ENTREATY OF FUZZY INTERVAL-VALUED EDAS METHOD IN ORDER PREFERENCE OF CUSTOMERS FOR RANKING OPTIMIZATION

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ABSTRACT

The growing need of a research lab in automotive confirmatory tests is increasing day by day in the competitive market. Testing plays an important part in time and cost to meet the durability and quality requirements of the customers. Decision Making Models [DMM] with order preference supports well in optimizing the process scheduling time and utilization of machines. The analyzed data is of with multi-criterion constraints and unreliable parameters. As the constraints in analyzed data belongs to [-R, R], the problem is modelled with generalized Fuzzy Interval Valued set. The defined FIVs are justified using Novel Accuracy of Membership and Non-Membership values. The unconventionality of the work discussed in this paper is applying FIVs in the existing Evaluation by Distance Average Sum [EDAS] method. The weight values of the criterion are calculated using the Average Distance [AD] formula. In general, Fuzzy VIKOR and Fuzzy TOPOSIS helps in identifying the closeness co-efficient of the parameters. Particularly, VIKOR plays a vital role on group utility and TOPOSIS on Max/Min of negative and positive ideal solutions respectively. Here, the proposed FIVEDAS method is framed with the Relative Distance Values [RDA] and so it provides us an ideal ranking in order preference. The results are compared with the existing lab process utility time in First-Come-First Serve method.

Key Words: Fuzzy Interval Valued set; EDAS, positive average measure; negative average measure; normalized weighted sum; score values.

1.0 INTRODUCTION

Managing big data analytics and predictive analysis is the increasing demand for data science [1]. The involvement of a crowd and a group of ordinary people performing tasks addresses the time-constrained task assignment problem using IoT massiveness strategic setting [22]. The complex multi-criteria decision-making problems will have both qualitative and quantitative parameters. Uncertainty may cause due to unclear / vagueness data or by the subjective viewpoint of decision-makers [7]. Statistical solutions will not accurately measure human behavior imprecision and are examined and pointed out by Dubois and Prade [2, 9]. Fuzzy set concept approaches in a better way rather than statistical and probabilistic methods. Hence emerged the fuzzy data analysis. The fuzzy concept was widely applied in Operations Research, Control Theory, etc. It is the best-opted logic for the real-world problems of uncertainty. The theory of fuzzy was acquaint with Zadeh [2] as an effective method in decision-making problems. Bellman with Zadeh [11] proposed MCDM problems. MCDM plays a vital role in personnel selection in the fuzzy environment. The decision maker's judgment on order preferences will be affected by its uncertainty.

In [3, 4, 5,6], the AHP method was explained in detail to measure the weight of the criteria and this method is a well-known method for calculating weights. Another method of calculating weight is ELECTRE method, proposed by Rogers [5]. For providing the best agenda in the selection process the VIKOR method was familiarized by Opricovic in the year 1998 [8]. In this method, the best suitable criteria must have high group utility. EDAS is the projected method in the decision problems with multi-criteria for choosing the best alternatives or finding the order preference. This method is noted as a useful method for ranking the alternatives with conflicting criteria. EDAS gives an ideal solution similar to SAW, VIKOR, and TOPOSIS methodologies [11]. In 2015, Keshavarg Ghorabace, Zavadskas, Olfat, and Turskis introduced the EDAS method with average value, negative and positive measures [14]. The best-known application of this method was given a solution to the traffic problem in airways [15,19]. Here they used AHP for calculating weight values. It was the best-proposed method for problems in the fuzzy environment [13].

Keshavarz Ghorabace applied the method for supplier selection problem and used sensitivity analysis to calculate the criterion's weights to get stable and valid results. Also, they extend this method to Fuzzy interval-valued 2nd type sets [12, 13]. In 2017, Keshavarz applied it for an interval-valued intuitionistic set of the data containing membership and non-membership with a degree of hesitancy [13]. Ragaventhiran J and Syed Thouheed Ahmed [21] in their paper explained that the required quantity of significant features will be extracted from the tokens through embedding technique has been employed using embedding layer .This proposed model adopting interval valued fuzzy soft set combines the soft sets, for individual applications. The determination of individual values is very much helpful through the FIVEDAS evaluation model. It is applicable in many real-life applications like ranking optimization, medical diagnosis, interval estimation, and students answerscripts prediction models.

In this paper the validation process time and machine utility are optimized. The problem defined is identified with multi-criterion and with more uncertainty. Hence the data is defined with Fuzzy Interval Valued rough set with average boundaries and hence the classical EDAS is computed for the FIVSs. The algorithm is coded for FIVEDAS method with the newness in fixing the weights of criterion and fuzzy values in interval form. The result is compared with the existing first-come-first-serve method. In Section-2 we give the basic definitions related to the proposed method and then a detailed description about the method with its algorithm in Section-3. Section -4 explains about the classical EDAS method and Section- 5 gives a detail explanation on the conversion of EDAS method into FIVEDAS method with justification. The next Section-6 discusses the interpretation of the model with the data and results. Then the section-7 flourishes the comparative results and section-8 goes with result discussion. Finally, the last section-9 says the future work of the research to be extended.

