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Logistics Center Location Selection Approach Based on Neutrosophic Multi-Criteria Decision Making

Abstract

As an important and interesting topic in supply chain management, the concept of fuzzy set theory has been widely used in logistics center location in order to improve the reliability and suitability of the logistics center location with respect to the impacts of both qualitative and quantitative factor. However fuzzy set cannot deal with the indeterminacy involving with the problem. So the concept of single – valued neutrosophic set due to Wang et al. (2010) is very helpful to deal with the problem. A neutrosophic approach is a more general and suitable approach in order to deal with neutrosophic information than fuzzy set. Logistics center location selection is a multi-criteria decision making process involving subjectivity, impresion and fuzziness that can be easily represented by single-valued neutrosophic sets. In this paper, we use the score and accuracy function and hybrid score accuracy function of single- valued neutrosophic number and ranking method for single- valued neutrosophic numbers to model logistics center location problem. Finally, a numerical example has been presented to illustrate the proposed approach.

Keywords

Logistic center, multi-criteria group decision making, hybrid score-accuracy function, single valued neutrosophic set, single valued neutrosophic number.

1. Introduction

Logistics systems have become essential for economic development and the normal function of the society, and suitable site selection for the logistics center has direct impact on the efficiency of logistics systems. So it is necessary to adopt a scientific approach for site selection. The logistic center location selection problem can be considered as multi-criteria decision making (MCDM) problem. Classical MCDM [1, 2, 3] problems deal with crisp numbers that is the ratings and the weights of the criteria are represented by crisp numbers. However, it is not always possible to present the information by crisp numbers. In order to deal this situation fuzzy set (FS) introduced by Zadeh [4] in 1965 can be used. It is very useful for many real life problems involving uncertainty. In 1986, Atanassov [5] grounded the notion of intuitionistic fuzzy set (IFS) by introducing non-membership function as independent component. However, it cannot handle indeterminacy part of the real life problems that exist in many real applications. Then in 1998, Smarandache proposed the neutrosophic set (NS) theory [6,7, 8, 9] which is the generalization of FS and IFS.

From scientific or engineering point of view, the neutrosophic set and set- theoretic view, operators need to be specified. Otherwise, it will be difficult to apply in the real applications. Therefore, Wang et al. [10] defined a single valued neutrosophic set (SVNS) and then provided the set theoretic operations and various properties of SVNS. The works on SVNS and their hybrid structure in theories and application have been progressing rapidly. Hence it is most important to conduct researches on MCDM approach based on SVNS environment. Biswas et al. [11] presented entropy based grey relational analysis method for multi-attribute decision making under SVNS. Ye [12] proposed the co-relation co-efficient of SVNSs for single-valued neutrosophic MCDM problem. While selecting the location for the logistics center not only quantitative factors likes costs, distances but also qualitative factors. Such as environmental impacts and governmental regulations should be taken into consideration. Tuzkaya et al. [13] presented an analytic network process approach to deal locating undesirable facilities. Badri [14] studied a method combinjing analytical hierarchy process (AHP) and goal programming model approach for international facility location problem. Chang and Chung [15] proposed a multi-criteria genetic optimization for distibution network problems. Liang and Wang [16] proposed a fuzzy multicriteria decision making method for facility site selection. Chu [17] proposed facility location selection using fuzzy TOPSIS under group decision. Recently, Pramanik and Dalapati [18] presented generalized neutrosophic soft multi criteria decision making based on grey relational analysis by introducing generalized neutrosophic soft weighted average operator. In this paper we present logistic center location model using score and accuracy function and hybrid score accuracy function of single-valued neutrosophic number due to Ye [19]. Finally, a numerical example has been provided to illustrate the proposed approach.

Rest of the paper has been organized in the following way. Section 2 presents preliminaries of neutrosophic sets and section 3 presents criteria for logistic center location selection. Section 4 is devoted to present modeling of logistic center location seclection problem. Section 5 presents a numerical example of the logistic center location selection problem. In Section 6 we presents conclusion.

2. Mathematical preliminaries

In this section, we will recall some basic definitions and concepts that are useful to develop the paper.

