEP-TR [21]. Turhan [22] uses soft computing method i.e ANN to estimate the heat load of the building. They used the parameters like U-wall, total window area, building area/volume ratio and total surface area in his model. A very few studies categorize alternative buildings based on their energy performance using multi-criteria decision-making but no one has used the MCDM method based on the proximity index value. Most studies consider the criteria such as geometry shape, mechanical system, location, climate data, building envelope, and cogeneration for the building models, and the effect of each criterion on building energy demand was analyzed.

The soft computing methods like Fuzzy Logic have become innovative tools to reduce the total error in the attribute. Fuzzy logic is well growing method which describes the knowledge using the linguistic variables in a descriptive human like manner. The fuzzy systems having some set of rules which make it user friendly and this set of rules are derived from quantitative description.

From the literature reviewed above, it has been observed that a lot of works have been performed by the researchers to optimize building parameters. To the best knowledge of authors, no work has been performed on the building energy efficient model using AHP and PIV, which proves the novelty of this work

For the new building, energy-efficient buildings can be made by considering the optimal value of building envelope parameters. Building envelope parameters play a significant role when the new design of the building to be considered. There are several building envelope parameters some of them are shading coefficient, U-wall, and window to wall ratio. But in the case of the pre-existing building, the building envelope parameters are fixed. So this type of building can be turned into energy-efficient buildings by a focus on HVAC parameters and internal load parameters. By providing optimal values of HVAC parameters and internal load parameters pre-existing buildings are easily converted into the energy-efficient building.

Therefore this study focus on the three main parameters and their sub parameters to achieved energy efficient building. There are many researches on the building sector to achieve energy efficient building but none of them use PIV and AHP in building energy. This study apply AHP to find the weight of each criteria and its importance in the building energy consumption, After that rank the alternative buildings on the basis of their energy performance and identify the best building model for the energy-efficient building among the alternatives using the Multi-Criteria Decision Making approach. Multi-Criteria Decision Making method involves both qualitative and quantitative factors. These approaches are used to choose the probable optimal solution.

In this study, we analyze the different building models and identify the best building model for the energy-efficient buildings among the alternative models using a multi-criteria decision-making method. The study will identify the influence of inputs on the building model. It also provides the weight of each parameter and the optimal values of the parameters to achieve an energy-efficient building model among the alternative building models. The study aims to identify the significance of the main and sub parameters on the consumption of building energy and identify the best suitable energy-efficient model among the different models.

Nomenclature	
U	Overall heat transfer coefficient
AHP	Analytic Hierarchy Process
PIV	Proximity index value
FL	Fuzzy Logic
MCDM	Multi-Criteria Decision-Making
COP	Coefficient of Performance
DM	Decision Matrix
WPI	Weighted Proximity Index
CR	consistency ratio

2. Method:

By using the Proximity Index value technique [23], the proposed method is based on the proximity of alternatives to the best feasible value. The difference between each option's normalised value and the best available alternative is the proximity index value. The Proximity Index values are linearly summed for all the criteria (with attribute weights taken into account) to obtain the Overall Proximity Index value of each alternative model. The aggregate weighted normalised distance of alternatives from the optimal alternative is determined in this way.

The importance of criteria weight in determining the total proximity index value of an option is critical. Each parameter's weight has a variable consistency ratio. So, in order to discover an optimal solution, the weight of the criteria must have the least amount of inaccuracy. As a result, the weights of the criterion were determined using two methods: an AHP and non-linear programming criteria weight estimate. Thomas L. Saaty invented the AHP method [24] in 1970, and it has been examined all across the world. This strategy is useful for determining the purpose of a decision problem and evaluating alternatives. The AHP works by establishing priority for alternatives as well as the criteria used to evaluate them.

Formulation of the decision problem

Step 1: By specifying criteria and models, you may create the decision problem's purpose. Assign various criteria values to the various models.

Step 2: Define the Decision Matrix (DM)
Each row assigns to one alternative source of the decision matrix and each column assigned to the criterion.