2.0 PRELIMINARIES

2.1 Fuzzy Set

A fuzzy set $F = \{(\alpha, \mu_{f(\alpha))} / \alpha \epsilon A$ and $\mu f(\alpha_1) \epsilon [0,1]\}$, where $\mu_{f(\alpha))}$ is the membership function whose value takes from the interval [0,1].

2.2 Fuzzy Triangular Number

A fuzzy triangular number is a three-part number satisfying the following conditions:
(i) The lower boundary to Mid Value number is an increasing number.
(ii) Mid Value to Upper boundary number is a decreasing number.
(iii) For $\alpha_{1\leq} \alpha_{\leq} \alpha_2 / \alpha_{2\leq} \alpha_{\leq} \alpha_{3,}$

$$\mu_{f(\alpha)} = \begin{cases} \alpha < \alpha_1 \ \& \ \alpha > \alpha_2 \\ \alpha - \alpha_1 / \alpha_2 - \alpha_1 \,;\, \alpha_1 \leq \alpha \leq \alpha_2 \\ \alpha_3 - \alpha / \alpha_3 - \alpha_2 \,;\, \alpha_2 \leq \alpha \leq \alpha_3 \,. \end{cases} \quad (1)$$

The difference in assigning fuzzy interval valued set in our data is that we are fixing the membership values for the numerical data instead of linguistic. So triangular formula is used to fix the lower and upper boundaries like a rough fuzzy set. This was explained with example set of values before framing the decision matrix.

2.3 Fuzzy Interval Valued Set Operators

For Fuzzy Interval Valued Sets $I_1= (\alpha_1, \alpha_2)$ and $I_2= (\beta_1, \beta_2)$, below are the basic operations applied between the two FIVS. These operators are used in the proposed method.

(i) Addition of I_1 and I_2 given by,
   i. $I_1 + I_2 = (\alpha_1 + \beta_1, \alpha_2 + \beta_2)$.
(ii) Subtraction of I_1 and I_2 given by,
   i. $I_1 - I_2 = (\alpha_1 - \beta_2, \alpha_2 - \beta_1)$.
(iii) Multiplication of I_1 and I_2 given by,
   i. $I_1 x\ I_2 = (\min(\alpha_1 \beta_1, \alpha_2 \beta_2), \max(\alpha_1 \beta_1, \alpha_2 \beta_2))$.
(iv) Division of X and Y given by,
   i. $I_1 / I_2 = (\min(\alpha_1/\beta_1, \alpha_1/\beta_2), \max(\alpha_2/\beta_1, \alpha_2/\beta_2))$.

3.0 FUZZY INTERVAL VALUED EVALUATION BY DISTANCE AVERAGE SUM METHOD

Step 1: Analyze the data and fix the criteria and alternatives to make the FIVDM – Fuzzy Interval Valued Decision Matrix.

Step 2: The weight of the alternatives is calculated using average distance formula,

$$\hat{W}_J = \left| \sum_{i=1}^{n} бij/n - \sum_{i=1}^{n} \alpha ij/n \right|$$

Step 3: Get the average value matrix
$\bar{A} = [\bar{A}_j]_{1 \times m}$ for j = 1,2,3…., m by using the formula,
$\bar{A}_j = \sum_{i=1}^{n} [\alpha ij, бij]/n$; j = 1,2,3…, m

Step 4: Here, we have only beneficiary criteria, and so we are using only the positive and negative average values for beneficiary criterion as,

$[\bar{A}_{ij}]^+ = \max [(0,0), ((\alpha ij, бij) - \bar{A}_j)] / \bar{A}_j$
$[\bar{A}_{ij}]^- = \max [(0,0), (\bar{A}_j - (\alpha ij, бij))] / \bar{A}_j$

If there is any cost criterion, then we use the formulas,

$[\bar{A}_{ij}]^+ = \max [(0,0), (\bar{A}_j - (\alpha ij, бij))] / \bar{A}_j$
$[\bar{A}_{ij}]^- = \max [(0,0), ((\alpha ij, бij) - \bar{A}_j)] / \bar{A}_j$

Step 5: Fix the positive and negative averages matrices by means of the previous step values.

