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Mining MAGDM Problems with Triangular Vague Sets

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Abstract- In recent years vague set theory has received more and more attention, because many of the real life problems are information in the form of vague values. In this paper an attempt is made to study on triangular vague sets from various perspectives of algebraic properties, graphical representations and practical applications. Operators, namely triangular vague ordered weighted averaging (TVOWA) operator and the triangular vague hybrid aggregation (TVHA) operator are defined for multiple attribute group decision making (MAGDM) problems. Based on the triangular vague weighted arithmetic averaging (TVWAA) operator, the TVHA operator and the Hamming distance function for triangular vague sets, a model is developed to solve the Multiple Attribute Group Decision Making (MAGDM) problems. This proposed model is explained with an illustration.

Index Terms- vague sets, triangular vague sets, triangular vague ordered weighted averaging operator, triangular vague hybrid aggregation operator, multiple attribute group decision making.

I. Introduction

Fuzzy set theory has long been introduced to handle inexact and imprecise data by Zadeh's (1973) seminal paper, since in the real world there is vague information about different applications, such as in sensor databases, we can formalize the measurements from different sensors to a vague set. In fuzzy set theory, each object $u \in U$ is assigned a single real value, called the grade of membership, between zero and one. (Here U is a classical set of objects, called the universe of discourse). Gau & Buehrer (1994) point out that the drawback of using the single membership value in fuzzy set theory is that the evidence for $u \in U$ and the evidence against $u \in U$ are in fact mixed together. In order to tackle this problem, Gau & Buehrer (1994) proposed the notion of Vague Sets (VSs), which allow using interval-based membership instead of using point-based membership as in FSs. The interval-based membership generalization in VSs is more expressive in capturing vagueness of data. However, VSs are shown to be equivalent to that of Intuitionistic Fuzzy Sets (IFSs) (Bustince & Burillo (1996)). For this reason, the interesting features for handling vague data that are unique to VSs are largely ignored.

Since Zadeh introduced fuzzy set (FSs) theory , several new concepts of higher-order FSs have been proposed. Among them, intuitionistic fuzzy sets (IFSs), proposed by Atanassov (1989), provide a flexible mathematical framework to cope, besides the presence of vagueness, with the hesitancy originating from imperfect or imprecise information. IFSs use two characteristic functions to express the degree of membership (belongingness) and the degree of non-membership (non-belongingness) of elements of the universe to the IFSs. Therefore, the idea of using positive and (independently) negative information becomes the core of IFSs. This idea is natural in real life human discourse and action, and as an obvious consequence, is well-known and widely studied in psychology and other social sciences. In fact, IFSs, interval-valued fuzzy sets (IVFSs) and vague sets can be viewed as three equivalent generalizations of fuzzy sets (Bustince & Burillo (1996)). However, they are different as IFSs force a user to explicitly consider positive and negative information independently. On the other hand, while employing IVFSs, the user's attention is forced on positive information (in an interval) only. So the two concepts, IFSs and IVFSs, are different in application. In this paper MAGDM of triangular vague sets are combined with data mining methods to make the decision making process an easy one.

Data mining, also known as knowledge discovery in databases, provides efficient automated techniques for discovering potentially useful, hidden knowledge or relations among data from large databases (Han & Kamber, 2006). Data mining functions include classification, clustering, prediction, regression, and link analysis (associations), etc. Data analysts are primarily concerned with discerning trends in the data and thus a system that provides approximate answers in a timely fashion would suit their requirements better. Mining association rules represent an unsupervised data mining method that allows identifying interesting associations, correlations between items, and frequent patterns from large transactional databases and this problem was first introduced by Agrawal et al.,(1993). Haleh et al., (2012) have applied data mining techniques in MCDM problems involving educational databases to evaluate question weights in scientific examinations. Kweku-Muata & Osei-Bryson, (2004) worked on the evaluation of decision trees through MCDM approaches. Kaplan, (2006) proposed a solid waste management system model and optimization using MCDM applications and data mining techniques. The case study provided by Peng et al., (2011) demonstrated that combining data mining and MCDM methods provided objective and comprehensive assessments of huge data sets. Khan et al., (2008) provide various means where data mining techniques enhances the Decision Support Systems.

Some Multi criteria decision making models were proposed by Chen & Tan, (1994) and Cheng, (2000). Li, (1999; 2005; 2008) proposed MADM models based on LINMAP methods for intuitionistic fuzzy sets. Li & Nan, (2011) extended the TOPSIS method of decision making and Liu, (2009), Liu & Wang, (2007) and Liu et al. (2012) worked on multiple attribute decision making with triangular fuzzy numbers and intuitionistic fuzzy sets. Wei, (2008; 2010), Wei et al. (2012) and Wei & Zhao, (2012) introduced various tools for multiple attribute group decision making problems. Mining Association rules under various circumstances were presented by Lin et al. (2007), Wu & Olson, (2006) and Zhang et al. (2006). Robinson et al. (2012) introduced mining of correlation rules for educational data. Hayez et al. (2012) and Power et al. (2011) discussed various decision support systems for effective decision making. Szmidt & Kacprzyk, (2000; 2002; 2003) introduced different distance measures for decision making problems where liu, (2004) and Robinson & Amirtharaj, (2011; 2012) utilized different distance measures in different situations of decision problems. Aggregation operators similar to that proposed by Xu & Yager, (2006) are newly proposed for triangular vague sets and utilized for multiple attribute decision making problems in this paper. A new mining algorithm for triangular vague sets is introduced in the decision making algorithm for reducing the decision variables from the final ranking of the alternatives in the multiple attribute decision making problem. The problem will be illustrated with a numerical example.

II. VAGUE SETS

The grade of membership of an element x in a vague set is represented by a vague value $[t_X, 1-f_X]$ in [0,1], where t_x indicates the degree of truth, f_x indicates the degree of false, $1-t_X-f_X$ indicates the unknown part, $0 \le t_X \le 1-f_X \le 1$, and $t_X+f_X \le 1$. The notion of vague sets is similar to that of intuitionistic fuzzy set, and both of them are generalizations of the notion of fuzzy sets.