Step 3: Construction of Normalization matrix of the data
Because distinct criteria have different values in different units, their values should be normalised on the same scale. These values are normalised using vector normalisation, as shown in equation (1).

$$r_i = \frac{x_i}{\sqrt{\sum_{i=1}^{m} x_i^2}} \tag{1}$$

Step 4: Construction of Weighted normalized Decision Matrix

The weight of each criterion is calculated by the AHP methods. With the help of these weights, the weighted normalized decision matrix of alternative models corresponding to the criterion is calculated by equation (2).

$$v_j = w_j * r_i \tag{2}$$

Step 5: Determination of Weighted Proximity Index (WPI)

Determine the good and negative attributes. Evaluate the closeness index of each alternative model among the Criterion for the alternative model. Equation is used to calculate the weighted proximity index matrix (3).

$u_i = v_{max} - v_i$ For benefit attribute

$u_i = v_i - v_{min}$ For cost attribute (3)

Step 6: evaluation of Overall Proximity Value
Using equation (4), the overall proximity value is calculated for each alternative model.

$$d_i = \sum_{j=1}^{n} u_j \tag{4}$$

Step 7: Ranking

Based on proximity index value, ranking the alternative models. Choose the optimal model among the alternatives which has the least overall proximity value.

3. Criteria and priority vector:

The criteria for the building analysis are determined using the studies and expert opinions like architecture and engineers. After the studies and expert opinion, the main criteria for building analysis are building envelope, internal loads, and HVAC system [25]. These main criteria are further categorized into their sub-parameters. The building envelope is categorized into five sub-parameters and the internal load has three sub-parameters. HVAC systems have five sub-parameters. Finally, there are 13 parameters on which the building model analyze. Based on these 13 parameters, the optimum building model for energy-efficient is to be selected using the AHP, and proximity index method.

Table 3.1: Criteria of Building Model

Main criteria	Sub-parameters				
building envelope (C1)	External wall U value (C11)	Roof U value (C12)	Window U value (C13)	Shading coefficient (C14)	Window wall ratio (C15)
internal loads (C2)	Lightning density (C21)	Equipment density (C22)	Occupant density (C23)	-	
HVAC system (C3)	Cooling set point (C31)	Fresh air (C32)	COP (C33)	Fan efficiency (C34)	pump efficiency (C35)

The first step is to make the pairwise comparison matrix of the criteria. The value of the consistency ratio (CR) for these criteria is less than 0.1, hence the results are acceptable. The comparison matrix of the main criteria and their sub-criteria are shown in tables 3.2, 3.3, 3.4, and 3.5.

Table 3.2: Comparison matrix of main criteria weights

	Building envelope C1	internal loads C2	HVAC system C3
C1	1	5	8
C2	0.2	1	4
C3	0.125	0.25	1

Table 3.3: Comparison matrix of building envelope parameters weights

	C11	C12	C13	C14	C15
C11	1	7	3	2	4
C12	0.1428	1	0.5	0.333	0.25
C13	0.333	2	1	0.333	0.5
C14	0.5	3	3	1	0.333
C15	0.25	4	2	3	1

Table 3.4: Comparison matrix of Internal- loads parameters weights

	C21	C22	C23
C21	1	2	4
C22	0.5	1	4
C23	0.25	0.25	1

Table 3.5: Comparison of HVAC system parameters weights

	C31	C32	C33	C34	C35
C31	1	3	0.1428	2	2
C32	0.333	1	0.125	0.333	0.333
C33	7	8	1	8	7
C34	0.5	3	0.125	1	0.5
C35	0.5	3	0.1428	2	1

4. Result:

Energy used in the building is optimized by optimizing the building parameters like building envelope, internal loads, and HVAC system parameters. Building envelope parameter further divided into five sub-parameters i.e External wall U value, Roof U value, window U value, shading coefficient, and window wall ratio. By selecting the optimal values of these parameters, energy consumption by the building will minimize. Using the technique AHP, the weights of each main criteria parameter is calculated as shown in figure 1. Figure 1 shows building envelope has a high weightage parameter as compared to other main factors. So in the case of designing a new building, the building envelope plays a significant role.