Definition 1: Neutrosophic sets [6, 7, 8, 9]

Let $\mathcal{P}$ be a universe of discourse with a generic element in $\mathcal{P}$ denoted by p. A neutrosophic set Z in $\mathcal{P}$ is characterized by a truth-membership function $t_Z(p)$, an indeterminacy-membership function $i_Z(p)$ and a falsity-membership function $f_Z(p)$ and defined by

$Z = \{ <p, t_Z(p), i_Z(p), f_Z(p)>: p \in \mathcal{P}\}$.The function $t_Z(p)$, $i_Z(p)$ and $f_Z(p)$ are real standard or nonstandard subsets of $]^-0, 1^+[$ i.e., $t_Z(p) : \mathcal{P} \rightarrow]^-0, 1^+[$,

$i_Z(u): \mathcal{P} \rightarrow]^-0, 1^+[$, and $f_Z(u) : \mathcal{P} \rightarrow]^-0, 1^+[$ Hence, there is no restriction on the sum of $t_Z(p)$, $i_Z(p)$ and $f_Z(p)$ and $^-0 \leq t_Z(p) + i_Z(p) + f_Z(p) \leq 3^+$.

Definition 2: Single valued neutrosophic sets [10].

Let $\mathcal{P}$ be a universe of discourse with a generic element in $\mathcal{P}$ denoted by p. A single valued neutrosophic set M in $\mathcal{P}$ is characterized by a truth-membership function $t_M(p)$, an indeterminacy-membership function $i_M(p)$ and a falsity-membership function $f_M(p)$. It can be expressed as $M = \{< p, (t_M(p), i_M(p), f_M(p)) >: p \in \mathcal{P}, t_M(p), i_M(p), f_M(p) \in [0, 1]\}$. It should be noted that there is no restriction on the sum of $t_M(p)$, $i_M(p)$ and $f_M(p)$. Therefore, $0 \leq t_M(p) + i_M(p) + f_M(p) \leq 3$.

Definition 3: **Single valued neutrosophic number (SVNN) [19]**

Let $\mathcal{P}$ be a universe of discourse with generic element in $\mathcal{P}$ denoted by p. A SVNS M in $\mathcal{P}$ is characterized by a truth-membership function $t_M(p)$, a indeterminacy-membership function $i_M(p)$ and a falsity-membership function $f_M(p)$. Then, a SVNS M can be written as follows: $M = \{<p, t_M(p), i_M(p), f_M(p)>: p \in \mathcal{P}\}$, where $t_M(p), i_M(p), f_M(p) \in [0, 1]$ for each point p in $\mathcal{P}$. Since no restriction is imposed in the sum of $t_M(p)$, $i_M(p)$ and $f_M(p)$, it satisfies $0 \leq t_M(p) + i_M(p) + f_M(p) \leq 3$. For a SVNS M in $\mathcal{P}$ the triple $< t_M(p), i_M(p), f_M(p) >$ is called single valued neutrosophic number (SVNN).

Definition 4: Complement of a SVNS [10]

The complement of a single valued neutrosophic set M is denoted by M′and defined as

$M' = \{<p: t_{M'}(p), i_{M'}(p), f_{M'}(p)>, p \in \mathcal{P}\}$,

where $t_{M'}(p) = f_M(p)$, $i_{M'}(p) = \{1\} - i_M(p)$, $f_{M'}(p) = t_M(p)$.

For two SVNSs M_1 and M_2 in $\mathcal{P}$, M_1 is contained in the M_2, i.e. $M_1 \subseteq M_2$, if and only if $t_{M_1}(p) \leq t_{M_2}(p)$, $i_{M_1}(p) \geq i_{M_2}(p)$, $f_{M_1}(p) \geq f_{M_2}(p)$ for any p in $\mathcal{P}$.

Two SVNSs M_1 and M_2 are equal, written as $M_1 = M_2$, if and only if $M_1 \subseteq M_2$ and $M_2 \subseteq M_1$.

2.1. Conversion between linguistic variables and single valued neutrosophic numbers

A linguistic variable simply presents a variable whose values are represented by words or sentences in natural or artificial languages. Importance of the decision makers may be differential in the decision making process. Ratings of criteria can be exressed by using linguistic variables such as very poor (VP), poor (P), good (G), very good (VG), excellent (EX), etc. Linguistic variables can be transformed into single valued neutrosophic numbers as given in the Table- 1.

2.2 Ranking methods for SVNNs

Now we recall the definition of the score function, accuracy function, and hybrid score-accuracy function of a SVNN, and the ranking method for SVNNs.