In 1965, Zadeh proposed the theory of fuzzy sets. Roughly speaking, a fuzzy set is a class with fuzzy boundaries. Let U be the universe of discourse, U={u_1, u_2, …, u_n}. the grade of membership of an element u_i in a fuzzy set is represented by a real value between zero and one, where $u_i \in U$. It is pointed out that this single value combines the evidence for $u_i \in U$ and the evidence against $u_i \in U$. It does not indicate the evidence for $u_i \in U$ and the evidence against $u_i \in U$, respectively, and it does not indicate how much there is of each. Furthermore it is pointed out that the single value tells us nothing about its accuracy. Some arithmetic operations between vague sets are presented in the following sections. A vague set $\tilde{A}$ in the universe of discourse U is characterized by a truth-membership function $t_{\tilde{A}}$, $t_{\tilde{A}}: U \to [0,1]$, and a false-membership function $f_{\tilde{A}}$, $f_{\tilde{A}}: U \to [0,1]$, where $t_{\tilde{A}}(u_i)$ is a lower bound of the grade of membership of u_i derived from the evidence for u_i, $f_{\tilde{A}}(u_i)$ is a lower bound on the negation of u_i derived from the evidence against u_i, and $t_{\tilde{A}}(u_i)+f_{\tilde{A}}(u_i) \le 1$. The grade of membership of u_i in the vague set $\tilde{A}$ is bounded by a subinterval $[t_{\tilde{A}}(u_i), 1-f_{\tilde{A}}(u_i)]$ of [0,1]. The vague value $[t_{\tilde{A}}(u_i), 1-f_{\tilde{A}}(u_i)]$ indicates that the exact grade of membership $\mu_{\tilde{A}}(u_i)$ of u_i is bounded by $t_{\tilde{A}}(u_i) \le \mu_{\tilde{A}}(u_i) \le 1-f_{\tilde{A}}(u_i)$, where $t_{\tilde{A}}(u_i)+f_{\tilde{A}}(u_i) \le 1$. For example, a vague set $\tilde{A}$ in the universe of discourse U is shown in Fig. 1.

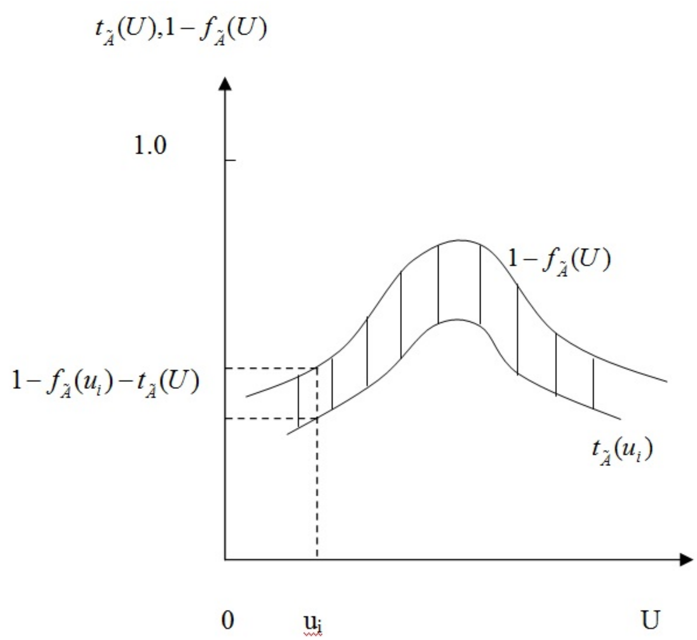

Fig 1: A Vague set.

Where the universe of discourse U is a finite set, a vague set $\tilde{A}$ of the universe of discourse U can be represented as

$$\tilde{A} = \sum_{i=1}^{n} [t_{\tilde{A}}(u_i), 1 - f_{\tilde{A}}(u_i)] / u_i$$

Where the universe of discourse U is an infinite set, a vague set $\tilde{A}$ of the universe of discourse U can be represented as

$$\tilde{A} = \int_U [t_{\tilde{A}}(u_i), 1 - f_{\tilde{A}}(u_i)] / u_i,\ u_i \in U$$

.

Definition:

Let $\tilde{A}$ be a vague set of the universe of discourse U with the truth-membership function $t_{\tilde{A}}$ and the false-membership function $f_{\tilde{A}}$, respectively. The vague set $\tilde{A}$ is convex if and only if for all u_1, u_2, in U,

$t_{\tilde{A}}(\lambda u_1 + (1-\lambda)u_2) \geq Min(t_{\tilde{A}}(u_1), t_{\tilde{A}}(u_2)), \quad 1 - f_{\tilde{A}}(\lambda u_1 + (1-\lambda)u_2) \geq Min(1 - f_{\tilde{A}}(u_1), 1 - f_{\tilde{A}}(u_2)),$

where $\lambda \in [0,1]$.

ARITHMETIC OPERATIONS OF TRIANGULAR VAGUE SETS

Definition: A vague set $\tilde{A}$ of the universe of discourse U is called a normal vague set if $\exists u_i \in U$, such that $1 - f_{\tilde{A}}(u_i) = 1$. That is, $f_{\tilde{A}}(u_i) = 0$.

Definition: A vague number is a vague subset in the universe of discourse U that is both convex and normal.

In the following, we introduce some arithmetic operations of triangular vague sets.

Let us consider the triangular vague set $\tilde{A}$ shown in Fig. 2, where the triangular vague set $\tilde{A}$ can be parameterized by a tuple

$\langle [(a,b,c);\mu_1],[(a,b,c);\mu_2] \rangle$.

For convenience, the tuple $\langle [(a,b,c);\mu_1],[(a,b,c);\mu_2] \rangle$ can also be abbreviated into $\langle [(a,b,c);\mu_1;\mu_2] \rangle$, where $0 \leq \mu_1 \leq \mu_2 \leq 1$.

