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Design of Simplified Triangular Fuzzy Topsis: A Case Study on Supplier Selection

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Abstract: Multi Criteria Decision Making (MCDM) techniques solve problems which involve multiple objectives under the presence of conflicting decision criteria. Among different MCDM techniques Triangular Fuzzy TOPSIS is widely applied in fuzzy environment. This work proposes a novel approach in Triangular Fuzzy TOPSIS by finding and applying better normalization technique, weight method and a Modified Fuzzy Relative Closeness Coefficient (MFRCC). It compares various normalization techniques and weight methods to find the better technique which improves the ranking efficiency of triangular fuzzy TOPSIS. In order to evaluate the proposed methodology, the metric such as sensitivity analysis, rank reversal, time complexity, space complexity, repeated ranking, rank occurrence and relative closeness efficiency are applied. It is applied in the supplier chain management to find the suitable supplier based on conflicting criteria. The adaptability of Triangular Fuzzy TOPSIS is validated using metrics with respect to supplier chain management. The proposed methodology attains better results compared with other methodologies.
Keywords: Multi Criteria Decision Making (MCDM), Triangular Fuzzy TOPSIS, Normalization techniques, AHP, weight method, metric suite, evaluation techniques, MCDM comparative analysis

I. INTRODUCTION

The process of discovering and selecting alternatives based on the values and preferences of the Decision Maker (DM) is termed as ‘Decision Making’. The objective of any decision is identifying the best alternative which possesses the highest possibility of success compared to other alternatives under certain criteria. Multi Criteria Decision Making (MCDM) is a technique of evaluating how to rank, sort or classify different alternatives based on a set of criteria (Belton et al., 2001). It is one of the most accepted and well known branches in decision making environment, which offers the methodology for decision making analysis when dealing with problems that involve multiple objectives under the presence of a number of conflicting decision criteria (Triantaphyllou, 2006).

For MCDM many kinds of techniques are available such as Analytic Hierarchy Process (AHP), Simple Additive Weighting (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), COmplex PRoportional ASsessment (COPRAS) and other MCDM techniques. In decision making, certain data cannot be represented using numbers hence, linguistic (natural language) variables play an important role and fuzzy logic is applied to represent these variables.

In MCDM, fuzzy MCDM plays a vital role and it has many techniques such as Grey Relational Analysis (GRA), Fuzzy Analytic Hierarchy Process (FAHP), Fuzzy TOPSIS and other technique. Fuzzy TOPSIS is one of the well known and the most acceptable methodology among several methodologies available under fuzzy MCDM (Li and Yang, 2009). It is applied in fuzzy environment for multi criteria decision to identify the best alternative.

The working methodology of fuzzy TOPSIS consists of many techniques. For example in fuzzy TOPSIS, each alternative has a performance rating for each attribute, which represents the characteristics of the alternative. It is common that performance ratings for different attribute are measured by different units. To transform performance ratings into a compatible measurement unit, normalization procedures are used. Hence, MCDM methods often use one normalization procedure to achieve compatibility between different measurement units. For example, SAW uses linear max normalization (Yeh, 2003), TOPSIS uses vector normalization procedure (Yoon and Hwang., 1995), ELECTRE uses vector normalization (Figueira et al., 2005) and AHP uses linear sum based normalization (Satty, 1994). Among different normalization techniques a better normalization technique can be identified and it can be applied to fuzzy TOPSIS to improve its ranking preference.

Likewise, various weight methods which are applied in MCDM can be compared and it can be applied in Fuzzy TOPSIS to improve the ranking. Similarly, for each step of fuzzy TOPSIS can be improved by applying better technique. Today many kinds of MCDM techniques have been developed to solve various kinds of decision problems. These MCDM methods have to be evaluated to better understand its performance. From the literature it has been found that very limited evaluation techniques have been developed for MCDM techniques. In this research, a metric suite is designed to evaluate the proposed methodology from the fuzzy TOPSIS. The metric suite consists of existing evaluation parameters as well as newly designed parameters.

The rest of the paper has been organized as, section 2 describes the prior research, section 3 compares various normalization techniques, section 4 compares different weight methods, section 5 designs the simplified triangular fuzzy TOPSIS, section 6 designs metric suite to evaluate the proposed technique, section 7 discuss the results of simplified triangular fuzzy TOPSIS and section 8 concludes the paper.

II. PRIOR RESEARCH

A. Fuzzy Multi Criteria Decision Making (Fuzzy MCDM)

Fuzzy sets were introduced by (Zadeh, 1965) to manipulate the data and information without statistical uncertainties. It was exclusively designed to signify mathematical ambiguity and to provide formalized tools to deal with the indistinctness essential to many problems. The theory of fuzzy logic provides a mathematical strength to capture the doubts associated with human cognitive processes, such as thoughts and analysis.

When the information is vague, ambiguous and uncertain, classical MCDM method is not suitable for the decision makers and the fuzzy set theory allows us to integrate incomplete information, unquantifiable information, partially ignorant facts and non obtainable information into the decision models. (Bellman and Zadeh, 1970) introduced the first approach regarding decision making in a fuzzy environment. Fuzzy Multi-Criteria Decision Making (FMCDM) has provoked great interest in operations research, decision science, systems engineering, and management science. Different kinds of FMCDM methods have been developed to address multi criteria decision making problems with completely known and unknown users preferred choices (Xu and Chen, 2007).

The latest research on this topic has continually improved MCDM and solved linguistic and cognitive fuzziness problems. For example, (Ling, 2006) presents a fuzzy MCDM method in which the criteria weights and decision matrix elements (criteria values) are fuzzy variables.

B. Fuzzy Topsis

During the last two decades, an extension of the classical TOPSIS to the fuzzy environment was widely investigated and a large number of fuzzy TOPSIS methods have been developed in the literature. The generalized TOPSIS method is transformed into Fuzzy TOPSIS method to address the decision making problems under fuzzy environment (Chen and Hwang, 1992), (Hwang and Yoon, 1981). (Triantaphyllou and Lin, 1996) developed a fuzzy TOPSIS method based on fuzzy arithmetic operations, which leads to a relative closeness on behalf of each alternative in fuzzy environment. This fuzzy TOPSIS method produced a fuzzy relative closeness which was poorly indistinct and over inflated because of the motivation of fuzzy arithmetic operations. (Chen, 2000) described the score of each alternative and the weight of each criterion in the form of natural language which could be articulated in triangular fuzzy numbers. Then, the distance between two triangular fuzzy numbers are calculated using the vertex method.

(Choi and Chang, 2006) developed a two-phased semantic optimization modelling approach for strategic supplier selection and allocation problems. AHP is applied to predict the weights of criterion and TOPSIS method is employed for ranking in order to solve the supplier selection. (Chu and Lin, 2003) proposed a fuzzy TOPSIS approach for the selection of robot where the rating of each alternatives based on different conflicting criteria and the weights of all criteria were described in 'Linguistic Terms' represented by fuzzy numbers. (Wang and Elhag, 2006) presented a programming solution related to nonlinear procedure using a fuzzy TOPSIS methodology based on alpha level set. (Zhang and Lu, 2003) presented an integrated fuzzy group decision making method in order to deal with the fuzziness of preferences of the decision makers. (Abo-Sinna and Amer, 2005) extended the TOPSIS method to resolve the large scale multi-objective programming problems related to nonlinear procedures, and further considered the situation involving fuzzy parameters (Abo-Sinna et al., 2006).

The fuzzy TOPSIS is classified into three types such as triangular, trapezoidal and interval data. Among the three types trapezoidal fuzzy TOPSIS has been widely applied. The next section describes the various steps of triangular fuzzy TOPSIS.

C. Triangular Fuzzy TOPSIS

The structure of Triangular Fuzzy TOPSIS is depicted in Figure 1.

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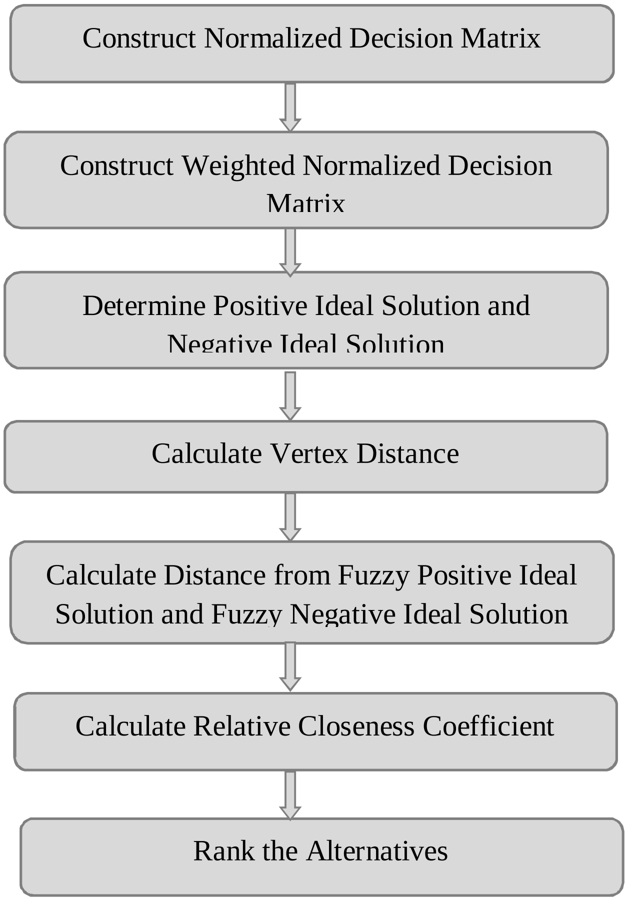

Figure 1: Generalized steps for Triangular Fuzzy TOPSIS

In Generalized Triangular Fuzzy TOPSIS (GTF-TOPSIS), Max-Min normalization technique is applied to normalize the rating of each alternative. The efficiency of the algorithm lies in normalization technique. In order to improve the efficiency of the algorithm, we have applied various normalization techniques and choose the better technique for the proposed Simplified Triangular Fuzzy TOPSIS (STF-TOPSIS) algorithmSimilarly, AHP method is used to estimate the weight of each criterion in GTF-TOPSIS. We have applied various weight methods to find the better method for the proposed approach. GTF-TOPSIS uses a standard Relative Closeness Coefficient (RCC) technique to determine the ranking order of the set of alternatives. We have modified the RCC technique to improve the ranking order of the alternativesTo evaluate the performance of MCDM methodologies very limited evaluation techniques have been developed. The next section describes about MCDM evaluation techniques.

D. Evaluation of topsis

From the literature review it has been found that most of the MCDM approaches have been evaluated in terms of sensitivity analysis, rank reversal, time complexity and space complexity. Table 1 describes about various evaluation techniques applied in MCDM.

