VNS Based MADM-Strategy Under Possibility Environment

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Abstract
In this paper, we propose a Variable Neighborhood Search (VNS) algorithm based on Multi-Attribute Decision-Making (MADM) strategy under possibility environment. Further, we provide a numerical example to show the applicability and rationality of the proposed MADM strategy.

Keywords MADM-Strategy · Variable neighborhood search · Possibility mean · Fuzzy set

Mathematics Subject Classification 03E72 · 40A05 · 40F05 · 40G15 · 60B10 · 60A86 · 60E05

1 Introduction
In 1965, Zadeh [1] grounded the notion of fuzzy set (FS) theory to deal with uncertainty events in the real world. Further, it has an ingressive amount of study for a different aspect. Interestingly, when felt that probability measure was unable to represent all fact of uncertainty theory, then possibility theory come into the image by Zadeh [2] in 1978. Thereafter, Dubois and Prade [3] introduced qualitative and quantitative approach to possibility theory in 1988. Kovalerchuk [4] in 2017 introduced the relationships between probability and possibility theories.
In 1997, Mladenovic and Hansen [5] proposed the Variable Neighborhood Search (VNS) algorithm, which is a framework for building heuristics based upon systematic changes of neighborhoods both in a descent phase, to find a local minimum, and in a perturbation phase, to escape from the corresponding valley. VNS algorithm represents a flexible framework for building heuristics for approximately solving combinatorial and non-linear continuous optimization problems. VNS search is the systematic change of neighborhood within a possible randomized local search algorithm that yields a simple and effective metaheuristic for combinatorial and global optimization. Contrary to the other metaheuristic based on local search methods. Rather than following a path, VNS explores more distant neighborhoods of the present solution, jumping from it to a new one and when an improvement is made. In this method, the solution’s beneficial qualities (e.g., many variables are already at their optimal value) are frequently preserved and exploited to find interesting surrounding solutions. Furthermore, to get from these adjacent solutions to local optima, a local search routine is used continuously. The variable neighborhood search algorithm is the step-wise change of neighborhood within the possible random variable. By using a distinct neighborhood sample as the value of the proposed function, it will move on to the next neighbour only when the value of the proposed function is slightly better than the first (or existing objective function) neighbour sample. Hansen and Mladenovic published Variable Neighborhood Search: Principles and Applications [6] in 2001. Hansen et al. investigated variable neighborhood search: methods and applications [7].

A VNS-algorithm heuristic has two parts: an improvement phase for potentially improving a given solution and a shaking phase for perhaps resolving local minima entrapment. The improvement phase and shaking method, as well as the neighborhood change step, are alternated until a predetermined stopping threshold is reached. VNS algorithm has successfully been applied in the field of design of experiment by finding the optimum allocation of experimental units with predictors into two treatment groups by Dash and Hore [8]. Later on, Hore [9] studied the VNS-algorithm to achieve an optimal allocation design for known covariates. At first, the concept of MAMD (Multiple Attribute Decision Making) was introduced by Hwang and Yoon [10] in their study of multiple attribute decision making methods and applications in 1981. In the field of fuzzy set theory, the MAMD was introduced by Chen, and Hwang [11] in 1992 on fuzzy multiple attribute decision making: methods and applications. After that, many authors around the globe contributed their work in this field [12–16]. Application of Neutrosophic Similarity Measures in Covid-19 [17] published by Das et al., and Separation Axioms on Spatial Topological Space and Spatial Data Analysis [18] studied by Das et al.

This twenty-first century is called the era of information. Big data refers to datasets that are not only large, but also diverse and rapidly changing, making standard tools and procedures ineffective. Huge volumes of data have become available to decision makers in the digital age. Due to the increasing rise of such data, methods to handle and extract value and information from these datasets must be investigated and given. However, decision-makers must be able to extract useful information from a wide range of constantly changing data, including everyday transactions, customer experience, and social network data. Big data analytics, which is the application of advanced analytics techniques to large amounts of data, can give such value. An introduction to
business data mining [19] has been widely studied by Olson and Shi. The notion of Optimization based data mining [20] was introduced by Shi et al. Internet of things, real-time decision making and artificial intelligence [21] analyzed by Tien in the year 2017. Afterward, Advances in Big Data Analytics [22] were studied by Shi in 2022.