Some arithmetic operations between triangular vague sets are as follows:

Case 1: Consider the triangular vague sets $\tilde{A}\ and\ \tilde{B}$ shown in Fig. 3, where

$$\tilde{A} = \langle [(a_1,b_1,c_1);\mu_1],[(a_1,b_1,c_1);\mu_2] \rangle$$
$$= \langle [(a_1,b_1,c_1);\mu_1;\mu_2] \rangle$$
$$\tilde{B} = \langle [(a_2,b_2,c_2);\mu_1],[(a_2,b_2,c_2);\mu_2] \rangle$$
$$= \langle [(a_2,b_2,c_2);\mu_1;\mu_2] \rangle$$

And $0 \leq \mu_1 \leq \mu_2 \leq 1$. The arithmetic operations between the triangular vague sets $\tilde{A}\ and\ \tilde{B}$ are defined as follows:

$$\tilde{A} \oplus \tilde{B} = \langle [(a_1,b_1,c_1);\mu_1],[(a_1,b_1,c_1);\mu_2] \rangle \oplus \langle [(a_2,b_2,c_2);\mu_1],[(a_2,b_2,c_2);\mu_2] \rangle$$
$$= \langle [(a_1+a_2, b_1+b_2, c_1+c_2);\mu_1],[(a_1+a_2, b_1+b_2, c_1+c_2);\mu_2] \rangle$$
$$= \langle [(a_1+a_2, b_1+b_2, c_1+c_2);\mu_1;\mu_2] \rangle$$

.

$$\tilde{B}\Theta\tilde{A} = \left\langle \left[\left(a_2, b_2, c_2 \right); \mu_1 \right], \left[\left(a_2, b_2, c_2 \right); \mu_2 \right] \right\rangle \Theta \left\langle \left[\left(a_1, b_1, c_1 \right); \mu_1 \right], \left[\left(a_1, b_1, c_1 \right); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[\left(a_2 - c_1, b_2 - b_1, c_2 - a_1 \right); \mu_1 \right], \left[\left(a_2 - c_1, b_2 - b_1, c_2 - a_1 \right); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[\left(a_2 - c_1, b_2 - b_1, c_2 - a_1 \right); \mu_1; \mu_2 \right] \right\rangle$$

$$\tilde{A} \otimes \tilde{B} = \left\langle \left[\left(a_1, b_1, c_1 \right); \mu_1 \right], \left[\left(a_1, b_1, c_1 \right); \mu_2 \right] \right\rangle \otimes \left\langle \left[\left(a_2, b_2, c_2 \right); \mu_1 \right], \left[\left(a_2, b_2, c_2 \right); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[\left(a_1 \times a_2, b_1 \times b_2, c_1 \times c_2 \right); \mu_1 \right], \left[\left(a_1 \times a_2, b_1 \times b_2, c_1 \times c_2 \right); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[\left(a_1 \times a_2, b_1 \times b_2, c_1 \times c_2 \right); \mu_1; \mu_2 \right] \right\rangle$$

$$\tilde{B} \varnothing \tilde{A} = \left\langle \left[\left(a_2, b_2, c_2 \right); \mu_1 \right], \left[\left(a_2, b_2, c_2 \right); \mu_2 \right] \right\rangle \varnothing \left\langle \left[\left(a_1, b_1, c_1 \right); \mu_1 \right], \left[\left(a_1, b_1, c_1 \right); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[\left(a_2 / c_1, b_2 / b_1, c_2 / a_1 \right); \mu_1 \right], \left[\left(a_2 / c_1, b_2 / b_1, c_2 / a_1 \right); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[\left(a_2 / c_1, b_2 / b_1, c_2 / a_1 \right); \mu_1; \mu_2 \right] \right\rangle.$$

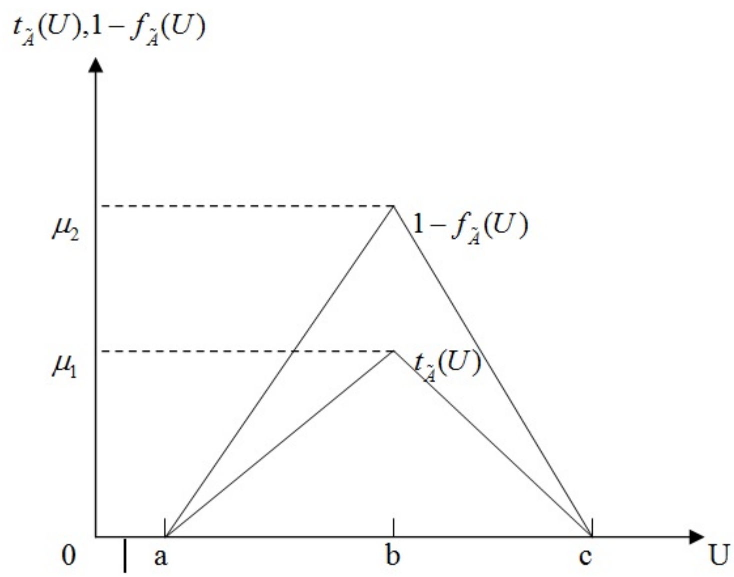

Fig: 2. A Triangular Vague Set.

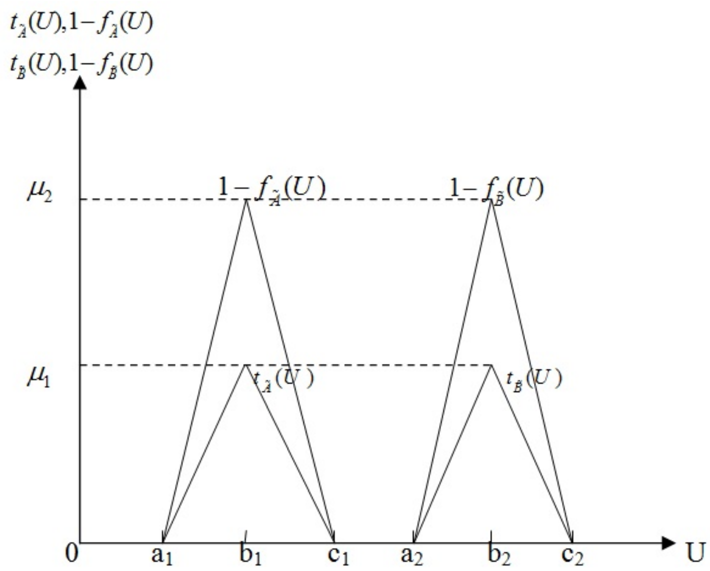

Fig: 3. Triangular Vague Set $\tilde{A}\ and\ \tilde{B}$ **(case 1).**

Case 2:

