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Fuzzy-TODIM for Industrial Robot Selection

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***Abstract*— Robot selection is a complex decision making process in industrial context due to advanced features and facilities that are continuously being incorporated into the robots by different robot manufacturers. Recently, global marketplace has made absolutely difficult for the manufacturing organizations to withstand without adopting new tools and technologies, due to increased market competitiveness, higher customers' expectation for quality products, reduced delivery time, lowered production cost and increased product range. With the advent of wide variety of robot types and models with distinct features; it increases complexity and diversity in their application areas offered by different robotic products. Therefore, selecting the most appropriate robot has now become very difficult and complicated job. In order to facilitate accurate decision making for robot selection, in this paper, a fuzzy based Multi-Criteria Decision Making (MCDM) tool has been highlighted. TODIM (*Tomada de Decisión Inerativa Multicritero*) coupled with Generalized Fuzzy Numbers (GFNs) set theory has been utilized herein to determine the most preferable robot from amongst possible candidate alternatives. The study explores both subjective and objective data in relation to robot selection attributes/criteria. Application potential of fuzzy based TODIM has been highlighted in this paper.**

Keywords - Robot selection; Multi-Criteria Decision Making (MCDM); TODIM (*Tomada de Decisión Inerativa Multicritero*); Generalized Fuzzy Number (GFNs) sets; Fuzzy-TOPSIS

1. BACKGROUND

An industrial robot is a reprogrammable multifunctional manipulator designed to move materials, parts, tools or other devices by means of variable programmed motions and to perform a variety of other tasks. Industrial robots can perform repetitious, difficult and hazardous tasks (like assembly, machine loading, material handling, spray painting and welding) with precision, and can also significantly improve quality and productivity of the manufacturing organizations [1]. In order to improve product quality and increase productivity, robot selection has always been an important issue for manufacturing companies. The robot selection criteria data set may be objective, subjective or combination of both. Due to involvement of a large number of subjective attributes. Subjectivity of linguistic human judgment is often vague, imprecise and incomplete in nature. Fuzzy logic [2], [3] has the capability of dealing with such inconsistent evaluation information efficiently. Selection of an appropriate robot for a particular industrial application is a typical Multi-Criteria Decision Making (MCDM) problem. Several approaches for robot selection have already been proposed by the past researchers [4], [5], [6], [7], [8], [9].

Reference [10] proposed a fuzzy TOPSIS method for robot selection. Reference [9] introduced a decision model for robot selection based on Quality Function Deployment (QFD) and fuzzy linear regression. Reference [11] presented a decision support system based on the fuzzy set theory to aid the manager in the selection of a preferred robot for a particular application. Reference [12] aimed at solving multiple-criteria decision making problems in relation to robot selection by exploring VIKOR method. In the context of multi criteria decision making, it has been found that application of TODIM (*Tomada de Decisión Inerativa Multicritero*) has got partial usage. The method is based on a description, proved by empirical evidence, of how decision-makers' effectively make decisions in the face of risk. It has been noted that most of the existing MCDM tools are unable to capture or take into account the risk attitude/preferences of the decision maker. The first MCDM method based on prospect theory was proposed by [13]. In the original mathematical formulation of TODIM (an acronym in Portuguese for Iterative multi-criteria decision making), the rating of alternatives, which composes the decision matrix, is represented by crisp values (crisp-TODIM). The TODIM method has many similarities with the PROMETHEE method; whereas, the preference function as computed in PROMETHEE is replaced by the prospect function.

The TODIM method has been applied to rental evaluation of residential properties [14]. In another reporting, reference [15] reported application of the TODIM based MCDM approach for natural gas destination in Brazil. However, aforesaid formulation of crisp-TODIM is unable to tackle subjective evaluation data. Hence, traditional TODIM needs to be extended further so that benefits of utilizing fuzzy set theory, to tackle incomplete and uncertain decision making information (subjective human judgment), can be well articulated. In this paper, the ranking order of all alternative robots has been obtained taking into account of different robot selection attributes (subjective and objective attributes); the paper hence aims at extending the crisp-TODIM for linguistic reasoning under group decision making motivated by the work by [16]. Empirical result proves the applicability of this MCDM method to solve such type of complex industrial decision making problems. Procedural hierarchy and application potential of the fuzzy based TODIM approach has been illustrated in detail in this reporting.

