IMPROVED FUZZY SET THEORY FOR SOLVING MULTI CRITERIA DECISION MAKING PROBLEMS IN PRODUCT DESIGN

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Abstract: Multi Criteria Decision Making (MCDM)aims to provide decision forproblems under complex decision making environmentwhich considered as critical task in various applications such as product design, service provider selection and quality selection.In literature, some efficient techniques are available to find the optimal selection with respect to the criteria. These methods are fails to attain high selection accuracy due to increased cost, unwanted data entry, low quality of product and wastage of time. Hence, in this proposed methodology, improved Hierarchical-Fuzzy (H-Fuzzy)set theory is designed to solve the MCDM problems in product design applications. The proposed H-Fuzzy theory is used to optimal selection of product tool selection by using normalized average weight gain operation. The proposed H-Fuzzy set theory is working based on two main steps such as priority weighting and normalized weighting. The priority weighting is achieved in H-Fuzzy theory and the overall priority weights alternatives determined. Based on these overall priority weights, the alternatives are ranked. The ranking process is considered as final step of proposed methodology which selected the optimal product tool. The proposed H-Fuzzy set theory is implemented in a MATLAB platform and its performances were evaluated. The statistical measurements are considered to analysis the performance of the proposed methodology such as accuracy, sensitivity, specificity, and kappaand error measurement. The outcome shows that the proposed model is better than the previous ones.

Keywords: *Criteria, Alternative, H-Fuzzy, Accuracy, product design, MCDM problems, weighting*

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1. INTRODUCTION

The requirement ofMCDMraises in the process of Selection tools, Software selection and Solid transportation selections for decision making [1]. This decision making requires input parameters for optimizing the selection process. This selection is made by differentiating the alternatives and ranks it accordingly. Ranking byMCDM technique requires some qualitative and quantitative factors which may help to examine alternatives. An optimal selection can be made from the alternatives by utilizing a set of multiple criteria [3]. In this MCDM approach the alternatives are compared in weightage matrix methods. Thismethod includes qualitative and quantitative comparison, where qualitative analysis consists of style and reliability and quantitative analysis includes cost and fuel economy [4]. An alternative decision is made on equipment tool selection when it justifies in all the criteria of decisions. Reliability, Style, fuel economy and cost are the factors to be considered in product design. MCDM is effectively utilized for product design hence it is an approach to compute decisions under specifications. This approach has some unique characteristics namely different units of measurement among the criteria, the presence of quite different alternatives and the presence of multiple non-commensurable and conflicting criteria.

MCDM approach works for both certainty and uncertainty conditions [5]. In certainty conditions the decisions are made with relevant data and in uncertainty conditions, the decision is critical because of limited data. Similarly the active and passive experiment of MCDM can be solved using a mathematical model. Moreover passive experiment requires different approaches which rise issues during the construction of information matrix. The data collectedtodevelop primary matrix, it creates in MCDM problems which are challenging to be quantified. The MCDM problem [6] must be solved by decision making process which enables the high accuracy with huge amount of input data. The decision making is a principle of ranking of alternatives by using comparison matrix. However it ranks with an estimation of non-critical data. Ranking of alternatives in MCDM problem undergoes sensitivity analysis. The sensitivity analysis [7]is to identify the input data which are then transformed to decision matrix. Based on sensitivity analysis, the ranking alternatives are modified. The variation of sensitivity parameters may initiate the decision making problems.

The decision making approach includes multi set of decision alternatives for selection process. In the decision making process, set theory is used to selection process which considered as main progress to enable proper decisions related to problems. Generally, different types of methods are available to solve MCDM issues by enable the proper decisions such as Analytical Hierarchy Process (AHP) [8], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [9], Analytic Network Process (ANP) set theory and Fuzzy Set theory. TOPSIS method utilizes high degree of distance method to comparewhich neglects the alternatives accordingly. However, this method provides the inappropriate decisions.Similarly, AHP is used to solve the MCDM problems by provides the best decisions but it has a weak decision making solution and it trap to identify and weight of designing problem. Additionally, ANP [10] is unable to provide perfect ranking alternatives. And, fuzzy set theory permits the combination of qualitative and quantitative with a partially known data into a decision making process. In this fuzzy set theory decisions are made to quantify the uncertainty and to handle the partial data involved in the process of decision making. This theory allows mathematical operators and the programming approach to apply in the fuzzy system model. The fuzzy set theory may fails to obtain the appropriate solution in complex decision making process. The abovementioned drawbacks are motivated by design a best method to enable the proper decision in MCDM problems.

The remaining part of the paper is organized as follows, section 2 briefs on the literature review in which the previously existing techniques related to solve MCDM problemsand section 3 presents a detailed description in the proposed methodology related to selection of product. Additionally, the detail description of the proposed hierarchical fuzzy set theory with the product design selection is presented in section 3. Section 4 presents the simulation results obtained by implementing the proposed method. Finally, section 5 briefs the conclusion part of the research.

2. LITERATURE REVIEW

Many different methods are designed by researchers to solve MCDM problems with various applications. Some of the methods are reviewed in this section which useful to identify the problem formulation of proposed methodology.

Chang *et al,*[11] presented R-Studio approach for decision-making to support for the selection of the most optimal smartphone and its tariff plan from number of taxi service operators as alternatives. Real data by considering the characteristics of smart phone were taken as weightage for calculation. However, the weights change did not affect the ranking change of the criteria hence this approach was unable to make an appropriate decision.

Triantaphyllou*et al,* [12] have been developed multimodal approach when discussing with some issues faced when implementing MCDM theory for methodological problems. It was every time crucial for the user to find the main alternatives in the respective field. However, this approach was giving different answers for the same issue and the accuracy of this method is highly desirable.