Consider the triangular vague sets $\tilde{A}\ and\ \tilde{B}$ shown in Fig. 4, where

$$\tilde{A} = \left\langle \left[(a_1, b_1, c_1); \mu_1 \right], \left[(a_1, b_1, c_1); \mu_2 \right] \right\rangle,$$

$$\tilde{B} = \left\langle \left[(a_2, b_2, c_2); \mu_3 \right], \left[(a_2, b_2, c_2); \mu_4 \right] \right\rangle,$$

and $0 \le \mu_3 \le \mu_1 \le \mu_4 \le \mu_2 \le 1$. The arithmetic operations between the triangular vague sets $\tilde{A}\ and\ \tilde{B}$ are defined as follows:

$$\tilde{A} \oplus \tilde{B} = \left\langle \left[(a_1, b_1, c_1); \mu_1 \right], \left[(a_1, b_1, c_1); \mu_2 \right] \right\rangle \oplus \left\langle \left[(a_2, b_2, c_2); \mu_3 \right], \left[(a_2, b_2, c_2); \mu_4 \right] \right\rangle$$
$$= \left\langle \left[(a_1 + a_2, b_1 + b_2, c_1 + c_2); Min(\mu_1, \mu_3) \right], \left[(a_1 + a_2, b_1 + b_2, c_1 + c_2); Min(\mu_2, \mu_4) \right] \right\rangle,$$

$$\tilde{B} \Theta \tilde{A} = \left\langle \left[(a_2, b_2, c_2); \mu_3 \right], \left[(a_2, b_2, c_2); \mu_4 \right] \right\rangle \Theta \left\langle \left[(a_1, b_1, c_1); \mu_1 \right], \left[(a_1, b_1, c_1); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[(a_2 - c_1, b_2 - b_1, c_2 - a_1); Min(\mu_1, \mu_3) \right], \left[(a_2 - c_1, b_2 - b_1, c_2 - a_1); Min(\mu_2, \mu_4) \right] \right\rangle$$

$$\tilde{A} \otimes \tilde{B} = \left\langle \left[(a_1, b_1, c_1); \mu_1 \right], \left[(a_1, b_1, c_1); \mu_2 \right] \right\rangle \otimes \left\langle \left[(a_2, b_2, c_2); \mu_3 \right], \left[(a_2, b_2, c_2); \mu_4 \right] \right\rangle$$
$$= \left\langle \left[(a_1 \times a_2, b_1 \times b_2, c_1 \times c_2); Min(\mu_1, \mu_3) \right], \left[(a_1 \times a_2, b_1 \times b_2, c_1 \times c_2); Min(\mu_2, \mu_4) \right] \right\rangle$$

$$\tilde{B} \varnothing \tilde{A} = \left\langle \left[(a_2, b_2, c_2); \mu_3 \right], \left[(a_2, b_2, c_2); \mu_4 \right] \right\rangle \varnothing \left\langle \left[(a_1, b_1, c_1); \mu_1 \right], \left[(a_1, b_1, c_1); \mu_2 \right] \right\rangle$$
$$= \left\langle \left[(a_2 / c_1, b_2 / b_1, c_2 / a_1); Min(\mu_1, \mu_3) \right], \left[(a_2 / c_1, b_2 / b_1, c_2 / a_1); Min(\mu_2, \mu_4) \right] \right\rangle.$$

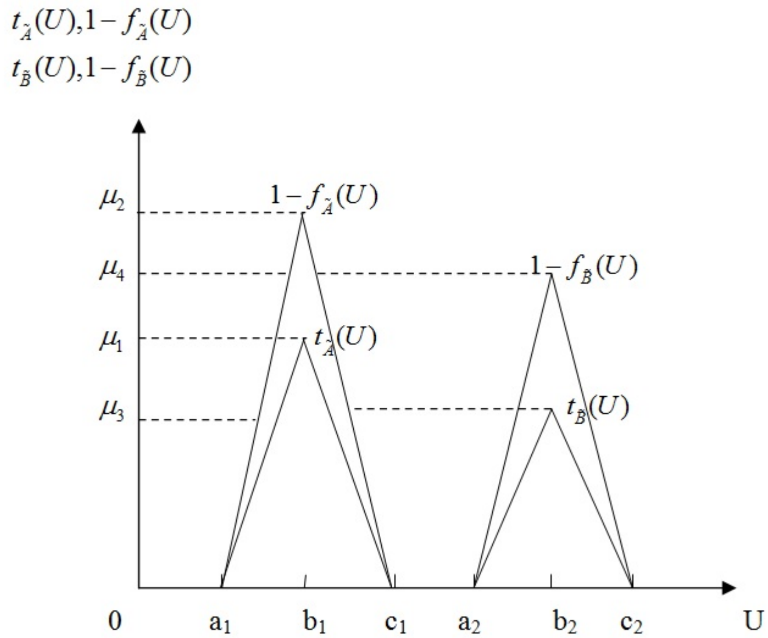

Fig: 4. Triangular Vague Set $\tilde{A}\ and\ \tilde{B}$ **(case 2).**

MULTIPLE ATTRIBUTE GROUP DECISION MAKING WITH TRIANGULAR VAGUE NUMBERS

Definition:

Let $\widetilde{a_1} = ([a_1, b_1, c_1]; t_{a_1}, f_{a_1})$ and $\widetilde{a_2} = ([a_2, b_2, c_2]; t_{a_2}, f_{a_2})$ be two triangular vague numbers, then the normalized Hamming distance between $\widetilde{a_1}$ and $\widetilde{a_2}$ is defined as follows:

$$d(\widetilde{a_1}, \widetilde{a_2}) = \frac{1}{8}\left(\left|(1 + t_{a_1} - f_{a_1})a_1 - (1 + t_{a_2} - f_{a_2})a_2\right| + \left|(1 + t_{a_1} - f_{a_1})b_1 - (1 + t_{a_2} - f_{a_2})b_2\right| + \left|(1 + t_{a_1} - f_{a_1})c_1 - (1 + t_{a_2} - f_{a_2})c_2\right|\right)$$

Definition:

For a normalized triangular vague decision making matrix, $\tilde{R} = (\tilde{r}_{ij})_{m\times n} = ([a_{ij}, b_{ij}, c_{ij}]; t_{ij}, f_{ij})_{m\times n}$ where $0 \le a_{ij} \le b_{ij} \le c_{ij} \le 1.$ $0 \le t_{ij} + f_{ij} \le 1,$ the triangular vague positive ideal solution and triangular vague negative ideal solution are defined as follows,

$\tilde{r}^{+}$= ([a^+, b^+, c^+,]; t^+, f^+,) = ([1,1,1]; 1,0) ; $\tilde{r}^{-}$= ([a^-, b^-, c^-,]; t^-, f^-) = ([0, 0, 0]; 0,1).

