Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Consensus-based Fuzzy TOPSIS Approach for Supply Chain Coordination: Application to Robot Selection Problem

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Abstract:
In hotly competitive international industrial and economic environments, supply chain coordination (SCC) is one of active research topics in production and operation management. In this research work, we present a new consensus-based fuzzy TOPSIS approach for supply chain coordination problem. It is formulated as a multi-criteria group decision making (MCGDM) problem and solved by combining consensus-based possibility measure with TOPSIS method in a fuzzy environment. To demonstrate the applicability of the proposed approach, a simple example of robot selection problem is presented and the numerical results analyzed. Moreover, using the Levenshtein distance, the deviation between individual solutions and group solution is analyzed.

Keywords: Supply Chain Coordination, MCGDM, Consensus, Fuzzy Logic, TOPSIS, Possibility Measure, CCSD Method, Levenshtein Distance, Robot Selection.

1. INTRODUCTION

Nowadays, in hotly competitive international industrial and economic environments, supply chain coordination (SCC) is one of active research topics in production and operation management. The literature is very rich with studies dedicated to SCC such as production and distribution coordination (Kim et al. (2005)), procurement and production coordination (Munson and Rosenblatt (2001)), production and inventory coordination (Grubbstrm and Wang (2003)) and distribution and inventory coordination (Yokoyama (2002)). According to Malone and Crowston (1994) *"coordination is the act of managing dependencies between entities and the joint effort of entities working together towards mutually defined goals"*.

Several authors (Arshinder et al. (2008), Cárdenas-Barrón (2007), Piplani and Fu (2005), etc.) realized the need to develop new approaches for supply chain coordination problems. However, some existing approaches shared costs and price information (Yao and Chiou (2004)), where other have set up networks of inventory management information systems (Verwijmeren et al. (1996)) to coordinate efficiently supply chain activities.

More and more, supply chain partners collectively make a number of tactical and strategic decisions to achieve mutually defined goals. Some of these decisions are for selection problems *i.e.,* selection of machine tools, selection of supply chain partners, selection of suppliers–suppliers, selection of transportation system, etc., which require consideration of a number of criteria for evaluation. Due to this reason, the supply chain coordination problem is considered as multi-criteria decision making (MCDM) problem in group decision making environment in this research work.

This paper addresses the development of a new consensus-based fuzzy TOPSIS approach for strategic selection problem of supply chain coordination. The problem is formulated as a multi-criteria group decision making (MCGDM) problem and solved by combining consensus-based possibility measure with TOPSIS method in a fuzzy environment. To demonstrate the applicability of the proposed approach, a simple example of robot selection problem is presented and the numerical results analyzed.

The rest of the paper is organized as follows. Section 2 presents the problem under consideration. Section 3 shows the proposed approach. Section 4 considers an illustrative example dealing with robot selection problem. Moreover, to evaluate the deviation between individual solutions and group solution, the Levenshtein distance is used. Section 5 concludes the paper with some future research work directions.

2. PROBLEM ENVIRONMENT

In this study, we have k experts respectively $E_1, \ldots, E_k$ in charge of the evaluation and ranking of a set of alternatives denoted $A_1, \ldots, A_m$. Alternatives are evaluated in terms of n conflicting criteria denoted respectively $C_1, \ldots, C_n$. Each expert (E) is brought to express his preferences for each alternative relative to each criterion in a fuzzy environment through a matrix called *preference matrix* denoted $D = [x_{ij}]_{m\times n}$. As the group of experts usually have conflicting preferences, the first phase of our approach

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is to find a *consensus* among the experts. Once consensus is reached, the second phase addresses the problem of ranking and selecting alternatives according to the assessment of the experts. The next section describes more in details the two phases of our approach.