Dagdeviren*et al,* [13] exhibitedan integrated Analytic hierarchy process (AHP) and Preference ranking organization method for enrichment evaluation (PROMOTHEE) approach for decision making which can be termed as Analytical network process (ANP) and digraph and matrix approach to solve selection problem. This approach makes use of matrix to solve this problem. However this approach was unable to solve decision making in location problem.

Quan*et al,* [14] have been developed a hybrid MCDM model that identifies the issue on green supplier for including a wide amount of decision maker tool. This method includes ant colony algorithm for utilizing the cluster based sub groups in decision making. However, while transforming linguistic assessments of alternatives the data were lost or got distorted.

Yager*et al,* [15] have developed a model for hybrid decision making approach solved the problem when there was a need for prioritization criteria for decision making. This paper also investigated that the modelling of the matrix with respect to weightage can be associated with the lower and higher order priority. However this approach increased the cost while implementing this approach to a realistic environment.

Sodhi*et al,* [16] have intimated an implicit feedback scheme for making decisions by combining MCDM and Inductive Logical Programming (ILP) approach. This method determines a set of optimal locations to make a complete analysis over the alternatives and then utilizes a criteria for making decisions. This method consists of tie-line oscillations observability, bus voltage observability and voltage control area observability. However, loss of a transmission line resulted in observability of some of the buses in the power system network.

Choi *et al,* [17] have intimated a multi criteria recommendation method for analysing the web usage behaviour of a customer in real time. From the database the user preference data are taken as the product weights of the in the form of inequalities. However the solution based on this method were incomplete to make an appropriate decision.

Chiu *et al,* [18] have developed Minimum Manhattan distance approach thatutilized geometric interpretations which limited the subjective alternatives to be an input to the decision makers. This approach provided a systematic way that generated weights and resulted in an equivalent knee selection method. However, this approach needsprior data information in realistic implementation. Moreover the equivalence was made based on the differentiation of the objective functions and this differentiation was not an appropriate one.

Agrawal *et al,*[19] have discriminated fuzzy-based integrated approach which utilized an assessment framework for estimating the decisions with a suitable security of web application that focussed on the perception of product design. This was done using a methodology which combineda negligible method for selecting web application. However, this study required n number of parameters for calculation.

Yuen*et al,* [20] have provoked a Cognitive Network Process theory set to resolve the decision making issue. This method constructed a pairwise opposite matrix that were validated by the index and calculated the prioritization operator. Decision was made based on these results. However, these results were not helpful for prioritizing and finding the decisions in a quantified manner.

3. Proposed System model

MCDM problems with a finite set of possible alternatives grouped in a matrix are considered. The MCDM problem is raised in different applications which select a subset of alternatives evaluated by various criteria. Decision making problem is directly related to decision makers. Decision makers must be trained to understand the preference. Selected alternative must be the best one for tool selection. This paper emphasized the process of decision making by H-Fuzzy technique. This technique selects best alternative from the rank of alternatives.Figure 1 represents the overall block diagram of the proposed methodology.

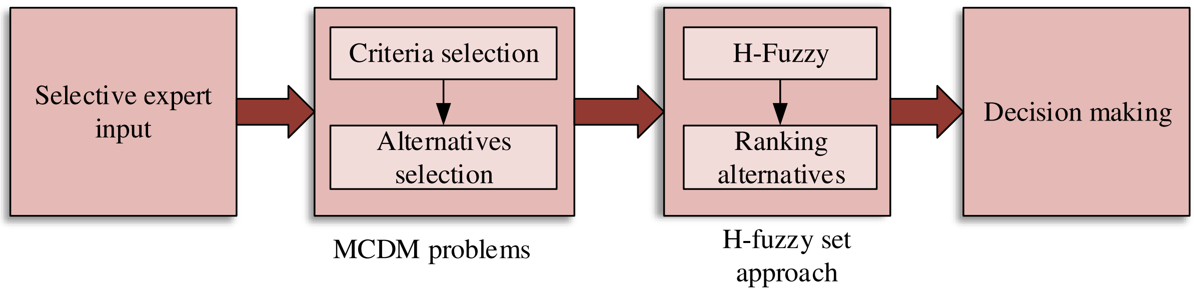

Figure 1: Architecture ofProposed methodology

The objective of this research is to develop a decision making model to solve MCDM problem in the tool selection applications. The H-Fuzzy set theory is utilized in this decision making model used in the product design applications. The detail description of the proposed design is presented as follows,

(i) MCDM problems

A. Selective expert input

Gathering opinion from the experts in the same field is taken as input to system. The expert opinions are collected as weightage value in trapezoidal numbers. This weightage values are used to construct a primary normalised matrix. The matrix results in a multiple criteria, with a set of decision makers and a set of alternatives. For every multi criteria problem there is a membership function for mapping in the matrix. Reliability, sensitivity, accuracy and the characteristic of the component are input parameters for quantitative measurement.

B. Criteria selection

A group of sample experts predict the ratings of product which directly affect accuracy. Each elementof matrix is obtained from the mean value of cognitive ratio compared to other. This pairwise comparison of i^{th} element to the j^{th} element is denoted as a_{ij}.These group of direct matrices are obtained from an average matrix K.Each element in the matrix is the average value of the expert's direct matrices.