SOME ARITHMETIC AGGREGATION OPERATORS WITH TRIANGULAR VAGUE NUMBERS

Definition: Let $\tilde{a}_j\ , j = 1, 2, \ldots, n$ be a collection of triangular vague numbers. Let the collection of all TVNs be denoted by Q. The Triangular Vague Weighted Arithmetic Averaging (*TVWAA*) operator is defined as:

TVWAA: $Q^n \rightarrow Q$

$$TVWAA\left(\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_n\right) = \sum_{j=1}^{n} \tilde{a}_j \omega_j$$

$$= \left(\left[\sum_{j=1}^{n} a_j\omega_j\ , \sum_{j=1}^{n} b_j\omega_j\ , \sum_{j=1}^{n} c_j\omega_j\right]; 1 - \prod_{j=1}^{n}(1 - t_{a_j})^{\omega_j}\ , \prod_{j=1}^{n}(f_{a_j})^{\omega_j}\right)$$

where, $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ is the weight vector of $\tilde{a}_j\ , j = 1, 2, \ldots, n$ and for $\omega_j > 0,\ \sum_{j=1}^{n}\omega_j = 1.$

Definition: Let $\tilde{a}_j \ , j = 1, 2, \ldots, n$ be a collection of TVNs. Then a Triangular Vague Fuzzy Ordered Weighted Averaging *(TVOWA)* operator of dimension *n* is a mapping *TVOWA:* $Q^n \rightarrow Q$, that has an associated vector $w = (w_1, w_2, \ldots, w_n)^T$ such that $w_j > 0,$ and $\sum_{j=1}^{n} w_j = 1.$

$$TVOWA_w\left(\tilde{a}_1 \ ,\tilde{a}_2, \ldots \ ,\tilde{a}_n\right) = \sum_{j=1}^{n} \tilde{a}_{\sigma(j)} w_j$$

Furthermore,

$$= \left(\left[\sum_{j=1}^{n} a_{\sigma(j)} w_j \ , \sum_{j=1}^{n} b_{\sigma(j)} w_j \ , \sum_{j=1}^{n} c_{\sigma(j)} w_j \right]; 1 - \prod_{j=1}^{n} (1 - t_{\tilde{a}_{\sigma(j)}})^{w_j} \ , \prod_{j=1}^{n} (f_{\tilde{a}_{\sigma(j)}})^{w_j} \right)$$

Where $\left(\sigma(1), \sigma(2), \ldots, \sigma(n)\right)$ is a permutation of (1,2,....,n) such that $\tilde{a}_{\sigma(j-1)} \geq \tilde{a}_{\sigma(j)}$ for all *j=2,....,n.*

Definition: A Triangular Vague Hybrid Aggregation*(TVHA)* operator of dimension n is the mapping *TVHA:* $Q^n \rightarrow Q$ that has an associated vector $w = (w_1, w_2, \ldots, w_n)^T$ such that $w_j > 0,$ and $\sum_{j=1}^{n} w_j = 1.$ Furthermore,

$$TVHA_{\omega,w}\left(\tilde{a}_1 \ ,\tilde{a}_2, \ldots \ ,\tilde{a}_n\right) = \sum_{j=1}^{n} \dot{\tilde{a}}_{\sigma(j)} \ w_j$$

$$= \left(\left[\sum_{j=1}^{n} \dot{a}_{\sigma(j)} w_j \ , \sum_{j=1}^{n} \dot{b}_{\sigma(j)} w_j \ , \sum_{j=1}^{n} \dot{c}_{\sigma(j)} w_j \right]; 1 - \prod_{j=1}^{n} (1 - \dot{t}_{\tilde{a}_{\sigma(j)}})^{w_j} \ , \prod_{j=1}^{n} (\dot{f}_{\tilde{a}_{\sigma(j)}})^{w_j} \right)$$

Where $\dot{\tilde{a}}_{\sigma(j)}$ is the j^{th} largest of the weighted *TVNs* $\dot{\tilde{a}}_j$, where $\dot{\tilde{a}}_j = \tilde{a}_j^{n\omega_j}, \ j = 1, 2 \ldots n$, $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ be the weight vector of $\tilde{a}_j \ , j = 1, 2, \ldots, n$ and for $\omega_j > 0, \ \sum_{j=1}^{n} \omega_j = 1,$ *n* is the balancing co-efficient.

ALGORITHM FOR MINING FUZZY CORRELATION RULES

The fuzzy correlation rules mining method in this section will be done in the same pattern as proposed in the works of Thiagarasu & Umasankar, (2016).

$$fsupp(\{F_X, F_Y\}) = \frac{\sum_{i=1}^{n} \min(f_j(t_i) / f_j \in \{F_X, F_Y\})}{n} \qquad (1)$$

$$fconf(F_X \Rightarrow F_Y) = \frac{fsupp(\{F_X, F_Y\})}{fsupp(\{F_X\})} \qquad (2)$$

Assume that $F = \{ f_1, f_2, \ldots, f_m \}$ be a set of fuzzy items; $T = \{t_1, t_2, \ldots, t_n\}$ be a random sample with n fuzzy data records, and each sample record t_i is represented as a vector with m values, $\left(f_1(t_i), f_2(t_i), \ldots, f_m(t_i) \right),$ where $f_j(t_i)$ is the degree that fuzzy item f_j occurs in record t_i, $f_j(t_i) \in [0,1]$.

And next, three predefined thresholds are needed to be defined. Here, s_f is the minimal fuzzy support; c_f is the minimal fuzzy confidence; r_f is the minimal fuzzy correlation coefficient. The procedure of mining fuzzy correlation rules is described as the follows:

Step i: Transform the Vague dataset into a fuzzy set using any of the transformation technique.

Step ii: The fuzzy support of each fuzzy item $f_i \in F,\ f\text{supp}(f_i)$ is computed by using formula (2.3).

Step iii: Let $L_1 = \left\{ f_p \middle| f_p \in F,\ f\text{supp}(f_p) \geq s_f \right\}$ be the set of frequent fuzzy itemsets whose size is equal to 1.