2. F-TODIM: Exploration of Fuzzy Distance Measure

Let us consider the fuzzy decision matrix $\mathbf{A}$, which consists of alternatives and criteria, described by:

$$\mathbf{A} = \begin{array}{c} \\ A_1 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \cdots\cdots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \tag{1}$$

Here, $A_1, A_2, \ldots, A_m$ are alternatives, $C_1, C_2, \ldots, C_n$ are criteria, $\tilde{x}_{ij}$ are triangular fuzzy numbers, where $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ indicates the rating of the alternative A_i with respect to criterion C_j. The weight vector $\mathbf{W} = (w_1, w_2, \ldots w_n)$ composed of the individual weights $w_j (j = 1,2,\ldots,n)$ for each criterion C_j satisfying $\sum_{j=1}^{n} w_j = 1$.

The fuzzy TODIM method, for short, F-TODIM, which is an extension of TODIM, is described in the following steps:

Step 1: The criteria are normally classified into two types: benefit and cost. The fuzzy decision matrix $\tilde{\mathbf{A}} = [\tilde{x}_{ij}]$ with $i = 1,2,\ldots,m$, and $j = 1,2,\ldots,n$ is normalized which results the correspondent fuzzy decision matrix $\tilde{\mathbf{R}} = [\tilde{r}_{ij}]_{m\times n}$.

The fuzzy normalized value $\tilde{r}_{ij}$ is calculated as:

Here B and C are the set of benefit criteria and cost criteria, respectively, and

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \quad j \in B; \tag{2}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad j \in C; \tag{3}$$

$$c_j^* = \max_i c_{ij}, \ if \ \ j \in B; \qquad a_j^- = \min_i a_{ij}, \ if \ \ j \in C. \tag{4}$$

The normalization method mentioned above is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to [0, 1].

Step 2: Calculate the dominance of each alternative $\tilde{A}_i$ over each alternative $\tilde{A}_j$ using the following expression:

$$\delta\left(\tilde{A}_i, \tilde{A}_j\right) = \sum_{c=1}^{m} \phi_c\left(\tilde{A}_i, \tilde{A}_j\right) \quad \forall (i, j) \tag{5}$$

The term $\phi_c\left(\tilde{A}_i, \tilde{A}_j\right)$ represents the contribution of the criterion c to the function $\delta\left(\tilde{A}_i, \tilde{A}_j\right)$ when comparing the alternative i with alternative j. w_{rc} Indicates the weight of the criterion c divided by the reference criterion (Highest weight) r. The parameter θ represents the attenuation factor of the losses, which can be tuned according to the problem at hand.

Here,

$$\phi_c\left(\tilde{A}_i, \tilde{A}_j\right) = \begin{cases} \sqrt{\dfrac{w_{rc}}{\sum_{c=1}^{m} w_{rc}} . d\left(\tilde{x}_{ic}, \tilde{x}_{jc}\right)} & \text{If } \left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right] > 0 \\ 0, & \text{If } \left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right] = 0 \\ -\dfrac{1}{\theta}\sqrt{\dfrac{\sum_{c=1}^{m} w_{rc}}{w_{rc}} . d\left(\tilde{x}_{ic}, \tilde{x}_{jc}\right)} & \text{If } \left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right] < 0 \end{cases} \tag{6}$$

In this expression, $m(\tilde{x}_{ic})$ and $m(\tilde{x}_{jc})$ stands for the defuzzified values of the fuzzy number $\tilde{x}_{ic}$ and $\tilde{x}_{jc}$, respectively. The term $d\left(\tilde{x}_{ic}, \tilde{x}_{jc}\right)$ designates the distance between the two fuzzy numbers $\tilde{x}_{ic}$ and $\tilde{x}_{jc}$, as defined in Eq. (8). Three cases can occur in Eq. (6): (i) if the value $\left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right]$ is positive, it represents a gain; (ii) if the value $\left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right]$ is zero, there is neither loss nor gain; (iii) if the value $\left[m(\tilde{x}_{ic}) - m(\tilde{x}_{jc})\right]$ is negative, it represents a loss. The final matrix of dominance is obtained by summing up the partial matrices of dominance of each criterion.