In this paper, we introduce the concept of discrete possibility mean and variance. Then, in the possibility environment, we offer a MADM-strategy based on VNS. We also provide a numerical example to demonstrate the applicability and logic of our suggested MADM method.

The remaining part of this article has been split into the following sections:

In Sect. 2, we present some existing definitions and results that are relevant to the main results of this article. In Sect. 3, we introduce the notion of discrete possibility mean and variance under the possibility environment. In Sect. 4, we propose an MADM strategy based on VNS algorithm under the possibility environment. Section 5 deals with the validation of the proposed MADM strategy. In Sect. 6, a comparative study has been conducted to validate the results obtained from the proposed MADM strategy. Finally, in Sect. 7, wrap up the work presented in this article.

2 Preliminaries and Definitions

In this section, we present some definitions and results those are relevant to the main results of this article.

**Definition 2.1.** [2] Assume that $\tilde{W}$ be a fixed set. Then $N$, a fuzzy set over $\tilde{W}$ is defined as $N = \{(g, T_N(g)); g \in \tilde{W}\}$, where $T_N(g) \in [0,1]$ is the membership value of $g \in \tilde{W}$.

**Definition 2.2.** [2] Let $A$ be a fuzzy subset of $\tilde{W}$. Let $\prod_k$ be a possibility distribution associated with the variable $K$, which take the value $\tilde{W}$. Then, the possibility measure $\pi(A)$ of $A$ is defined by:

$$\text{Poss}\{K \text{ is } A\} \triangleq \prod_k(A),$$

$$\triangleq \sup_{u \in U} \{\mu_A(u) \wedge \pi_k(u)\},$$

where $\mu_A$ is the membership function for $A$.

**Definition 2.3.** [2] The possibility distribution function associated with $K$ (or the possibility distribution function of $\prod_k$) is denoted by $\pi_k$ and is defined numerically equal to the membership function of fuzzy set $F$. i.e., $\pi_k \triangleq \mu_F$, where $\pi_k(u)$ is the possibility that $k = \mu$, is equal to the grade of membership $\mu_F(u)$.

3 Possibility Mean and Variance

In this section, we procure the notion of Possibility mean and Possibility variance of discrete fuzzy numbers, and furnish few illustrative examples on them.

**Definition 3.1.** Let $F_1, F_2, \ldots, F_m$ be the $m$ different fuzzy sets together with grade of membership associated with each element for $n$ different object such as $x_1, x_2, \ldots, x_n$;
where the membership value lies between 0 to 1. The set are \( F_1 = \{(x_1, \mu_1(F_1)), (x_2, \mu_2(F_1)), \ldots, (x_n, \mu_n(F_1))\}, F_2 = \{(x_1, \mu_1(F_2)), (x_2, \mu_2(F_2)), \ldots, (x_n, \mu_n(F_2))\}, \ldots, F_m = \{(x_1, \mu_1(F_m)), (x_2, \mu_2(F_m)), \ldots, (x_n, \mu_n(F_m))\}, \) where \( \mu_i(F_j) \) be the membership value of the \( j \)th object.

Then, the possibility mean value of discrete fuzzy number for any object \( x_i \) is define as

\[
\overline{X}_i^F = \left( x_i, \frac{1}{m} \sum_{j=1}^{m} \mu_i(F_j) \right); \quad i = 1, 2, \ldots, n \quad \text{and} \quad j = 1, 2, \ldots, m \quad \text{and} \quad \frac{1}{m} \sum_{j=1}^{m} \mu_i(F_j) = \mu_i(F)
\]

Therefore, the mean value fuzzy set is \( F = \{(x_1, \mu_1(F)), (x_2, \mu_2(F)), \ldots, (x_n, \mu_n(F))\} \).

**Example 3.1.** Consider seven students in a class are denoted by \( X_1, X_2, X_3, X_4, X_5, X_6, X_7 \) and their marks in different subjects in fuzzy notation be Physics \( (P) \), Chemistry \( (C) \), Mathematics \( (M) \), Statistics \( (S) \), English \( (E) \). Let \( P, C, M, S, E \) be the fuzzy sets, where the membership value corresponding to the compatibility of marks in different subjects as follows.