Step iv: Let $C_2 = \{(F_A, F_B)\}$ be the set of all combinations of two elements belong to L_1, where $F_A, F_B \in L_1,\ F_A \neq F_B$. That is, C_2 is generated by L_1 joint with L_1. Because F_A and F_B are the element of L_1, the size of each element of C_2 is 2.

Step v: For each element of C_2, (F_A, F_B) the fuzzy support, $f\text{supp}(\{F_A, F_B\})$ is computed by using formula (1) and then the fuzzy correlation between F_A and F_B, $r_{A,B}$, is computed, too. Since $r_{A,B}$ is computed from the random sample T, $r_{A,B}$ is needed to be tested to determine if it is really greater than the minimal fuzzy correlation coefficient r_f, The formula for testing is as follows:

$$t = \frac{r_{A,B} - r_f}{\sqrt{\dfrac{1 - r_{A,B}^2}{n-2}}}$$

Compare the computed t value to $t_{1-\alpha(n-2)}$, where $t_{1-\alpha(n-2)}$ is the $(1-\alpha)^{th}$ percentile in the t distribution with degree of freedom n-1. If we obtain the t value which is greater than the predefined minimal fuzzy correlation coefficient.

Step vi: For each element, whose fuzzy support is greater than or equal to s_f and fuzzy correlation coefficient passes the test, of C_2, then it is an element of L_2. Hence, L_2 is the set of the frequent combinations of two fuzzy itemsets, and still, the size of each element of L_2 is 2.

Step vii: Next, each C_k, $k \geq 3$, is generated by L_{k-1} joint with L_{k-1}. Assume that (F_W, F_X) and (F_Y, F_Z) are two elements of L_{k-1}, where $F_X = F_Y$. If the size of the combinations $(F_X, \{F_W, F_Z\})$ is k, and (F_W, F_Z) is also a frequent combination of two fuzzy itemsets, then the combination $(F_X, \{F_W, F_Z\})$ is a element with size k of C_k. For each element of C_k, its fuzzy support and fuzzy correlation coefficient are still used to find the elements of L_k.

Step viii: When each L_k, $k \geq 2$, is obtained, for each element of L_k, (F_G, F_H), two candidate fuzzy correlation rules, $F_G \rightarrow F_H$ and $F_H \rightarrow F_G$ can be generated. If the fuzzy confidence of a rule is greater than or equal to c_f, then it is considered as an interesting fuzzy correlation rule.

The algorithm won't stop until no next C_{k+1} can be generated.

AN APPROACH TO GROUP DECISION MAKING WITH TRIANGULAR VAGUE INFORMATION

We shall investigate the multiple group decision making (MAGDM) problems based on the TVWAA and TVHA operator in which both the attribute weights and the expert weights take the form of real numbers, attribute values take the form of triangular vague numbers. Let A={A_1, A_2,...,A_m} be a discrete set of alternatives, and G={G_1, G_2,...,G_n}be the set of attributes, w=(w_1,w_2,.....,w_n) is the weighting vector of the attribute G_j (j=1, 2,……n), where $w_j \in [0,1]$, $\sum_{j=1}^{n} w_j = 1$. Let, D={ D_1, D_2,…….D_t } be the set of decision makers, V= (V_1, V_2,…,V_n) be the weighting vector of decision makers, with $V_k \in [0,1]$, $\sum_{k=1}^{t} V_k = 1$. Suppose that, $\widetilde{R_k} = (\tilde{r}_{ij}^{(k)})_{m\times n}$ =([$a_{ij}^{(k)}$, $b_{ij}^{(k)}$, $c_{ij}^{(k)}$,]; $u_{ij}^{(k)}$, $v_{ij}^{(k)}$ $)_{mxn}$ is the triangular intuitionistic fuzzy decision matrix, $u_{ij}^{(k)} \in [0,1]$, $v_{ij}^{(k)} \in [0,1]$, $u_{ij}^{(k)} + v_{ij}^{(k)} \le 1$. i=1, 2, …,m; j=1,2,…,n; k=1,2,…,t. In the following, we apply the TVWAA and TVHA operator to multiple attribute group decision making based on triangular vague information the method involves the following steps.

step:1 Utilize the decision information given in the triangular vague decision matrix $\widetilde{R_k}$, and the TVWAA operator,

$$\tilde{r}_i^{(k)} = \left([a_i^{(k)}, b_i^{(k)}, c_i^{(k)}];\ u_i^{(k)},\ v_i^{(k)}\right)$$
$$= TVWAA_w\left(\tilde{r}_{i1}^{(k)}, \tilde{r}_{i2}^{(k)}, \ldots\ldots, \tilde{r}_{in}^{(k)}\right), i = 1,2, \ldots\ldots m, \quad k = 1,2, \ldots. t.$$

to derive the individual overall preference triangular intuitionistic fuzzy values $\widetilde{r_i}$(k) of the alternative A_i.

Step:2 Utilize the TVHA operator, $\widetilde{r_i} = \left([a_i, b_i, c_i]; u_i, v_i\right)$

$$= TVHA_{v,w}\left(\tilde{r}_i^{(1)}, \tilde{r}_i^{(2)}, \ldots\ldots \tilde{r}_i^{(t)}\right), i = 1,2, \ldots\ldots m.$$

to derive the collective overall preference triangular vague values of the alternative A_i, where, v=(v_1, v_2,…,v_n) be the weighting vector of decision makers, with $V_k \in [0,1]$, $\sum_{k=1}^{t} V_k = 1$; w=(w_1, w_2,……, w_n) is the associated weighting vector of the TVHA operator.

Step:3 To calculate the normalized Hamming distance between $\widetilde{a_1}$ and $\widetilde{a_2}$ is defined as follows:

$$d(\widetilde{a_1}, \widetilde{a_2}) = \frac{1}{8}\left(\left|(1 + t_{a_1} - f_{a_1})a_1 - (1 + t_{a_2} - f_{a_2})a_2\right| + \left|(1 + t_{a_1} - f_{a_1})b_1 - (1 + t_{a_2} - f_{a_2})b_2\right| + \left|(1 + t_{a_1} - f_{a_1})c_1 - (1 + t_{a_2} - f_{a_2})c_2\right|\right)$$

Step:4 The mining algorithm stated above will be utilized to remove the unwanted or less important decision variables from the decision making system (steps (i-viii)).

Step:5 Rank all the alternatives A_i (i=1,2,…..,m) and select one in accordance with the above distance calculated.