3. PROPOSED APPROACH

3.1 Consensus

The consensus is defined as the full and unanimous agreement among the experts regarding all the possible alternatives. However, the chances for reaching such a full agreement are rather low and it allows the experts to differentiate between only two states, namely, the existence and absence of consensus (Singh and Benyoucef (2013)). In this reseach work, to arrive at a consensus between experts, we adapt the Certainty Compliance (H_s^j) (Sharif Ullah (2005)) in the algorithm proposed by Noor-E-Alam et al. (2011) (see Fig.3). The algorithm is based on the possibility theory of fuzzy logic (Noor-E-Alam et al. (2011)). A fuzzy number is defined as $V = \{X, \mu_{V(X)}, X \in \Re\}$. In this paper, we use the Trapezoidal Fuzzy Numbers $TrFN$ to better represent the information, expert's preferences and minimize vagueness. $\tilde{z}_r = (a_r, b_r, c_r, d_r)$ represents a $TrFN$, with the membership function:

$$\mu_{V(X)} = \begin{cases} \frac{x-a_r}{b_r-a_r} & a_r \le x \le b_r \\ 1 & b_r \le x \le c_r \\ \frac{d_r-x}{d_r-c_r} & c_r \le x \le d_r \\ 0 & otherwise \end{cases}$$

To express the information tainted by ambiguity and information processing of experts, we define a set of seven Quantifiers ($Q_s, \quad s = 1, \ldots, 7$), *i.e.,* Very Poor (VP), Medium Poor (MP), Medium Fair (MF), Fair (F), Medium Good (MG), Good (G), Very Good(VG) (Fig. 2) and the eleven $TrFN$ *i.e.,* Absolutely False (AF), Mostly False (MF), Quite False (QF), Probably False (PF), Somewhat False (SF), Not Sure (NS), Somewhat True (ST), Probably True (PT), Quite True (QT), Mostly True (MT) and Absolutely True (AT) (Fig. 1).

Experts have the ability to define the desired set of quantifiers for each criterion. For each criterion (C_j), the probability of quantifiers (G_s^j), the possibility of quantifiers (T_s^j) and ω_s^j are computed using (1), (2) and (3):

$$\sum_s G_s^j \times T_s^j \le \omega_s^j \tag{1}$$

$$T_s^j = G_s^j + U \tag{2}$$

$$\omega_s^j = Min_s\{1 - G_s^j + \sum_s (G_s^j)^2\} \tag{3}$$

where, U is the possibility transfer bound.

From (1) and (2), we have:

$$U \le \frac{\omega_s^j - \sum_s (G_s^j)^2}{\sum_s G_s^j} \tag{4}$$

The possibility transfer constant (D_s^j) is selected such as $D_s^j \in [0, U]$.

From our illustrative example (section 4), let us consider creterion C_6 and alternative R_1 with four quantifiers respectively, MP (Medium Poor), F (Fair), MG (Medium Good) and G (Good) *i.e.,* $Q_4 = (MP, F, MG, G)$. Four experts E_1, E_2, E_3 and E_4 provide their preference against C_6 as follows: the preferences of E_1 and E_2 are MG and the preferences of E_3 and E_4 are G. Hence, from (1), (2), (3) and (4), $(G_4^6) = (0/4, 0/4, 2/4, 2/4)$, $\omega_4^6 = 0.75$, $U = D_4^6 = 0.25$ and $T_4^6 = (0.25, 0.25, 0.75, 0.75)$.

To obtain crisps values for each TrFN, we use α-cut that defines the confidence interval for level α whose which can have more confidence. This confidence interval is defined as follows:

$[B_r^L, B_r^U]$ $\forall r = 1 \ldots (n \cdot m \cdot k)$
where,

$$B_r^L = (b_r - a_r)\alpha + a_r \ \forall r = 1 \ldots (n \cdot m \cdot k)$$

$$B_r^U = (d_r - c_r)\alpha + d_r \ \forall r = 1 \ldots (n \cdot m \cdot k)$$

After obtaining the interval, the *Optimism Index* I_r that is a convex combination, is applied to get the crips values.

$$I_r = \gamma B_r^L + (1 - \gamma) B_r^U \ \ \forall \gamma \in [0, 1] \ \forall r = 1 \ldots (n \cdot m \cdot k)$$

To aggerger all criteria and select the collective preference of all the experts, the *Certainty Compliance* H_s^j Sharif Ullah (2005) was used for determine how clearly the alternative under consideration is known. It is calculated in the same manner as in Sharif Ullah (2005).