Table 1 Evaluation techniques applied in MCDM

SL. No.	Purpose	Author and Year	Technique used	Applications	Evaluation method / parameters	Outcome
1.	Weapon selection using the AHP and TOPSIS methods under fuzzy environment	(Metin et al., 2008)	Integration of AHP with Fuzzy TOPSIS	Weapon selection problem	–	Efficiency and accuracy of the proposed method is evaluated
2.	AHP-TOPSIS framework for	(Madjid et al., 2006)	Adjusted TOPSIS & Modified	Human spaceflight	Ranking Reversal	Proposed model possess certain features: Analytical,

	human spaceflight mission		TOPSIS	mission planning		Comprehensive, Structured and Flexible
3.	COTS evaluation using modified TOPSIS and ANP	Huan-Jyh Shyur., 2006	Combined ANP and modified TOPSIS	"Off-line production data analysis system'' selection project	–	Overall performance of the proposed method is effective
4.	Evaluating initial training aircraft under a fuzzy environment	(Tien-Chin et al., 2006)	Fuzzy TOPSIS	Training aircraft problem	Evaluation criteria: Reliability, Accessibility, Fuel capacity, Power plant, Operating speed, Take-off distance, Landing distance, etc.	KT-1 posses the largest Relative Closeness Coefficient Value
5.	An approach to generalization of fuzzy TOPSIS method	(Ludmila et al., 2013)	Implements aggregation with generalized fuzzy TOPSIS	–	–	–
6.	Fuzzy TOPSIS approach for group multi-criteria supplier selection problem	(Akram et al., 2011)	AHP is integrated with TOPSIS	Supplier selection	Efficiency and Performance	Decision making is more effective
7.	MCDM based on trust and Reputation in Supply Chain	(Liu et al., 2014)	K-Mean Clustering	trust and reputation in Supply Chain	Simulation - Practical Supply Chain setting with multi-agents platform	effectively filter unfair ratings
8.	Prioritized multi-criteria decision making based on preference relations	(Xiaohan et al., 2013)	prioritized MCDM methods	-	By using a simple example this method is evaluated	weights associated with criteria and the preference relations among alternatives are explored
9.	Personalization of Traveler's Information in Public Transportation	(Soumaya et al., 2013)	MCDM approach to personalize systems	Personalization of Traveller's Information in Public Transportation	Validated by applying it to personalize a system in intelligent transport field.	Provides effective solution for reducing complexity when searching information
10.	A Robust Hybrid MCDM Methodology	(Senthil et al.,2014)	a hybrid method using AHP and TOPSIS	Contractor evaluation and selection in third-party reverse logistics	Sensitivity Analysis(Exchange Each Criterion Weight)	Improves Robustness
11.	Comparative Analysis on Simplified	(Miranda et al., 2014)	TOPSIS, Simplified TOPSIS,	-	Time Complexity, Space Complexity Sensitivity	Simplified TOPSIS attains a better Result

	TOPSIS and COPRAS		COPRAS		Analysis and Ranking Reversal	
12.	New Interval-Valued Fuzzy Modified MCDM Method	Behnam et al., 2013	Interval-valued fuzzy modified TOPSIS	Robot selection problem	-	performance of alternatives against both subjective and objective criteria

From the literature review it has been found that most of the MCDM techniques and its applications have not been evaluated. To evaluate these techniques very limited parameters have been applied such as sensitivity analysis, rank reversal, time complexity and space complexity. From the literature it is evident that to evaluate the MCDM techniques very limited parameters are applied and these parameters are not considered as metrics. Other than these four parameters from the functionalities of the MCDM techniques a new kinds of parameters can be found out. From the existing and newly formed parameters MCDM techniques and its applications can be evaluated robustly. Hence, this research proposes a simplified methodology from Fuzzy TOPSIS and designs metric suite to evaluate the proposed methodology.

III. RESEARCH PROPOSAL

A new Triangular Fuzzy TOPSIS methodology is designed by considering the better normalization technique and weight method with updated relative closeness coefficient. In order to carry out this procedure supplier chain management under fuzzy environment is considered for a case study. The main procedure of fuzzy TOPSIS is applied to solve multi criteria decision making in supplier chain management has been described. Specifically, considering the fuzziness in the decision-making process, linguistic variables are used to assess the weights of all criteria and the ratings of each alternative with respect to different criterion in supplier chain management. Thus, the decision matrix is converted into a fuzzy form and normalized fuzzy decision matrix has been constructed once the Decision Maker's fuzzy ratings have been pooled. The weighted normalized fuzzy decision matrix has been built by combining the weights of each criterion to the normalized decision matrix.According to the concept of classical TOPSIS, we need to define a Fuzzy Positive Ideal Solution (FPIS) and a Fuzzy Negative Ideal Solution (FNIS), and then calculate the distance of each alternative from FPIS and FNIS, respectively. Finally, a Relative Closeness Coefficient (RCC) of each alternative is calculated to determine the ranking order of all alternatives. Similar to the classical TOPSIS method, a higher value of Relative Closeness Coefficient indicates the best alternative with respect to different criteria. In this research to evaluate the proposed methodology metrics has been designed. These metrics have been found from literature as well as from working procedure fuzzy TOPSIS. The proposed methodology has been evaluated using the metrics which are designed in this research.

IV. ANALYSIS OF TRIANGULAR FUZZY TOPSIS METHODOLOGY

In order to design a simplified triangular fuzzy TOPSIS, in this section various normalization and weight methods have been compared and identified. Similarly the relative closeness coefficient to the ideal solution has been modified. The identified techniques are applied in fuzzy TOPSIS and its process has been simplified which are described in the following sections.

A. Comparison of Various Normalization Techniques

In many applications, the rating of different alternatives for a given set of criteria will differ based on their units and it has a different range of possible values. In such case, it is often beneficial to convert all the ratings into a common range by normalizing the data.

Triangular Fuzzy TOPSIS generally use one particular normalization procedure without considering the suitability of other available procedures. Enormous efforts have been made to comparative studies of Triangular Fuzzy TOPSIS method, but no significant study is conducted on the suitability of normalization procedures used in Triangular Fuzzy TOPSIS method. This leaves the effectiveness of Triangular Fuzzy TOPSIS method in doubt and certainly raises the necessity to examine the effects of various normalization procedures on decision outcome when used with Triangular Fuzzy TOPSIS method. The different normalization techniques which are applied in Triangular Fuzzy TOPSIS are described as follows.

1) Vector Normalization
2) Linear Max-Min Normalization
3) Linear Sum based Normalization
4) Linear Max Normalization

5) Gaussian Normalization

B. Comparison of Various Weight Methods

The different weight methods which are considered research are

1) AHP Method
2) Entropy Method
3) Eigen Vector Method

C. Modification of Relative Closeness Coefficient

In this simplification process, the relative closeness coefficient has been modified to improve the ranking. The Relative closeness to the ideal solution C_i has been defined as,

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad \text{for} \quad i = 1,2,\dots,m \ \ \& \ \ 0 < C_i < 1$$

Where,

D_i^+ *positive ideal solution*

D_i^- *Negative ideal solution*

C_i relative closeness to ideal solution

The relative closeness to the ideal solution C_i has been modified as,

$$C_i = \frac{D_i^-}{D_i^*} \quad \text{for} \quad i = 1,2,\dots,m \ \ \& \ \ 0 < C_i < 1$$

The modified closeness to the ideal solution improves the ranking order of the alternatives according to the selected criterion.

V. SIMPLIFICATION OF TRIANGULAR FUZZY TOPSIS

comparing normalization linear sum based normalization achieves a better result when compared to other techniques. Similarly compared to other weight methods it is found that AHP gives better results. The identified normalization, weight method and relative closeness to the ideal solution have been applied in the fuzzy TOPSIS to improve the efficiency of the ranking of the alternative. In order to improve the efficiency of the algorithm, the above steps can be simplified as follows:

Step 1: Calculate the Distance of each alternative by applying the following Distance method.

The distance from Positive Ideal Solution is:

$$D_i^* = \sum_{j=1}^{n} d\left(\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_j} * w_j, \frac{a_{ij}}{\sum_{j=1}^{n} a_j} * w_j, \frac{a_{ij}}{\sum_{j=1}^{n} a_j} * w_j\right), S^*\right) \quad \text{for} \quad i = 1,2,\dots,m$$

Similarly, the distance from Negative Ideal Solution is:

$$D_i^- = \sum_{j=1}^{n} d\left(\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_j} * w_j, \frac{a_{ij}}{\sum_{j=1}^{n} a_j} * w_j, \frac{a_{ij}}{\sum_{j=1}^{n} a_j} * w_j\right), S^-\right) \quad \text{for} \quad i = 1,2,\dots,m$$

Step 2: Calculate the distance using vertex method.

$$d(\bar{a}_1, \bar{a}_2) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]}$$

Where *l1, l2* are the lower values, *m1, m2* are the medium values and *u1, u2* are the upper possible values.

Step 3: Calculate the relative closeness to the ideal solution C_i .

$$C_i = \frac{D_i^-}{D_i^*} \qquad \text{for} \quad i = 1,2,\dots,m \;\;\&\;\; 0 < C_i < 1$$

Step 4: Rank the alternatives by selecting the alternative with C_i closest to 1.

Figure 5: Stepwise procedure for Simplified Triangular Fuzzy TOPSIS methodology

Figure 2 shows the stepwise procedure for Simplified Fuzzy TOPSIS methodology where Linear sum based normalization techniques is applied to normalize the rating of each alternative. Similarly, AHP method is applied to estimate the weight of each criterion. The above stepwise procedure for the proposed methodology directly calculates the distance of each alternative from Fuzzy Positive and Negative Ideal Solution which definitely improve the efficiency of the algorithm.

A. Working Model of Simplified Triangular Fuzzy TOPSIS

The Simplified Triangular Fuzzy TOPSIS has been applied to supplier chain management. The data set has been collected from hardware suppliers. From this data set decision matrix for supplier chain management has been developed which is described as follows,ecision Matrix =

$$\begin{pmatrix}
[3,4,5] & [3,4,5] & [3,4,5] & [1,2,3] & [1,2,3] & [1,2,3] & [1,2,3] & [3,4,5] & [1,2,3] & [3,4,5] & [4,5,6] & [3,4,5] & [1,2,3] \\
[1,2,3] & [0,1,2] & [0,1,2] & [4,5,6] & [3,4,5] & [3,4,5] & [0,1,2] & [0,1,2] & [3,4,5] & [1,2,3] & [1,2,3] & [0,1,2] & [3,4,5] \\
[3,4,5] & [4,5,6] & [3,4,5] & [3,4,5] & [1,2,3] & [3,4,5] & [1,2,3] & [3,4,5] & [1,2,3] & [3,4,5] & [3,4,5] & [4,5,6] & [1,2,3] \\
[4,5,6] & [3,4,5] & [3,4,5] & [3,4,5] & [3,4,5] & [2,3,4] & [3,4,5] & [3,4,5] & [1,2,3] & [3,4,5] & [4,5,6] & [3,4,5] & [1,2,3] \\
[3,4,5] & [4,5,6] & [1,2,3] & [3,4,5] & [1,2,3] & [1,2,3] & [1,2,3] & [1,2,3] & [3,4,5] & [3,4,5] & [3,4,5] & [4,5,6] & [3,4,5] \\
[4,5,6] & [3,4,5] & [3,4,5] & [3,4,5] & [4,5,6] & [3,4,5] & [3,4,5] & [3,4,5] & [0,1,2] & [3,4,5] & [4,5,6] & [3,4,5] & [1,2,3] \\
[3,4,5] & [2,3,4] & [0,1,2] & [3,4,5] & [3,4,5] & [1,2,3] & [0,1,2] & [0,1,2] & [2,3,4] & [0,1,2] & [2,3,4] & [2,3,4] & [1,2,3] \\
[1,2,3] & [3,4,5] & [1,2,3] & [3,4,5] & [4,5,6] & [3,4,5] & [0,1,2] & [1,2,3] & [2,3,4] & [1,2,3] & [1,2,3] & [3,4,5] & [3,4,5] \\
[1,2,3] & [0,1,2] & [0,1,2] & [3,4,5] & [1,2,3] & [3,4,5] & [3,4,5] & [1,2,3] & [0,1,2] & [1,2,3] & [1,2,3] & [0,1,2] & [1,2,3] \\
[3,4,5] & [1,2,3] & [0,1,2] & [3,4,5] & [1,2,3] & [1,2,3] & [3,4,5] & [0,1,2] & [0,1,2] & [3,4,5] & [3,4,5] & [1,2,3] & [0,1,2]
\end{pmatrix}$$

Triangular Fuzzy Number is usually represented by triplet (a_1, a_2, a_3) where a_1 denotes the minimum possible value; a_2 denotes the most possible value and a_3 represent the maximum possible value.

