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 (Grubbström 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 Chion (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 $A_1, \ldots, A_n$. 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...
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 research work, to arrive at a consensus between experts, we adapt the Certainty Compliance \( H_s \) (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 \( V = \{ X, \mu_{V(X)} | X \in \mathbb{R} \} \). In this paper, we use the Trapezoidal Fuzzy Numbers \( TrFN \) to better represent the information, expert’s preferences and minimize vagueness. \( z_r = (a_r, b_r, c_r, d_r) \) represents a \( TrFN \), with the membership function:

\[
\mu_{V(X)} = \begin{cases} \frac{x-a_r}{b_r-a_r} & a_r \leq x \leq b_r \\ 1 & b_r \leq x \leq c_r \\ \frac{d_r-x}{d_r-c_r} & c_r \leq x \leq d_r \\ 0 & \text{otherwise} \end{cases}
\]

To express the information tainted by ambiguity and information processing of experts, we define a set of seven Quantifiers \( Q_s \), \( s = 1, \ldots, 7 \), 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 \( C_s \), the probability of quantifiers \( G_s^i \), the possibility of quantifiers \( T_s^i \) and \( \omega_s^i \) are computed using (1), (2) and (3):

\[
\sum_s G_s^i \times T_s^j \leq \omega_s^i \quad (1)
\]

\[
T_s^i = G_s^i + U \quad (2)
\]

\[
\omega_s^i = \min_s \{ 1 - G_s^i + \sum_s (G_s^j)^2 \} \quad (3)
\]

where, \( U \) is the possibility transfer bound.

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

\[
U \leq \frac{\omega_s^i - \sum_s (G_s^i)^2}{\sum_s G_s^i} \quad (4)
\]

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

From our illustrative example (section 4), let us consider criterion \( C_6 \) and alternative \( R_i \) 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), \( (G_s^i) = (0/4,0/4,2/4,2/4) \), \( \omega_s^i = 0.75 \), \( U = D_s^i = 0.25 \) and \( T_s^i = (0.25,0.25,0.75,0.75) \).

To obtain crps values for each \( TrFN \), we use \( \alpha \)-cut that defines the confidence interval for level \( \alpha \) 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 crps 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 \( H_s \) (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. 1. Used fuzzy trapezoidal membership functions for information processing.](image1.png)

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

![Fig. 2. Used fuzzy trapezoidal membership functions for experts preferences.](image2.png)
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 $\mathbb{R}^n$, where $n$ is the number of attributes and $\mathbb{R}$ 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:

\[
\tilde{V} = [\tilde{v}_{ij}]_{m \times n} \quad i = 1, \ldots, m \quad j = 1, \ldots, n
\]

where $\tilde{v}_{ij}$ 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 ($\text{IFIRP}$, $A^+$) and fuzzy anti-ideal reference point ($\text{FAIRP}$, $A^-$) can be defined as:

\[
A^+ = (\tilde{v}^-_1, \tilde{v}^-_2, \ldots, \tilde{v}^-_n) = \left\{ \left( \max_i \tilde{v}_{ij} | i = 1, \ldots, m \right) \right\}, \quad j = 1, \ldots, n
\]

\[
A^- = (\tilde{v}^-_1, \tilde{v}^-_2, \ldots, \tilde{v}^-_n) = \left\{ \left( \min_i \tilde{v}_{ij} | i = 1, \ldots, m \right) \right\}, \quad j = 1, \ldots, n
\]

**Step 3:** Calculate the distances of each initial alternative to $\text{IFIRP}$ and $\text{FAIRP}$. The distance of each alternative from $\text{IFIRP}$ and $\text{FAIRP}$ can be derived respectively as:

\[
d^+_i = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}^+_j) \quad i = 1, \ldots, m \quad j = 1, \ldots, n
\]

\[
d^-_i = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}^-_j) \quad i = 1, \ldots, m \quad j = 1, \ldots, n
\]

Where the distance can be defined as follows:

\[
d(\tilde{a}_i, \tilde{a}_j) = \frac{1}{6} \left( (a_i-a_j)^2 + 2(b_i-b_j)^2 \right)
\]  

\[
+ 2((c_1-c_2)^2 + ((d_1-d_2)^2)^2
\]