$[\bar{A}]^+ = [\bar{A}_{ij}]^+_{nm.}$
$[\bar{A}]^- = [\bar{A}_{ij}]^-_{nxm}$

Step 6: Next to calculate the sum of weighted average positive and negative values by,

$[ȿ_i]^+ = \sum_{j=1}^{m} \hat{W}j \,.\, [\bar{A}_{ij}]^+$
$[ȿ_i]^- = \sum_{j=1}^{m} \hat{W}j \,.\, [\bar{A}_{ij}]^-$

Step 7: Using the sum of the weighted averages, calculate the Normalized sum value by,

$N_r [ȿ_i]^+ = [ȿ_i]^+ / \max [ȿ_i]^+$
$N_r [ȿ_i]^- = [ȿ_i]^- / \max [ȿ_i]^-$ for i=1,2,3…., n

Step 8: Finally, to calculate the appraisal values of the alternatives by,

$Aȿ_i = N_r [ȿ_i]^+ + N_r [ȿ_i]^- / 2$

Step 9: Finally, the score values of the alternatives give the rank values of the alternatives consuming the base formula,

$ȿ_r = \left| Aȿ_i(бij) – Aȿ_i(\alpha ij) \right|$

4.0 EDAS METHOD

Evaluation based on Distance Average Sum method is first framed for ABC classification of inventory items. In 2015, Keshavarz in a paper stated that it can also be applied for other MAMC problems. Based on PDA and NDA the averages calculated results in efficient appraisal and score values. In 2017, he examined and stated it can be focused over the situation which undergoes both objective and subjective evaluations. Performed the sensitivity analysis and concluded that it is the method with more uniformity compared to other methods like TOPOSIS, ELECTRE, VIKOR [10].

EDAS method is established to grip the supplier Selection problem by Keshavarz Ghorabace in 2016. This MAMC/ MCDM problem's assessment encompasses with many internal and external parameters [17]. The pre-requisite occurrence may touch the parametric values repeatedly leads to uncertainty. To aspect the global request of supply many MCDM methods like MULTIMOORA, hierarchy method in fuzzy space with 2-tupules, GRA methods were urbanized. Comparatively EDAS method shows good proficiency with fewer reckoning steps. The firmness and adeptness were examined with the conclusion of consistency on incompatible criterion by Keshavarz in his paper in 2016. In 2020, Shaaban.M and L.M.Abd El practical this method to optimize the parameters in Diesel Engine system and the weights are designed using Informative Entropy method. Demonstrated as a competent tool using sensitivity analysis [16]. Tabasam Rashid, Asif Ali .ID and Yu-Ming Chu [18] pragmatic EDAS strategy to select robot. The outcome is paralleled with VIKOR and sensitivity examination done under the ratio 80:1. Finalize that this method is with more immovability and reliability. Here, we proposed Fuzzy Interval Valued rough set with average boundaries and hence the classical EDAS is computed for the FIVSs.

5.0 FIVEDAS IN INVESTIGATED DATA

The data from a testing lab with the test criteria are noted with the customer desires. The route of customer selection followed in the lab is the first-come-first-serve method and based on the availability of the testing machines. Coming to the utility of the machines, if the selection of customers is planned, then it will provide more utilization. Also, the customer expectations will not be the same or fixed at all times. Here comes the uncertainty and hence the data suited for the fuzzy environment. To provide the best order preference on customer selection, the EDAS method is applied after defining the fuzzy interval valued for each alternative related to the criteria. In the analyzed data, we have five criteria with 48 alternatives. While noting the criterion requirement of customers, some do not need to propose the maximum criteria except one or two. So, those customers' values can be included without preference order and considered to be included during idle time or resembling process to join. Henceforth, we now have 18 alternatives(customers) and 5 criterion as: High Temperature, Low Temperature, Temperature Cycle Test, Humidity Cycle Test and Temperature Humidity Test, . Clustering is defined as ordering an undifferentiated textual report into a cluster that is, reports within clusters have high parallelism compared to others but heterogeneous with respect to other cluster reports, discussed by Syed Thouheed Ahmed [20]. In the decomposition process the cluster forms will supports in parallelism. Here decomposition is done directly without any strategy as we are giving membership values for numerical data. Based on the triangular fuzzy concept, a fixed average value of each criterion aspects given and hence defined fuzzy interval-valued set. The fuzzy triangular valued set is used with average of criterion which gives us the rough set boundary values.

6.0 NUMERICAL INTERPRETATION USING FIVEDAS METHOD

6.1 Decision Matrix

As discussed above, the decision matrix values are fixed using generalization of fuzzy triangular number using [B] fuzzy rough set. In the three-part number, generalization was done by combining averages of overall criterion range for lower and upper boundary. Finally, we give the fuzzy interval valued set as fixing the boundary values by the alternatives mapping into the criterion range. Here, the midpoint is the most satisfiable value as that in classical basic concept but in this generalized method, for both sides we are assigning the membership value based on alternatives. Left side says about the lower satisfactory boundary and right side says about the upper satisfactory boundary. For the 1st criteria, the maximum low temperature is 75 and maximum high temperature is 105. Take the average of all low temperature and of all high temperature for fixing the boundaries. Define the membership value of each corresponding alternatives that maps the criterion aspect in fuzzy triangular curve.