Stepwise procedure for Simplified Triangular Fuzzy TOPSIS methodology

Step 1: Construct normalized decision matrix by using the linear-sum normalization method.

$$r_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_j} \qquad \text{for} \quad i = 1,\dots,m; \quad j = 1,\dots,n$$

where a_{ij} is the original rating of the decision matrix & r_{ij} is the normalized value of the decision matrix.

$$r_{ij} =$$

$$\left\{ \begin{pmatrix}
[0.0375,0.0282,0.0223] & [0.0411,0.0310,0.0244] & [0.0789,0.0526,0.0373] & [0.0112,0.0127,0.0122] & [0.0156,0.0169,0.0156] \\
[0.0125,0.0141,0.0134] & [0,0.0078,0.0098] & [0,0.0132,0.0149] & [0.0449,0.0318,0.0245] & [0.0469,0.0339,0.0260] \\
[0.0375,0.0282,0.0223] & [0.0548,0.0388,0.0293] & [0.0789,0.0526,0.0373] & [0.0337,0.0255,0.0204] & [0.0156,0.0169,0.0156] \\
[0.0500,0.0352,0.0268] & [0.0411,0.0310,0.0244] & [0.0789,0.0526,0.0373] & [0.0337,0.0255,0.0204] & [0.0469,0.0339,0.0260] \\
[0.0375,0.0282,0.0223] & [0.0548,0.0388,0.0293] & [0.0263,0.0263,0.0224] & [0.0337,0.0255,0.0204] & [0.0156,0.0169,0.0156] \\
[0.0500,0.0352,0.0268] & [0.0411,0.0310,0.0244] & [0.0789,0.0526,0.0373] & [0.0337,0.0255,0.0204] & [0.0625,0.0424,0.0313] \\
[0.0375,0.0282,0.0223] & [0.0274,0.0233,0.0195] & [0,0.0132,0.0149] & [0.0337,0.0255,0.0204] & [0.0469,0.0339,0.0260] \\
[0.0125,0.0141,0.0134] & [0.0411,0.0310,0.0244] & [0.0263,0.0263,0.0224] & [0.0337,0.0255,0.0204] & [0.0625,0.0424,0.0313] \\
[0.0125,0.0141,0.0134] & [0,0.0078,0.0098] & [0,0.0132,0.0149] & [0.0337,0.0255,0.0204] & [0.0156,0.0169,0.0156] \\
[0.0375,0.0282,0.0223] & [0.0137,0.0155,0.0146] & [0,0.0132,0.0149] & [0.0337,0.0255,0.0204] & [0.0156,0.0169,0.0156]
\end{pmatrix} \right.$$

[0.0189,0.0190,0.0169]	[0.0256,0.0253,0.0216]	[0.0769,0.0506,0.0360]	[0.0345,0.0308,0.0248]	[0.0526,0.0367,0.0276]
[0.0566,0.0381,0.0282]	[0,0.0127,0.0144]	[0,0.0127,0.0144]	[0.1034,0.0615,0.0413]	[0.0175,0.0183,0.0166]
[0.0566,0.0381,0.0282]	[0.0256,0.0253,0.0216]	[0.0769,0.0506,0.0.360]	[0.0345,0.0308,0.0248]	[0.0526,0.0367,0.0276]
[0.0377,0.0289,0.0226]	[0.0769,0.0506,0.0360]	[0.0769,0.0506,0.0360]	[0.0345,0.0308,0.0248]	[0.0526,0.0367,0.0276]
[0.0189,0.0190,0.0169]	[0.0256,0.0253,0.0216]	[0.0256,0.0253,0.0216]	[0.1034,0.0615,0.0413]	[0.0526,0.0367,0.0276]
[0.0566,0.0381,0.0282]	[0.0769,0.0506,0.0360]	[0.0769,0.0506,0.0360]	[0,0.0154,0.0165]	[0.0526,0.0367,0.0276]
[0.0189,0.0190,0.0169]	[0,0.0127,0.0144]	[0,0.0127,0.0144]	[0.0690,0.0462,0.0331]	[0,0.0092,0.0110]
[0.0566,0.0381,0.0282]	[0,0.0127,0.0144]	[0.0256,0.0253,0.0216]	[0.0690,0.0462,0.0331]	[0.0175,0.0183,0.0166]
[0.0566,0.0381,0.0282]	[0.0769,0.0506,0.0360]	[0.0256,0.0253,0.0216]	[0,0.0154,0.0165]	[0.0175,0.0183,0.0166]
[0.0189,0.0190,0.0169]	[0.0769,0.0506,0.0360]	[0,0.127,0.0144]	[0,0.0154,0.0165]	[0.0526,0.0367,0.0276]

[0.0488,0.0347,0.0265]	[0.0411,0.0310,0.0244]	[0.0303,0.0274,0.0226]
[0.0122,0.0139,0.0133]	[0,0.0078,0.0098]	[0.0909,0.0548,0.0376]
[0.0366,0.0278,0.0221]	[0.0548,0.0388,0.0293]	[0.0303,0.0274,0.0226]
[0.0488,0.0347,0.0265]	[0.0411,0.0310,0.0244]	[0.0303,0.0274,0.0226]
[0.0366,0.0278,0.0221]	[0.0548,0.0388,0.0293]	[0.0909,0.0548,0.0376]
[0.0488,0.0347,0.0265]	[0.0411,0.0310,0.0244]	[0.0303,0.0274,0.0226]
[0.0244,0.0208,0.0177]	[0.0274,0.0233,0.0195]	[0.0303,0.0274,0.0226]
[0.0122,0.0139,0.0133]	[0.0411,0.0310,0.0244]	[0.0909,0.0548,0.0376]
[0.0122,0.0139,0.0133]	[0,0.0078,0.0098]	[0.0303,0.0274,0.0226]
[0.0366,0.0278,0.0221]	[0.0137,0.0155,0.0146]	[0,0.0137,0.0150]

Normalized Decision Matrix

Step 2: Construct the weighted normalized decision matrix by assigning different value (weight) to each criteria.

$$v_{ij} = w_j * r_{ij} \qquad \text{for} \quad i = 1, \dots, m; \quad j = 1, \dots, n$$

where w_j is the weight for j criterion.

w_j =

([0.158] [0.078] [0.083] [0.027] [0.052] [0.087] [0.042] [0.104] [0.082] [0.093] [0.046] [0.057] [0.084])

Weight for the Original Decision Matrix v_{ij} =

[0.0059,0.0036,0.0024]	[0.0032,0.0024,0.0014]	[0.0034,0.0044,0.0024]	[0.0003,0.0003,0.0003]	[0.0007,0.0009,0.0005]
[0.0020,0.0018,0.0014]	[0,0.0006,0.0006]	[0,0.0011,0.0009]	[0.0012,0.0009,0.0005]	[0.0020,0.0018,0.0008]
[0.0059,0.0036,0.0024]	[0.0043,0.0030,0.0017]	[0.0034,0.0044,0.0024]	[0.0009,0.0007,0.0004]	[0.0007,0.0009,0.0005]
[0.0079,0.0045,0.0029]	[0.0032,0.0024,0.0014]	[0.0034,0.0044,0.0024]	[0.0009,0.0007,0.0004]	[0.0020,0.0018,0.0008]
[0.0059,0.0036,0.0024]	[0.0043,0.0030,0.0017]	[0.0011,0.0022,0.0014]	[0.0009,0.0007,0.0004]	[0.0007,0.0009,0.0005]
[0.0079,0.0045,0.0029]	[0.0032,0.0024,0.0014]	[0.0034,0.0044,0.0024]	[0.0009,0.0007,0.0004]	[0.0026,0.0022,0.0010]
[0.0059,0.0036,0.0024]	[0.0021,0.0018,0.0011]	[0,0.0011,0.0009]	[0.0009,0.0007,0.0004]	[0.0020,0.0018,0.0008]
[0.0020,0.0018,0.0014]	[0.0032,0.0024,0.0014]	[0.0011,0.0022,0.0014]	[0.0009,0.0007,0.0004]	[0.0026,0.0022,0.0010]
[0.0020,0.0018,0.0014]	[0,0.0006,0.0006]	[0,0.0011,0.0009]	[0.0009,0.0007,0.0004]	[0.0007,0.0009,0.0005]
[0.0059,0.0036,0.0024]	[0.0011,0.0012,0.0008]	[0,0.0011,0.0009]	[0.0009,0.0007,0.0004]	[0.0007,0.0009,0.0005]

[0.0016,0.0011,0.0008]	[0.0003,0.0011,0.0005]	[0.0080,0.0053,0.0034]	[0.0011,0.0025,0.0018]	[0.0049,0.0034,0.0014]
[0.0049,0.0005,0.0013]	[0,0.0005,0.0003]	[0,0.0013,0.0014]	[0.0033,0.0050,0.0030]	[0.0016,0.0017,0.0008]
[0.0049,0.0011,0.0013]	[0.0003,0.0011,0.0005]	[0.0080,0.0053,0.0034]	[0.0011,0.0025,0.0018]	[0.0049,0.0034,0.0014]
[0.0033,0.0021,0.0011]	[0.0009,0.0021,0.0008]	[0.0080,0.0053,0.0034]	[0.0011,0.0025,0.0018]	[0.0049,0.0034,0.0014]
[0.0016,0.0011,0.0008]	[0.0003,0.0011,0.0005]	[0.0027,0.0026,0.0020]	[0.0033,0.0050,0.0030]	[0.0049,0.0034,0.0014]
[0.0049,0.0021,0.0013]	[0.0009,0.0021,0.0008]	[0.0080,0.0053,0.0034]	[0,0.0013,0.0012]	[0.0049,0.0034,0.0014]
[0.0016,0.0005,0.0008]	[0,0.0005,0.0003]	[0,0.0013,0.0014]	[0.0022,0.0038,0.0024]	[0,0.0009,0.0006]
[0.0049,0.0005,0.0013]	[0,0.0005,0.0003]	[0.0027,0.0026,0.0020]	[0.0022,0.0038,0.0024]	[0.0016,0.0017,0.0008]
[0.0049,0.0021,0.0013]	[0.0009,0.0021,0.0008]	[0.0027,0.0026,0.0020]	[0,0.0013,0.0012]	[0.0016,0.0017,0.0008]
[0.0016,0.0021,0.0008]	[0.0009,0.0021,0.0008]	[0,0.0013,0.0014]	[0,0.0013,0.0012]	[0.0049,0.0034,0.0014]

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$$\begin{pmatrix}
[0.0022,0.0016,0.0015] & [0.0023,0.0008,0.0006] & [0.0025,0.0018,0.0006] \\
[0.0006,0.0006,0.0007] & [0,0.0002,0.0003] & [0.0076,0.0035,0.0010] \\
[0.0017,0.0013,0.0012] & [0.0031,0.0010,0.0008] & [0.0025,0.0018,0.0006] \\
[0.0022,0.0016,0.0015] & [0.0023,0.0008,0.0006] & [0.0025,0.0018,0.0006] \\
[0.0017,0.0013,0.0012] & [0.0031,0.0010,0.0008] & [0.0076,0.0035,0.0010] \\
[0.0022,0.0016,0.0015] & [0.0023,0.0008,0.0006] & [0.0025,0.0018,0.0006] \\
[0.0011,0.0010,0.0010] & [0.0016,0.0006,0.0005] & [0.0025,0.0018,0.0006] \\
[0.0006,0.0006,0.0007] & [0.0023,0.0008,0.0006] & [0.0076,0.0035,0.0010] \\
[0.0006,0.0006,0.0007] & [0,0.0002,0.0003] & [0.0025,0.0018,0.0006] \\
[0.0017,0.0013,0.0012] & [0.0008,0.0004,0.0004] & [0,0.0009,0.0004]
\end{pmatrix}$$

Weighted Normalized Decision Matrix

Step 3: Determine the Positive Ideal Solution (PIS) & Negative Ideal Solution (NIS).

$$S^* = \{ v_{1j}^*, v_{2j}^*, v_{3j}^*, \ldots, v_{mj}^* \},$$
where $v_{ij}^* = \{ \max(v_{ij}) \text{ if } j \in J;\ \min(v_{ij}) \text{ if } j \in J^- \}$

$$S^- = \{ v_{1j}^-, v_{2j}^-, v_{3j}^-, \ldots, v_{mj}^- \},$$
where $v_{ij}^- = \{ \min(v_{ij}) \text{ if } j \in J;\ \max(v_{ij}) \text{ if } j \in J^- \}$

J is associated with benefit criteria, and J^- is associated with cost criteria.

$$S^* = \left\{ \begin{array}{c}
([0.0079,0.0045,0.0029]\quad [0.0043,0.0030,0.0017]\quad [0.0034,0.0044,0.0024]\quad [0.0012,0.0009,0.0005]\quad [0.0026,0.0022,0.0010]) \\
([0.0049,0.0021,0.0013]\quad [0.0009,0.0021,0.0008]\quad [0.0080,0.0053,0.0034]\quad [0.0033,0.0050,0.0030]\quad [0,0.0009,0.0006]) \\
([0.0022,0.0016,0.0015]\quad [0,0.0002,0.0003]\quad [0.0076,0.0035,0.0010])
\end{array} \right\}$$

Positive Ideal Solution

$$S^- = \left\{ \begin{array}{c}
([0.0020,0.0018,0.0014]\quad [0,0.0006,0.0006]\quad [0,0.0011,0.0009]\quad [0.0003,0.0003,0.0003]\quad [0.0007,0.0009,0.0005]) \\
([0.0016,0.0011,0.0008]\quad [0,0.0005,0.0003]\quad [0,0.0013,0.0014]\quad [0,0.0013,0.0012]\quad [0,0.0034,0.0014]) \\
([0.0006,0.0006,0.0007]\quad [0,0.0010,0.0008]\quad [0,0.0009,0.0004])
\end{array} \right\}$$