Step 3: Calculate the global value of the alternative i by normalizing the final matrix of dominance according to the following expression:

$$\xi_i = \frac{\sum \delta(i, j) - \min \sum \delta(i, j)}{\max \sum \delta(i, j) - \min \sum \delta(i, j)} \tag{7}$$

Ordering the values ξ_i provides the rank of each alternative. The best alternatives are those that have higher value ξ_i. Two triangular fuzzy number $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ then the distance between them is computed as (*vertex method*):

$$d\left(\tilde{x}_{ic}, \tilde{x}_{jc}\right) = \sqrt{\frac{1}{3}\left[(a_1 - b_2)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \tag{8}$$

A triangular fuzzy number let $\tilde{a} = (a_1, a_2, a_3)$ can be defuzzified as following

$$m(\tilde{a}) = \frac{(a_1 + a_2 + a_3)}{3} \tag{9}$$

3. Case Empirical Illustration

In this empirical illustration, a decision making scenario has been generated for evaluation and selection of industrial robots. For this specific sort of study, a consolidated database considering information in relation to objective criteria as well as subjective criteria have been explored. A total number of thirteen criteria have been evaluated with respect to seven choices (alternatives). The criteria includes Load capacity (C_1), Repeatability (C_2), Maximum tip speed (C_3), Memory capacity (C_4), Manipulator reach (C_5), Man-machine interface (C_6), Programming flexibility (C_7), Vendor's service contract (C_8), Positioning accuracy (C_9), Safety (C_{10}), Environmental performance (C_{11}), Reliability (C_{12}) and Maintainability (C_{13}). Out of thirteen considered criteria, first five criteria i.e. C_1 to

C_5 have been objective in nature and corresponding numeric values have been collected from past literature [17]. The remaining eight criteria i.e. C_6 to C_{13} have been assessed subjectively by the Decision-Makers' (DMs). In the known set of attributes (objective criteria) only repeatability has been considered as the non-beneficial attribute whilst other attributes treated as beneficial in nature. All the subjective criteria have been considered as beneficial in nature. Here we have considered a combination of objective data and subjective data. Objective data set can be solved through classical TODIM approach presented by [13] and [14], whereas the subjective data part is solved using F-TODIM method in exploration of fuzzy distance measure approach. A 7-member linguistic term set has been chosen for assigning priority weight and the rating of the criteria and alternatives respectively and shown in Table I.

The decision making committee which consists of four decision-makers have been instructed to provide their consent in order to determine the priority weight against individual criterion (C_1 to C_{13}), for each subjective criterion (C_6-C_{13}) over each alternatives as shown in Table II. Decision makers were also asked to provide the ratings for all available alternatives in linguistic term according to the Table I. The input received from the decision makers were processed through basics fuzzy rules and converted in appropriate fuzzy numbers. The initial decision making matrix was formed by combining the quantitative and qualitative information and shown in Table III.

Objective data for attributes shown in Table III [C_1 to C_5] have been normalized by classical TODIM approach [13], [14] and for subjective attributes [C_6 to C_{13}], Eq. (2) and Eq. (3) are used for beneficial and non-beneficial attribute(s) respectively. Aggregated fuzzy ratings for subjective criteria have been normalized by using Eq. (2). After the normalization of the initial decision making matrix fuzzy distance measure was also computed for each pair of alternatives with respect to different criteria at this point using Eq. (8). The corresponding fuzzy numbers have been converted in to the crisp form by using Eq. (9) and the crisp normalized decision making matrix is shown in Table IV.