High temperature: Overall requirements are 75, 80, 85, 90, 95, 100, 105 whose average is 90. Fix the Midvale = 90 in the fuzzy triangular curve. So, the lower boundary is 75 and upper boundary as 105. Requirement of A_1 in C^{*}_{1} is 85. So, the membership value of the first alternative for first criteria is 0.6 as it lies in the left side of the curve. Therefore, using equation (1) the IVF of A1→ C1 is [0.6,0.6]. Likewise, the membership values for all other alternatives against the criterions given in the below decision matrix.

Table 1: Generalized Fuzzy Triangular Number

$\tilde{C}1$	$\tilde{C}2$	$\tilde{C}3$	$\tilde{C}4$	$\tilde{C}5$
(0.67,0.67)	(0.54,0.54)	(0.23, 0.25)	(0.39, 0.79)	(0.43, 0.56)
(0.67,0.67)	(0.1, 0.1)	(0.29, 0.51)	(0.31, 0.79)	(0.56, 0.56)
(0.67,0.67)	(0.1, 0.1)	(0.25, 0.42)	(0.09, 0.89)	(0.56, 0.68)
(0.67,0.67)	(0.1, 0.1)	(0.25, 0.42)	(0.09, 0.89)	(0.56, 0.68)
(0.67,0.67)	(0.1, 0.1)	(0.25, 0.42)	(0.14, 0.55)	(0.05, 0.61)
(0 , 0 .67)	(0.1, 0.9)	(0.29, 0.30)	(0.39, 0.92)	(0.41, 0.56)
(1 , 1)	(0.9, 0.9)	(0.29, 0.32)	(0.14, 0.55)	(0.86, 0.94)
(1 , 1)	(0.1, 0.9)	(0.29, 0.32)	(0.57, 0.95)	(0.81, 0.81)
(0.67,0.67)	(0.1, 0.1)	(0.17, 0.25)	(0.10, 0.66)	(0.81, 0.81)
(0.67,0.67)	(0.1, 0.9)	(0.29, 0.32)	(0.57, 0.95)	(0.43, 0.56)
(0 , 0 .67)	(0.1, 0.9)	(0.17, 0.25)	(0.10, 0.66)	(0.81, 0.81)
(1 , 1)	(0.1, 0.1)	(0.29, 0.32)	(0.57, 0.95)	(0.05, 0.61)
(0.67,0.67)	(0.9, 0.9)	(0.29, 0.30)	(0.17, 0.8)	(0.81, 0.81)
(0.67,0.67)	(0.9, 0.9)	(0.29, 0.30)	(0.17, 0.8)	(0.81, 0.81)
(0 , 0 .67)	(0.1, 0.9)	(0.29, 0.30)	(0.17, 0.8)	(0.43, 0.56)
(0.67,0.67)	(0.1, 0.1)	(0.17, 0.25)	(0.17, 0.8)	(0.81, 0.81)
(0.67,1)	(0.1, 0.1)	(0.17, 0.25)	(0.39, 0.92)	(0.81, 0.81)
(0 , 0)	(0.1, 0.1)	(0, 0.17)	(0.57, 0.95)	(0.68, 0.94)

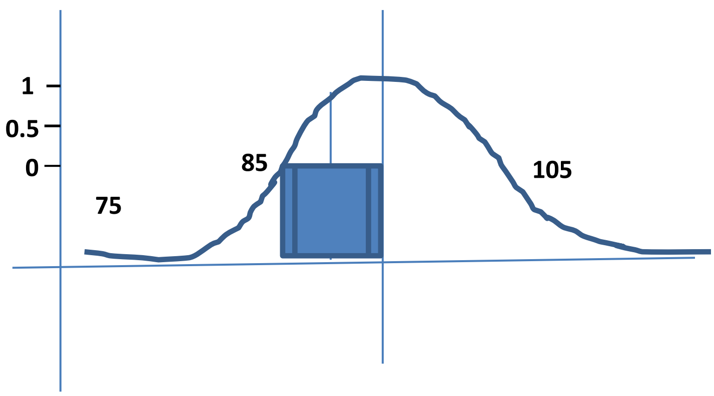

Fig.1: Generalized Fuzzy Triangular Number

6.2 NOVEL ACCURACY OF MEMBERSHIP AND NON-MEMBERSHIP VALUES.

Let $\{S_I\ [0, 1]\}$ be the collection of intervals contained in the Universal set [0, 1]. Then the Fuzzy Intuitionistic Interval Set applied by Jeevaraj Selvaraj & Abhijit Majumdar, in the year 2021 as,

$$A = \{x,\ \mu_\alpha(x),\ \beta_\alpha(x) : x \in X\} \tag{3}$$

where $\mu_\alpha(X)$: $X \rightarrow S_I\ [0, 1]$, $\beta_\alpha(X)$: $X \rightarrow S_I\ [0, 1]$ with the condition, $0 < \sup \mu_\alpha(x) + \sup \beta_\alpha(x) \leq 1$. The intervals $\mu_\alpha\ (x)$ and $\beta_\alpha(x)$ represents the membership and non-membership values for $x \in X$. Hence, A can be defined in element as lower and upper boundaries [16].

$$\text{(ie.,) } A = (x,\ [\mu_{\alpha\ L}\ (x),\ \mu_{\alpha\ U}\ (x)],\ [\beta_{\alpha\ L}\ (x),\ \beta_{\alpha\ U}\ (x)]) : x \in X \tag{4}$$

where $0 < \mu_{\alpha\ U}(x) + \beta_{\alpha\ U}(x) \leq =1$.