Negative Ideal Solution

Step 4: Let $\bar{a}_1 = (l_1, m_1, u_1)$ and $\bar{a}_2 = (l_2, m_2, u_2)$ be two Triangular Fuzzy Number, then the vertex method is defined to calculate the distance between them as

$$d(\bar{a}_1, \bar{a}_2) = \sqrt{\frac{1}{3}[(l_1-l_2)^2+(m_1-m_2)^2+(u_1-u_2)^2]}$$

$$d(v_{ij}, S^*) = \begin{pmatrix}
[0.0013] & [0.0007] & [0] & [0.0006] & [0.0014] & [0.0020] & [0.0007] & [0] & [0.0021] & [0.0032] & [0] & [0.0014] & [0.0031] \\
[0.0039] & [0] & [0] & [0] & [0.0005] & [0] & [0] & [0] & [0] & [0.0011] & [0.0012] & [0] & [0] \\
[0.0013] & [0] & [0] & [0.0002] & [0.0014] & [0] & [0.0007] & [0] & [0.0021] & [0.0032] & [0.0004] & [0.0019] & [0.0031] \\
[0] & [0.0007] & [0] & [0.0002] & [0.0005] & [0.0010] & [0] & [0] & [0.0021] & [0.0032] & [0] & [0.0014] & [0.0031] \\
[0.0013] & [0] & [0.0019] & [0.0002] & [0.0014] & [0.0020] & [0.0007] & [0.0035] & [0] & [0.0032] & [0.0004] & [0.0019] & [0] \\
[0] & [0.0007] & [0] & [0.0002] & [0] & [0] & [0] & [0] & [0] & [0.0032] & [0] & [0.0014] & [0.0031] \\
[0.0013] & [0.0015] & [0] & [0.0002] & [0.0005] & [0.0020] & [0] & [0] & [0.0010] & [0] & [0.0008] & [0.0009] & [0.0031] \\
[0.0039] & [0.0007] & [0.0019] & [0.0002] & [0] & [0] & [0] & [0.0035] & [0.0010] & [0.0011] & [0.0012] & [0.0014] & [0] \\
[0.0039] & [0] & [0] & [0.0002] & [0.0014] & [0] & [0] & [0.0035] & [0] & [0.0011] & [0.0012] & [0] & [0.0031] \\
[0.0013] & [0.0022] & [0] & [0.0002] & [0.0014] & [0.0020] & [0] & [0] & [0] & [0.0032] & [0.0004] & [0.0005] & [0]
\end{pmatrix}$$

Vertex Distance for Positive Ideal Solutio

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$$d(\mathrm{v}_{ij}\,,\ S^{-}) \ =$$

$$\begin{pmatrix} [0.0026] & [0.0026] & [0.0028] & [0] & [0] & [0] & [0.0004] & [0.0053] & [0.0010] & [0] & [0.0012] & [0.0005] & [0.0016] \\ [0] & [0] & [0] & [0.0006] & [0.0009] & [0.0020] & [0] & [0] & [0.0031] & [0.0022] & [0] & [0] & [0.0047] \\ [0.0026] & [0.0029] & [0.0028] & [0.0004] & [0] & [0.0020] & [0.0004] & [0.0053] & [0.0010] & [0] & [0.0008] & [0] & [0.0016] \\ [0.0039] & [0.0022] & [0.0028] & [0.0004] & [0.0009] & [0.0010] & [0.0011] & [0.0053] & [0.0010] & [0] & [0.0012] & [0.0005] & [0.0016] \\ [0.0026] & [0.0029] & [0.0009] & [0.0004] & [0] & [0] & [0.0004] & [0.0018] & [0.0031] & [0] & [0.0008] & [0] & [0.0047] \\ [0.0039] & [0.0022] & [0.0028] & [0.0004] & [0.0014] & [0.0020] & [0.0011] & [0.0053] & [0] & [0] & [0.0012] & [0.0005] & [0.0016] \\ [0.0026] & [0.0015] & [0] & [0.0004] & [0.0009] & [0] & [0] & [0] & [0.0021] & [0] & [0.0004] & [0.0009] & [0.0016] \\ [0] & [0.0022] & [0.0009] & [0.0004] & [0.0014] & [0.0020] & [0] & [0.0018] & [0.0021] & [0.0022] & [0] & [0.0005] & [0.0047] \\ [0] & [0] & [0] & [0.0004] & [0] & [0.0020] & [0.0011] & [0.0018] & [0] & [0.0022] & [0] & [0] & [0.0016] \\ [0.0026] & [0.0007] & [0] & [0.0004] & [0] & [0] & [0.0011] & [0] & [0] & [0] & [0.0008] & [0.0014] & [0] \end{pmatrix}$$

Vertex Distance for Negative Ideal Solution

Step 5: Calculate the Distance of each alternative from FPIS and FNIS.

The distance from Fuzzy Positive Ideal Solution is:

$$\mathrm{D}_i^{*} \ = \ \sum_{j=1}^{n} d(\mathrm{v}_{ij}\,,\ S^{*}) \qquad \text{for} \quad i = 1, \ldots, m$$

Similarly, the distance from Fuzzy Negative Ideal Solution is:

$$\mathrm{D}_i^{-} \ = \ \sum_{j=1}^{n} d(\mathrm{v}_{ij}\,,\ S^{-}) \qquad \text{for} \quad i = 1, \ldots, m$$

$$\mathrm{D}_i^{*} \ = \ ([0.0166] \quad [0.0066] \quad [0.0143] \quad [0.0122] \quad [0.0166] \quad [0.0087] \quad [0.0113] \quad [0.0149] \quad [0.0144] \quad [0.0112])$$

Distance from Positive Ideal Solution

$$\mathrm{D}_i^{-} \ = \ ([0.0175] \quad [0.0135] \quad [0.0198] \quad [0.0219] \quad [0.0175] \quad [0.0223] \quad [0.0103] \quad [0.0181] \quad [0.0090] \quad [0.0070])$$

Distance from Negative Ideal Solution

Step 6: Calculate the relative closeness to the ideal solution C_i .

$$\mathrm{C}_i \ = \ \frac{\mathrm{D}_i^{-}}{\mathrm{D}_i^{*}} \qquad \text{for} \ \ i = 1,2, \ldots, m \ \& \ 0 < \ \mathrm{C}_i \ < 1$$

$$\mathrm{C}_i \ = \ ([0.5132] \quad [0.6716] \quad [0.5803] \quad [0.6414] \quad [0.5139] \quad [0.7196] \quad [0.4771] \quad [0.5478] \quad [0.3852] \quad [0.3856])$$

Relative Closeness Coefficient

Step 7: Rank the alternatives by selecting the alternative with C_i closest to 1.

$$S6 \ > S2 \ > S4 \ > S3 \ > S8 > S5 > S1 > S7 > S10 > S9$$

Ranking order

Obviously, a large value of index C_i indicates that the alternative is close to the fuzzy positive ideal solution and far from the fuzzy negative ideal solution, and then this alternative will give a high ranking order. The Computation of vertex distance to calculate the distance of each alternative from FPIS and FNIS, converts the triangular fuzzy matrix into a normal decision matrix there by ranking order of alternatives can be easily made using relative closeness coefficient.

Generally, TOPSIS method has been evaluated by the application aspects. In this approach, standard parameters are used to evaluate the TOPSIS technique. A new kind of evaluation parameters are proposed from the working model of TOPSIS. From these existing and new evaluation parameters, metric is designed to evaluate the efficiency of the proposed TOPSIS method.

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VI. METRICS FOR TOPSIS TECHNIQUE

A. *Standard Parameters for Evaluation*

In order to evaluate the proposed methodology with the existing approach, several standard parameters are applied to measure the efficiency. Some of the standard parameters that are discussed in this research are listed below:

- Time Complexity
- Space Complexity
- Sensitivity Analysis
- Ranking Reversal

B. *Additional Parameters for Evaluation*

In order to evaluate the proposed approach with the existing work, several additional parameters are applied to measure the efficiency of the proposed algorithm. Some of the additional parameters that are discussed in this work are listed below:

- Repeated Ranking
- Rank Occurrence
- Relative Closeness Efficiency

1) *Repeated Ranking:* Repeated Ranking is defined as number of ranks that are repeated. Repeated ranking metric is denoted by R_{RR}. It is the ratio of number of ranks repeated to Total number of items. Let N_{RR} be the number of ranks repeated and TNI be the Total number of items.

$$R_{RR} = \frac{N_{RR}}{TNI} * 100\%$$

Repeated ranking metric value lies from 0 to 100% and lower the value of this ratio depicts better performance in ranking.

2) *Rank Occurrence:* Rank Occurrence is defined as number of times the ranks occurred. Rank Occurrence metric is denoted by R_{RO}. It is the ratio of number of repeated rank occurrence to Total number of items. Let N_O be the number of repeated rank occurrence and TNI is the Total number of items.

$$R_{RO} = \frac{N_O}{TNI} * 100\%$$

Rank Occurrence metric value lies from 0 to 100%. Lower the value of this ratio depicts efficient ranking.

3) *Relative Closeness Efficiency:* Relative closeness efficiency represent the result is closest to the target solution. Relative closeness efficiency metric. Relative closeness efficiency metric is denoted by R_{RC}. It is the ratio of summation of Relative Closeness Coefficient (RCC) value subtracted from the target value (i.e. 1) to Total number of items. Let ratio of Relative closeness efficiency be denoted by R_{RC} and it is calculated by the following equation. Let RCC_i be the Relative Closeness Coefficient value and TNI be the Total number of items.

$$R_{RC} = \frac{\sum_{i=1}^{m}(1 - RCC_i)}{TNI} * 100\%$$

Relative Closeness efficiency metric value lies from 0 to 100%. Higher the value of R_{RC} indicates that the result is closest to the target solution.

VII. EXPERIMENTATION

The data set has been collected from various hardware suppliers. 10 samples out of 162 collected data are used for this proposed work.

A. *Criteria*

There are certain criteria available to select the best supplier. The suitable supplier is chosen based on the following criteria which are described in Table 2.

Table 8: Supplier selection criteria

On time delivery – C1	Urgent delivery – C2
Warranty period – C3	Financial stability – C4

Delivery lead time – C5	Accessibility – C6
Reliability – C7	Testability – C8
Product cost – C9	Ordering cost – C10
Transportation cost – C11	Rejection of defective product – C12
Cost of support service – C13	

To conduct this experiment we have selected MATLAB 7.9.0.529 (R2009b). The collected 162 dataset are taken for this experiment and data have been entered and saved in MS Excel. Then the data have been processed in MATLAB 7.9.0.529 (R2009b) and the results are shown in Table 9.

VIII. RESULTS AND DISCUSSION

By performing the Fuzzy TOPSIS procedure to supplier data set against the alternatives (users) based on the four criteria the following results are obtained. From these results it is clearly seen that the alternative with the highest Relative Closeness Coefficient is considered as the best user for the given information. The existing method Generalized Triangular Fuzzy TOPSIS (GTF-TOPSIS) and the proposed method Simplified Triangular Fuzzy TOPSIS (STF-TOPSIS) are implemented with the same inputs to obtain the best and the least alternatives.

A. *Efficiency of Various Normalization Techniques*

The efficiency of various normalization techniques can be determined by the following two metrics.

1) Computation time of the algorithm (Time Complexity)
2) Space required by the algorithm (Space Complexity)

Table 3 describes the Time and Space Complexity of various normalization techniques

Table 3: Complexities of various Normalization Techniques

METHODS	TIME COMPLEXITY (Seconds)	SPACE COMPLEXITY (Bytes)
Vector Normalization	0.003784	2344
Linear Max-Min Normalization	0.005287	3056
Linear Max Normalization	0.002026	2912
Linear Sum based Normalization	0.001464	2336

From the Table 3 it is observed that the Linear Sum based Normalization technique achieves less computation time and Space Complexity. The above techniques are applied in the supplier chain management and the performance of the various normalization techniques are measured using time and space complexity. Table 4 and the graph depicted in Figure 2 are describes the relative closeness coefficient of various normalization techniques obtained using different matrix size.