Partial matrices of dominance for all the pairs of alternatives has been calculated by using Eq. (6) for subjective attributes only while for the objective attributes Partial matrices of dominance can be calculated as by [14]. Now final matrices of dominance have been calculated using Eq. (5) and shown in Table V. Finally global measures of all alternatives have been computed using Eq. (7) and presented in Table VI. Rank obtained on the basis of higher is better, shown below:

$\mathbf{R_3 > R_1 > R_2 > R_6 > R_4 > R_7 > R_5}$

4. Conclusion

TODIM in integration with fuzzy set theory has been successfully applied to the robot selection problem for a data set combination of objective and subjective information. Robot 3 (R3) is the highest ranked robot followed by Robot (R1) whereas Robot 5 (R5) is worst choice for this particular case. This calculation was carried out by considering the value of attenuation factor $\theta = 1$, further this can be extend by varying the value of θ. Industries may accept this appraisement module as a test-kit towards performance valuation and assortment of an appropriate robot to fulfill the specific requirements. This may also help in benchmarking of robot manufactures with respect to product variety, reliable and safe functionality- performance and robustness-flexibility in usage.

The work has introduced a conceptual illustrative example i.e. an empirical case study, rather than a real world application.

Validity and accuracy of these decision making modules need to be investigated. Apart from triangular fuzzy numbers there exists trapezoidal, bell-shaped, Gaussian fuzzy numbers (corresponding membership functions). It is worth of investigating which fuzzy membership function offers the most reliable decision outcome.

REFERENCES

[1] V. M. Athawale, and S. Chakraborty, "A comparative study on the ranking performance of some multi-criteria decision-making methods for industrial robot selection," International Journal of Industrial Engineering Computations, Vol. 2, No. 4, 2011, pp. 831–850.

[2] L. A. Zadeh, "Fuzzy Sets," Information and Control, Vol. 8, No. 3, 1965, pp. 338–353.

[3] V. Kapoor, and S. S. Tak, "Fuzzy application to the analytic hierarchy process for robot Selection," Fuzzy Optimization and Decision Making, Vol. 4, No. 3, 2005, pp. 209–234.

[4] P.P. Bhangale, V.P. Agrawal, and S.K. Saha, "Attribute based specification, comparison and selection of a robot," Mechanism and Machine Theory, Vol. 39, No. 12, 2004, pp. 1345–1366.

[5] C.H. Goh, Y.C.A. Tung and C.H. Cheng, "A revised weighted sum decision model for robot selection," Computers and Industrial Engineering, Vol. 30, No. 2, 1996, pp. 193-199.

[6] M. Khouja and D. E. Booth "Fuzzy Clustering Procedure for Evaluation and Selection of Industrial Robots," Journal of Manufacturing Systems, Vol. 14, No. 4, 1995, pp. 244-251.

[7] C. Parkan and M.L.Wu, "Decision-making and performance measurement models with applications to robot selection," Computers & Industrial Engineering, Vol. 36, No. 3, 1999, pp. 503-523.

[8] R. V. Rao and K.K. Padmanabhan, "Selection, identification and comparison of industrial robots using digraph and matrix methods," Robotics and Computer-Integrated Manufacturing, Vol. 22, No. 4, 2006, pp. 373–383.

[9] E. E. Karsak, "Robot Selection using an Integrated Approach based on Quality Function Deployment and Fuzzy Regression," International Journal of Production Research, Vol. 46, No. 3, 2008, pp. 723-738.

[10] T. C. Chu and Y. C. Lin, "A fuzzy TOPSIS method for robot selection," The International Journal of Advanced Manufacturing Technology, Vol. 21, No. 4, 2003, pp. 284-290.

[11] C. Y. Wu, "Robot selection decision support system: A fuzzy set approach," Mathematical and Computer Modelling, Vol. 14, 1990, pp. 440-443.

[12] K. Devi, "Extension of VIKOR method in intuitionistic fuzzy environment for robot selection," Expert Systems with Applications, Vol. 38, No. 11, 2011, pp. 14163–14168.

[13] L. F. A. M Gomes and M. M. P. P. Lima, "TODIM: Basics and application to multi-criteria ranking of projects with environmental impacts," Foundations of Computing and Decision Sciences, Vol. 16, No. 4, 1992, pp. 113–127.