Consider the FIIVS A = (x, [a1, b1], [a2, b2]) where $\mu_\alpha(x)$ = [a1, b1] and $\beta_\alpha(x)$ = [a2, b2], then the novel accuracy for the defined FIIVS is verified by the formula,

$$Ɲ_a(x) = a1-(1-a1-a2) +b1(1-b1-b2) / 2 \text{ where } Ɲ_a(x) \in [-1,1] \quad (5)$$

The verified accuracy table for the defined FIVS are given below in the matrix form. The non-membership is directly calculate using

$$\beta_\alpha(x) = 1- \mu_\alpha(x) \quad (6)$$

In Table 1: a11=(0.67, 0.67) which is the membership values. Equation (6) gives non-membership values of a11= (0.33. 0.33), Therefore, the novel accuracy $Ɲ_a(\alpha_{11})$ = 0.67- (1-0.67-0.33) +0.67-(1-0.67-0.33)/2 = 0.34

Table 2: Novel Accuracy level for the FIVS in Decision Matrix

Novel Accuracy/Alt	$Ɲ_{a1}(\alpha_{ij})$	$Ɲ_{a2}(\alpha_{ij})$	$Ɲ_{a3}(\alpha_{ij})$	$Ɲ_{a4}(\alpha_{ij})$	$Ɲ_{a5}(\alpha_{ij})$
A_1	0.34	0.54	0.24	0.59	0.495
A_2	0.34	0.1	0.4	0.55	0.56
A_3	0.34	0.1	0.34	0.49	0.62
A_4	0.34	0.1	0.34	0.49	0.62
A_5	0.34	0.1	0.34	0.35	0.33
A_6	0.34	0.5	0.34	0.66	0.49
A_7	1	0.9	0.31	0.35	0.9
A_8	1	0.5	0.31	0.76	0.81
A_9	0.34	0.1	0.21	0.38	0.81
A_{10}	0.34	0.5	0.31	0.76	0.495
A_{11}	0.34	0.5	0.21	*0.38*	0.81
A_{12}	1	0.1	0.31	0.76	0.33
A_{13}	0.34	0.9	0.34	0.49	0.81
A_{14}	0.34	0.9	0.34	0.49	0.81
A_{15}	0.34	0.5	0.34	0.49	0.495
A_{16}	0.34	0.1	0.21	0.49	0.81
A_{17}	0.84	0.1	0.21	0.66	0.81
A_{18}	0	0.1	0.09	0.76	0.81

In the accuracy matrix all the calculated values are in the limit [-1,1] as stead in (5). Three values in the table are 1 which shoes the fixed membership value is 1, the left limit but with less accuracy. The values which are closer to 0 is with more accuracy rate.

6.3 Weight Values For The Criterion

Calculate the weight values of the criteria by using step-2. In Particular, the first weight is calculated as

$$\sum_{i=1}^{n} \text{бij}/n = 0.71 \text{ and } \sum_{i=1}^{n} \alpha\text{ij}/n = 0.58$$
$$\therefore \hat{W}_1 = 0.13$$

Likewise, the values of other weights as follows

$$\hat{W}_2 = 0.17,\ \hat{W}_3 = 0.18,\ \hat{W}_4 = 0.24,\ \hat{W}_5 = 0.49.$$

The weight constraint condition is that $\sum_{j=1}^{m} \hat{W}j = 1$ to be satisfied.

$$\sum_{j=1}^{5} \hat{W}j = 1.1 \approx 1$$

6.4 Average Value Matrix for The Given Data

The average values of each criterion are calculated by step-3 formula 2.

$$\bar{A} = [\bar{A}_j]_{1 \times m} = [(0.58,0.71)\ \ (0.25,0.48)\ \ (0.21,0.32)\ \ (0.28,0.72)\ \ (0.59,0.72)]$$

Using the average row matrix value calculate the positive average values.

In the decision matrix we have the a11 value as (0.67, 0.67)
So, by step:3 & 4 we can calculate,

$[\bar{A}_{i1}]^+$ for A_1 as max [(0,0), ((0.67,0.67) -(0.58, 0.71)] / (0.58, 0.71)
= max [(0,0), (0.67-0.71, 0.67-0.58)] / (0.58, 0.71) [using (b)]
= max [(0,0), (-0.04, 0.09)] / (0.58, 0.71)
= (0, 0.09) / (0.58, 0.71)
= (min (0,0), max (0.16,0.13)) [using (d)]
= (0, 0.16).