Table 4: Comparison of various Normalization techniques using Matrix Size

METHODS	Relative Closeness Coefficients		
	Matrix size		
	50 x 13	100 x 13	150 x 13
Vector Normalization	0.5246	0.5445	0.5708
Linear Max-Min Normalization	0.0038	0.0041	0.0074
Linear Max Normalization	0.1454	0.1462	0.1515
Linear Sum based Normalization	0.5524	0.5843	0.6119
Gaussian Normalization	0.5303	0.5549	0.5823

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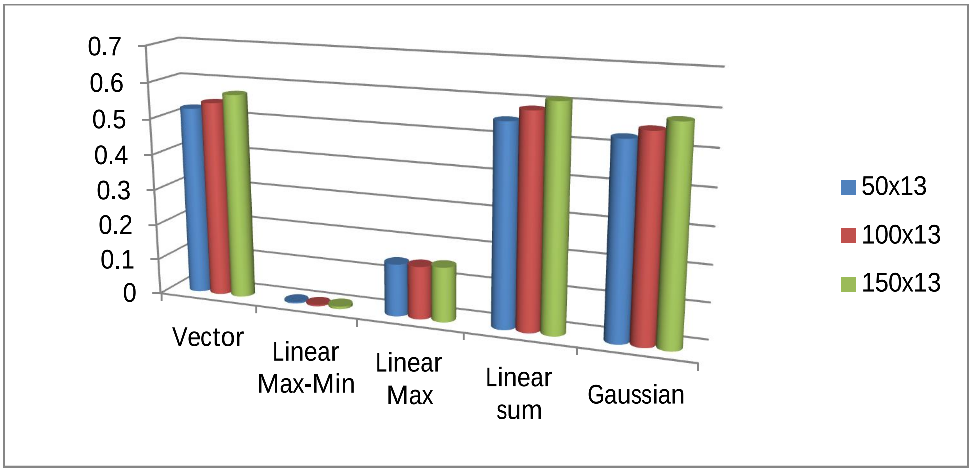
Figure 2: Comparison of various normalization techniques using matrix size



Similarly Table 5 and graph depicted in Figure 3 are describes the results obtained for various normalization techniques using sparsity matrix.

Table 5: Comparison of various Normalization techniques using Sparsity

METHODS	Relative Closeness Coefficients		
	SPARSITY		
	10%	20%	30%
Vector Normalization	0.4896	0.3505	0.3983
Linear Max-Min Normalization	0.0040	0.0037	0.0026
Linear Max Normalization	0.1275	0.1125	0.0871
Linear Sum based Normalization	0.4999	0.4722	0.4701
Gaussian Normalization	0.5014	0.4734	0.4409

Figure 3: Comparison of various Normalization techniques using Sparsity

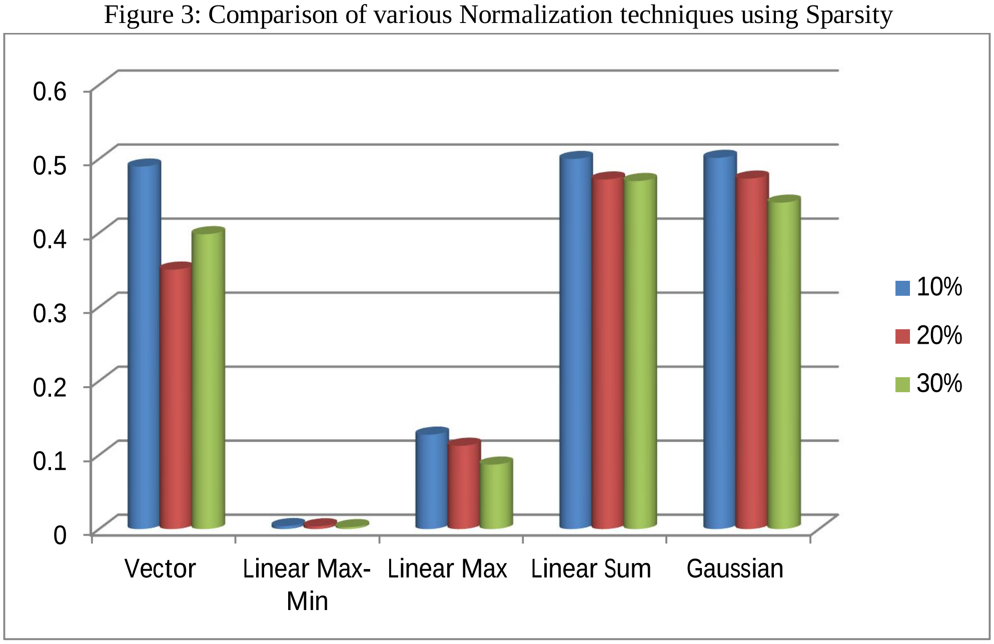
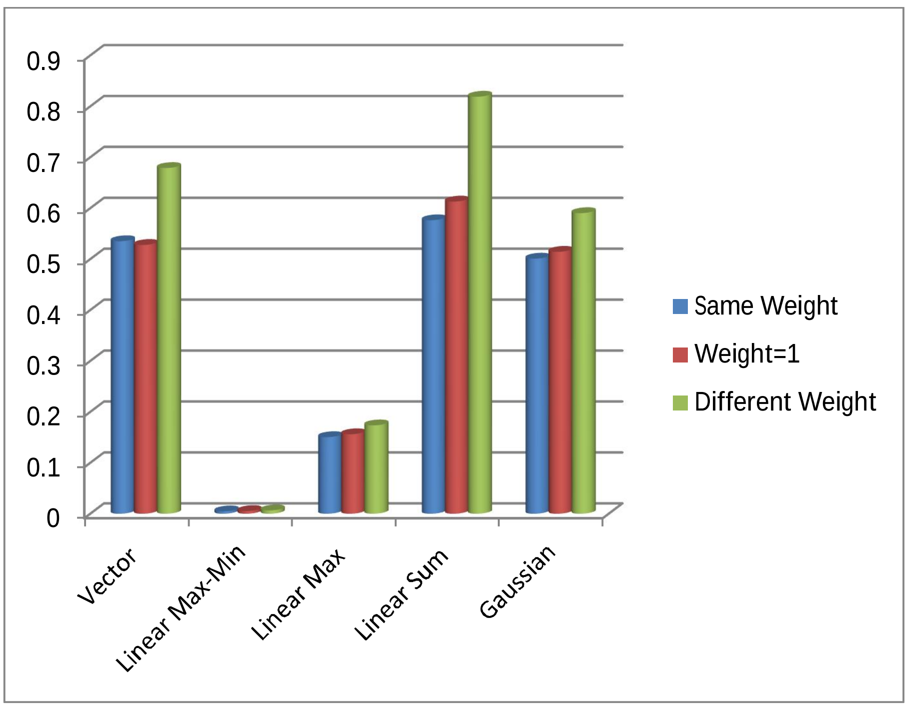


Table 6 and graph depicted in Figure 4 are describes the results obtained for various normalization techniques using different weight.

Table 6: Comparison of various Normalization techniques using Different Weight

METHODS	Relative Closeness Coefficients		
	SPARSITY		
	SAME WEIGHT	WEIGHT=1	DIFFERENT WEIGHT
Vector Normalization	0.5351	0.5278	0.6789
Linear Max-Min Normalization	0.0046	0.0052	0.0065
Linear Max Normalization	0.1504	0.1561	0.1735
Linear Sum based Normalization	0.5763	0.6130	0.8189
Gaussian Normalization	0.5009	0.5143	0.5903

Figure 4: Comparison of various Normalization techniques using Different Weight



By considering the matrix size, sparsity and different weights of each normalization linear sum based normalization achieves a better result when compared to other techniques. Similarly, Triangular Fuzzy TOPSIS uses one particular weight method without considering the suitability of other available methods. This leads the necessity to examine the effects of various weight methods on decision outcome when used with Triangular Fuzzy TOPSIS method.

B. Efficiency of Various Weight Methods

The efficiency of various weight methods can be determined by the following two metrics.

1) Time Complexity

2) Space Complexity

Table 7 shows the Time Complexity and Space Complexity of various weight methods.

Table 7: Complexities of various Weight Method

METHODS	TIME COMPLEXITY (Seconds)	SPACE COMPLEXITY (Bytes)
AHP Method	0.001008	2336
Entropy Method	0.003822	3160
Eigen Vector Method	0.001820	2486

The above methods are applied in the supplier chain management and the performance of the various weight methods are measured using time and space complexity. From the Table 7 it is observed that the AHP weight method achieves less Time Complexity as well as the Space Complexity.

C. The impact of Relative Closeness Coefficient for ranking order

Table 8 describes the ranking order of Generalized Triangular Fuzzy TOPSIS when it is applied on the collected supplier dataset are observed as follows:

Table 8: Result obtained for GTF-TOPSIS

TOPSIS Methodology	Relative Closeness Coefficients	Rank
Generalized Triangular Fuzzy TOPSIS	0.0971	7
	0.1700	2
	0.1683	4
	0.1698	3
	0.1166	6
	0.2031	1
	0.0888	8
	0.1286	5
	0.0055	10
	0.0059	9

Table 9 describes the ranking order of Simplified Triangular Fuzzy TOPSIS when it is applied on the collected supplier dataset are observed as follows:

Table 9: Result obtained for STF-TOPSIS

TOPSIS Methodology	Relative Closeness Coefficients	Rank
Simplified Triangular Fuzzy TOPSIS	0.5132	7
	0.6716	2
	0.5803	4
	0.6414	3
	0.5139	6
	0.7196	**1**
	0.4771	8
	0.5478	5
	0.3852	10
	0.3856	9

When comparing the Generalized Triangular Fuzzy TOPSIS and Simplified Triangular Fuzzy TOPSIS, the Relative Closeness Coefficient of Simplified Triangular Fuzzy TOPSIS achieves a better result, as well as the ranking order has not been changed.

From the above Table 10 it is observed that the ranking order of the alternatives seems to be same for both the GTF-TOPSIS and STF-TOPSIS methodology. STF-TOPSIS attains a higher Relative Closeness Coefficient value. The Relative Closeness Coefficient value 1 indicates that the corresponding alternative is the best user to receive the information in a supplier chain management. The alternative which receives 0 Relative Closeness Coefficient value appears to be the least user for the corresponding information. The graph which is depicted in Figure 7 shows the difference in the Relative Closeness Coefficient of GTF-TOPSIS and STF-TOPSIS algorithms.

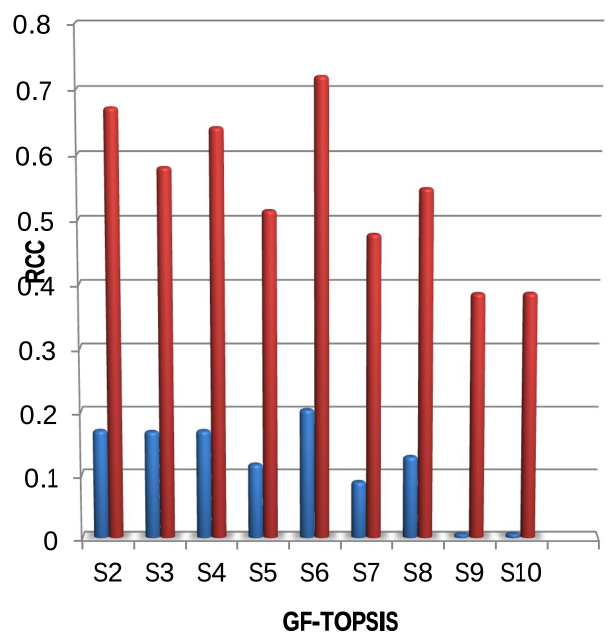


Figure 7: Comparison of GTF-TOPSIS and STF-TOPSIS

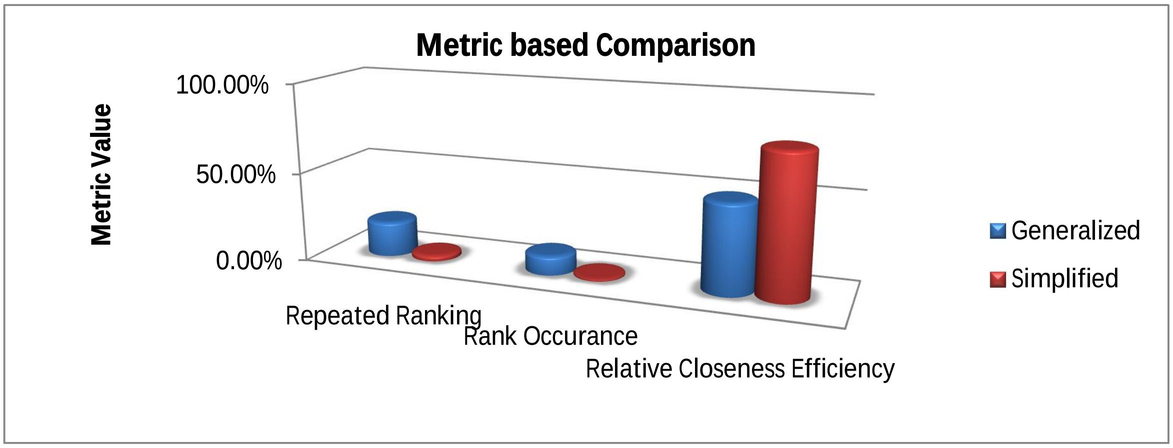
Relative Closeness Coefficient

When both methodologies are incorporated in supplier chain management, same ranking order has been obtained even though variation observed in the decision making process. The efficiency of Generalized and Simplified Triangular Fuzzy TOPSIS based on the Metrics such as repeated ranking, rank occurrence and relative closeness efficiency is described in Table 10 as well as in the graph depicted in Figure 8.