Fig. 1. Used fuzzy trapezoidal membership functions for information processing

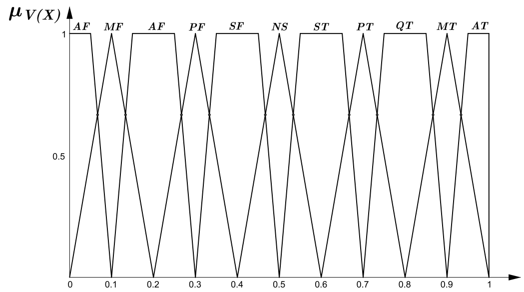


Fig. 2. Used fuzzy trapezoidal membership functions for experts preferences

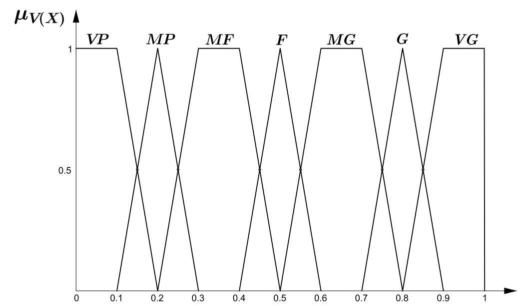
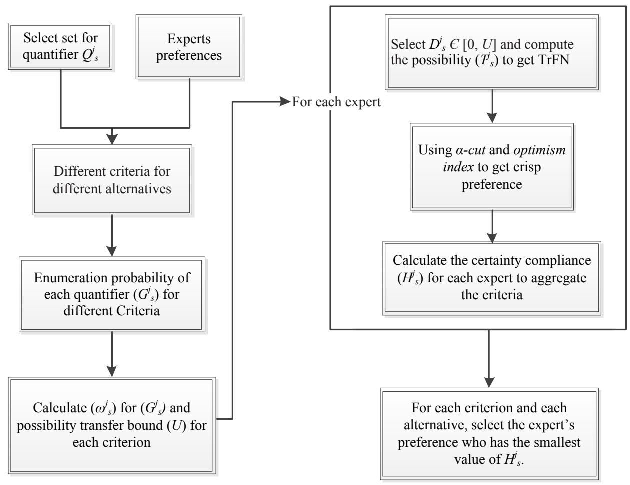


Fig. 3. Used consensus process



3.2 Ranking

For the second phase of our approach, we use the fuzzy *TOPSIS* (Technique for Order Preference by Similarity to Ideal Solution), developed by Hwang and Yoon (1981). TOPSIS is based upon:

(1) Coombs axiom of choice (see Coombs (1958) and Zeleny (1982)),
(2) The notions of reference points namely the perceived ideal and anti-ideal alternatives and
(3) The Euclidean distance as a measure of closeness between two points in the metric space $\Re^n$, where n is the number of attributes and $\Re$ the set of reals.

A number of fuzzy TOPSIS based methods and applications have been developed in recent years (Wang et al. (2009), Wang and Chang (2007), Kahraman et al. (2007)). The fuzzy TOPSIS method can be outlined as follows (Krohling and Campanharo (2011); Chen (2000)).

Step 1: Construct weighted fuzzy collective preferences matrix The weighted fuzzy collective preferences matrix can be computed by multiplying the importance weights of the evaluation criteria and the values in the fuzzy collective preferences matrix $\tilde{D} = [\tilde{x}_{ij}]_{m\times n}$. The weighted fuzzy collective preferences matrix $\tilde{V}$ is defined as:

$$\tilde{V} = [\tilde{v}_{ij}]_{m\times n} \qquad i = 1,\ldots,m \qquad j = 1,\ldots,n \tag{5}$$

$$\tilde{v}_{ij} = \tilde{x}_{ij} \times \tilde{w}_{ij} \qquad i = 1,\ldots,m \qquad j = 1,\ldots,n \tag{6}$$

where $\tilde{w}_{ij}$ is fuzzy weight of the criteria C_j.