\[
P = \{(x_1, 0.70), (x_2, 0.81), (x_3, 0.56), (x_4, 0.52), (x_5, 0.59), (x_6, 0.30), (x_7, 0.49)\};
C = \{(x_1, 0.48), (x_2, 0.49), (x_3, 0.76), (x_4, 0.61), (x_5, 0.66), (x_6, 0.71), (x_7, 0.72)\};
M = \{(x_1, 0.72), (x_2, 0.83), (x_3, 0.85), (x_4, 0.89), (x_5, 0.73), (x_6, 0.76), (x_7, 0.71)\};
S = \{(x_1, 0.47), (x_2, 0.78), (x_3, 0.63), (x_4, 0.67), (x_5, 0.81), (x_6, 0.81), (x_7, 0.65)\};
E = \{(x_1, 0.83), (x_2, 0.87), (x_3, 0.77), (x_4, 0.71), (x_5, 0.61), (x_6, 0.54), (x_7, 0.56)\}.
\]

Then, the mean value of discrete fuzzy number for student \( X_1 \) with respect to different subjects is.

\[
\overline{X}_1^F = (x_1, \text{sum of membership value of different subjects divided by total number of subjects}).
= (x_1, 0.648).
\]

Then, the mean value of discrete fuzzy number for all seven students is

\[
\overline{X}^F \{ (x_1, 0.65), (x_2, 0.76), (x_3, 0.71), (x_4, 0.68), (x_5, 0.68), (x_6, 0.64), (x_7, 0.63) \}.
\]

**Example 3.2.** In the above example, another types of students mark-sheets in fuzzy corresponding to different student are given below:

\[
X_1 = \{(P, 0.70), (C, 0.48), (M, 0.72), (S, 0.47), (E, 0.83)\};
X_2 = \{(P, 0.81), (C, 0.49), (M, 0.83), (S, 0.78), (E, 0.87)\};
X_3 = \{(P, 0.56), (C, 0.76), (M, 0.85), (S, 0.63), (E, 0.77)\};
X_4 = \{(P, 0.52), (C, 0.61), (M, 0.89), (S, 0.67), (E, 0.71)\};
\]
\[
X_5 = \{(P, 0.59), (C, 0.66), (M, 0.73), (S, 0.81), (E, 0.61)\};
X_6 = \{(P, 0.30), (C, 0.71), (M, 0.76), (S, 0.81), (E, 0.54)\};
X_7 = \{(P, 0.49), (C, 0.72), (M, 0.71), (S, 0.65), (E, 0.56)\}.
\]

The mean values of different subject marks obtained by students are presented as follows:
\[
\{(P, 0.57), (C, 0.63), (M, 0.78), (S, 0.69), (E, 0.70)\}.
\]

**Definition 3.2.** Let \( F_1, F_2, \ldots, F_m \) be \( m \) different fuzzy sets together with the grade of membership associated with each element for \( n \) different objects such as \( x_1, x_2, \ldots, x_n \), where the membership value lying between 0 to 1. Then, the possibility variance is defined as follows:
\[
V(x_i^F) = \frac{1}{n} \sum_{i=1}^{n} (x, \mu_i(F_i) - X_i^F)^2.
\]

Mathematically, it is denoted by \( V(F_i) = \{(x_1, V(x_1^F)), (x_2, V(x_2^F)), \ldots, (x_n, V(x_n^F))\} \).

**Definition 3.3.** Let \( F_1, F_2, \ldots, F_m \) be the \( m \) fuzzy sets containing \( n \) elements. Each fuzzy set \( F_i \) is associated with the grade of membership \( \mu_i(F_i) \in [0, 1] \), where \( i = 1, 2, 3, \ldots, n \). The square root of the variance of \( m \) different sets is said to be possibility standard deviation. Mathematically, it is denoted as follows:
\[
\sqrt{V(F_i)} = \left\{ x_1, \sqrt{V(x_1^F)}, x_2, \sqrt{V(x_2^F)}, \ldots, x_n, \sqrt{V(x_n^F)} \right\}.
\]

**Definition 3.4.** Possibility coefficient of variation is 100 times the coefficient of dispersion based on the possibility standard deviation. Mathematically, it is denoted by.
\[
P_{-C.V.} = \frac{\text{Possibility Standard Deviation}}{\text{Possibility Mean}} \times 100.
\]

**4 SVPos-N-MADM Strategy Based on VNS Algorithm:**

In this section, we develop a Single-Valued Possibility Number (SVPos-N) based MADM strategy using the Variable-Neighborhood-Search (VNS) algorithm.