But a few places we get the min / max values below zero or above one, at those places we consider the values as zero. If the values exit the limit value of the boundary in an interval, here it is [0,1] it should not have the membership values inside the boundary. Hence considered as zero.

Here, for $[\bar{A}_{i2}]^+$, A_1 faces the above explained condition is one among the values.

Table 3: Positive average measures of alternatives

Cri/Alt	$[\bar{A}_{i1}]^+$	$[\bar{A}_{i2}]^+$	$[\bar{A}_{i3}]^+$	$[\bar{A}_{i4}]^+$	$[\bar{A}_{i5}]^+$
A_1	(0, 0.16)	(0.13, 0.6)	(0, 0.2)	(0, 0.71)	(0,0)
A_2	(0, 0.16)	(0, 0)	(0,0)	(0, 0.71)	(0,0)
A_3	(0, 0.16)	(0, 0)	(0,1)	(0, 0.85)	(0,0.17)
A_4	(0, 0.16)	(0, 0)	(0,1)	(0, 0.85)	(0,0.17)
A_5	(0, 0.16)	(0, 0)	(0,1)	(0, 0.96)	(0,0.05)
A_6	(0, 0.16)	(0, 0)	(0, 0.43)	(0, 0.89)	(0,0)
A_7	(0.41,0.72)	(0, 0)	(0, 0.52)	(0, 0.96)	(0.19,0.61)
A_8	(0.41,0.72)	(0, 0)	(0, 0.52)	(0, 0.93)	(0.13,0.37)
A_9	(0, 0.16)	(0, 0)	(0, 0.19)	(0, 0.53)	(0.13,0.37)
A_{10}	(0, 0.16)	(0, 0)	(0, 0.52)	(0, 0.93)	(0,0)
A_{11}	(0, 0.16)	(0, 0)	(0, 0.19)	(0, 0.53)	(0.13,0.37)
A_{12}	(0.41,0.72)	(0, 0)	(0, 0.52)	(0, 0.93)	(0,0.05)
A_{13}	(0, 0.16)	(0, 0)	(0, 0.43)	(0, 0.72)	(0.13,0.37)
A_{14}	(0, 0.16)	(0, 0)	(0, 0.43)	(0, 0.72)	(0.13,0.37)
A_{15}	(0, 0.16)	(0, 0)	(0, 0.43)	(0, 0.72)	(0,0)
A_{16}	(0, 0.16)	(0, 0)	(0, 0.19)	(0, 0.72)	(0.13,0.37)
A_{17}	(0, 0.72)	(0, 0)	(0, 0.19)	(0, 0.89)	(0.13,0.37)
A_{18}	(0,0)	(0, 0)	(0, 0)	(0, 0.93)	(0,0.59)

Table 4: Negative average measures of alternatives

Cri/Alt	$[\bar{A}_{i1}]^-$	$[\bar{A}_{i2}]^-$	$[\bar{A}_{i3}]^-$	$[\bar{A}_{i4}]^-$	$[\bar{A}_{i5}]^-$
A_1	(0, 0.07)	(0, 0)	(0, 0.43)	(0, 0.46)	(0.04, 0.4)
A_2	(0, 0.07)	(0.3, 0.79)	(0, 0.14)	(0, 0.57)	(0.04, 0.27)

A_3	(0, 0.07)	(0.3, 0.79)	(0, 0)	(0, 0.88)	(0, 0.27)
A_4	(0, 0.07)	(0.3, 0.79)	(0, 0)	(0, 0.88)	(0, 0.27)
A_5	(0, 0.07)	(0.3, 0.79)	(0, 0)	(0, 0.81)	(0, 0.93)
A_6	(0, 1)	(0, 0.79)	(0, 0.14)	(0, 0.46)	(0.04, 0.53)
A_7	(0, 0)	(0, 0)	(0, 0.14)	(0, 0.81)	(0,0)
A_8	(0, 0)	(0, 0.79)	(0, 0.14)	(0, 0.54)	(0,0)
A_9	(0, 0.07)	(0.3, 0.79)	(0, 0.71)	(0, 0.96)	(0,0)
A_{10}	(0, 0.07)	(0, 0.79)	(0, 0.14)	(0, 0.54)	(0.04, 0.4)
A_{11}	(0, 1)	(0, 0.79)	(0, 0.71)	(0, 0.96)	(0,0)
A_{12}	(0, 0)	(0.3, 0.79)	(0, 0.14)	(0, 0.54)	(0, 0.93)
A_{13}	(0, 0.07)	(0, 0)	(0, 0.14)	(0, 0.76)	(0,0)
A_{14}	(0, 0.07)	(0, 0)	(0, 0.14)	(0, 0.76)	(0,0)
A_{15}	(0, 1)	(0, 0.79)	(0, 0.14)	(0, 0.76)	(0.04, 0.4)
A_{16}	(0, 0.07)	(0.3, 0.79)	(0, 0.71)	(0, 0.76)	(0,0)
A_{17}	(0, 0)	(0.3, 0.79)	(0, 0.71)	(0, 0.46)	(0,0)
A_{18}	(0, 0.07)	(0.3, 0.79)	(0.13, 1)	(0, 0.54)	(0, 0.07)

Similar to the procedure followed in the previous table, here calculated the negative average values by using step 3 & 4. The change is the deviation noted from the average row matrix to each value in the decision matrix.