Step 2: Determine the ideal and anti-ideal alternatives Because the trapezoidal fuzzy numbers are included in the interval $[0, 1]$, the fuzzy ideal reference point ($FIRP$, A^+) and fuzzy anti-ideal reference point ($FAIRP$, A^-) can be defined as:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_j^+) = \left\{\left(\max_i \tilde{v}_{ij} | i = 1,\ldots,m\right)\right\}. \qquad j = 1,\ldots,n \tag{7}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_j^-) = \left\{\left(\min_i \tilde{v}_{ij} | i = 1,\ldots,m\right)\right\}. \qquad j = 1,\ldots,n \tag{8}$$

Step 3: Calculate the distances of each initial alternative to FIRP and FAIRP The distance of each alternative from $FIRP$ and $FAIRP$ can be derived respectively as:

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+) \quad i = 1,\ldots,m \quad j = 1,\ldots,n \tag{9}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \quad i = 1,\ldots,m \quad j = 1,\ldots,n \tag{10}$$

Where the distance can be defined as follows:

$$d(\tilde{a_1}, \tilde{a_2}) = \sqrt{\frac{1}{6}\left[((a_1 - a_2))^2 + 2((b_1 - b_2))^2 + 2((c_1 - c_2))^2 + ((d_1 - d_2))^2\right]} \tag{11}$$

Step 4: Obtain the closeness coefficient and rank the order of alternatives Calculate the closeness coefficient (CC) of each alternative as:

$$CCi = \frac{d_i^-}{d_i^- + d_i^+} \qquad i = 1,\ldots,m \tag{12}$$

An alternative with index CC_i approaching 1 indicates that the alternative is close to the $FIRP$ and far from the $FAIRP$. Rank each CC of each alternative in descending order. The alternative with the highest CC value will be the best choice.

In order to determine the weights of different criteria, the *CCSD (Correlation Coefficient and Standard Deviation)* method Wang and Luo (2010) is used. CCSD uses the concept of standard deviation between the criteria and their correlation coefficients through a nonlinear optimization model where the objective function is minimized:

$$\text{Min Z=} \quad \sum_{j=1}^{n}\left(w_j - \frac{\sigma_j\sqrt{1-\xi_j}}{\sum_{k=1}^{n}\sigma_k\sqrt{1-\xi_k}}\right)^2 \tag{13}$$

s.t:

$$\sum_{j=1}^{n} w_j = 1, \quad w_j \geq 0, \qquad j = 1,\ldots,n \tag{14}$$

where, w_j is the weight of C_j, σ_j is the standard deviation of C_j and ξ_j is the correlation coefficient between the values of C_j.

The main steps of the proposed approach are as follows:
Phase I: Consensus

- **Step 1.** Select the quantifier's set and collect the fuzzy preferences of the experts for each criterion and alternative.
- **Step 2.** For each criterion C_j, compute G_s^j, ω_s^j and U.
- **Step 3.** For each criterion C_j, select $D_s^j \in [0, U]$ and calculate T_s^j.
- **Step 4.** Apply the α-cut and *Optimism index* to get the crisp preference.
- **Step 5.** Calculate the Certainty Compliance H_s^j for each expert to aggregate the criteria.
- **Step 6.** For each criterion C_j and each alternative A_i, select the expert's preference who has the smallest value of H_s^j.

Phase II: Ranking

- **Step 1.** Enumerate the weights of the criteria using CCSD method using Eqs.(13)-(14).
- **Step 2.** Give the linguistic scales of for each fuzzy collective preference using Fig.(2)
- **Step 3.** Construct the weighted fuzzy collective preferences matrix using (5)-(6).
- **Step 4.** Determine the ideal and anti-ideal alternatives using Eqs.(7)-(8).
- **Step 5.** Calculate the distances of each initial alternative to FIRP and FAIRP using Eqs.(9)-(11).
- **Step 6.** Obtain the closeness coefficient and rank the order of alternatives using Eqs.(12).
- **Step 7.** Rank the order of alternatives and select the highest ranking alternative as best alternative.