C. Selection of alternatives

Initialisation matrix is computed from the element of average matrix. It has a weightage value which is provided by a Decision Maker (DM).Comparison matrix K gives number of criteria's to make decision. Value of each element and its reciprocal is considered as alternatives. Its average range is unit value, which is expressed as $a_{ij}.a_{ji} = 1$.The objects of the matrix is compared to a threshold value to find the alternatives. Result obtained is classified as severely high, moderately high, high, low, moderately low and severely low values. Comparison is done row wise and been provided as an alternative. Similarly for each row the alternative values are computed in the increasing order of the matrix. An optimal value $\alpha = 0.5$ is selected and the normalised matrix with alternatives of n dimension is obtained. In a matrix of $n \times n$, is set of alternatives.

(ii) H-Fuzzy decision making approach.

In this proposed method, a hierarchical fuzzy set theory is used to rank alternatives and select the appropriate one. This approach takes comparison matrix for decision making. It is not consistent or there remains a large interval among overall weights of the alternatives. Then, the components in the matrix are compared pairwise which affects weightage value of the products. To analyse the outcome, sensitivity analysis is performed when a certain variable has transformed from one state to other. Comparison matrix consists of partial weightage value or newly changed value it results in confused state at decision making. This is evaluated as fluctuation in the weightage of the elements in the matrix. Pairwise comparison matrix is a positive square with respect to the criterion. These comparative values are fuzzy numbers even if the comparison matrix alternatives do not have enough stability. H-Fuzzy is utilised here to resolve the issue to make decisions. Each complex decisionsare examined with respect to the desired hierarchy. This hierarchy is arranged in the form of tree to implement the set theory.

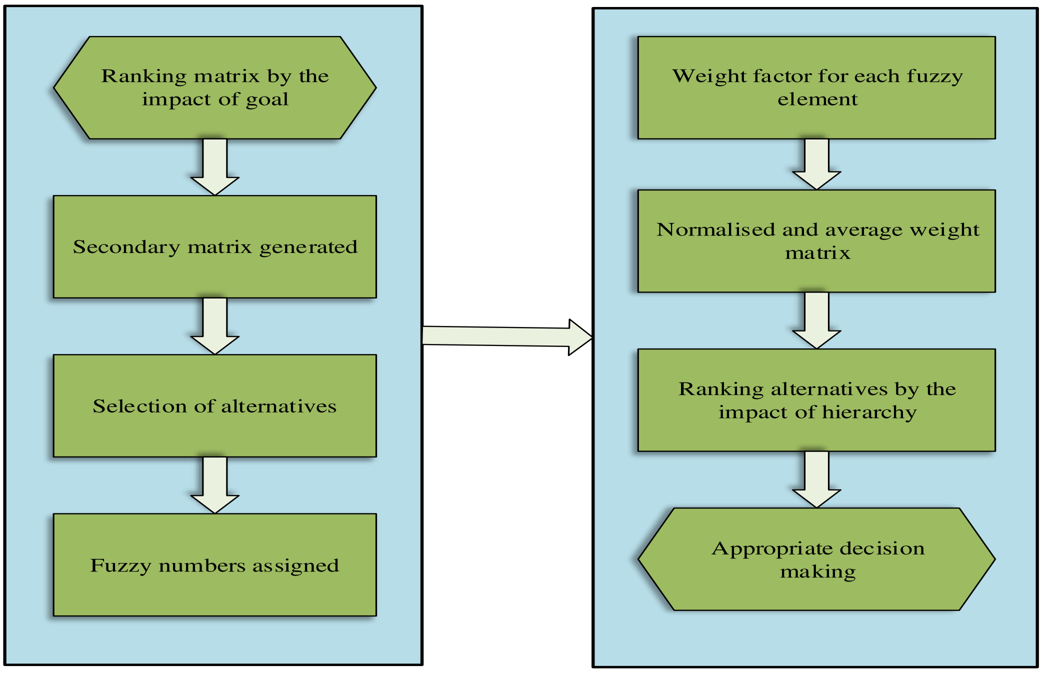

Figure 2: Structure of H-fuzzy

Constructing triangular Fuzzy values with respect to one criterion mapped with various characteristics. Here pairwise comparison is the major task performed repeatedly until the desired hierarchy is attained. In the next stage the linguistic variables (i.e. partial weightage or changed weightage value) converted to crisp numbers and trapezoidal numbers. The trapezoidal numbers ranges from 0 to 1.This membership function is utilized in this proposed method for its simplicity to deal with the uncertainty value of the elements. This approach is mainly constructed for handling the complex decision-making issues. It includes various set of conflicting criteria and alternatives. It also reduces the degree of comparison between the alternatives. Main objective of this H-Fuzzy is to evaluate a best decision based on the pair wise comparison of both criteria and alternatives. MCDM problems create a rise in the count of criteria and the alternatives which cannot be handled by other methods.H-Fuzzy proposed in this method builds a weight vector and the pairwise comparison matrix mathematically.

Step 1: Ranking of alternatives by the impact of goal

Compare the first two alternatives and if one is dominated by the other, the dominated one is discarded. Then the un-discarded alternative is compared to the third alternative and any of the dominated alternative is discarded. This comparison is repeated till the last one. A terminative method is implemented to discard the unacceptable ones. DM is set up with the cut off values and the alternatives less than the pre-set values will be eliminated. In this the cut off values is the main key source for eliminating the alternatives.

Step 2: Construct a secondary decision matrix

Primary decision matrix is obtained, next the performance ratings of each tool with respect to the quantitative criteria is evaluated. The linguistic variables of the fuzzy set areused to generate a decision matrix based on H-fuzzy. Equation (1) represents the generated matrix.

$$M_D = \begin{bmatrix} \widetilde{a_{11}} & \widetilde{a_{12}} \cdots & \widetilde{a_{1(p+t)}} \\ \widetilde{a_{21}} & \widetilde{a_{22}} \cdots & \widetilde{a_{2(p+t)}} \\ \vdots & \ddots & \vdots \\ \widetilde{a_{r1}} & \widetilde{a_{r2}}\cdots & \widetilde{a_{r(p+t)}} \end{bmatrix}_{K\times D} \quad (1)$$

Where, K is the alternative for element $i, i = 1,2,\ldots,r$, D represents the evaluation criterion $j, j = 1,2,\ldots,p+t$, and a_{ij} is denoted for the computed value performance rating of a tool.