[14] L.F.A.M. Gomes and L.A.D. Rangel, "An application of the TODIM method to the multi-criteria rental evaluation of residential properties," European Journal of Operational Research, Vol. 193, No. 1, 2009, pp. 204-211.

[15] L.F.A.M. Gomes, L.A.D. Rangel and F.J.C. Maranhãoc, "Multi-criteria analysis of natural gas destination in Brazil: An application of the TODIM method," Mathematical and Computer Modelling, Vol. 50, No. 1-2, 2009, pp. 92-100.

[16] R.A. Krohling and T.T.M.D. Souza, "Combining prospect theory and fuzzy numbers to multi-criteria decision making," Expert Systems with Applications, Vol. 39, No. 13, 2012, pp. 11487-11493.

[17] S. Mondal and S. Chakraborty, "A solution to robot selection problems using data envelopment analysis," International Journal of Industrial Engineering Computations, Vol. 4, No. 3, 2013, pp. 355-372.

TABLE I

LINGUISTIC SCALES AND CORRESPONDING FUZZY REPRESENTATION FOR CRITERIA WEIGHT AND CRITERIA RATING WITH RESPECT TO ALTERNATIVES

Performance rating	Importance weight	Triangular fuzzy numbers
Very Poor (VP)	Very Low (VL)	(0, 0, 0.15)
Poor (P)	Low (L)	(0, 0.15, 0.3)
Medium Poor (MP)	Medium Low (ML)	(0.15, 0.3 0.5)
Medium (M)	Medium (M)	(0.3, 0.5, 0.65)
Medium Good (MG)	Medium High (MH)	(0.5, 0.65, 0.8)
Good (G)	High (H)	(0.65, 0.8, 1.0)
Very Good (VG)	Very High (VH)	(0.8, 1.0, 1.0)

TABLE III

SUBJECTIVE WEIGHTS FOR ROBOT SELECTION ATTRIBUTES AS GIVEN BY THE DMS

Criteria	Aggregated fuzzy weight	Crisp weight	$W_{rc} = crisp / \max$
C_1	(0.725,0.900,1.000)	0.875	0.968
C_2	(0.688, 0.850, 1.000)	0.846	0.936
C_3	(0.763, 0.950, 1.000)	0.904	1.000
C_4	(0.613, 0.763, 0.950)	0.775	0.857
C_5	(0.763, 0.950, 1.000)	0.904	1.000
C_6	(0.725, 0.900, 1.000)	0.875	0.968
C_7	(0.725, 0.900, 1.000)	0.875	0.968
C_8	(0.575, 0.725, 0.900)	0.733	0.811
C_9	(0.575, 0.725, 0.900)	0.733	0.811
C_{10}	(0.500, 0.650, 0.800)	0.650	0.719
C_{11}	(0.575, 0.725, 0.900)	0.733	0.811
C_{12}	(0.650, 0.80, 1.000)	0.817	0.903
C_{13}	(0.575, 0.725, 0.900)	0.733	0.811

TABLE IIIII

INITIAL DECISION MAKING MATRIX (COMBINATION OF OBJECTIVE AND SUBJECTIVE DATA)