Definition 5: **Score function and accuracy function [19]**

The score function and accuracy function of the SVNN b= (t(b), i(b), f(b)) can be expressed as follows:

$S(b) = (1+t(b) - f(b))/2$ for $s(b) \in [0, 1]$ (1)

$ac(b) = (2 + t(b) - f(b) - i(b))/3$ for $h(b) \in [0, 1]$ (2)

For the score function of a SVNN b, the truth membership t(b) is bigger and the falsity-membership f(b) are smaller, than the score value of the SVNN a is greater. For the accuracy function of a SVNN b if the sum of t(b), 1-i(b) and 1-f(b) is bigger, then the statement is more affirmative, i.e., the accuracy of the SVNN b is higher. Based on score and accuracy functions for SVNNs, two theorems are stated below.

Theorem 1.

For any two SVNNs b_1 and b_2, if $b_1 > b_2$, then $s(b_1) > s(b_2)$.

Proof: See [19].

Theorem 2.

For any two SVNNs b_1 and b_2, if $s(b_1) = s(b_2)$ and $b_1 \geq b_2$, then $ac(b_1) \geq ac(b_2)$.

Prof: See [19]

Based on theorems 1 and 2, a ranking method between SVNNs can be given by the following definition.

Definition 6: [19]

Let b_1 and b_2 be two SVNNs. Then, the ranking method can be defined as follows:

1. If $s(b_1) > s(b_2)$, then $b_1 > b_2$;
2. If $s(b_1) = s(b_2)$ and $ac(b_1) \geq ac(b_2)$, then $b_1 \geq b_2$;

3. Criteria for logistics center location selection

We choose the most appropriate location on the basis of six criteria adapted from the study [20], namely, cost (K_1), distance to suppliers (K_2), dsistance to customers (K_3), conformance to governmental regulations and laws (K_4), quality of service (K_5) and environmental impact (K_6).

4. MCGDM method based on hybrid – score accuracy functions under single-valued neutrosophic environment

Assume that $B = \{B_1, \ldots, B_n\} (n \geq 2)$ be the set of logistics centers, $K = \{K_1, K_2, \ldots, K_\rho\} (\rho \geq 2)$ be the set of criteria and $E = \{E_1, E_2, \ldots, E_m\}$ $(m \geq 2)$ be the set of decision makers or experts. The weights of the decision makers and criteria are not previously assigned, where the information about the weights of the decision- makers is completely unknown and information about the weights of the criteria is incompletely known in the group decision making problem. In such a case, we develop a method based on the hybrid score – accuracy function for MCDM problem with unknown weights under single-valued neutrosophic environment using linguistic variables. The steps for solving MCGDM by proposed approach have been presented below.

Step – 1

Formation of the decision matrix

In the group decision process, if m decision makers or experts are required in the evaluation process, then the s-th (s = 1, 2,…, m) decision maker can provide the evaluation information of the alternative B_i (i = 1, ..., n) on the criterion K_j (j = 1, ..., ρ) in linguistic variables that can be expressed by the SVNN (see Table 1). A MCGDM problem can be expressed by the following decision matrix:

$$M_s = (b^s_{ij})_{n\times\rho} = \begin{pmatrix} & K_1 & K_2 & \dots & K_\rho \\ B_1 & b^s_{11} & b^s_{12} & \dots & b^s_{1\rho} \\ B_2 & b^s_{21} & b^s_{22} & & b^s_{2\rho} \\ . & . & . & \dots & . \\ B_n & b^s_{n1} & b^s_{n2} & \dots & .b^s_{n\rho} \end{pmatrix} \quad (3)$$

$B^s_{ij} = \{(K_j, t^s_{B_i}(K_j), i^s_{B_i}(K_j), f^s_{B_i}(K_j)/K_j \in K\}$

Here $0 \le t^s_{B_i}(K_j) + i^s_{B_i}(K_j) + f^s_{B_i}(K_j) \le 3$

$t^s_{B_i}(K_j) \in [0, 1], i^s_{B_i}(K_j) \in [0, 1], f^s_{B_i}(K_j) \in [0, 1]$

For s = 1, 2, ..., m, j =1, 2, … ρ, i = 1, 2, …n,

For convenience $b^s_{ij} = (t^s_{ij}, i^s_{ij}, f^s_{ij})$ is denoted as a SVNN in the SVNS B^s_{ij} (s =1, 2, ..., m, i = 1, ..., n, j = 1, ..., ρ)