Step 3: Selection of alternatives for the secondary decision matrix

Previously obtained matrix consists of performance ratings of tools as fuzzy numbers. H-Fuzzy ranking method is implemented in this matrix. This matrix determines the ranking order of all tools with respect to each evaluated element. Assume that, the ranking results can be taken as $D_1, D_2, \ldots, D_{p+t}$ are $A_j > A_j > \cdots > A_j$; $A_r > A_j > \cdots > A_i$ and $A_r > A_i > \cdots > A_j$. The modified matrix can be given as shown in equation (2)

$$M_{Dm} = \begin{array}{c} 1^{st} \\ 2^{nd} \\ \vdots \\ r^{th} \end{array} \begin{bmatrix} A_j & A_r \cdots & A_r \\ A_r & A_j \cdots & A_i \\ \vdots & \ddots & \vdots \\ A_i & A_i & A_j \end{bmatrix}_{K\times D} \quad (2)$$

The performance ratings of two or more tools with regard to one evaluation element are similar. The tools are then assigned with same rank. They are converted to their respective performance. Tools in the ranking matrix are considered with their weighted difference interval between the evaluated values. Therefore the above ranking matrix will be then converted to a weighted ranking matrix. Weightage value of this matrix $\alpha = 0.5$. Weight-ranking matrix can be represented as shown in equation (3)

$$\begin{array}{c} 1^{st} \\ 2^{nd} \\ \vdots \\ r^{th} \end{array} \begin{bmatrix} R_{1j} & R_{2j} \cdots & R_{r(p+t)} \\ R_{1r} & R_{2r} \cdots & R_{i(p+t)} \\ \vdots & \ddots & \vdots \\ R_{1i} & R_{2i} \ldots & R_{j(p+t)} \end{bmatrix}_{k\times d} = \begin{array}{c} 1^{st} \\ 2^{nd} \\ \vdots \\ r^{th} \end{array} \begin{bmatrix} W_{1j} & W_{2j} \cdots & W_{r(p+t)} \\ W_{1r} & W_{2r} \cdots & W_{i(p+t)} \\ \vdots & \ddots & \vdots \\ W_{1i} & W_{2i} \ldots & W_{j(p+t)} \end{bmatrix}_{k\times d} \quad (3)$$

Where, $W_{1j} = W_{c1}{}^{\alpha} \times a_{ji}{}^{\alpha}$; $W_{1r} = W_{r1}{}^{\alpha} \times a_{r1}{}^{\alpha}$ and $W_{1i} = W_{1i}{}^{\alpha} \times a_{1i}{}^{\alpha}$. Weightage of tools W is calculated from i with respect to j. Regarding the above matrix, aggregated weight of each object in the matrix is assigned with different ranks. This can be termed as a_r within the first rank of matrix. Criteria of $C_{(p+t)}$ for the aggregated weight of the tool a_r is calculated by summing and calculating the respective elements in the matrix. It is denoted as W_1. Similarly other aggregate weight of the product tools in different ranks can be examined.

Step 4: Fuzzy number assigned for each alternative

Matrix values are taken as input to trapezoidal functions. Values in the trapezoidal functions are categorised in the range of 1,2, …9. The membership function can be expressed as

$$\omega_a(T) = \begin{cases} \frac{T}{Me-L} - \frac{l}{Me-L}, & T \in [L, Me] \\ \frac{T}{Me-H} - \frac{l}{Me-H}, & T \in [Me, H] \\ 0, & Otherwise \end{cases} \quad (4)$$

Where, T is the fuzzy membership element, L is the lower limit, Me is the medium and H is the High limit range. Here, the linguistic values are converted to fuzzy numbers. It represents the comparative significance of the two attributes in the matrix.

Step 5:Weight factor for each fuzzy element

By obtaining matrix in the form of fuzzy numbers, geometric mean value is calculated so as to merge the expert's proficiency appropriately. From values in matrix an H-Fuzzy based pair-wise comparison is been done to assemble the matrix and rank it accordingly. The modified matrix can be expressed as in equation (5)

$$\widetilde{P_d} = \begin{bmatrix} \widetilde{d_{11}} & \widetilde{d_{12}} \cdots & \widetilde{d_{1n}} \\ \widetilde{d_{21}} & \widetilde{d_{22}} \cdots & \widetilde{a_{2n}} \\ \vdots & \ddots & \vdots \\ \widetilde{d_{r1}} & \widetilde{d_{r2\cdots}} & \widetilde{d_{nn}} \end{bmatrix} \tag{5}$$

Where,

$$d_{ij} = \left(\prod_{j=1}^{n} d_{ij}{}^{\alpha}\right)^{\frac{1}{n}} \tag{6}$$

Where, d_{ij} represents the n decision expert's choice of the i^{th} attribute over the j^{th} attribute.This geometrical mean is calculated for categorizing the matrix according to its weightage of each factor.