6.5 Average Sum Value Matrix For The Given Data:

Now from the positive and negative average matrices the average weighted sum for both and positive and negative calculated by step 6. Each boundary values are multiplied with the respective weight values and added to get the average.

Table 5: Sum of weighted positive and negative average measures of alternatives.

Weighted Average Sum/Alt	**[ş$_i$]$^+$**	**[ş$_i$]$^-$**
A_1	(0.03, 0.49)	(0.05, 0.31)
A_2	(0,0.33)	(0.07,0.49)
A_3	(0,0.53)	(0.07,0.61)
A_4	(0,0.53)	(0.07,0.61)
A_5	(0,0.56)	(0.07,0.67)
A_6	(0,0.46)	(0.05, 0.598)
A_7	(0.08,0.65)	(0, 0.37)
A_8	(0.07,0.61)	(0, 0.44)
A_9	(0.02,0.32)	(0.07,0.69)
A_{10}	(0, 0.49)	(0.05, 0.496)
A_{11}	(0.02,0.32)	(0, 0.81)
A_{12}	(0.05, 0.57)	(0.07,0.56)
A_{13}	(0.02,0.43)	(0, 0.36)
A_{14}	(0.02,0.43)	(0, 0.36)
A_{15}	(0,0.39)	(0.05, 0.67)
A_{16}	(0.02,0.41)	(0.07,0.60)
A_{17}	(0.02,0.55)	(0.07,0.46)
A_{18}	(0, 0.49)	(0.08,0.45)

6.6 Normalized Average Value Matrix for The Given Data

The normalized sum values are calculated by the deviations of each boundary to the maximum of all the lower and upper boundary values respectively as explained in step 7.

Table 6: Normalized positive and negative average measures of alternatives

Normalized Average values/ Alt	$N_r [ş_i]^+$	$N_r [ş_i]^-$
A_1	(0.38, 0.75)	(0.06,0.30)
A_2	(0, 0.51)	(0.88,0.61)
A_3	(0,0.82)	(0.88,0.75)
A_4	(0,0.82)	(0.88,0.75)
A_5	(0,0.86)	(0.88,0.83)
A_6	(0,0.71)	(0.06,0.74)
A_7	(1,1)	(0,0.46)
A_8	(0.9,0.94)	(0,0.54)
A_9	(0.3,0.49)	(0.88,0.85)
A_{10}	(0,0.75)	(0.06,0.61)
A_{11}	(0.3,0.49)	(0,1)
A_{12}	(0.6,0.88)	(0.88,0.69)
A_{13}	(0.3,0.66)	(0,0.44)
A_{14}	(0.3,0.66)	(0,0.44)
A_{15}	(0,0.6)	(0.06,0.83)
A_{16}	(0.3,0.63)	(0.88,0.74)
A_{17}	(0.3,0.85)	(0.88,0.57)
A_{18}	(0,0.75)	(1,0.56)

6.7 Appraisal, Score And Rank Values For The Given Data:

Finally, the Appraisal values are calculated by taking the average of each of the lower boundary and upper boundary stated in step 8 and hence deduce the distance between the boundaries which gives the score values. The maximum distance in the nadir solution will describes the values are in the domain during pareto optimal walk and minimum distance for ideal solution for subjective values. Hence, the maximum distance of the alternatives with criterion concludes the order of preference.

Table 7: Appraisal, Score values, and Rank of alternatives

Appraisal, Score & Rank Values/	$A_{ş_i}$	$ş_r$	**Rank**
A_1	(0.22,0.53)	0.75	1
A_2	(0.44,0.56)	0.12	14
A_3	(0.44,0.79)	0.35	9
A_4	(0.44,0.79)	0.35	9
A_5	(0.44,0.85)	0.41	6
A_6	(0.03,0.73)	0.7	2
A_7	(0.5,0.75)	0.25	12
A_8	(0.45,0.75)	0.3	11
A_9	(0.59,0.67)	0.08	17
A_{10}	(0.03,0.68)	0.65	4
A_{11}	(0.15,0.75)	0.6	5