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

\[
CC_j = \frac{d^-_j}{d^+_j + d^-_j} \quad i = 1, \ldots, m
\]

An alternative with index $CC_j$ approaching 1 indicates that the alternative is close to the $\text{IFIRP}$ and far from the $\text{FAIRP}$. 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:

\[
\min Z = \sum_{j=1}^{n} \left( w_j - \frac{\sigma_j \sqrt{1 - \xi_j}}{\sum_{k=1}^{n} \sigma_k \sqrt{1 - \xi_k}} \right)^2
\]

s.t.: \[\sum_{j=1}^{n} w_j = 1, \quad w_j \geq 0, \quad j = 1, \ldots, n\]

where $w_j$ is the weight of $C_j$, $\sigma_j$ is the standard deviation of $C_j$ and $\xi_j$ 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 $G^+_j$, $\omega^+_j$, and $U$.
- **Step 3.** For each criterion $C_j$, select $D^*_j \in [0, U]$ and calculate $T^*_j$.
- **Step 4.** Apply the $\alpha$-cut and Optimism index to get the crisp preference.
- **Step 5.** Calculate the Certainty Compliance $H^*_j$ 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 $H^*_j$.  

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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.

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

### Table 3. Probabilities for different quantifiers \( G_i^j \) for all criteria of alternative \( R_1 \)

<table>
<thead>
<tr>
<th>( C_j )</th>
<th>( G_1 )</th>
<th>( G_2 )</th>
<th>( G_3 )</th>
<th>( G_4 )</th>
<th>( G_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_1 )</td>
<td>( (0, 0, 0, 0.25, 0.5, 0.25, 0) )</td>
<td>( (0, 0.75, 0.25, 0, 0, 0) )</td>
<td>( (0, 0, 0.25, 0, 0.5, 0.25) )</td>
<td>( (0, 0.25, 0.25, 0.5, 0) )</td>
<td>( (0.25, 0, 0, 0.5, 0.25) )</td>
</tr>
</tbody>
</table>

In step 3, \( \omega_i^j \) for \( G_i^j \) and \( U \) are calculated as shown in Table 4.

### Table 4. \( \omega_i^j \) of the various criteria for alternative \( R_1 \)

<table>
<thead>
<tr>
<th>( C_i )</th>
<th>( \omega_1 )</th>
<th>( \omega_2 )</th>
<th>( \omega_3 )</th>
<th>( \omega_4 )</th>
<th>( \omega_5 )</th>
<th>( \omega_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_1 )</td>
<td>0.75</td>
<td>0.81</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>0.38</td>
<td>0.38</td>
<td>0.38</td>
<td>0.38</td>
<td>0.88</td>
<td>0.63</td>
</tr>
<tr>
<td>( C_3 )</td>
<td>0.38</td>
<td>0.38</td>
<td>0.38</td>
<td>0.38</td>
<td>0.88</td>
<td>0.63</td>
</tr>
<tr>
<td>( C_4 )</td>
<td>0.38</td>
<td>0.38</td>
<td>0.38</td>
<td>0.38</td>
<td>0.88</td>
<td>0.63</td>
</tr>
<tr>
<td>( C_5 )</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
</tr>
</tbody>
</table>

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

### Table 5. Possibility transfer constant \( D \) and possibility \( T_i^j \) of the various criteria for alternative \( R_1 \) and expert \( E_1 \)

<table>
<thead>
<tr>
<th>( C_j )</th>
<th>( D_i^j )</th>
<th>( T_i^j )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_1 )</td>
<td>0.38</td>
<td>( (0.38, 0.38, 0.38, 0.38, 0.88, 0.63, 0.38) )</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>0.38</td>
<td>( (0.38, 0.38, 0.38, 0.38, 0.88, 0.63, 0.38) )</td>
</tr>
<tr>
<td>( C_3 )</td>
<td>0.25</td>
<td>( (0.25, 0.25, 0.25, 0.75, 0.75) )</td>
</tr>
</tbody>
</table>