Step – 2

Calculate hybrid score – accuracy matrix

The hybrid score – accuracy matrix $H^s = (h^s_{ij})_{n\times\rho}$ (s = 1, 2……, m; i = 1, 2, ..., n; j = 1, 2, …, ρ) can be obtained from the decision matrix $M_s = (b^s_{ij})_{n\times\rho}$. The hybrid score-accuracy matrix H^s expressed as

$$H^s = (h^s_{ij})_{n\times\rho} = \begin{pmatrix} & K_1 & K_2 & \dots\dots & K_\rho \\ B_1 & h^s_{11} & h^s_{12} & \dots & h^s_{1\rho} \\ B_2 & h^s_{21} & h^s_{22} & & h^s_{2\rho} \\ . & . & \dots & . & \\ B_n & h^s_{n1} & h^s_{n2} & \dots & .h^s_{n\rho} \end{pmatrix} \quad (4)$$

$$h^s_{ij} = \frac{1}{2}\alpha\,(1 + t^s_{ij} - f^s_{ij}) + \frac{1}{3}\,(1-\alpha)\,(2 + t^s_{ij} - i^s_{ij} - f^s_{ij}) \quad (5)$$

Where $\alpha \in [0, 1]$. When $\alpha = 1$ the equation (3) reduces to equation (1) and when $\alpha = 0$, the equation reduces to equation (2).

Step – 3

Calculate the average matrix

Form the obtained hybrid-score–accuracy matrix, the average matrix $H^{*}=(h^{*}_{ij})_{n\times\rho}$ (s =1, 2, ..., m; i = 1, 2, ..., n; j = 1, 2, ..., ρ) is

expressed by $$H^{*}=(h^{*}_{ij})_{n\times\rho}=\begin{pmatrix} & K_1 & K_2 & \ldots\ldots & K_\rho \\ B_1 & h^{*}_{11} & h^{*}_{12}\ldots & & h^{*}_{1\rho} \\ B_2 & h^{*}_{21} & h^{*}_{22} & & h^{*}_{2\rho} \\ . & . & \ldots & . & \\ B_n & h^{*}_{n1} & h^{*}_{n2}\ldots & & .h^{*}_{n\rho} \end{pmatrix} \quad (6)$$

Here $$h^{*}_{ij}=\frac{1}{m}\sum_{s=1}^{m}(h^{s}_{ij}) \quad (7)$$

Ye [19] defined the collective correlation co-efficient between H^{s} (s = 1, 2, ..., m) and H^{*} as follows.

$$\Omega_s=\sum_{i=1}^{n}\frac{\sum_{j=1}^{\rho}h^{s}_{ij}h^{*}_{ij}}{\sqrt{\sum_{j=1}^{\rho}(h^{s}_{ij})^2}\sqrt{\sum_{j=1}^{\rho}(h^{*}_{ij})^2}} \quad (8)$$

Step – 4

Determination decision maker's weights

In decision making situation, the decision makers may exhibit personal biases and offer unduly high or low preference values with respect to their preferred or repugnant objects. In order to deal such cases, very low weights to these false or biased opinions can be assigned. Since the "mean value" reflects the distributing center of all elements of the set, the average matrix H^{*} represents the maximum compromise among all individual decisions of the group. In this sense, a hybrid score accuracy matrix H^{s} is closer to the average one H^{*}. Then the preference value of the s-th decision maker is closer to the average value and his/her evaluation is more reasonable and more important. Therefore, the weight of the s-th decision maker is bigger. Ye [19] defined weight model for decision maker as follows:

$$\gamma_s=\frac{\Omega_s}{\sum_{s=1}^{m}\Omega_s}, \quad 0\leq\gamma_s\leq 1, \sum_{s=1}^{m}\gamma_s=1 \text{ for } s = 1, 2, \ldots, m. \quad (9)$$

Step – 5

Calculate collective hybrid score – accuracy matrix

For the weight vector $\gamma=(\gamma_1,\gamma_2,\ldots,\gamma_m)^T$ of decision makers obtained from equation (6), Ye [19] accumulates all individual hybrid score – accuracy matrix $H^s = (h_{ij}^{s})_{n\times\rho}$ (s = 1, 2,..., m; i = 1, 2, ..., n; j = 1, 2, ..., ρ) into a collective hybrid score accuracy matrix

$$H=(h_{ij})_{n\times\rho} = \begin{pmatrix} & K_1 & K_2 & \ldots\ldots & K_\rho \\ B_1 & h_{11} & h_{12}\ldots & & h_{1\rho} \\ B_2 & h_{21} & h_{22} & & h_{2\rho} \\ . & . & \ldots & . & \\ B_n & h_{n1} & h_{n2} & \ldots & .h_{n\rho} \end{pmatrix} \quad (10)$$