A_{12}	(0.74,0.79)	0.05	18
A_{13}	(0.15,0.55)	0.4	7
A_{14}	(0.15,0.55)	0.4	7
A_{15}	(0.03,0.72)	0.69	3
A_{16}	(0.59,0.69)	0.1	16
A_{17}	(0.59,0.71)	0.12	14
A_{18}	(0.5,0.66)	0.16	13

7.0 RESULTS

Order Preference of the Costumer for the analyzed data is **A1 > A6 > A15 > A10 >A11 >A5 >A14 = A13 > A4 = A3 > A8 > A7 > A18 > A17 = A2 > A16 > A9 > A12.** The result shows there are three equal preferences in order. Hence, we can club the products for test as per the similarity closeness. Cross verifying about the second similarity of order in table.1 we can directly note that **A_3**, and **A_4 is** having the membership values satisfying with all five criterion are equal. This judges the results which is acceptable. The same similarity can be noted for the first similarity **A_{13}** and **A_{14}**. Now coming to the third similarity **A_2** and **A_{17}** the table doesn't show the equal membership values across the criterion. Verifying with positive and negative averages, sum and normalized values these two alternatives have the slight difference of values, but on taking mid-point average, that is the appraisal value **A_2 is** (0.44, 0.56) and **A_{17} is** (0.59, 0.71). From these the score value of distance on boundaries will be same. Hence both alternatives converge on the same limit. Converging to the same limit belongs to the same interval or in the same neighborhood, so clubbing of products will be possible even though it has different membership values. The similarity index which leads to clustering that reduces the parametric numbers to perform. Here out of 18 alternatives 3 parameters forms cluster and reduces to 15 under order preference.

7.1 Comparative Study Results

The existing First-Cum-First Serve method the time requirement for completing the validation in process is given below:

Table 8 : Validation Time Requirement

Cri/Alt Validation Time	$\tilde{C}_1$ [Hrs]	$\tilde{C}_2$ [Hrs]	$\tilde{C}_3$ [Hrs]	$\tilde{C}_4$ [Hrs]	$\tilde{C}_5$ [Hrs]	Total Time[Hrs]
A_1	72	24	240	240	168	744
A_2	96	48	240	240	168	792
A_3	94	24	240	240	168	766
A_4	24	24	240	240	144	672
A_5	24	24	240	240	168	696
A_6	24	24	240	240	168	696
A_7	24	48	240	240	168	720
A_8	24	24	240	240	168	696
A_9	72	24	240	240	144	720
A_{10}	24	24	240	240	168	696
A_{11}	24	24	240	240	168	696
A_{12}	98	48	240	240	168	794
A_{13}	24	24	240	240	168	696
A_{14}	72	24	240	240	144	720
A_{15}	24	48	240	240	168	720
A_{16}	24	24	240	240	168	696
A_{17}	72	48	240	240	168	768
A_{18}	24	24	240	240	168	696

EXISTING RESULT: Total time of validation to complete the requirements of validation for a cycle is **12,984 Hrs**.

FIVEDAS METHOD RESULT:

A **1** > **A 6** > **A 15** > **A 10** > A **11** > A **5** > A 14 = A 13 > A 4 = A 3 > A **8** > A **7** > A **18** > A 17 = A 2 > A **16** > A **9** > A **12.**

Here the combined products are having slight variation in total time requirement. Selecting the maximum time requirement of the both will support in clustering, as the product with less time requirement can be stopped in validating further and the other with maximum requirement will go off with the validation. The proposed method results with the total time of validation to complete the validation for a cycle is **10, 848 Hrs**. Hence the proposed model **optimizes(minimize) the time consumption of 2,136 Hrs** in validation process. Based on the data, the utility of the machines can be optimized (maximized) with approximately 3 more requirements.

8.0 CONCLUSION

The result of the rank list shows that there are three equal preferences between the alternatives. It is because of the order closeness of expectations of the customer for testing. Also, the data values are defined in the fuzzy interval-valued set to balance uncertainty. So, on calculating positive and negative measures, the normalized weighted sum for positive and negative values, appraisal values, and score values 0 is considered if there is a value of more than one or less than zero in any of the operations applied. The method not only provides the order preference, but also the clusters or clubbing of products. So, we could combine the products for testing in the lab and maximize the utility of machines to the optimal, instead of going the regular first-come-first-served classical strategy. By the similarity index and closeness score clubbing of products comes at two places. Clustering of products also occurs at one place for $\mathbf{A_2}$ and $\mathbf{A_{17}}$, this is because of the same limit convergence which makes the products to be in a single neighborhood. Therefore, the utilization of the machines can be done more and hence to optimize time and profit constraints. Here the profit constraints represent the time saved and so next set of customers can be taken under consideration for testing. The fuzzy interval-based optimization can be further improved by adopting to different classification algorithms, and ensemble models. Experimenting the model with different ensemble models can help in improving the performance in ranking and order preference. Based on the effectiveness and efficiency improvement the approach can be implemented in global optimization which supports the overall optimized utility of validation process.

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