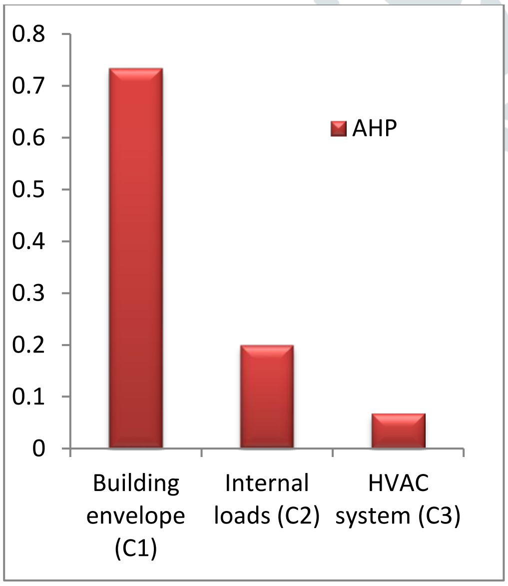

Figure 1: weights of the main criteria for the building

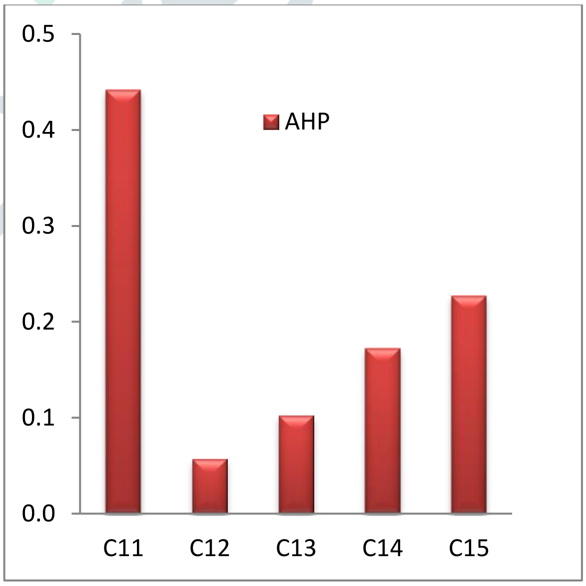

Figure 2: Weightage of building envelope parameters

Among the Building envelope, there are five sub-parameters; their weights are shown in figure 2. As shown in figure 2, external wall U value plays an important role in the energy-efficient building, and after external wall, window wall ratio is a second important factor for the energy-efficient building. Roof U value has the least weightage among these parameters.

Similarly, the internal load has three sub-parameters in which lightning density plays a significant role in energy-efficient building. The weights of each sub-parameter are shown in figure 3. As shown in figure 3, the Lightning density and equipment density are the important factor to achieve the optimal model of the building. Lightning density and equipment density parameters indicate the amount of energy produced within the building. So for an energy-efficient building, there should be a minimum amount of energy produced in the building.