Step 6:Normalised and Average Weight Matrix

The fuzzy weights are examined by normalisation and the weight of the i^{th} criterion with respect to the j^{th} alternative. It can be given as equation (7)

$$\widetilde{\Gamma_\iota} = \widetilde{d_\iota} \otimes (\widetilde{d_1 \oplus d_2 \oplus}\, \widetilde{d_3} \dots \dots \oplus d_n)^{-1} \tag{7}$$

Where,$\widetilde{\Gamma_\iota}$ is fuzzy weight value. Normalised weight criteria can be calculated as

$$N_i = \frac{\widetilde{\Gamma_1} \oplus \widetilde{\Gamma_2} \dots\dots \oplus \widetilde{\Gamma_n}}{n} \tag{8}$$

And then the average of the normalised criteria can be calculated as

$$AN_i = \frac{N_i}{N_1 \oplus N_2 \dots\dots \oplus N_n} \tag{9}$$

Equation (9) is used to find the normalised and average matrix. It is then ranked based on H-Fuzzy.

Step 7:Ranking alternatives by the impact of hierarchy

For defuzzified ranking of alternatives consists of average of maximized value, centre of area and α-cut methods for prediction. In this research, centre of area method is utilized as there is no requirement of the preferences from any alternatives. The ranking of alternatives is done based on the best non fuzzy values obtained for each alternative using this method. The mathematical expression for calculating Best Non-Fuzzy Performance metric is given as

$$BNP_m = \frac{(H\Gamma_1 - L\Gamma_1) + (Me\Gamma_1 - L\Gamma_1)}{3} + L\Gamma_1 \tag{10}$$

Step 8: Decision making

The variations of results show that the ratings of alternatives are sensitive to the weights. Based on this obtained values for each alternative in the matrix, the decision is made. H-Fuzzy implemented to the product design for tool selection for making appropriate decisions.

4. Simulation Results

Results obtained by implementing the proposed approach are presented in this section. The expert opinion for each product is utilised as input and a matrix is generated accordingly. The alternatives in this matrix are ranked by Hierarchical fuzzy set theory and the decision is made respectively. The proposed methodology is designed to select the optimal tool especially in product design applications. The product design dataset is used to evaluate the performance of the proposed methodology which collected from open source system [22]. Data set values are evaluated with 1 response variable, 5 categorical machine and product attributes and 11 numerical attributes. The dataset contains 13186 observations. The performance of the proposed model is shown with a comparison to the existing methods.The algorithm is applied to the platform of MATLAB having Intel (R) Core (TM) i5-3570S CPU processor with speed 3.10GHz to analyse the product of the proposed model. Analytical metrics utilized in this proposed approach are Sensitivity, RMSE error, Accuracy, Specificity and Kappa comparison.Applications are made in the realistic environment and the proposed model emulates better prediction than previously proposed ones.The proposed method is compared with existing methodssuch asMCDM_TOPSIS, MCDM_PROMOTHEE, MCDM_ANP and MCDM_AHP.The model used in this research is to give an accurate solution for decision making purpose in the product design application. The implementation parameters of the proposed methodology is presented in table 1.

Table 1: Implementation parameters of proposed method

Sr.No.	Method	Description	Value
1		Response variable	1
2	Dataset	Categorical machine	5
3		Product attributes	1
4		Numerical attributes	11
5		Membership function	Triangular
6		Number of inputs	1
7	Proposed H-Fuzzy set	Number of outputs	5
8		Sigma	$5.0e^{-5}$
9		Lambda	$5.0e^{-7}$
10		Number of rules	10

The proposed method is used to find outbest tools in product design applications. The proposed method is analysis through statistical measurements which provided in below section.

A. Sensitivity analysis

Sensitivity analysis is done for the proposed model in order to measure the performance of solving MCDM problem. Hierarchy level of the desired system by making sensitivity analysis through weight is resulted in the figure 3. It can be given as value of true positive divided by summation of true positive and false negative.

$$Sensitivity = \frac{TP}{TP+FN} \tag{11}$$

Sensitivity of the MCDM approaches namely TOPSIS results in 75%, likewise PROMOTHEE shows nearly 80% of sensitivity. ANP technique shows 70% sensitivity in the output. AHP presents 65% of sensitivity analysis. Proposed model with an increased sensitivity more than 80%.

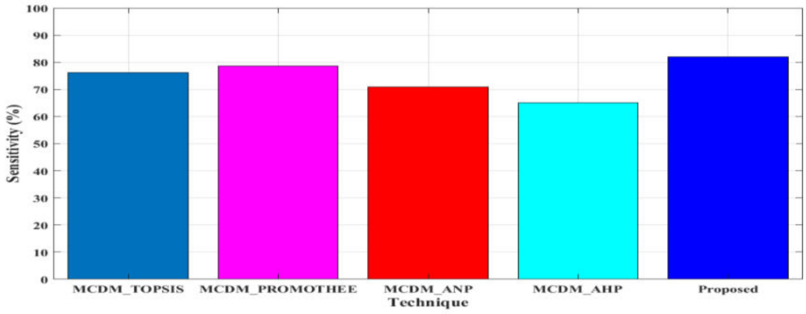

Figure 3: Sensitivity analysis of MCDM approaches and H-Fuzzy

This analysis is done using passive experiments, shows change in each factor with respect to its weight are then varied to calculate sensitivity. Measurement of sensitivity can be termed as true positive rate; it is a proportion of actual positives that accurately identified from pairwise comparison of matrix. It is a complementary to false negative rate.

B.RMSE error

Root mean square error (RMSE) is rapidly used to find the difference between the values predicted by a model and the observed values. It is a mathematical calculation of second variations to the observed one with its difference of quadratic mean. These calculations are performed over the matrix data which was used for estimation termed as RMSE errors. RMSE error shares an aggregate value for the magnitudes of the error in predicting the various values into a single prediction.It can be given as

$$RMSE\ Error = \sqrt{\frac{\sum_{i=1}^{n}(P-O)^2}{m}} \tag{12}$$

Here, i is the number of samples up to m, P is the predicted value and O is the observed value. RMSE error must be below 10% for an efficient system model. The comparison of this error value of the proposed model to the existing approach is shown in figure 4.