4. ILLUSTRATIVE EXAMPLE

To illustrate the applicability of the developed approach, we consider a simple example of a company interested by a new robot to perform a manufacturing task. A group of four experts E_1, E_2, E_3 and E_4 is in charge of selecting the most suitable robot from a set of four potential robots (alternatives) R_1, R_2, R_3 and R_4. The four robots differ on several characteristics that make them attractive for different reasons. In fact, they are evaluated by the experts according to six main criteria respectively C_1 (programming flexibility), C_2 (productivity) and C_3 (technical features) which are benefit criteria and C_4 (environment impact), C_5 (maintainability/regular maintenance) and C_6 (operation costs) which are cost criteria.

At the beginning, all the experts agree on all quantifier's set (Step 1, Table 1). Each expert is invited to select and communicate his preferences with respect to each criterion (Step 1, Table 2).

Table 1. Quantifier's set

C_j	Q_s
C_1	(VP, MP, MF, F, MG, G, VG)
C_2	(VP, MP, F, MG, G, VG)
C_3	(MP, MF, F, MG, G, VG)
C_4	(MP, F, MG, G, VG)
C_5	(MP, F, MG, G, VG)
C_6	(MP, F, MG, G)

Table 2. Experts preferences

R_i	C_j	E_1	E_2	E_3	E_4
R_1	C_1	F	G	MG	MG
	C_2	MP	F	MP	MP
	C_3	G	F	G	VG
	C_4	MG	F	G	G
	C_5	G	G	VG	MP
	C_6	MG	MG	G	G
R_2	C_1	VG	G	MP	MP
	C_2	G	VG	G	VG
	C_3	G	VG	G	F
	C_4	G	F	MG	MG
	C_5	MG	G	G	F
	C_6	MG	G	F	MG
R_3	C_1	G	G	G	G
	C_2	MG	F	G	G
	C_3	G	G	F	MP
	C_4	MG	MG	F	F
	C_5	MP	G	F	G
	C_6	F	G	MP	MP
R_4	C_1	F	F	MG	G
	C_2	MP	G	F	MP
	C_3	F	G	VG	VG
	C_4	MP	G	VG	VG
	C_5	G	F	MP	G
	C_6	MG	MG	F	G

The next step concerns the Probability of each Quantifier G_s^j for different criteria. The results of execution of Step 2 showing G_s^j of the alternative R_1 for all criteria are shown in Table 3.

Table 3. Probabilities for different quantifiers G_s^j for all criteria of alternative R_1

C_j	G_s
C_1	(0, 0, 0, 0.25, 0.5, 0.25, 0)
C_2	(0, 0.75, 0.25, 0, 0, 0)
C_3	(0, 0, 0.25, 0, 0.5, 0.25)
C_4	(0, 0.25, 0.25, 0.5, 0)
C_5	(0.25, 0, 0, 0.5, 0.25)
C_6	(0, 0, 0.5, 0.5)

In step 3, ω_s^j for G_s^j and U are calculated as shown in Table 4.

Table 4. ω_s^j of the various criteria for alternative R_1

C_j	C_1	C_2	C_3	C_4	C_5	C_6
ω_s^j	0.75	0.81	0.75	0.75	0.75	0.75
U	0.38	0.19	0.38	0.38	0.38	0.25

After calculating the bound U, each expert is invited to choose his $D_s^j \in [0, U]$. Thereafter the Possibility T_s^j is calculated as is shown without the Table 5 (Step 4).