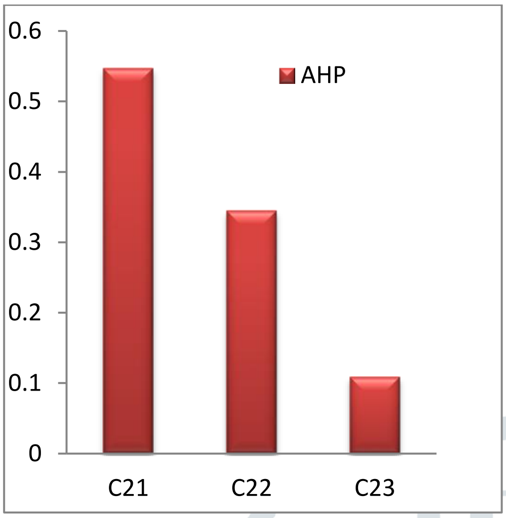

Figure 3: Weights of the internal load parameters

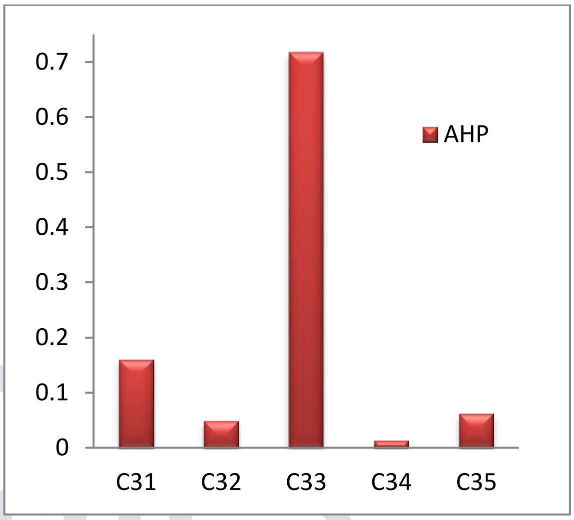

Figure 4: weights of the HVAC system parameters

The HVAC system has five sub-parameters, among these parameters; fan efficiency, pump efficiency, and fresh air are the least significant since their weights are the least as shown in figure 4. As shown in figure 4, COP has the highest weightage among the HVAC system parameters; it means COP is the most significant factor in achieving energy-efficient buildings.

The weights of all thirteen parameters are calculated using the AHP, There is a very small difference between the weights of the HVAC parameters using these two methods, therefore rank the alternative models using the weightage of the parameters obtained from AHP method. For ranking the models to select the best optimal model of the building PIV method is used. The decision matrix used for the PIV method is shown in table 4.1.

Table 4.1: Decision matrix

	Uwall	Uroof	Uwindow	SC	WWR	Lightning density	equipment	occupant density	cooling pt	fresh air	cop	fan eff	pump eff
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
MODEL 1	0.3	0.15	1.5	0.3	0.07	5	5	5	20	20	3	0.5	0.5
MODEL 2	0.4	0.2	2	0.35	0.15	7	10	8	21	23	3.5	0.55	0.55
MODEL 3	0.6	0.25	2.5	0.4	0.2	10	15	12	22	26	4	0.6	0.6
MODEL 4	0.8	0.3	3	0.45	0.25	15	20	16	23	29	4.5	0.65	0.65
MODEL 5	1.5	0.35	3.5	0.5	0.3	20	25	20	24	32	5	0.7	0.7

Normalized decision Matrix for the alternative models using the equation (1) is shown in table 4.2

Table 4.2: Normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
MODEL 1	0.160356745	0.258199	0.258199	0.330289	0.149274	0.176887284	0.13483997	0.167694618	0.40572	0.33952	0.330289	0.370117	0.370117
MODEL 2	0.213808994	0.344265	0.344265	0.385337	0.319874	0.247642198	0.26967994	0.268311388	0.426006	0.390448	0.385337	0.407128	0.407128
MODEL 3	0.32071349	0.430331	0.430331	0.440386	0.426498	0.353774569	0.40451992	0.402467083	0.446292	0.441376	0.440386	0.44414	0.44414
MODEL 4	0.427617987	0.516398	0.516398	0.495434	0.533123	0.530661853	0.53935989	0.536622777	0.466578	0.492304	0.495434	0.481152	0.481152
MODEL 5	0.801783726	0.602464	0.602464	0.550482	0.639748	0.707549138	0.67419986	0.670778471	0.486864	0.543232	0.550482	0.518163	0.518163

Weighted normalized decision Matrix for the alternative models using equation (2) is shown in table 4.3