In our day-to-day life, we face difficulty when we need to choose a suitable alternative from a set of possible alternatives. For that, we should have to plan a strategy to take the appropriate decision.

Let \( L = \{L_1, L_2, \ldots, L_p\} \) be the family of possible alternatives. Let \( A = \{A_1, A_2, \ldots, A_q\} \) be the family of attributes. The decision maker provides their evaluation information
for each alternative \(L_i (i = 1, 2, \ldots, p)\) against the attribute \(A_j (j = 1, 2, \ldots, q)\) in terms of SVPos-N. By utilizing all the information provided by the decision-makers, we can form a decision matrix.

The following are the steps of the proposed MADM-algorithm:

**Step 1** Formulate the decision matrix using SVPos-N.

According to the decision-maker’s evaluation information for each alternative \(L_i (i = 1, 2, \ldots, n)\) against the attributes \(A_j (j = 1, 2, \ldots, m)\), we can build a decision matrix corresponding to the membership function \(m_j(F_j)\) for each attribute.

The decision matrix (\(D_{Ma}^\) ) can be expressed as:

\[
\begin{array}{cccc}
A_1 & A_2 & \ldots & A_m \\
L_1 & (x_{11}, \mu_{11}(F)) & (x_{12}, \mu_{12}(F)) & \ldots & (x_{1m}, \mu_{1m}(F)) \\
L_2 & (x_{21}, \mu_{21}(F)) & (x_{22}, \mu_{22}(F)) & \ldots & (x_{2m}, \mu_{2m}(F)) \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
L_n & (x_{n1}, \mu_{n1}(F)) & (x_{n2}, \mu_{n2}(F)) & \ldots & (x_{nm}, \mu_{nm}(F))
\end{array}
\]

**Step 2** Determine the possibility mean of all attributes against each alternative.

Determination of the possibility mean value for each attribute is an important task for any multi-attribute decision-making model. If the possibility mean of the attributes is completely known in a MADM problem, then the decision-maker can use the possibility mean function of \(L\), which is defined as follows:

\[
F = \{(L_1, \mu_1(F)), (L_2, \mu_2(F)), \ldots, (L_n, \mu_n(F))\}.
\]

**Step 3** Select two samples.

Consider the whole alternative divided into two different parts. First part contains \(n\) alternatives and second part contains \((N-n)\) alternatives. Such as:

\[
\tilde{\mu}_r = \{(L_1, \mu_1(F)), (L_2, \mu_2(F)), \ldots, (L_n, \mu_n(F))\}.
\]

\[
\tilde{v}_s = \{(L_{(n+1)}, \mu_{(n+1)}(F)), (L_{(n+1)}, \mu_{(n+1)}(F)), \ldots, (L_n, \mu_n(F))\}, r = 1, 2, \ldots, n; s = n + 1, n + 2, \ldots, N; \text{selection of } n \text{ based on decision maker. Consider } N(\tilde{u}_r) \text{ as the neighborhood of } \tilde{u}_r.
\]

**Step 4** Determine the objective function.

In this step, the decision maker finds the objective function of the first set of alternatives and the value of the objective function calculated by \(z_1 = \text{Pos}_C.V(\tilde{\mu}_r) = \frac{\text{Possibility Standard Deviation}}{\text{Possibility Mean}} \times 100\).

**Step 5** Composition all possible neighbor of \(\tilde{u}_r\).

Composition of the neighborhood of \(\tilde{u}_r\) is denoted by \(N(\tilde{u}_{r(i)}) = \{\tilde{u}_{r(i)}, \tilde{v}_{s(j)}\}\), where \(\tilde{N}(\tilde{u}_{r(i)}) = \{\tilde{u}_r - \tilde{u}_{i}\}, i = 1, 2, \ldots, n; \text{i.e., } \tilde{u}_{r(i)} \text{ contains } (n-1) \text{ attributes.} \tilde{v}_{s(j)} \text{ is the attributes of the second sample.}

**Step 6** Determine the objective function for all allocation.
Calculate the objective function $\text{Pos}_{\text{C.V}}(\tilde{\mu}(\tilde{u}_{r(i)}))$ for all allocation and find the minimum objective function by $z_2 = \min\{\text{Pos}_{\text{C.V}}(\tilde{\mu}(\tilde{u}_{r(i)})) : i = 1, 2, \ldots, n\}$.