Table 5. Possibility transfer constant D and possibility T_s^j of the various criteria for alternative R_1 and expert E_1

C_j	D_s	T_s
C_1	0.38	(0.38, 0.38, 0.38, 0.63, 0.88, 0.63, 0.38)
C_2	0.19	(0.19, 0.94, 0.44, 0.19, 0.81, 0.81)
C_3	0.38	(0.38, 0.38, 0.63, 0.38, 0.88, 0.63)
C_4	0.38	(0.38, 0.63, 0.63, 0.88, 0.38)
C_5	0.38	(0.63, 0.38, 0.38, 0.88, 0.63)
C_6	0.25	(0.25, 0.25, 0.75, 0.75)

In step 5, using the membership functions (Fig.1) we obtain the $TrFN$, then applying the α-cut with $\alpha = 0.8$ and Optimisme Index with $\gamma = 0.5$ to get a crisps values shown in the Table 6.

Table 6. Trapezoidal fuzzy number $TrFN$ and crisp values I_r of the various criteria for alternative R_1 and expert E_1

C_j	TrFN	I_r
C_1	(SF, SF, SF, ST, MT, ST, SF)	(0.4, 0.4, 0.4, 0.6, 0.9, 0.6, 0.4)
C_2	(QF, AT, SF, QF, QT, QT)	(0.2, 0.95, 0.4, 0.2, 0.8, 0.8)
C_3	(SF, SF, ST, SF, MT, ST)	(0.4, 0.4, 0.6, 0.4, 0.9, 0.6)
C_4	(SF, ST, ST, MT, SF)	(0.4, 0.6, 0.6, 0.9, 0.4)
C_5	(ST, SF, SF, MT, ST)	(0.6, 0.4, 0.4, 0.9, 0.6)
C_6	(PF, PF, QT, QT)	(0.3, 0.3, 0.8, 0.8)

In the step 6, we calculate Certainty Compliance H_s^j for each expert to aggregate the criteria (Table 7). Then select the experts preference who has the smallest value of H_s^j as shown in the last column.

Table 7. Certainty compliance H_s^j of the various criteria and experts for alternative R_1

C_j	E_1	E_2	E_3	E_4	Experts Preferences
C_1	0.71	0.54	0.63	0.46	Medium Good(E_4)
C_2	0.42	0.53	0.57	0.45	Medium Poor(E_1)
C_3	0.7	0.57	0.63	0.5	Very Good(E_4)
C_4	0.68	0.6	0.64	0.56	Good(E_4)
C_5	0.68	0.6	0.64	0.56	Medium Poor(E_4)
C_6	0.5	0.5	0.5	0.62	Good(E_3)

At the end, we obtain the following collective preferences matrix using $TrFN$ (Table 8) and therefore the crisp collective preferences matrix (Table 9):

Table 8. Collective preference matrix using $TrFN$

Consensus	C_1	C_2	C_3	C_4	C_5	C_6
R_1	MG	MP	VG	G	MP	G
R_2	MP	VG	F	MG	F	G
R_3	G	MG	MP	MG	G	MP
R_4	G	MP	VG	VG	G	MG

Table 9. Crisp collective preference matrix

Consensus	C_1	C_2	C_3	C_4	C_5	C_6
R_1	0.65	0.2	0.9	0.8	0.2	0.8
R_2	0.2	0.9	0.5	0.65	0.5	0.8
R_3	0.8	0.65	0.2	0.65	0.8	0.2
R_4	0.8	0.2	0.9	0.9	0.8	0.65

The next step (Phase II, Step 1) concerns the determination of the criteria weights using CCSD method. The weights are determined by solving the nonlinear optimization problem obtained using Wang and Luo (2010) model. The LINGO software is used to solve the nonlinear problem. The weights are $w_1 = 0.18$, $w_2 = 0.25$, $w_3 = 0.19$, $w_4 = 0.3$, $w_5 = 0.18$, $w_6 = 0.17$. Table 10 presents the fuzzy and weighted collective preferences for criterion C_1.