Table 4.3: Weighted normalized decision matrix using AHP weights

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
MODEL 1	0.05193955	0.010741	0.019313	0.041616	0.024824	0.019245337	0.00923654	0.003620527	0.004301	0.001086	0.015854	0.000329	0.001521
MODEL 2	0.069252733	0.014321	0.025751	0.048553	0.053195	0.026943471	0.01847308	0.005792843	0.004516	0.001249	0.018496	0.000362	0.001673
MODEL 3	0.1038791	0.017902	0.032189	0.055489	0.070927	0.038490673	0.02770961	0.008689264	0.004731	0.001412	0.021139	0.000395	0.001825
MODEL 4	0.138505466	0.021482	0.038627	0.062425	0.088658	0.05773601	0.03694615	0.011585686	0.004946	0.001575	0.023781	0.000428	0.001978
MODEL 5	0.259697749	0.025063	0.045064	0.069361	0.10639	0.076981346	0.04618269	0.014482107	0.005161	0.001738	0.026423	0.000461	0.00213

The overall proximity index value of the five different models is calculated using equation (4) and their ranking are shown in table 4.4

Table 4.5.: Overall Proximity Index and rank matrix

Building models	Proximity Index (AHP)	Rank (AHP)
MODEL 1	0.0613	1
MODEL 2	0.1157	2
MODEL 3	0.1812	3
MODEL 4	0.2544	4
MODEL 5	0.4142	5

The proximity index value is calculated for the five different models of the building. Using the overall proximity value method, the alternatives were ranked and the optimum building model was obtained. As shown in table 4.5, building model 1 has the least proximity index value among the five models of the building, so the optimal model for energy-efficient buildings is model 1.

5. Conclusion and Discussion:

In this paper, we analyze the building parameters and their significance by calculating their weightage. The weight of parameters is calculated and finds that among the three main criteria building envelope has the highest weightage, and among the sub-parameter of the building envelope, external wall U-value parameters have high weightage which shows that it is a significant and most considered factor in energy-efficient buildings. Similarly among the sub-parameters of HVAC systems and internal loads, COP and Lightning density parameters have the highest weightage, which indicates their significance in energy-efficient buildings, based on these significance of all parameters, the optimal model is identifying by the MCDM technique. The optimal values of parameters can be applied for the new building which is under construction as well as the pre-existing buildings. In pre-existing buildings, we can focus more on internal loads and HVAC systems, and also by providing the optimal values of the parameters of the HVAC system and internal loads, energy consumption in the building will reduce and can achieve energy-efficient building status. But for the new buildings which are to be under construction, engineers and architect can give more importance to building envelope parameters to achieve energy-efficient buildings. And take the parameters based on weights for consideration.

Based on the results, COP is the most significant factor, and the cooling set point is the second most significant factor for minimizing the energy consumption in the building. Energy consumption in the building is decreased by selecting appropriate lightning density inside the building because lightning density plays a vital role in energy-efficient buildings. Fan efficiency is the most negligible factor in energy-efficient building design

By knowing the significance of main criteria and sub-criteria to the energy demand. we can significantly reduce the energy consumption in the building. This study will help the engineer and architect to achieve energy-efficient building by giving more focus on those parameters which have high weightage and are significant to the energy demand. This study will help to achieve energy-efficient building for both types of building that is pre-existing building and new or under construction building. Using the criteria weights of parameters, it is easy in considering the building parameter for achieving energy-efficient buildings. The limitation of the study is that not calculated the energy consumption in the building, and in future studies more soft computing methods and fuzzy logic techniques can be applied to buildings to achieve energy-efficient buildings.

REFERENCES:

[1] Sbci U. Buildings and climate change: a summary for decisionmakers. Paris: United Nations Environmental Programme, Sustainable Buildings, and Climate Initiative; 2009. p. 1–62.

[2] Xing Y, Hewitt N, Griffiths P. Zero-carbon buildings refurbishment—a Hierarchical pathway. Renew Sustain Energy Rev 2011; 15:3229–36.

[3] Ibn-Mohammed T, Greenough R, Taylor S, Ozawa-Meida L, Acquaye A. Operational vs. embodied emissions in buildings—a review of current trends. Energy Build 2013; 66:232–45.

[4] Robert A, Kummert M. Designing net-zero energy buildings for the future climate, not for the past. Build Environ 2012; 55:150–8.

[5] Mills E, Friedman H, Powell T, Bourassa N, Claridge D, Haasl T, et al. The cost-effectiveness of commercial-buildings commissioning; 2004.