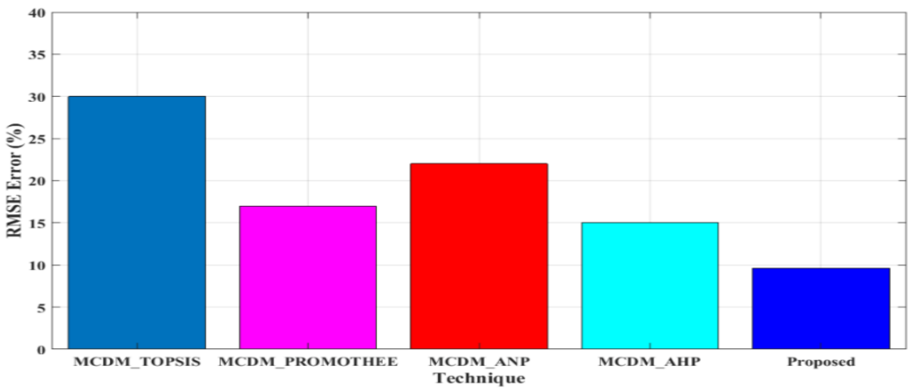

Figure 4: RMSE error comparative representation

From figure 4, the RMSE error ranges are continuously varied for each MCDM methods. RMSE errors are up to 30 % when fuzzy is not implemented to the model. When H-Fuzzy is implemented the error decreases below 10%. MCDM –AHP shows 15% of RMSE error and TOPSIS applied to the system results high range of error. Compared to four algorithms implemented proposed methodology result in least error level.

C.Accuracy

It is a measurement used for analysing which model is best on performing the desired applications. It is done by examining the reliable values and the patterns between variables in a data set depends on the input of the collected data. It can also be defined as the number of true positives and true negatives to the ratio of the summation value of true positives, true negatives, false positives and false negatives. It can be calculated as

$$Accuracy = \frac{TP}{TP+FN} \tag{13}$$

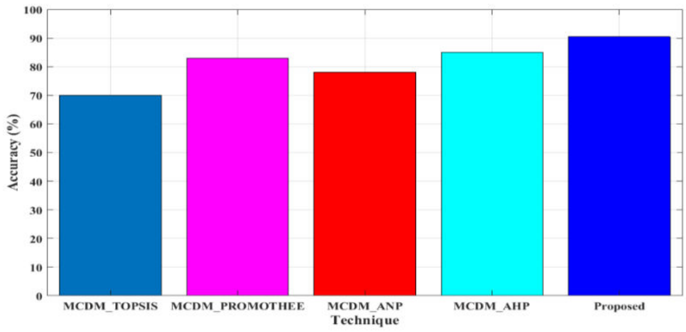

Figure 5: Graphical representation of Accuracy

In Figure 5 it is represented that the accuracy of the other models are relatively low. Proposed model is comparatively high. Accuracy level measures shown that the proposed approach shows a high level accuracy of about 90% in the decision making. MCDM_AHP results in 85% of accuracy and the MCDM_ANP shows 75% of accuracy. Traditional techniques namely MCDM_TOPSIS and PROMOTHEE results with 70 and 82% of accuracy respectively. Hence the proposed model shows an improved accuracy rate due to the lower specificity and higher sensitivity of the system.

D. False positive rate

An accuracy metric measured as a subset of machine learning models is False Positive rate. To get accuracy, it must have some notion of the true state of things. To perform multiple comparisons, a false positive ratio is usedto find probability of falsely rejecting null hypothesis for each element. It can be given as below equation,

$$FP_r = \frac{FP}{FP+TN} \tag{14}$$

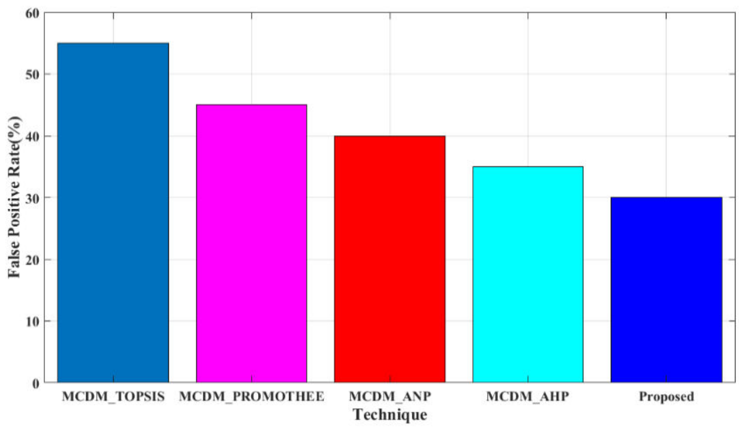

Figure 6: Representation of False Positive Rate

The false positive rate is calculated as the ratio between the number of negative events wrongly categorized as positive and the total number of actual negative events. Accuracy can then be directly measured by comparing the outputs of models with this ground truth. The termination of alternatives appropriately from the matrix in turn increases the accuracy of the system. From figure 6 the analysis result shows that MCDM_ANP technique has a lower false positive rate which in turn affects the system. MCDM_TOPSIS and PROMOTHEE shows fluctuated FPR which result in a confused state of the system. Proposed model results in 30 % of false positive rate which is helpful for an enhanced performance.