**Step 7** Determine the improved sample.

Compare $z_1$ and $z_2$ if $z_1 > z_2$, then take $z^* = z_2$ as the minimum one as improved sample. Otherwise, $z^* = z_1$.

**Step 8** Repetition of the Steps from 5 to 7.

In this step, we continue to repeat the steps until all the $N$th units are examined.

**Step 9** Ranking of the alternatives.

A ranking of alternatives is prepared based on the ascending order of accumulated measure values. The alternative associated with the smallest measure value among target neighborhood is the most suitable alternative.

**Step 10** End.

The flow chart of the proposed MADM-strategy is given below:

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5 Validation of the Proposed MADM-Strategy

In this section, we validate the proposed MADM-strategy by solving the following numerical example (Fig. 1).

5.1 Example 5.1. “Location Selection for Primary Health Center”

The Primary Health Centre (PHC) was established to provide rural health care, especially in India, with single physician clinics for minor treatments, which is the government-funded public health care center. PHC initiatives allow all individuals and families in a community to participate fully. At every stage of life, services are given at a cost that the community and country can afford. PHC, on the other hand, is a health approach that goes beyond the standard health-care system and focuses on social development to promote health equity. PHC encompasses all aspects of health care, involving access to services, the social environment, and lifestyle. Thus, primary healthcare and public health measurement, taken together, may be considered the cornerstones of universal health systems. The World Health Organization (WHO) elaborates on the goals of PHC as defined by three major categories, "empowering people and communities, multi-sectoral policy and action, and the cornerstone of integrated health services is primary care and important public health functions." Based on these definitions, PHC cannot only assists a person once they have been diagnosed with a sickness or disorder, but can also actively avoid such problems by comprehending the person as a whole.

This ideal model of healthcare was established in the "Amla Ata Declaration" of the International Conference on "Primary Health Care" held in Amla Ata, Kazakhstan in 1978, and has since been a basic notion of the WHO’s objective of health. The Alma-Ata Conference sparked a "Primary Health Care movement" of professionals and institutions, governments and civil society organizations, researchers, and activist movements to address the "politically, socially, and economically unacceptable" health imbalance in all countries. PHC was influenced by a variety of circumstances.
The flow chart of the proposed MADM-strategy is given below:

![Flow chart of the Proposed MADM Strategy](image)

**The National Rural Health Mission (NRHM) was launched in India under much hope and expectation, which takes special health care to areas that have weak public health indicators. The Indian Public Health Standards (IPHS) document has been revised keeping in view the changing protocols of an existing programme and introducing a new programme for non-communicable disease. Flexibility is allowed to suit the diverse needs of the state and region. The Bhore committee in 1946 gave the idea of PHC as a basic health unit to provide as close to the people as possible. The health planners in India have visualized the PHC and its sub-center as the proper infrastructure to provide health services to rural populations. To build this kind of essential**
primary health center in rural areas of India, we have to consider few attributes. To choose a plot, there are lots of things we have to take in our consideration.

The most common problems at the time of selection of a location are as follows:

(i) Number of Population Density in That Local Area;
(ii) Communication Facilities;
(iii) Availability of Electricity;
(iv) Water Facilities;
(v) Nearest Hospital Distance.

Therefore, the selection of a location to build a PHC by the government can be considered a MAMD-problem. After initializing, the screening committee selects seven major alternatives, namely $L_1, L_2, L_3, L_4, L_5, L_6$ and $L_7$ for further evaluation. For the selection of the perfect location, the decision-maker selects four attributes namely $O_1$: Number of population density in that location, $O_2$: Communication facilities, $O_3$: Availability of electricity, $O_4$: Water facility, and $O_5$: Distance of this location to the nearest government hospital.

Then, the MADM-strategy is presented as follows:

By using the evaluation information of all the alternatives given by the decision-makers, we prepare the decision matrix as follows (Table 1):

|   | $O_1$ | $O_2$ | $O_3$ | $O_4$ | $O_5$ |
|---|-------|-------|-------|-------|-------|
| $L_1$ | 0.6   | 0.5   | 0.4   | 0.3   | 0.9   |
| $L_2$ | 0.7   | 0.7   | 0.6   | 0.8   | 0.5   |
| $L_3$ | 0.8   | 0.3   | 0.8   | 0.7   | 0.5   |
| $L_4$ | 0.6   | 0.5   | 0.8   | 0.4   | 0.9   |
| $L_5$ | 0.7   | 0.6   | 0.4   | 0.6   | 0.7   |
| $L_6$ | 0.7   | 0.5   | 0.4   | 0.9   | 0.4   |
| $L_7$ | 0.6   | 0.4   | 0.3   | 0.4   | 0.8   |

By selecting the first alternative of $\tilde{\sigma}_s$, the neighborhood of $\tilde{\Sigma}_r$ is (Table 2).