Table 10: Efficiency of Generalized and Simplified Triangular Fuzzy TOPSIS based on the Metric

Metric Name	Generalized	Simplified
Repeated Ranking	19.75%	3.09%
Rank Occurrence	10.74%	1.35%
Relative Closeness Efficiency	49.60%	78.47%

Figure 8: Efficiency of GTF and STF-TOPSIS based on the metric



From the Figure 8 it has been shown that the repeated ranking metric value for Simplified approach seems to be less when compared with generalized approach. It indicates that the efficiency of ranking is higher when there are a minimum number of ranks are repeated. Similarly, the impact of rank occurrence also affects the ranking order. Lower value of rank occurrence leads to accurate ranking. Relative closeness efficiency result from Table 10 shows that Simplified approach seems to be better when compared to generalized approach. Higher value of Relative closeness efficiency indicates that the result is close to the target solution.

D. Time and Space Complexity of GTF-TOPSIS and STF-TOPSIS

The efficiency of these two algorithms can be determined by the computational time required by those algorithms. The time complexity comparison of various TOPSIS algorithms is described in Table 11.

Table 11: Time Complexity of Generalized and Simplified Triangular Fuzzy TOPSIS

TOPSIS Methodology	Time Complexity (Seconds)
Generalized Triangular Fuzzy TOPSIS	0.03815
Simplified Triangular Fuzzy TOPSIS	0.01928

These two algorithms are compared based on the computation time of each algorithm. In this comparison, the computational time of STF-TOPSIS is 0.01928 seconds and it yields highest Relative Closeness Coefficient value of 1 when compared with the GTF-TOPSIS algorithm. The comparative analysis of TOPSIS algorithms with respect to Time Complexity is described in Figure 9.

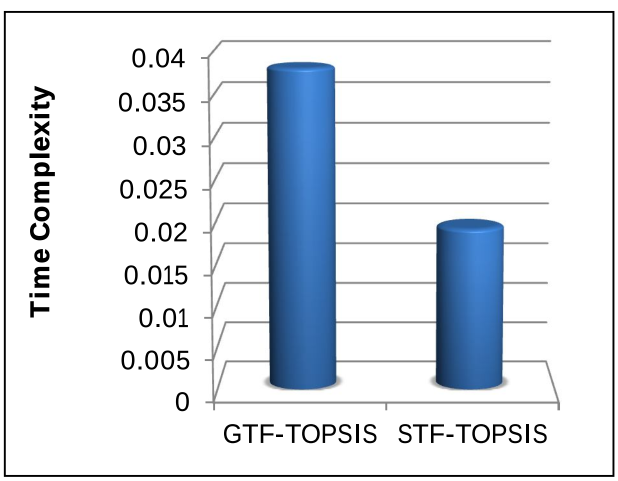


Figure 9: Computation Time for GTF-TOPSIS and STF-TOPSIS

Similarly the efficiency can also be determined by the space required by these two algorithms. The comparison of space complexity of various TOPSIS algorithms is described in Table 12.

Table 12: Space Complexity of Generalized and Simplified Triangular Fuzzy TOPSIS

TOPSIS Methodology	Space Complexity (Bytes)
Generalized Triangular Fuzzy TOPSIS	2912
Simplified Triangular Fuzzy TOPSIS	2336

These two TOPSIS algorithms are compared based on the space required by each algorithm. In this comparison, the space required by STF-TOPSIS is 2336 bytes which yields the highest performance efficiency when compared to the GTF-TOPSIS algorithm. The comparative analysis of TOPSIS algorithms with respect to Space Complexity is described in Figure 10.

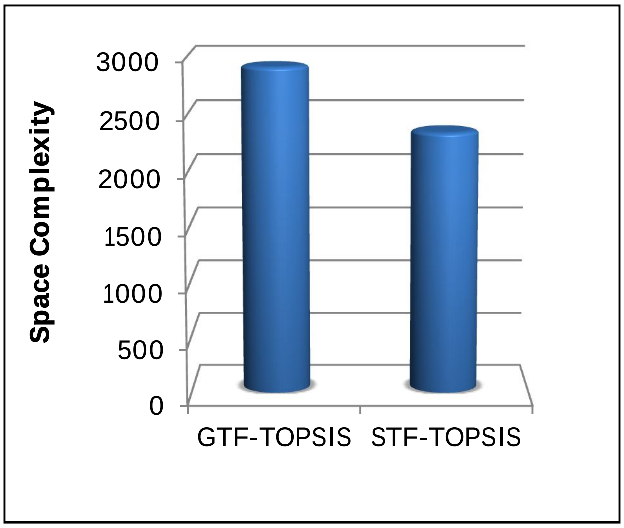


Figure 10: Space required by the GTF-TOPSIS and STF-TOPSIS

The proposed approach attains a better result in the aspects of Time Complexity and Space Complexity by simplifying the steps of a Triangular Fuzzy TOPSIS method, as well as applying various normalization technique and weight method. Similarly, the modified Relative Closeness Coefficient technique has improved the ranking order. The next section describes the results obtained on GTF-TOPSIS and STF-TOPSIS using sensitivity analysis.

E. Sensitivity Analysis of GTF-TOPSIS and STF-TOPSIS

The data in MCDM problems are imprecise and changeable. Therefore, an important step in many applications of MCDM is to perform a sensitivity analysis on the input data. Therefore, the proposed approach performs sensitivity analysis on the weights on the decision criteria. The Simplified Triangular Fuzzy TOPSIS approach formalizes a number of important issues on sensitivity analysis and derives some critical results. The main objective of a sensitivity analysis of an MCDM problem is to find out when the input data (i.e., the a_{ij} and wj values) are changed into new values and how the ranking of the alternatives will be changed. From the literature (Insua, 1990) it has been found that that decision making problems may be remarkably sensitive to several reasonable variations in the parameters of the problems. The conclusion of the research justified that necessity of sensitivity analysis in MCDM. The Sensitivity Analysis is performed on Generalized and Simplified Triangular Fuzzy TOPSIS methodologies based on various Weight are described in Table 13.

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Table 13: Sensitivity Analysis of GTF-TOPSIS and STF-TOPSIS

TOPSIS Methodology	Relative Closeness Coefficients	Rank
Generalized Triangular Fuzzy TOPSIS	0.5380 0.6001 0.6013 **0.7771** 0.5127	4 3 2 **1** 5
Simplified Triangular Fuzzy TOPSIS	0.5124 0.5962 16521 **0.7980** 04308	4 3 2 **1** 5

From this result, it is found that the proposed approach attains highest RCC value when compared to the existing approach. The efficiency of the proposed approach gets improved when sensitivity analysis is performed on the weights on decision criteria. Based on the result a graph has been plotted which is depicted in Figure 11.

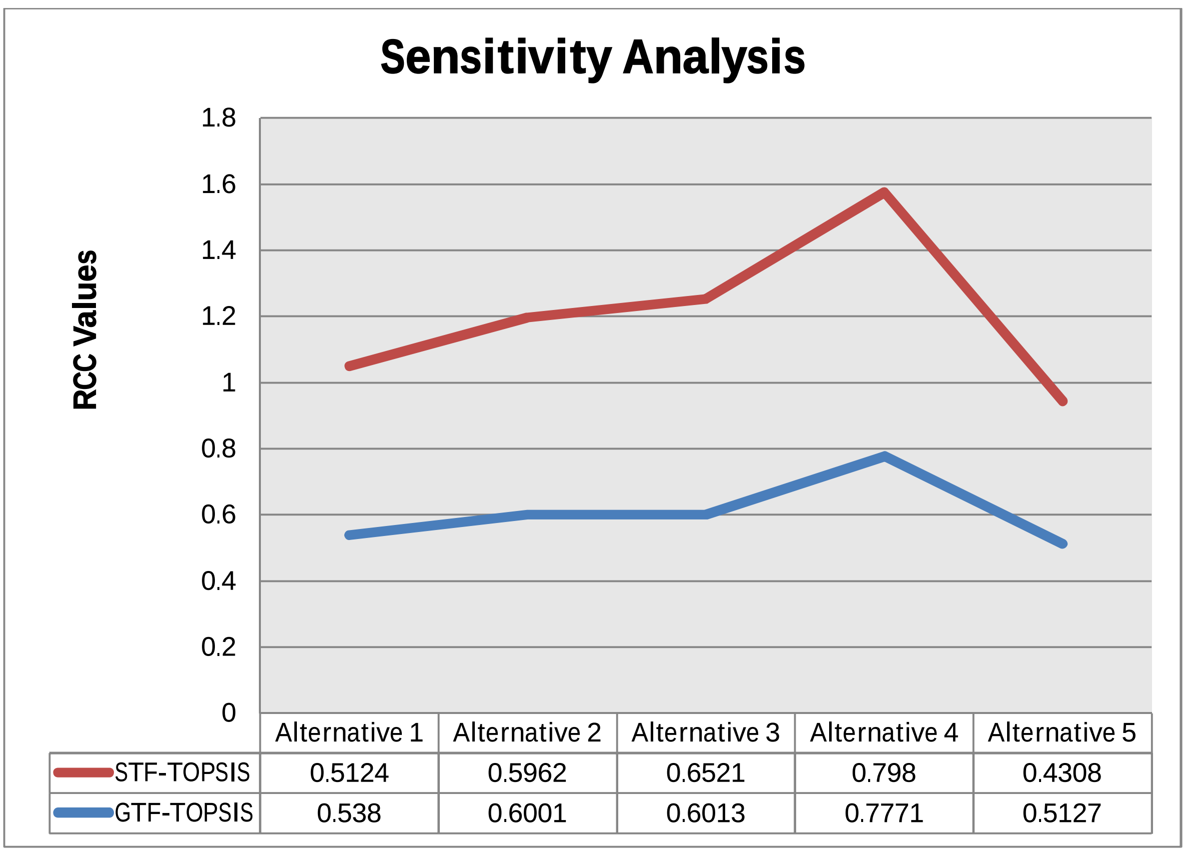

Figure 11. Sensitivity Analysis of various TOPSIS methods

The Sensitivity Analysis of Generalized and Simplified Triangular Fuzzy TOPSIS methodologies based on same Weight (i.e. equal preferences) are described in Table 14.