Alternatives	Objective criteria					Subjective criteria							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
R_1	60	0.4	2540	500	990	(0.725, 0.900, 1.000)	(0.613, 0.763, 0.950)	(0.650, 0.800, 1.000)	(0.613, 0.763, 0.950)	(0.650, 0.800, 1.000)	(0.575, 0.725, 0.900)	(0.650, 0.800, 1.000)	(0.538, 0.688, 0.850)
R_2	6.35	0.15	1016	3000	1041	(0.613, 0.763, 0.950)	(0.650, 0.813, 0.950)	(0.575, 0.725, 0.900)	(0.650, 0.800, 1.000)	(0.725, 0.900, 1.000)	(0.500, 0.650, 0.800)	(0.763, 0.950, 1.000)	(0.650, 0.800, 1.000)
R_3	6.8	0.1	1727	1500	1676	(0.400, 0.575, 0.725)	(0.438, 0.613, 0.775	0.613, 0.763, 0.950)	(0.613, 0.763, 0.950)	(0.575, 0.725, 0.900)	(0.613, 0.763, 0.950)	(0.500, 0.650, 0.800)	(0.613, 0.763, 0.950)
R_4	10	0.2	1000	2000	965	(0.075, 0.225, 0.400)	(0.300, 0.500, 0.650)	(0.188, 0.363, 0.525)	(0.300, 0.500, 0.650)	(0.113, 0.238, 0.400)	(0.300, 0.500, 0.650)	(0.188, 0.350, 0.538)	(0.300, 0.500, 0.650)
R_5	2.5	0.1	560	500	915	(0.538, 0.688, 0.850)	(0.500, 0.650, 0.800)	(0.688, 0.850, 1.000)	(0.575, 0.725, 0.900)	(0.650, 0.800, 1.000)	(0.500, 0.650, 0.800)	(0.650, 0.800, 1.000)	(0.575, 0.725, 0.900)
R_6	4.5	0.08	1016	350	508	(0.000, 0.150, 0.300)	(0.000, 0.075, 0.225)	(0.000, 0.150, 0.300)	(0.000, 0.000, 0.150)	(0.000, 0.113, 0.263)	(0.000, 0.150, 0.300)	(0.225, 0.400, 0.575)	(0.300, 0.500, 0.650)
R_7	3	0.1	1778	1000	920	(0.450, 0.613, 0.763)	(0.400, 0.575, 0.725)	(0.300, 0.500, 0.650)	(0.400, 0.575, 0.725)	(0.450, 0.613, 0.763)	(0.450, 0.613, 0.763)	(0.450, 0.613, 0.763)	(0.400, 0.575, 0.725)

TABLE IVV
CRISP NORMALIZED DECISION MATRIX

Alternatives	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**C_8**	**C_9**	**C_{10}**	**C_{11}**	**C_{12}**	**C_{13}**
R_1	1	0.2	1	0.17	0.59	0.88	0.82	0.82	0.78	0.82	0.77	0.82	0.69
R_2	0.11	0.53	0.4	1	0.62	0.78	0.85	0.73	0.82	0.88	0.68	0.9	0.82
R_3	0.11	0.8	0.68	0.5	1	0.57	0.64	0.78	0.78	0.73	0.82	0.65	0.78
R_4	0.17	0.4	0.39	0.67	0.58	0.23	0.51	0.36	0.48	0.25	0.51	0.36	0.48
R_5	0.04	0.8	0.22	0.17	0.55	0.69	0.68	0.85	0.73	0.82	0.68	0.82	0.73
R_6	0.08	1	0.4	0.12	0.3	0.15	0.11	0.15	0.05	0.13	0.16	0.4	0.48
R_7	0.05	0.8	0.7	0.33	0.55	0.61	0.6	0.48	0.57	0.61	0.64	0.61	0.57

TABLE V
FINAL MATRICES OF DOMINANCE

Alternatives	**R_1**	**R_2**	**R_3**	**R_4**	**R_5**	**R_6**	**R_7**
R_1	0.00	-10.27	-7.95	-2.29	-3.25	-0.77	-2.73
R_2	-8.42	0.00	-7.36	0.86	-2.05	-0.26	-2.31
R_3	-11.26	-9.98	0.00	-0.57	-4.78	0.58	-0.11
R_4	-23.97	-22.56	-22.29	0.00	-18.65	-2.47	-15.84
R_5	-11.42	-13.21	-10.14	-4.38	0.00	-1.85	-3.50
R_6	-30.84	-28.60	-28.44	-16.33	-23.92	0.00	-22.89
R_7	-19.09	-18.03	-14.50	-2.60	-8.21	0.85	0.00

TABLE VI

OVERALL VALUE (GLOBAL MEASURES) OF ALTERNATIVES

Alternatives	$\sum_{j=1}^{n}\delta(A_i, A_j)$	ξ	**Ranking order**
R_1	-27.25	0.94	3
R_2	-19.53	1.00	1
R_3	-26.11	0.95	2
R_4	-105.77	0.34	6
R_5	-44.51	0.81	4
R_6	-151.03	0.00	7
R_7	-61.59	0.68	5