[6] Mills E. Building commissioning: a golden opportunity for reducing energy costs and greenhouse gas emissions. Lawrence Berkeley National Laboratory; 2010.

[7] Lam JC, Hui SC. Sensitivity analysis of energy performance of office buildings. Build Environ 1996; 31:27–39.

[8] Reddy TA, Maor I, Jian S, Panjapornporn C. Procedures for reconciling computer-calculated results with measured energy data. ASHRAE Research Project; 2006.

[9] M.Manfren, N.Aste, R.Moshksar. Calibration and uncertainty analysis for computer models-A meta-model based approach for integrated building simulation, Applied Energy 103 (2013) 627-641.

[10] Y.Heo, R. Choudhary, G. Augenbroe. Calibration of building energy models for retrofit analysis under uncertainty, Energy and Buildings 47 (2012) 550-560.

[11] A. Boyano, P. Hernandez, O.Wolf. Energy demands and potential savings in European office buildings: Case studies based on Energy Plus simulations, Energy and Buildings 65 (2013) 19-28.

[12] Turhan, C., Kazanasmaz, T., Uygun, I. E., Ekmen, K. E., & Akkurt, G. G. (2014). Comparative study of a building energy performance software (KEP-IYTE-ESS) and ANN-based building heat load estimation. Energy and Buildings, 85, 115-125.

[13] Mavromatidis, G., Acha, S., & Shah, N. (2013). Diagnostic tools of energy performance for supermarkets using Artificial Neural Network algorithms. Energy and Buildings, 62, 304-314.

[14] S.K. Kwok, Y. E.W.M.Lee, A study of the importance of occupancy to building cooling load in prediction by intelligent approach, Energy Conversion and Management 52 (2011) 2555-2564.

[15] Q. Li, Q.L. Meng, J.J. Cai, H. Yoshino, A. Mochida. Predicting hourly cooling load in the building: A comparison of support vector machine and different artificial neural networks, Energy Conversion and Management 50 (2009) 90-96.

[16] T.Kazanasmaz. Fuzzy logic model to classify effectiveness of daylighting in an office with a movable blind system, Building and Environment, 69 (2013), 22-34.

[17] L. Ciabottoni, M.Grisostomi,G.Ippoliti, S.Longhi. Fuzzy logic home energy consumption modeling for residential photovoltaic plant sizing in the new Italian scenario, Energy74 (2014), 359-367.

[18] M.Kabak, E.Köse, O.Kırılmaz, S.Burmaoğlu. A fuzzy multi-criteria decision-making approach to access building energy performance, Energy and Buildings 72 (2014), 382-389.

[19] L. Chiabottoni, M.Grisostomi,G.Ippoliti, S.Longhi, Fuzzy logic home energy consumption modeling for residential photovoltaic plant sizing in the new Italian scenario, Energy74 (2014), 359-367.

[20] M.Kabak, E.Köse, O.Kırılmaz, S.Burmaoğlu. A fuzzy multi-criteria decision-making approach to access building energy performance, Energy and Buildings 72 (2014), 382-389.

[21] National Building Energy Performance Calculation Methodology of Turkey. (No: YİG/2010-02)), Turkish Official Journal (2010).

[22] Turhan, C., Kazanasmaz, T., and Gökçen Akkurt, G. (2017). Performance indices of soft computing models to predict the heat load of buildings in terms of architectural indicators. Journal of Thermal Engineering, 3(4), 1358-1374. doi:10.18186/journal-of-thermal-engineering.330180

[23] Sameera Mufazzal, S.M. Muzakkir. A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals, Computers & Industrial Engineering 2018;119:427-438

[24] Saaty TL. How to make a decision: The Analytic Hierarchy Process. (1990). European Journal of Operational Research, 48:9-26.

[25]Tao Yang, Yiqun Pan, Jiachen Mao, Yonglong Wang, Zhizhong Huang.An automated optimization method for calibrating building energy simulation models with measured data: Orientation and a case study, Applied Energy 2016;179:1220-1231.