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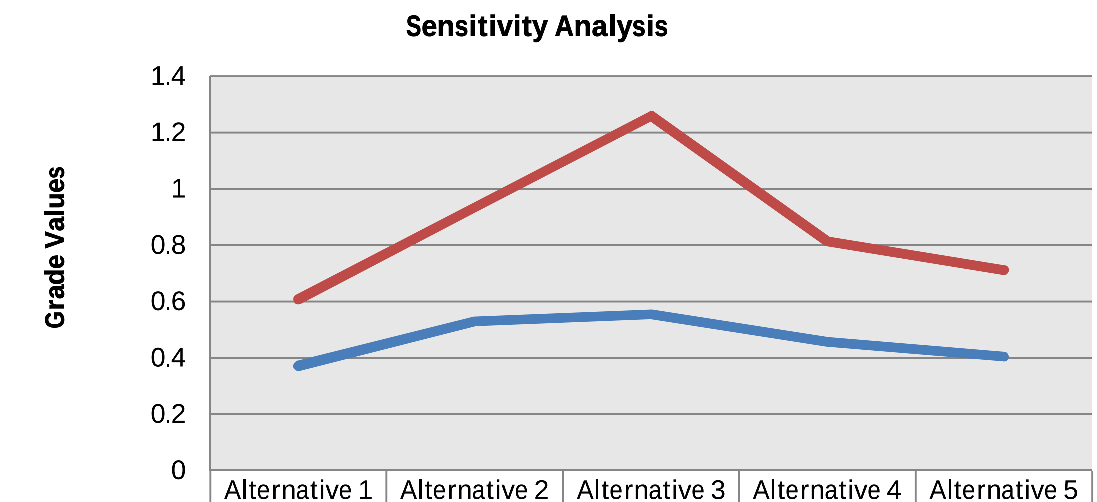
Table 14: Sensitivity Analysis of GTF-TOPSIS and STF-TOPSIS

TOPSIS Methodology	Relative Closeness Coefficients	Rank
Generalized Triangular Fuzzy TOPSIS	0.3721 0.5302 **0.5553** 0.4578 0.4047	5 2 **1** 3 4
Simplified Triangular Fuzzy TOPSIS	0.2359 0.4038 **0.7036** 0.3571 0.3063	5 2 **1** 3 4



	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5
STF-TOPSIS	0.2359	0.4038	0.7036	0.3571	0.3063
GTF-TOPSIS	0.3721	0.5302	0.5553	0.4578	0.4047

Figure 12. Sensitivity Analysis of various TOPSIS methods

The main advantage of sensitivity analysis is to estimate the relationship between input and output variables. The proposed algorithm performs efficiently when the input matrix has more sparse data. The proposed STF-TOPSIS algorithm is gradually evaluated by increasing the set of criteria and the set of alternatives.

F. Rank Reversal

In MCDM, several authors (Bana & Vansnick, 2008; Wang & Luo, 2009; Wang & Ehang, 2006) have looked into the rank reversal phenomenon which is the alteration of the ranking of alternatives by the addition (or deletion) of irrelevant alternatives. (Buede and Maxwell, 1995), (Wang and Luo, 2009) and (Zanakis et al., 1998) have conducted a series of rank reversal experiments to demonstrate the rank reversal phenomenon in TOPSIS. One of the problems associated with the use of MCDM techniques is a possibility to change a ranking of decision alternatives when an alternative is added or deleted. This phenomenon is known as rank reversal.

We have iterated the proposed algorithm several times in order to have statistically correct results. The ratio of total number of iterations and the number of decisions were calculated, which can be considered as the probability of rank reversal.

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As the result shows, the GTF-TOPSIS performance is not feasible. In that case, when the least alternative has been removed, the probability of rank reversal was about 10%. When compared to the original GTF-TOPSIS, the proposed algorithm STF-TOPSIS reduced the rank abnormality by 65% to 99% as shown in the Figure 13.

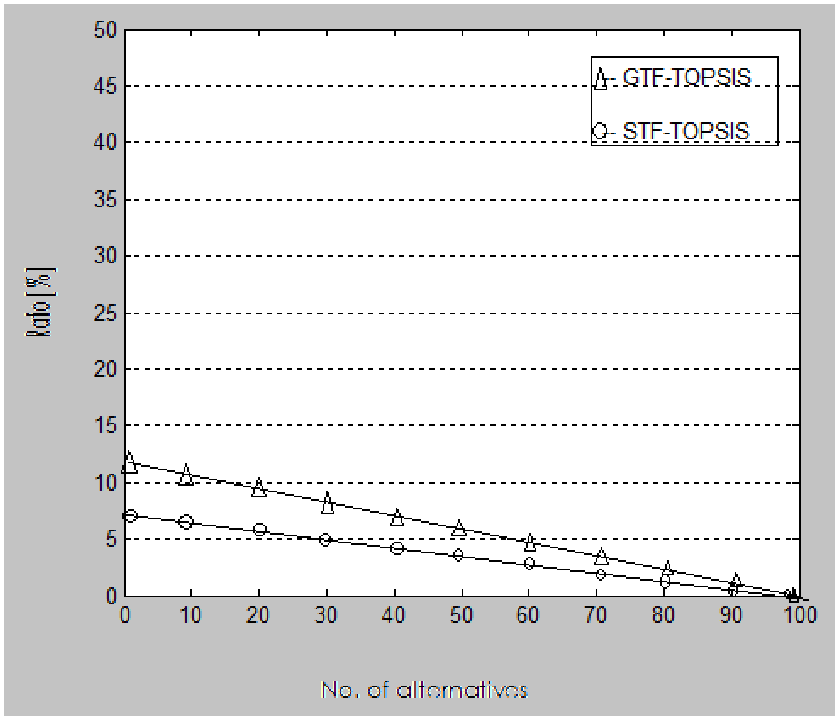

Figure 13. Ranking reversal of various TOPSIS methods

As a result of these findings it has been clearly shown that the performance of STF-TOPSIS is better than the performance of GTF-TOPSIS when it is evaluated using the metrics which are designed in this research. The same set of evaluation metrics has been applied to other kinds of MCDM techniques and it's applications to evaluate it. In the proposed methodology, to measure the similarity or regularity among the data-items, distance plays an important role. The distance measures are basically used to find the distance between the target alternative and the best and the worst condition. In this research, distance parameter is not investigated to identify its limitations. The proposed methodology can be extended to find better distance methodology to improve the ranking order.

IX. CONCLUSION

Multi criteria decision making is widely used for decision making problem where there are several factors involved to obtain the best solution. Different kinds of methodologies are applied to solve multi criteria decision problems. Among different kinds of fuzzy MCDM techniques Triangular Fuzzy TOPSIS is one of the most preferred approach when it is compared to interval data and trapezoidal methods.

The proposed simplified fuzzy TOPSIS method has been developed by simplifying the classical Triangular Fuzzy TOPSIS. This method works efficiently even though an alternative at the bottom of the ranking is detached from the comparison and the iterative approach provides a more reliable and exact result. The proposed method has been applied for supplier selection and best supplier is identified. The experimentation results indicate that proposed method shows better ranking order when it is compared to previous methods.

This research also have designed metrics suite to evaluate the MCDM methods. The simplified fuzzy triangular TOPSIS has been evaluated using metrics such as time complexity, space complexity, sensitivity analysis, ranking reversal, repeated ranking, rank occurrence and relative closeness efficiency. These metrics also has been validated with COPRAS method. In this validation, expect relative closeness coefficient all other metrics are have been validated with COPRAS method. In this validation, a metric which is specific to COPRAS has been designed. It shows that MCDM techniques require both generic and specific metrics. The proposed method has been designed by simplifying the steps of a triangular fuzzy TOPSIS method, as well as applying various normalization technique and weight method. Similarly, a new Relative Closeness Coefficient technique is applied to improve the ranking order of the alternatives. As a result of the study, the proposed method is realistic and convenient in predicting the appropriate supplier in supplier chain management with respect to multiple conflicting criteria.

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APPENDIX - A

ORIGINAL DECISION MATRIX

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
SUPPLIER1	4	4	4	2	2	2	2	4	2	4	5	4	2
SUPPLIER2	2	1	1	5	4	4	1	1	4	2	2	1	4
SUPPLIER3	4	5	4	4	2	4	2	4	2	4	4	5	2
SUPPLIER4	5	4	4	4	4	3	4	4	2	4	5	4	2
SUPPLIER5	4	5	2	4	2	2	2	2	4	4	4	5	4
SUPPLIER6	5	4	4	4	5	4	4	4	1	4	5	4	2
SUPPLIER7	4	3	1	4	4	2	1	1	3	1	3	3	2
SUPPLIER8	2	4	2	4	5	4	1	2	3	2	2	4	4
SUPPLIER9	2	1	1	4	2	4	4	2	1	2	2	1	2
SUPPLIER10	4	2	1	4	2	2	4	1	1	4	4	2	1
SUPPLIER11	1	4	2	1	1	2	4	3	4	4	1	4	4
SUPPLIER12	4	4	4	4	4	4	5	4	4	4	4	4	4
SUPPLIER13	2	4	2	2	1	4	1	2	1	4	2	4	2
SUPPLIER14	2	2	4	4	3	1	2	4	4	2	2	2	4
SUPPLIER15	3	4	2	5	2	4	4	2	2	2	3	4	2
SUPPLIER16	2	3	3	2	2	1	1	3	3	2	2	3	3
SUPPLIER17	4	4	4	2	2	2	2	4	2	4	5	4	2
SUPPLIER18	4	3	2	2	5	4	4	2	2	4	4	4	2
SUPPLIER19	3	4	4	1	2	5	4	4	4	2	3	5	3
SUPPLIER20	4	4	4	2	2	2	2	4	2	4	5	4	2
SUPPLIER21	1	4	2	2	1	4	3	2	4	4	1	4	4
SUPPLIER22	4	1	1	4	4	5	2	2	2	4	4	1	2
SUPPLIER23	4	3	2	2	4	3	4	2	2	4	4	3	3
SUPPLIER24	1	3	5	2	4	4	3	5	2	4	2	3	2
SUPPLIER25	5	2	4	4	2	3	3	4	3	4	5	2	3
SUPPLIER26	2	2	4	4	4	2	4	5	2	3	2	2	2
SUPPLIER27	2	2	2	4	4	4	4	2	4	4	2	2	4
SUPPLIER28	4	3	2	2	4	4	4	2	2	4	4	3	2
SUPPLIER29	4	2	2	2	1	2	2	1	4	3	4	2	4
SUPPLIER30	2	4	2	4	4	2	3	2	2	2	3	4	2
SUPPLIER31	4	2	3	5	4	2	4	3	2	2	4	2	3
SUPPLIER32	3	5	4	2	2	4	2	4	4	2	2	5	4
SUPPLIER33	4	4	4	5	5	2	4	4	2	2	4	4	3
SUPPLIER34	3	4	3	5	4	2	4	3	4	5	3	4	4
SUPPLIER35	4	4	2	4	5	4	2	2	2	2	4	5	2
SUPPLIER36	4	4	4	5	4	1	4	4	5	4	4	4	5
SUPPLIER37	1	4	2	4	3	3	1	2	4	2	2	4	4
SUPPLIER38	1	4	4	2	4	4	2	4	5	1	2	4	5
SUPPLIER39	2	4	4	2	1	1	2	4	2	4	2	4	2
SUPPLIER40	4	4	2	4	2	1	1	2	2	4	4	4	2
SUPPLIER41	4	1	2	1	4	4	2	2	2	4	4	1	1
SUPPLIER42	3	4	4	4	4	4	4	4	4	5	3	4	4
SUPPLIER43	4	2	3	2	4	1	2	3	2	1	4	2	2
SUPPLIER44	2	5	1	2	2	4	4	2	4	2	2	4	3