In step 5, using the membership functions (Fig.1) we obtain the \( TrFN \), then applying the \( \alpha \)-cut with \( \alpha = 0.8 \) and Optimisme Index with \( \gamma = 0.5 \) to get a craps 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 $E_1$

<table>
<thead>
<tr>
<th>$C_j$</th>
<th>$TrFN$</th>
<th>$I_r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_1$</td>
<td>(SF, SF, SF, ST, MT, SF)</td>
<td>(0.4, 0.4, 0.4, 0.6, 0.9, 0.6)</td>
</tr>
<tr>
<td>$C_2$</td>
<td>(QF, AT, SF, QF, QT, QT)</td>
<td>(0.2, 0.95, 0.4, 0.2, 0.8, 0.8)</td>
</tr>
<tr>
<td>$C_3$</td>
<td>(SF, SF, ST, SF, MT, ST)</td>
<td>(0.4, 0.4, 0.6, 0.4, 0.9, 0.6)</td>
</tr>
<tr>
<td>$C_4$</td>
<td>(SF, ST, MT, SF, ST)</td>
<td>(0.4, 0.6, 0.6, 0.9, 0.4)</td>
</tr>
<tr>
<td>$C_5$</td>
<td>(ST, SF, ST, MT, ST)</td>
<td>(0.6, 0.4, 0.4, 0.9, 0.6)</td>
</tr>
<tr>
<td>$C_6$</td>
<td>(PF, PF, QT, QT)</td>
<td>(0.3, 0.3, 0.8, 0.8)</td>
</tr>
</tbody>
</table>

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

Table 7. Certainty compliance $H^*_i$ of the various criteria and experts for alternative $R_1$

<table>
<thead>
<tr>
<th>$C_j$</th>
<th>$E_1$</th>
<th>$E_2$</th>
<th>$E_3$</th>
<th>$E_4$</th>
<th>Experts Preferences</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_1$</td>
<td>0.71</td>
<td>0.54</td>
<td>0.63</td>
<td>0.46</td>
<td>Medium Good($E_4$)</td>
</tr>
<tr>
<td>$C_2$</td>
<td>0.42</td>
<td>0.53</td>
<td>0.57</td>
<td>0.45</td>
<td>Medium Poor($E_1$)</td>
</tr>
<tr>
<td>$C_3$</td>
<td>0.7</td>
<td>0.57</td>
<td>0.63</td>
<td>0.5</td>
<td>Very Good($E_2$)</td>
</tr>
<tr>
<td>$C_4$</td>
<td>0.68</td>
<td>0.6</td>
<td>0.64</td>
<td>0.56</td>
<td>Good($E_1$)</td>
</tr>
<tr>
<td>$C_5$</td>
<td>0.68</td>
<td>0.6</td>
<td>0.64</td>
<td>0.56</td>
<td>Medium Poor($E_4$)</td>
</tr>
<tr>
<td>$C_6$</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.62</td>
<td>Good($E_3$)</td>
</tr>
</tbody>
</table>

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 $TrFN$

<table>
<thead>
<tr>
<th>Consensus</th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
<th>$C_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_1$</td>
<td>MG</td>
<td>MP</td>
<td>VG</td>
<td>G</td>
<td>MP</td>
<td>G</td>
</tr>
<tr>
<td>$R_2$</td>
<td>MP</td>
<td>VG</td>
<td>F</td>
<td>MG</td>
<td>F</td>
<td>G</td>
</tr>
<tr>
<td>$R_3$</td>
<td>G</td>
<td>MG</td>
<td>MP</td>
<td>MG</td>
<td>G</td>
<td>MP</td>
</tr>
<tr>
<td>$R_4$</td>
<td>G</td>
<td>MG</td>
<td>VG</td>
<td>G</td>
<td>MG</td>
<td>G</td>
</tr>
</tbody>
</table>