Table 10. Fuzzy and weighted collective preferences for criterion C_1

R_i	Fuzzy preference	Weighted preference
R_1	(0.5, 0.6, 0.7, 0.8)	(0.09, 0.11, 0.13, 0.14)
R_2	(0.1, 0.2, 0.2, 0.3)	(0.02, 0.04, 0.04, 0.05)
R_3	(0.7, 0.8, 0.8, 0.9)	(0.13, 0.14, 0.14, 0.16)
R_4	(0.7, 0.8, 0.8, 0.9)	(0.13, 0.14, 0.14, 0.16)

In next steps, the distance d_i^+ and d_i^- of each alternative to obtain the closeness coefficient (CC_i) for each alternative. The final results obtained by proposed *fuzzy TOPSIS* method are shown in Table 11. The best performer among the ten alternatives is alternative 4 (R_4). The overall performance ranking is $R_4 > R_2 > R_3 > R_1$.

Table 11. Closeness coefficient table

Alternatives	d_i^-	d_i^+	CC_i	Rank
R_1	0.54	5.47	0.09	4
R_2	0.61	5.4	0.1	2
R_3	0.55	5.46	0.091	3
R_4	0.65	5.35	0.11	1

To evaluate the difference of opinion between individual solutions (each expert) and the group solution using the consensus (Phase I) we restarted the Phase II of ranking involving only the preferences and judgments of each expert (Table 12).

Table 12. Ranking of each expert

Experts	Rank
E_1	$R_2 > R_3 > R_1 > R_4$
E_2	$R_2 > R_3 > R_4 > R_1$
E_3	$R_1 > R_2 > R_3 > R_4$
E_4	$R_4 > R_2 > R_3 > R_1$

To evaluate the deviation between individual solutions and group solution, we used the "Levenshtein Distance" (see Levenshtein (1966)) used in Computer Science. The Levenshtein Distance measure the minimum number of all necessary operations (number of insertions, deletions and substitutions) to transform one sequence into another. This metric is used for spell checking, speech recognition, plagiarism detection and, moreover, for DNA sequences analysis, etc. It is defined as follows:

$$L(p, q) = Min\{e + d + t\} \quad (15)$$

with:
e: number of insertions.
d: number of deletions.
t: number of substitutions.

For example, the Levenshtein distance between the sequence $p = \{12345\}$ and $q = \{51234\}$ is $L(p, q) = 2$ with $e = 1$, $d = 1$, $t = 0$.

Table 13 shows the Levenshtein distance between the group solution ($S^c = \{4231\}$) and individual solutions (S_k^i). We can see that $L(S^c, S_1^i) = L(S^c, S_2^i) = L(S^c, S_3^i) = 2$, which means that the difference between the three individual solutions and group solution is equal to two operations. Also, we have $L(S^c, S_4^i) = 0$, which confirms that the preferences of expert E_4 are close to the the group preferences. This is due to the preferences of the expert E_4

who has the smallest value of H_s^j, then his preferences are the most selected as group solution as shown in the last column of the Table 7.

Table 13. Deviation between individual and group solutions

Expert	***Ranking***	***Deviations***
$\boldsymbol{E_1}$	{2314}	2
$\boldsymbol{E_2}$	{2341}	2
$\boldsymbol{E_3}$	{1234}	2
$\boldsymbol{E_4}$	{4231}	0

5. CONCLUSIONS

In this paper, we have developed a new approach dedicated to strategic selection problem for supply chain coordination. The approach is based on the possibility measure theory and TOPSIS method in a fuzzy environment. A simple example of rebot selection problem is presented to demonstrate the applicability of the approach. Moreover, a sensitivity analysis using Levenshtein distance is conducted to evaluate the deviation between individual solutions and group solution.

For further works, we plan to explore other methods and models such as goal programming (GP), analytic hierarchy process (AHP), visekriterijumsko kompromisno rangiranje (VIKOR), elimination and choice translating reality (ELECTRE), etc. To integrate explicitly the experts preferences, other concepts like satisfaction functions and generalized criteria can be used. Furthermore, in order to provid more flexibility to the experts, we plan to use different types of data (fuzzy, crisp, intervals, etc.) and test several examples related to supplier selection problem, technology selection problem, plant location selection problem, information systems selection problem, etc.

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