III. ILLUSTRATED EXAMPLE

Let us suppose there is a risk Investment Company, which wants to invest a sum of money in the best option, there is a panel with five possible alternatives to invest the money the risk investment company must take a decision according to the following four attributes.

G_1 is the risk analysis
G_2 is the growth analysis
G_3 is the social political- impact analysis
G_4 is the environment impact analysis

The five possible alternatives A_i are to be evaluated using the triangular vague numbers by the three decision makers whose weighting vector γ=(0.45,0.20,0.35) under the four attributes whose weighting vector w=(0.4,0.1,0.2,0.3) and construct respectively, the decision matrices (5x4) are:

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$$\tilde{R}_1 = \begin{bmatrix} ([0.2,0.4,0.6];0.2,0.6) & ([0.1,0.2,0.4];0.4,0.3) & ([0.2,0.4,0.5];0.5,0.1) & ([0.2,0.6,0.9];0.4,0.2) \\ ([0.3,0.4,0.6];0.3,0.6) & ([0.2,0.5,0.7];0.3,0.6) & ([0.2,0.7,0.9];0.3,0.2) & ([0.2,0.4,0.6];0.1,0.2) \\ ([0.2,0.7,0.8];0.4,0.3) & ([0.2,0.6,0.9];0.2,0.4) & ([0.4,0.6,0.8];0.7,0.1) & ([0.1,0.2,0.8];0.4,0.2) \\ ([0.1,0.4,0.6];0.7,0.2) & ([0.4,0.5,0.6];0.1,0.5) & ([0.2,0.3,0.5];0.4,0.3) & ([0.3,0.4,0.7];0.1,0.6) \\ ([0.1,0.2,0.8];0.3,0.4) & ([0.2,0.5,0.8];0.3,0.4) & ([0.7,0.8,0.9];0.2,0.5) & ([0.3,0.4,0.8];0.2,0.4) \end{bmatrix}$$

$$\tilde{R}_2 = \begin{bmatrix} ([0.5,0.6,0.7];0.2,0.5) & ([0.3,0.4,0.8];0.7,0.2) & ([0.5,0.7,0.8];0.4,0.2) & ([0.4,0.5,0.6];0.5,0.2) \\ ([0.2,0.5,0.8];0.6,0.2) & ([0.5,0.6,0.7];0.6,0.3) & ([0.2,0.3,0.4];0.7,0.1) & ([0.2,0.3,0.4];0.4,0.2) \\ ([0.5,0.6,0.7];0.4,0.1) & ([0.3,0.5,0.6];0.5,0.2) & ([0.4,0.5,0.6];0.8,0.1) & ([0.2,0.4,0.5];0.5,0.3) \\ ([0.2,0.4,0.9];0.3,0.2) & ([0.2,0.3,0.8];0.4,0.3) & ([0.2,0.4,0.8];0.4,0.3) & ([0.5,0.6,0.8];0.4,0.2) \\ ([0.6,0.7,0.8];0.4,0.3) & ([0.4,0.5,0.7];0.2,0.6) & ([0.3,0.5,0.6];0.2,0.5) & ([0.2,0.5,0.7];0.5,0.4) \end{bmatrix}$$

$$\tilde{R}_2 = \begin{bmatrix} ([0.4,0.5,0.6];0.3,0.2) & ([0.3,0.4,0.6];0.4,0.5) & ([0.4,0.5,0.7];0.5,0.4) & ([0.2,0.4,0.5];0.1,0.4) \\ ([0.3,0.4,0.7];0.5,0.3) & ([0.2,0.5,0.7];0.3,0.2) & ([0.2,0.3,0.5];0.3,0.4) & ([0.1,0.6,0.7];0.5,0.2) \\ ([0.2,0.4,0.6];0.4,0.2) & ([0.1,0.4,0.6];0.5,0.3) & ([0.4,0.7,0.8];0.5,0.2) & ([0.3,0.4,0.5];0.3,0.6) \\ ([0.3,0.5,0.7];0.7,0.1) & ([0.2,0.5,0.8];0.4,0.1) & ([0.2,0.5,0.6];0.7,0.1) & ([0.2,0.3,0.7];0.4,0.2) \\ ([0.2,0.4,0.6];0.4,0.3) & ([0.6,0.7,0.9];0.5,0.3) & ([0.3,0.4,0.7];0.4,0.2) & ([0.2,0.4,0.5];0.3,0.4) \end{bmatrix}$$

Step-1

Utilize the decision information given in the triangular vague decision matrix $\widetilde{R_k}$, and the TVWAA operator to derive the individual overall preference triangular vague values $\tilde{r}_i$(k) of the alternative A_i. Let, $\tilde{a}_j$ be a collection of triangular vague numbers, and Let,

$$TVWAA\left(\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_n\right) = \sum_{j=1}^{n} \tilde{a}_j \omega_j$$

$$= \left(\left[\sum_{j=1}^{n} a_j \omega_j , \sum_{j=1}^{n} b_j \omega_j , \sum_{j=1}^{n} c_j \omega_j \right]; 1 - \prod_{j=1}^{n} (1 - t_{a_j})^{\omega_j} , \prod_{j=1}^{n} (f_{a_j})^{\omega_j} \right)$$

$$\tilde{r}_1(1) = ([(a_1 w_1 + a_2 w_2 + a_3 w_3 + a_4 w_4); (b_1 w_1 + b_2 w_2 + b_3 w_3 + b_4 w_4)(c_1 w_1 + c_2 w_2 + c_3 w_3 + c_4 w_4)];)1 - \left[(1-\mu_{a_1})^{w_1} (1-\mu_{a_2})^{w_2} (1-\mu_{a_3})^{w_3} (1-\mu_{a_4})^{w_4}\right], (\gamma_{a_1})^{w_1} (\gamma_{a_2})^{w_2} (\gamma_{a_3})^{w_3} (\gamma_{a_4})^{w_4})$$

$\tilde{r}_1^{(1)}$ =([0.19,0.38,0.65]; 0.3510,0.2814)

Similarly,

$\tilde{r}_2^{(1)}$ = ([0.24,0.47,0.67]; 0.2452,0.3464)
$\tilde{r}_3^{(1)}$ = ([0.21,0.52,0.81]; 0.4624,0.2195)
$\tilde{r}_4^{(1)}$ = ([0.21,0.39,0.61]; 0.4652,0.3305)
$\tilde{r}_5^{(1)}$ =([0.29,0.41,0.82]; 0.2517,0.4183)