SUPPLIER45	2	5	4	3	4	2	2	4	2	4	2	5	2
SUPPLIER46	2	2	1	2	3	4	4	1	2	1	2	2	2
SUPPLIER47	4	2	3	5	4	2	4	3	2	3	4	2	3
SUPPLIER48	4	2	3	4	3	3	2	3	4	4	4	2	4
SUPPLIER49	2	1	5	3	4	3	4	5	2	4	2	1	2
SUPPLIER50	4	2	3	5	4	2	4	3	3	3	4	2	2
SUPPLIER51	4	2	3	1	4	5	1	4	1	3	4	2	2
SUPPLIER52	4	4	5	3	1	2	1	5	4	2	4	4	4
SUPPLIER53	4	3	3	4	4	3	2	3	4	4	4	2	4
SUPPLIER54	3	1	4	1	3	2	5	4	4	2	3	1	4
SUPPLIER55	4	4	3	4	2	4	3	3	2	2	4	4	2
SUPPLIER56	4	4	2	2	2	2	5	2	4	4	3	4	4
SUPPLIER57	4	4	4	1	2	4	2	4	4	4	4	4	5
SUPPLIER58	4	2	3	4	4	3	2	3	5	4	4	2	4
SUPPLIER59	3	2	2	4	2	5	2	2	1	2	4	2	1
SUPPLIER60	2	4	2	2	4	2	2	2	4	3	2	3	4
SUPPLIER61	3	5	3	4	3	3	3	2	4	4	3	4	4
SUPPLIER62	2	3	4	3	5	4	4	4	1	1	1	2	1
SUPPLIER63	2	5	3	4	4	3	4	2	5	4	2	4	5
SUPPLIER64	5	5	2	3	4	4	3	2	4	4	5	5	4
SUPPLIER65	2	4	4	4	4	3	3	4	5	2	3	4	5
SUPPLIER66	4	5	1	4	4	5	4	1	4	4	4	5	4
SUPPLIER67	1	4	3	1	4	4	1	3	3	1	1	4	3
SUPPLIER68	1	3	4	2	4	5	4	3	4	3	1	2	4
SUPPLIER69	4	2	1	2	4	3	4	1	1	1	4	2	1
SUPPLIER70	4	4	1	4	4	2	3	1	2	1	4	4	2
SUPPLIER71	4	1	4	4	1	1	3	4	4	3	4	1	4
SUPPLIER72	5	4	4	3	4	4	4	4	4	4	5	4	4
SUPPLIER73	1	2	1	4	3	2	3	1	4	1	1	2	4
SUPPLIER74	2	2	4	3	4	3	1	4	2	4	3	2	2
SUPPLIER75	4	3	2	1	5	3	4	2	4	2	4	3	4
SUPPLIER76	1	2	3	2	2	2	1	3	3	4	1	2	3
SUPPLIER77	2	5	3	4	3	3	3	2	4	4	3	4	4
SUPPLIER78	4	4	3	4	3	4	3	2	3	3	4	4	3
SUPPLIER79	4	3	3	3	1	3	5	4	4	4	4	3	4
SUPPLIER80	2	5	3	4	3	3	3	2	4	4	3	4	4
SUPPLIER81	3	1	5	4	3	1	4	4	4	2	3	1	4
SUPPLIER82	2	4	2	4	4	4	5	2	1	1	3	4	1
SUPPLIER83	4	4	2	4	2	5	4	2	3	3	4	4	3
SUPPLIER84	2	1	2	3	1	4	4	2	3	5	3	1	3
SUPPLIER85	3	5	3	4	4	2	3	3	3	4	3	5	2
SUPPLIER86	4	2	3	3	4	4	3	2	2	5	4	2	2
SUPPLIER87	4	2	4	4	4	4	4	4	2	3	4	2	2
SUPPLIER88	4	4	3	4	3	4	3	2	3	3	4	4	3
SUPPLIER89	2	4	4	3	3	1	3	4	2	2	3	4	2
SUPPLIER90	3	3	2	2	4	4	3	2	4	3	3	2	4
SUPPLIER91	4	2	5	5	4	2	2	2	4	4	4	1	4
SUPPLIER92	4	1	4	4	3	4	1	4	5	5	2	4	4

SUPPLIER93	2	4	2	2	3	3	1	1	2	4	1	4	4
SUPPLIER94	4	1	4	4	1	2	1	2	4	2	1	2	4
SUPPLIER95	4	2	4	4	1	2	2	4	4	4	4	4	4
SUPPLIER96	2	5	4	4	4	4	4	2	4	4	4	1	4
SUPPLIER97	2	4	4	5	5	2	5	3	2	2	5	4	5
SUPPLIER98	2	4	3	4	4	2	5	5	4	2	4	5	4
SUPPLIER99	2	1	4	4	2	4	2	4	2	2	2	4	1
SUPPLIER100	5	2	5	5	4	2	4	4	4	4	4	2	4
SUPPLIER101	4	1	4	4	4	2	4	4	5	5	3	4	4
SUPPLIER102	2	4	2	2	2	5	4	4	2	4	4	5	4
SUPPLIER103	4	1	4	4	3	4	3	3	4	2	4	2	5
SUPPLIER104	4	3	3	4	3	4	5	4	4	4	3	2	4
SUPPLIER105	2	5	4	4	3	2	5	3	4	4	5	2	5
SUPPLIER106	2	4	4	5	5	3	4	4	2	2	5	4	4
SUPPLIER107	3	4	3	4	4	1	2	3	4	2	4	5	1
SUPPLIER108	2	2	5	4	3	4	4	5	2	2	2	4	4
SUPPLIER109	1	4	2	2	2	4	2	2	1	4	2	3	1
SUPPLIER110	4	4	4	2	2	4	2	4	4	4	4	4	4
SUPPLIER111	4	2	4	4	3	4	4	4	2	2	3	3	2
SUPPLIER112	2	4	4	3	3	3	4	4	3	4	3	4	3
SUPPLIER113	1	2	4	4	3	4	3	4	5	3	1	3	5
SUPPLIER114	2	2	2	4	3	4	4	3	3	5	3	3	3
SUPPLIER115	2	2	3	4	5	2	4	3	4	1	3	1	4
SUPPLIER116	4	4	2	1	2	1	4	3	5	4	4	4	5
SUPPLIER117	2	4	4	3	2	3	4	4	3	4	2	5	4
SUPPLIER118	1	4	2	3	2	5	3	3	4	1	1	4	4
SUPPLIER119	4	2	3	3	3	4	4	3	3	5	4	2	3
SUPPLIER120	4	4	4	2	3	5	3	4	2	2	4	4	3
SUPPLIER121	4	5	4	2	4	3	4	4	4	2	4	4	4
SUPPLIER122	2	4	4	3	3	3	4	4	3	4	3	4	3
SUPPLIER123	2	1	2	2	4	2	3	3	2	4	3	1	3
SUPPLIER124	3	4	3	4	2	3	2	3	2	3	4	4	3
SUPPLIER125	4	3	2	5	3	4	4	2	4	5	4	3	4
SUPPLIER126	4	4	5	4	2	4	3	5	3	5	4	4	3
SUPPLIER127	5	2	2	5	4	2	4	3	2	4	4	3	3
SUPPLIER128	4	5	4	4	1	4	4	4	4	5	4	5	4
SUPPLIER129	4	4	1	3	3	1	1	1	2	4	4	4	1
SUPPLIER130	4	5	1	4	4	3	2	1	4	3	4	5	4
SUPPLIER131	4	2	4	1	1	1	2	4	4	2	4	3	4
SUPPLIER132	4	2	4	2	1	1	4	4	2	4	4	2	3
SUPPLIER133	1	1	4	4	4	3	4	4	2	1	1	1	3
SUPPLIER134	4	4	5	4	4	4	3	5	4	4	4	4	4
SUPPLIER135	2	2	1	4	1	1	4	1	3	2	3	2	3
SUPPLIER136	4	3	2	2	4	4	3	3	2	2	4	3	1
SUPPLIER137	5	2	4	4	2	2	1	4	4	3	5	3	4
SUPPLIER138	2	2	1	3	3	4	2	1	1	2	2	2	1
SUPPLIER139	2	3	2	4	3	4	4	3	3	5	3	3	3
SUPPLIER140	4	2	2	2	2	5	4	1	2	4	4	2	3

SUPPLIER141	4	2	5	4	4	4	3	5	5	2	4	2	5
SUPPLIER142	3	5	4	4	3	4	4	4	5	2	3	5	5
SUPPLIER143	2	2	5	2	4	5	2	5	4	4	2	2	4
SUPPLIER144	4	4	4	4	4	4	5	4	5	1	4	4	5
SUPPLIER145	2	2	3	1	2	4	4	3	4	3	2	1	4
SUPPLIER146	4	1	4	2	2	4	5	4	2	4	4	1	3
SUPPLIER147	4	4	1	2	2	4	2	1	2	1	4	4	2
SUPPLIER148	2	4	2	1	4	4	2	2	4	1	2	4	4
SUPPLIER149	2	4	4	2	4	1	1	4	1	4	2	4	1
SUPPLIER150	4	5	4	4	3	4	4	4	4	4	4	5	4
SUPPLIER151	3	1	4	2	4	2	2	4	2	1	3	1	2
SUPPLIER152	1	2	2	4	2	4	3	2	2	4	2	2	2
SUPPLIER153	4	4	4	2	2	5	2	4	3	2	4	4	3
SUPPLIER154	1	1	3	4	2	2	2	3	2	4	1	1	2
SUPPLIER155	3	3	4	4	4	2	3	4	5	2	3	2	5
SUPPLIER156	3	4	3	2	4	2	4	3	4	3	3	4	4
SUPPLIER157	5	4	4	4	2	1	2	4	3	3	5	4	3
SUPPLIER158	3	3	4	4	4	2	2	4	5	2	3	2	5
SUPPLIER159	3	3	4	1	4	2	2	4	1	5	4	3	1
SUPPLIER160	5	2	1	1	4	4	4	1	3	2	5	2	4
SUPPLIER161	3	4	4	2	4	2	4	3	4	3	3	4	4
SUPPLIER162	4	2	3	5	3	1	4	3	1	2	4	2	1

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APPENDIX - B

RELATIVE CLOSENESS EFFICIENCY

0.5775	0.3776	0.6249	0.6650	0.4502	0.6963	0.5092	0.4407	0.4665	0.4902
0.2352	0.2534	0.1725	0.2362	0.1720	0.2557	0.2265	0.2537	0.2246	0.2261
0.3161	0.5829	0.4396	0.4365	0.5357	0.4125	0.5775	0.5473	0.5747	0.5775
0.3366	0.2368	0.3027	0.2533	0.2342	0.2752	0.2352	0.2350	0.1877	0.2352
0.3277	0.5279	0.5165	0.5054	0.6055	0.5313	0.3727	0.5495	0.4180	0.4486
0.3032	0.2046	0.2348	0.2537	0.2357	0.2343	0.2345	0.2348	0.2758	0.2337
0.5823	0.5521	0.6455	0.4289	0.5859	0.4973	0.3490	0.4497	0.4571	0.4824
0.2345	0.1721	0.2356	0.1725	0.1713	0.1888	0.2755	0.1068	0.2760	0.2763
0.5374	0.5067	0.5772	0.4324	0.4976	0.4567	0.5620	0.4927	0.5335	0.5618
0.1176	0.1732	0.1862	0.2533	0.1714	0.2030	0.2347	0.2353	0.1867	0.2347
0.6468	0.5808	0.5134	0.5049	0.6352	0.4549	0.5361	0.4837	0.5511	0.3599
0.3042	0.2781	0.2355	0.2053	0.2349	0.2352	0.1886	0.2355	0.1858	0.2341
0.4415	0.6212	0.3783	0.5394	0.4590	0.4828	0.4605	0.4412	0.5584	0.5306
0.2355	0.1180	0.1723	0.1731	0.1723	0.2062	0.2550	0.2765	0.1307	0.2046
0.5040	0.6139	0.3374	0.4876	0.5130	0.3414	0.3830	0.5564	0.5235	0.3830
0.2278	0.2370	0.2526	0.2535	0.2544	0.3020	0.2352	0.2353	0.2552	0.2352
0.5035	0.5364	0.5515	0.3649	0.4985	0.5346	0.6646	0.5564	0.5060	0.4525
0.2051	0.1063	0.2353	0.1164	0.1717	0.1715	0.2352	0.2353	0.2533	0.2347
0.4970	0.4948	0.3649	0.4897	0.4907	0.4520	0.4693	0.4780	0.5271	0.5879
0.1724	0.2067	0.3030	0.3367	0.2549	0.1725	0.1720	0.1722	0.1862	0.2363
0.4766	0.4625	0.5386	0.5682	0.4158	0.5204	0.4982	0.5468	0.4284	0.5551
0.1883	0.1719	0.1872	0.2360	0.1724	0.2354	0.1061	0.2351	0.2033	0.2362
0.6795	0.4740	0.4007	0.3931	0.4552	0.4294	0.4506	0.4384	0.5289	0.6837
0.2349	0.2353	0.2050	0.1713	0.0971	0.2062	0.1719	0.2049	0.1721	0.2356
0.6120	0.4740	0.3962	0.5101	0.4672	0.6033	0.5640	0.5411	0.4674	0.4610
0.2362	0.2353	0.1856	0.2347	0.1725	0.1734	0.2352	0.1085	0.2546	0.2053
0.5134	0.5365	0.4925	0.6069	0.3429	0.6318	0.5613	0.4618	0.4069	0.5060
0.3043	0.2767	0.1306	0.2370	0.3343	0.1717	0.2551	0.2246	0.1715	0.2535
0.5941	0.5315	0.5075	0.5973	0.4268	0.5918	0.5436	0.4408	0.4992	0.5754
0.1731	0.0983	0.2356	0.0995	0.1866	0.1874	0.2045	0.1871	0.2273	0.1735

0.5782	0.3814	0.6502	0.3859	0.4963	0.4622	0.5938	0.4924	0.5380	0.5343	0.4806	0.5925
0.1057	0.2520	0.2356	0.2247	0.1721	0.2352	0.2550	0.1720	0.1181	0.3040	0.2354	0.2044