E. Specificity

Sensitivity and specificity are inversely proportional, meaning that as the sensitivity increases, the specificity decreases.Specificity of a test, also referred to as true negative rate is proportion of samples that test negative.

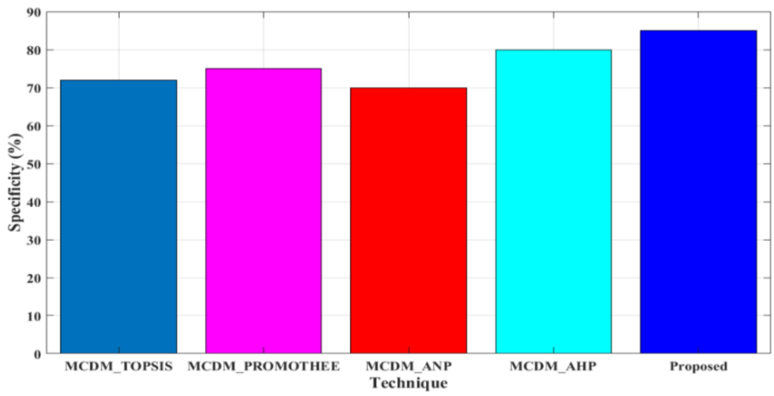

Figure 7: Specificity representation of different approaches

Measures of specificity termed as true negative rate, the proportion of negatives that are properly predicted like the percentage of appropriate product areidentified.It is complementary to the ratio of true negatives to the true negative and false positives. Figure 7 shows the variation in the specificity when compared to the previously existing techniques. From the graph it is understandable that the specificity of the proposed model is high about 85%. MCDM_ANP technique results in 70% of false positive rate. Hence when the H-Fuzzy is implemented to the system it results in enhanced decision making process.

F. Kappa

It is used in the measurement of inter-raterreliability, the chance of occurrence is measured by chance. Collected data are then measured and compared to the pre-set value and it reaches an extent to the measure of performance.

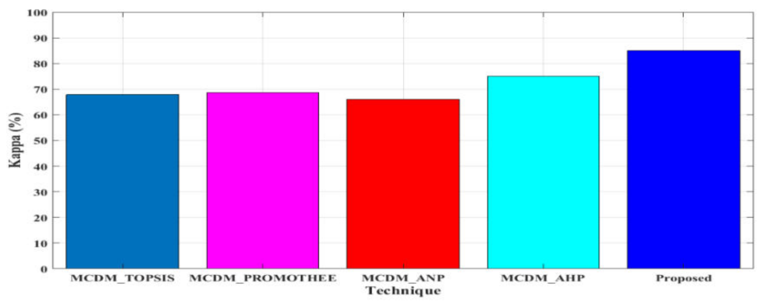

Figure 8: Representation of kappa comparative analysis in different approaches

Measurement of this extent to which the data collected are implemented to the same variable called as inter rater reliability, it is constructed in order to measure the possibility of the raters that normally with the probability of the occurrence of the disease. From figure 8 kappa value of the MCDM_TOPSIS, PROMOTHEE and ANP techniques are around the range of 60% which lowers the quantity of decision making. MCDM_AHP shows slightly high value i.e.75% at output. Finally when the H-Fuzzy is implemented the system shows more than 80% of kappa value.

G. Overall performance

The overall performance of the existing methods namely MCDM_PROMOTHEE, TOPSIS, ANP and AHP are compared to the proposed method. It shows that the accuracy level of the proposed approach reached 90%. RMSE error is comparatively low from the existing methods.

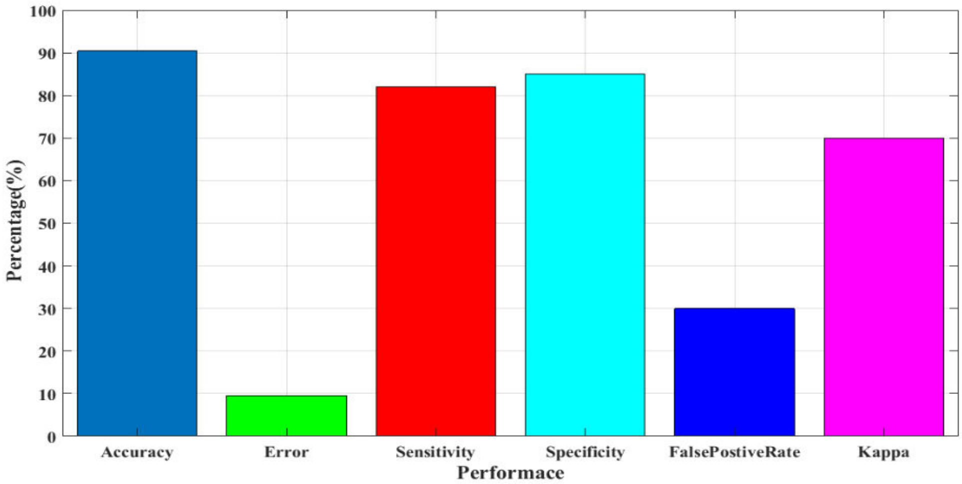

Figure 9: Overall performance representation of the proposed model.

Performance metrics sensitivity increased in the proposed model. From figure 9, the proposed methodology results in 82% of sensitivity and 84% of specificity percentages. False positive rate is 30% which increase the performance in decision making. Hence, by analysing the metrics of the proposed system model it is understandable that it is efficient in decision making.From the findings of the research, it is concluded that the results are more practical and realistic.