Table 9. Crisp collective preference matrix

<table>
<thead>
<tr>
<th>Consensus</th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
<th>$C_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_1$</td>
<td>0.65</td>
<td>0.2</td>
<td>0.9</td>
<td>0.8</td>
<td>0.2</td>
<td>0.8</td>
</tr>
<tr>
<td>$R_2$</td>
<td>0.2</td>
<td>0.9</td>
<td>0.5</td>
<td>0.65</td>
<td>0.5</td>
<td>0.8</td>
</tr>
<tr>
<td>$R_3$</td>
<td>0.8</td>
<td>0.65</td>
<td>0.2</td>
<td>0.65</td>
<td>0.8</td>
<td>0.2</td>
</tr>
<tr>
<td>$R_4$</td>
<td>0.8</td>
<td>0.2</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
<td>0.65</td>
</tr>
</tbody>
</table>

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 $C_1$

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>$R_1$</th>
<th>$R_2$</th>
<th>$R_3$</th>
<th>$R_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuzzy preference</td>
<td>(0.5, 0.6, 0.7, 0.8)</td>
<td>(0.1, 0.2, 0.2, 0.3)</td>
<td>(0.7, 0.8, 0.8, 0.9)</td>
<td>(0.7, 0.8, 0.8, 0.9)</td>
</tr>
<tr>
<td>Weighted preference</td>
<td>(0.09, 0.11, 0.13, 0.14)</td>
<td>(0.02, 0.04, 0.04, 0.05)</td>
<td>(0.13, 0.14, 0.14, 0.16)</td>
<td>(0.13, 0.14, 0.14, 0.16)</td>
</tr>
</tbody>
</table>

In next steps, the distance $d^+_i$ and $d^-_i$ of each alternative to obtain the closeness coefficient $(CC)$ 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

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>$d^+_i$</th>
<th>$d^-_i$</th>
<th>$CC_i$</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_1$</td>
<td>0.54</td>
<td>5.47</td>
<td>0.09</td>
<td>4</td>
</tr>
<tr>
<td>$R_2$</td>
<td>0.61</td>
<td>5.4</td>
<td>0.1</td>
<td>2</td>
</tr>
<tr>
<td>$R_3$</td>
<td>0.55</td>
<td>5.46</td>
<td>0.091</td>
<td>3</td>
</tr>
<tr>
<td>$R_4$</td>
<td>0.65</td>
<td>5.35</td>
<td>0.11</td>
<td>1</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Experts</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_1$</td>
<td>$R_2 &gt; R_3 &gt; R_1 &gt; R_4$</td>
</tr>
<tr>
<td>$E_2$</td>
<td>$R_2 &gt; R_3 &gt; R_1 &gt; R_4$</td>
</tr>
<tr>
<td>$E_3$</td>
<td>$R_1 &gt; R_2 &gt; R_3 &gt; R_4$</td>
</tr>
<tr>
<td>$E_4$</td>
<td>$R_4 &gt; R_2 &gt; R_3 &gt; R_1$</td>
</tr>
</tbody>
</table>

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:

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

with:

- $e$: number of insertions.
- $d$: number of deletions.
- $t$: number of substitutions.

For example, the Levenshtein distance between the sequences $p = \{12345\}$ 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 ($S^g = \{4231\}$) and individual solutions ($S^i$). We can see that $L(S^g, S^i_j) = L(S^i_1, S^i_j) = L(S^i_2, S^i_j) = 2$, which means that the difference between the three individual solutions and group solution is equal to two operations. Also, we have $L(S^i_3, S^i_j) = 0$, which confirms that the preferences of expert $E_1$ are close to the group preferences. This is due to the preferences of the expert $E_4$. 

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who has the smallest value of $H_j$, 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

<table>
<thead>
<tr>
<th>Expert</th>
<th>Ranking</th>
<th>Deviations</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_1$</td>
<td>2314</td>
<td>2</td>
</tr>
<tr>
<td>$E_2$</td>
<td>2341</td>
<td>2</td>
</tr>
<tr>
<td>$E_3$</td>
<td>1234</td>
<td>2</td>
</tr>
<tr>
<td>$E_4$</td>
<td>4231</td>
<td>0</td>
</tr>
</tbody>
</table>

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 robot 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 kompronomo nigaranje (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 provide 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.

REFERENCES