Here $h_{ij} = \Sigma_{s=1}^{m} \gamma_s h_{ij}^{s}$ (11)

Step – 6

Weight model for criteria

To deal decision making problem, the weights of the criteria can be given in advance in the form of partially known subset corresponding to the weight information of the criteria.

To determine weights of the critria Ye [19] introduced the following optimization model *:*

$$\text{Max } \omega = \frac{1}{n} \Sigma_{i=1}^{n} \Sigma_{j=1}^{\rho} \omega_j h_{ij} \quad (12)$$

Subject to

$\Sigma_{j=1}^{\rho} \omega_j = 1$

$\omega_j > 0$

Solving the linear programming problem (12), the weight vector of the criteria

$\omega = (\omega_1, \omega_2, ..., \omega_n)^T$ can be easily determined.

Step 7

Ranking of alternatives

In order to rank alternatives, all values can be summed in each row of the collective hybrid score-accuracy matrix corresponding to the criteria weights by the overall weight hybrid score-accuracy value of each alternative B_i (i = 1, 2, . . . , n):

$$\Psi(B_i) = \Sigma_{j=1}^{\rho} \omega^{i} h^{ij} \quad (13)$$

Based on the values of $\Psi(B_i)$ (i = 1, 2, ..., n), we can rank alternatives B_i (i = 1, 2, ..., n) in descending order and choose the best alternative.

Step – 8

End

5. Example of the Logistics Center Location Selection Problem

Assume that a new modern logistic center is required in a town. There are four location B_1 , B_2 , B_3 , B_4. A committee of four decision makers or experts namely, E_1 , E_2 , E_3 , E_4 has been formed to select the most appropriate location on the basis of six criteria adopted from the study [20], namely, cost (K_1), distance to suppliers (K_2), distance to customers (K_3), conformance to government regulation and laws (K_4), quality of service (K_5) and environmental impact (K_6). Thus the four decision makers use linguistic variables (see Table 1) to rate the alternatives with respect to the criterion and construct the decision matrices (see Table 2-5) as follows:

Table 1: *Conversion between linguistic variable and SVNNs*

	Linguistic term	*SVNNs*
1	*Very Poor(VP)*	*(.05,.95,.95)*
2	*Poor (P)*	*(.25,.75,.75)*
3	*Good (G)*	*(.50,.50,.50)*
4	*Very Good (VG)*	*(.75,.25,.25)*
5	*Excellent (EX)*	*(.95,.05,.05)*

Table 2: *Decision matrix for E_1 in the form of linguistic term.*

B_i	K_1	K_2	K_3	K_4	K_5	K_6
B_1	*VG*	*EX*	*VG*	*G*	*G*	*P*
B_2	*VG*	*G*	*G*	*EX*	*VG*	*VG*
B_3	*G*	*EX*	*EX*	*G*	*VG*	*G*
B_4	*EX*	*VG*	*G*	*EX*	*VG*	*VG*

Table 3: *Decision matrix for E_2 in the form of linguistic term.*

B_i	K_1	K_2	K_3	K_4	K_5	K_6
B_1	*VG*	*VG*	*VG*	*G*	*VG*	*P*
B_2	*EX*	*VG*	*VG*	*VG*	*P*	*P*
B_3	*P*	*EX*	*EX*	*VG*	*G*	*G*
B_4	*G*	*G*	*EX*	*VG*	*EX*	*EX*

Table 4: *Decision matrix for E_3 in the form of linguistic term.*

B_i	K_1	K_2	K_3	K_4	K_5	K_6
B_1	*VG*	*VG*	*EX*	*VG*	*VG*	*G*
B_2	*EX*	*G*	*EX*	*VG*	*EX*	*VG*
B_3	*P*	*EX*	*EX*	*VG*	*G*	*VG*
B_4	*G*	*G*	*VG*	*EX*	*EX*	*EX*