5. Conclusion

In this paper, a methodology was proposed based on H-Fuzzy for selecting the most suitable equipment tools. The ranking of the products are the outcome of this methodology. For dealing with uncertainty conditions and passive experiments in the MCDM approach solving MCDM problem is necessary. Proposed methodology applies trapezoidal function into H-Fuzzy for solving MCDM problems. The proposed method was practical for ranking machine tool alternatives with respect to multiple conflicting criteria. MCDM approaches namely TOPSIS, PROMOTHEE, ANP and AHP are analysed for solving this issue. But these methods fail in handling a rise in criteria with parameterization tools. However, most selection criteria are evaluated by decision-makers, and evaluations are subjective in terms of alternatives. Currently, there has been much research and subsequent application of MCDM models to evaluate MCDM problems. Hence, the proposed methodology with H-Fuzzy technique takes weightage of each product from the expert opinion for making decisions. The weightage values were formed as a matrix and the alternatives as calculated for each element in the matrix. Ranking of the matrix based on average normalised value was done. Selection of alternatives from this ranking matrix was made by calculating the best non fuzzy value in the matrix. This methodology results in a best optimal solution for decision making when implemented in a realistic environment.

References:

[1]. Onut, S., Kara, S.S. and Işik, E., 2009. Long term supplier selection using a combined fuzzy MCDM approach: A case study for a telecommunication company. Expert systems with applications, 36(2), pp.3887-3895.

[2]. Chiu, W.Y., Yen, G.G. and Juan, T.K., 2016. Minimum Manhattan distance approach to multiple criteria decision making in multiobjective optimization problems. IEEE Transactions on Evolutionary Computation, 20(6), pp.972-985.

[3]. Dursun, M. and Karsak, E.E., 2013. A QFD-based fuzzy MCDM approach for supplier selection. Applied Mathematical Modelling, 37(8), pp.5864-5875.

[4]. Sodhi, R., Srivastava, S.C. and Singh, S.N., 2011. Multi-criteria decision-making approach for multi-stage optimal placement of phasor measurement units. IET Generation, Transmission & Distribution, 5(2), pp.181-190.

[5]. Tontchev, N.T. and Hristov, N.D., 2011. Method for solving multiple criteria decision making (mcdm) problems in building-up by welding area. In VIII International Congress Machines, technologies, materials (Vol. 1, pp. 98-102).

[6]. Chen, I.S., 2016. A combined MCDM model based on DEMATEL and ANP for the selection of airline service quality improvement criteria: A study based on the Taiwanese airline industry. Journal of Air Transport Management, 57, pp.7-18.

[7]. Majumder, H. and Maity, K., 2018. Prediction and optimization of surface roughness and micro-hardness using grnn and MOORA-fuzzy-a MCDM approach for nitinol in WEDM. Measurement, 118, pp.1-13.

[8]. Wu, C.S., Lin, C.T. and Lee, C., 2010. Optimal marketing strategy: A decision-making with ANP and TOPSIS. International Journal of Production Economics, 127(1), pp.190-196.

[9]. Wang, C.N., Huang, Y.F., Cheng, I. and Nguyen, V.T., 2018. A multi-criteria decision-making (MCDM) approach using hybrid SCOR metrics, AHP, and TOPSIS for supplier evaluation and selection in the gas and oil industry. Processes, 6(12), p.252.

[10]. Agrawal, A., Alenezi, M., Kumar, R. and Khan, R.A., 2019. Measuring the sustainable-security of Web applications through a fuzzy-based integrated approach of AHP and TOPSIS. IEEE Access, 7, pp.153936-153951.

[11]. Chang, C.T., Zhao, W.X. and Hajiyev, J., 2019. An Integrated Smartphone and Tariff Plan Selection for Taxi Service Operators: MCDM and RStudio Approach. IEEE Access, 7, pp.31457-31472.

[12]. Triantaphyllou, E., Shu, B., Sanchez, S.N. and Ray, T., 1998. Multi-criteria decision making: an operations research approach. Encyclopedia of electrical and electronics engineering, 15(1998), pp.175-186.

[13]. Dağdeviren, M., 2008. Decision making in equipment selection: an integrated approach with AHP and PROMETHEE. Journal of intelligent manufacturing, 19(4), pp.397-406.

[14]. Quan, M.Y., Wang, Z.L., Liu, H.C. and Shi, H., 2018. A hybrid MCDM approach for large group green supplier selection with uncertain linguistic information. IEEE Access, 6, pp.50372-50383.

[15]. Yager, R.R., 2004. Modeling prioritized multicriteria decision making. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 34(6), pp.2396-2404.

[16]. Sodhi, R., Srivastava, S.C. and Singh, S.N., 2011. Multi-criteria decision-making approach for multi-stage optimal placement of phasor measurement units. IET Generation, Transmission & Distribution, 5(2), pp.181-190.

[17]. Choi, D.H. and Ahn, B.S., 2009. Eliciting customer preferences for products from navigation behavior on the web: A multicriteria decision approach with implicit feedback. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 39(4), pp.880-889.

[18]. Chiu, W.Y., Yen, G.G. and Juan, T.K., 2016. Minimum Manhattan distance approach to multiple criteria decision making in multiobjective optimization problems. IEEE Transactions on Evolutionary Computation, 20(6), pp.972-985.

[19]. Agrawal, A., Alenezi, M., Kumar, R. and Khan, R.A., 2019. Measuring the sustainable-security of Web applications through a fuzzy-based integrated approach of AHP and TOPSIS. IEEE Access, 7, pp.153936-153951.
[20]. Yuen, K.K.F., 2013. Fuzzy cognitive network process: comparisons with fuzzy analytic hierarchy process in new product development strategy. IEEE Transactions on Fuzzy Systems, 22(3), pp.597-610.
[21]. https://ieee-dataport.org/open-access/dataset-semiconductor-assembly-and-testing processes