$\tilde{r}_1^{(2)}$ = ([0.45,0.57,0.70]; 0.4053,0.2885)
$\tilde{r}_2^{(2)}$ = ([0.23,0.41,0.59]; 0.5735,0.1813)
$\tilde{r}_3^{(2)}$ = ([0.37,0.51,0.61]; 0.5552,0.1490)
$\tilde{r}_4^{(2)}$ = ([0.29.0.45,0.84]; 0.3618,0.2259)
$\tilde{r}_5^{(2)}$ = ([0.40,0.58,0.72]; 0.3807,0.3882)

$\tilde{r}_1^{(3)}$ = ([0.33,0.46,0.59]; 0.3051,0.3100)
$\tilde{r}_2^{(3)}$ = ([0.24,0.45,0.66]; 0.4469,0.2702)
$\tilde{r}_3^{(3)}$ = ([0.26,0.46,0.61]; 0.4050,0.2896)
$\tilde{r}_4^{(3)}$ = ([0.24,0.44,0.69]; 0.6041,0.1231)
$\tilde{r}_5^{(3)}$ = ([0.26,0.43,0.62]; 0.3830,0.3016)

Step-2

Utilize the TVHA operator to derive the collective overall preference triangular vague values $\tilde{r}_i$ of the alternative A_i. Consider,

$\tilde{r}_1^{(1)}$ =([0.19,0.38,0.65]; 0.3510,0.2814)
$\tilde{r}_1^{(2)}$ =([0.45,0.57,0.70]; 0.4053,0.2885)
$\tilde{r}_1^{(3)}$ =([0.33,0.46,0.59]; 0.3051,0.3100)

γ =(0.45,0.20,0.35) w=(0.4,0.4,0.2)

The TVHA operator is given by:

$$TVHA_{\omega,w}\left(\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_n\right) = \sum_{j=1}^{n} \dot{\tilde{a}}_{\sigma(j)}\, w_j$$

$$= \left(\left[\sum_{j=1}^{n} \dot{a}_{\sigma(j)} w_j, \sum_{j=1}^{n} \dot{b}_{\sigma(j)} w_j, \sum_{j=1}^{n} \dot{c}_{\sigma(j)} w_j\right]; 1 - \prod_{j=1}^{n}(1 - \dot{t}_{\tilde{a}_{\sigma(j)}})^{w_j}, \prod_{j=1}^{n}(\dot{f}_{\tilde{a}_{\sigma(j)}})^{w_j}\right)$$

Where, $\tilde{a}_{\sigma(j)}$ is the j[th] largest of the weighted triangular vague numbers $\left(\dot{\tilde{a}}_j = \tilde{a}_j^{n\gamma_j},\ j = 1,2 \ldots \ldots n\right)$, $\gamma = (\gamma_1, \gamma_{2 \ldots\ldots\ldots} \gamma_n)$ be the weight vector of $\tilde{a}_j$ (j=1,2,....,n), and $\gamma_i > 0, \sum_{j=1}^{n} = 1$, and n is the balancing co-efficient.

$$\tilde{r}_1 = \left(\left[\sum_{j=1}^{3} \dot{a}_{\sigma(j)} w_j, \sum_{j=1}^{3} \dot{b}_{\sigma(j)} w_j, \sum_{j=1}^{3} \dot{c}_{\sigma(j)} w_j\right]; 1 - \prod_{j=1}^{3}(1 - \dot{\mu}_{\tilde{a}_{\sigma(j)}})^{w_j}, \prod_{j=1}^{3}(\dot{\gamma}_{\tilde{a}_{\sigma(j)}})^{w_j}\right)$$

We get $\tilde{r}_1$=([0.3938,0.4822,0.6645]; 0.4172,0.3222)
Similarly,
$\tilde{r}_2$ =([0.2841,0.4651,0.6665]; 0.5327,0.2878)
$\tilde{r}_3$ =([0.3418,0.5209,0.7508]; 0.5346,0.2499)
$\tilde{r}_4$ =([0.3040,0.4444,0.7338]; 0.5311,0.2479)
$\tilde{r}_5$ =([0.3656,0.4909,0.7235]; 0.4196,0.3870)

Step-3

To calculate the normalized Hamming distance between $\widetilde{a_1}$ and $\widetilde{a_2}$ with the positive ideal solution, $\tilde{r}^+$=([1,1,1]; 1,0) using the distance formula:

$$d(\widetilde{a_1}, \widetilde{a_2}) = \frac{1}{8}\left(\left|(1 + t_{a_1} - f_{a_1})a_1 - (1 + t_{a_2} - f_{a_2})a_2\right| + \left|(1 + t_{a_1} - f_{a_1})b_1 - (1 + t_{a_2} - f_{a_2})b_2\right| + \left|(1 + t_{a_1} - f_{a_1})c_1 - (1 + t_{a_2} - f_{a_2})c_2\right|\right)$$

d_1 = 0.2817, d_2 = 0.1369, d_3 = 0.1311, d_4 = 0.1281, d_5 = 0.2892

Step-4

The mining algorithm stated above the numerical illustration will be utilized to remove the unwanted or less important decision variables from the decision making system (steps (i-viii)).

Step-5

After using the mining algorithm and ranking all the alternatives A_i (i=1,2,3,4,5), we get:

$A_4 < A_3 < A_2$.

Hence, the best alternative is A_4.

It can be observed that the less important alternatives A_1 and A_5 are removed from the ranking process because of the mining algorithm.

IV. CONCLUSION

In this paper, the MAGDM problems under triangular vague information was investigated, and a new method on decision making is proposed based on data mining techniques. In the context of data-modeling and decision making, the algorithm combines the mining of triangular vague correlation rules and MAGDM techniques for removing some of the uninteresting, unwanted and/or less-important decision variables from the decision making environment, especially when huge data is involved. Finally, an illustration was presented to demonstrate and validate the effectiveness of the proposed method.

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VIII. CONCLUSION

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APPENDIX

Appendixes, if needed, appear before the acknowledgment.

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The preferred spelling of the word “acknowledgment” in American English is without an “e” after the “g.” Use the singular heading even if you have many acknowledgments.

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