Table 5: *Decision matrix for E_4 in the form of linguistic term.*

B_i	K_1	K_2	K_3	K_4	K_5	K_6
B_1	*EX*	*VP*	*P*	*VG*	*VG*	*VG*
B_2	*G*	*G*	*EX*	*VG*	*G*	*EX*
B_3	*P*	*EX*	*VG*	*G*	*VG*	*VG*
B_4	*VG*	*VG*	*G*	*G*	*VG*	*G*

Step-1

Formation of the decision matrix

Decision matrix for E_1 in the form of SVNN

M_1 =

	K1	K2	K3	K 4	K5	K6
B1	(.75, .25, .25)	(.95, .05, .05)	(.75, .25, .25)	(.50, .50, .50)	(.50, .50, .50)	(.25,.75,.75)
B2	(.75, .25, .25)	(.50, .50, .50)	(.50, .50, .50)	(.95,.05, .05)	(.75, .25, .25)	(.75, .25, .25)
B3	(.50, .50, .50)	(.95, .05, .05)	(.95, .05, .05)	(.50, .50, .50)	(.75, .25, .25)	(.50, .50, .50)
B4	(.95, .05, .05)	(.75, .25, .25)	(.50, .50, .50)	(.95, .05, .05)	(.75, .25, .25)	(.75, .25, .25)

Decision matrix for E_2 in the form of SVNN

M_2 =

	K1	K2	K3	K4	K5	K6
B1	(.75,.25,.25)	(.75,.25,.25)	(.75,.25,.25)	(.50,.50,.50)	(.75,.25,.25)	(.25,.75,.75)
B2	(.95,.05,.05)	(.75,.25,.25)	(.75,.25,.25)	(.75,.25,.25)	(.25,.75,.75)	(.25,.75,.75
B3	(.25,.75,.75)	(.95,.05,.25)	(.95,.05,.05)	(.75,.25,.25)	(.50,.50,.50)	(.50,.50,.50)
B4	(.50,.50,.50)	(.50,.50,.50)	(.95,.05,.05)	(.75,.25,.25)	(.95,.05,.05)	(.95,.05,.05)

Decision matrix for E_3 in the form of SVNN

M_3 =

	K1	K2	K3	K4	K5	K6
B1	(.75,.25,.25)	(.75,.25,.25)	(.95,.05,.05)	(.75,.25,.25)	(.75,.25,.25)	(.50,.50,.50)
B2	(.95,.05,.05)	(.50,.50,.50)	(.95,.05,.05)	(.75,.25,.25)	(.95,.05,.05)	(.75,.25,.25)
B3	(.25,.75,.75)	(.95,.05,.05)	(.95,.05,.05)	(.75,.25,.25)	(.50,.50,.50)	(.75,.25,.25)
B4	(.50,.50,.50)	(.50,.50,.50)	(.75,.25,.25)	(.95,.05,.05)	(.95,.05,.05)	(.95,.05,.05)

Decision matrix for E_4 in the form of SVNN

M_4 =

	K1	K2	K 3	K4	K5	K6
B1	(.95,.05,.05)	(.05,.95,.95)	(.25,.75,.75)	(.75,.25,.25)	(.75,.25,.25)	(.75,.25,.25)
B2	(.50,.50,.50)	(.50,.50,.50)	(.95,.05,.05)	(.75,.25,.25)	(.50,.50,.50)	(.95,.05,.05)
B3	(.25,.75,.75)	(.95,.05,.05)	(.75,.25,.25)	(.50,.50,.50)	(.75,.25,.25)	(.75,.25,.25)
B4	(.75,.25,.25)	(.75,.25,.25)	(.50,.50,.50)	(.50,.50,.50)	(.75,.25,.25)	(.50,.50,.50)

Now we use the above method for single valued neutrophic group decision making to choice appropriate location. We take α *= 0.5 for demonstrating the computing procedure*

Step 2

Calculate hybrid score – accuracy matrix

Hybrid score- accuracy matrix can be obtained from above decision matrix using equation (5) are given below respectively.

Hybrid score-accuracy matrix for M_1

H^1 =

	K1	K2	K3	K4	K5	K6
B1	.75	.95	.75	.50	.50	.25
B2	.75	.50	.50	.95	.75	.75
B3	.50	.95	.95	.50	.75	.50
B4	.95	.75	.50	.95	.75	.75

Hybrid score-accuracy matrix for M_2

H^2 =

	K1	K2	K3	K4	K5	K6
B1	.75	.75	.75	.50	.75	.25
B2	.95	.75	.75	.75	.25	.25
B3	.25	.95	.95	.75	.50	.50
B4	.50	.50	.95	.75	.95	.95

Hybrid score-accuracy matrix for M_3

H^3 =

	K1	K2	K3	K4	K5	K6
B1	.75	.75	.95	.75	.75	.50
B2	.95	.50	.95	.75	.95	.75
B3	.25	.95	.95	.75	.50	.75
B4	.50	.50	.75	.95	.95	.95

Hybrid score-accuracy matrix for M_4

H^4 =

	K1	K2	K3	K4	K5	K6
B1	.95	.05	.25	.75	.75	.75
B2	.50	.50	.95	.75	.50	.95
B3	.25	.95	.75	.50	.75	.75
B4	.75	.75	.50	.50	.75	.50

Step – 3

Calculate the average matrix

Form the above hybrid score-accuracy matrix by using euation(7). We form the average matrix H^*

The average matrix

H^*=

	K1	K2	K3	K4	K5	K6
B1	.8000	0.625	0.675	0.625	0.6875	0.4375
B2	.7875	.5625	.7875	.8000	0.6125	0.6750
B3	.3125	.9500	.9000	.6250	.6250	0.6250
B4	.6750	.6250	.6750	.7875	.8500	.7875

The collective correlation co-efficent between H^s and H^* express follows by equation (8) :-

$$\Omega_s = \sum_{i=1}^{4} \frac{\sum_{j=1}^{6} h_{ij}^s h_{ij}^*}{\sqrt{\sum_{j=1}^{6}(h_{ij}^s)^2}\sqrt{\sum_{j=1}^{6}(h_{ij}^*)^2}}$$

$\Omega_1 = 3.907$

$\Omega_2 = 3.964$

$\Omega_3 = 4.124$

$\Omega_4 = 3.800$

Step – 4

Determination decision maker's weights

From the equation (9) we determine the weight of the four decision makers as follows :-

$\Omega_1 + \Omega_2 + \Omega_3 + \Omega_4 = 15.79509754$

$$\gamma_1 = \frac{\Omega_1}{\Omega_1 + \Omega_2 + \Omega_3 + \Omega_4}$$

$$= \frac{3.90705306}{15.79509754} = .247$$

$\gamma_2 = .251$

$\gamma_3 = .261$

$\gamma_4 = .240$

Step – 5

Calculate collective hybrid score – accuracy matrix

Hence the hybrid score-accuracy values of the different decision makers choice are aggregated by eq. (11) and the collective hybrid score-accuracy matrix can be formulated as follows:

H =

	K1	K2	K3	K4	K5	K6
B1	.798	.631	.682	.625	.688	.436
B2	.792	.563	.788	.799	.616	.673
B3	.312	.950	.902	.628	.622	.625
B4	.671	.622	.678	.792	.852	.792

Step – 6

Weight model for criteria

Assume that the information about criteria weights is incompletely known given as follows: weight vectors,

$0.1 \le \omega_1 \le 0.2$, $0.1 \le \omega_2 \le 0.2$,

$0.1 \le \omega_3 \le 0.25$, $0.1 \le \omega_4 \le 0.2$,

$0.1 \le \omega_5 \le 0.2$, $0.1 \le \omega_6 \le 0.2$

Using the linear programming model (12), we obtain the weight vector of the criteria as $\omega = [0.1, 0.1, 0.25, 0.2, 0.15, 0.2]^T$.

Step 7

Ranking of alternatives

Using euation (13) we calculate the over all hybrid score-accuracy values

$\Psi(B_i)$ *(i = 1, 2, 3, 4):*

$\Psi(B_1) = .06288$

$\Psi(B_2) = .7193$

$\Psi(B_3) = .6956$

$\Psi(B_4) = .7434$

Based on the above values of $\Psi(B_i)$ *(i = 1, 2, 3, 4) the ranking order of the locations are as follows:*

$B_4 > B_2 > B_3 > B_1$

Therefore the location B_4 *is the best location.*

Step – 8

End

6. Conclusion

In this paper we have presented modeling of logistics center location problem using the score and accuracy function, hybrid-score-accuracy function of SVNNs and linguistic variables under single-valued neutrosophic environment, where weight of the decision makers are completely unknown and the weight of criteria are incompletely known.

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