By selecting the second alternative of $\tilde{\sigma}_s$, the neighborhood of $\tilde{\Sigma}_r$ is (Table 3).

By selecting the third alternative of $\tilde{\sigma}_s$, the neighborhood of $\tilde{\Sigma}_r$ is (Table 4).

The objective function Pos_C.V$(\tilde{a}_r)$ for all allocation (Table 5):

The value of the minimum objective function by $z_2 = 4.098395$.

Here, $z_1 > z_2$. Therefore, $z^* = z_2$ as the minimum one as the improved set, and repeat the process until all of the alternatives are seen.
### Table 2 Neighborhood of the first alternative

| \( \tilde{N}(\bar{u}_{r(1)}) \) | 0.54, 0.66, 0.62, 0.60 |
|-----------------------------|-----------------------------|
| \( \tilde{N}(\bar{u}_{r(2)}) \) | 0.54, 0.66, 0.60, 0.64 |
| \( \tilde{N}(\bar{u}_{r(3)}) \) | 0.54, 0.60, 0.62, 0.64 |
| \( \tilde{N}(\bar{u}_{r(4)}) \) | 0.60, 0.66, 0.62, 0.64 |

### Table 3 Neighborhood of the second alternative

| \( \tilde{N}(\bar{u}_{r(5)}) \) | 0.54, 0.66, 0.62, 0.58 |
|-----------------------------|-----------------------------|
| \( \tilde{N}(\bar{u}_{r(6)}) \) | 0.54, 0.66, 0.58, 0.64 |
| \( \tilde{N}(\bar{u}_{r(7)}) \) | 0.54, 0.58, 0.62, 0.64 |
| \( \tilde{N}(\bar{u}_{r(8)}) \) | 0.58, 0.66, 0.62, 0.64 |

### Table 4 Neighborhood of the third alternative

| \( \tilde{N}(\bar{u}_{r(9)}) \) | 0.54, 0.66, 0.62, 0.50 |
|-----------------------------|-----------------------------|
| \( \tilde{N}(\bar{u}_{r(10)}) \) | 0.54, 0.66, 0.50, 0.64 |
| \( \tilde{N}(\bar{u}_{r(11)}) \) | 0.54, 0.50, 0.62, 0.64 |
| \( \tilde{N}(\bar{u}_{r(12)}) \) | 0.50, 0.66, 0.62, 0.64 |

### Table 5 Values of the objective function of different alternatives

| Objective function | Values |
|-------------------|--------|
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(1)}) \)) | 8.264463 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(2)}) \)) | 8.674594 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(3)}) \)) | 7.200823 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(4)}) \)) | 4.098395 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(5)}) \)) | 8.60663 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(6)}) \)) | 9.103422 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(7)}) \)) | 7.453297 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(8)}) \)) | 5.46504 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(9)}) \)) | 12.59132 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(10)}) \)) | 13.20414 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(11)}) \)) | 11.49231 |
| Pos.C.V (\( \tilde{N}(\bar{u}_{r(12)}) \)) | 11.88091 |

Now, we organize the values of numerous alternatives by comparing the various objection functions, and we get \( L_5 < L_3 < L_4 < L_2 < L_6 < L_1 < L_7 \). This implies that alternative \( L_5 \) is the best location for a primary healthcare center.
6 Comparative Study

To verify the proposed result based on the VNS under possibility environment, an investigation has been conducted for the purpose of comparison with the existing MADM technique [17] (Table 6).

From Table 6, it is clear that the alternative \( L_5 \) is the most appropriate alternative in both the MADM strategies.

7 Conclusions

In the paper, we have proposed an MADM-strategy based on the VNS algorithm under the possibility environment. Further, we have validated our proposed MADM strategy by solving an illustrative numerical example to demonstrate the effectiveness of the proposed MADM-strategy.

The proposed MADM-strategy can also be used to deal with other real-life applications such as teacher selection [19], brick selection [17], medical diagnosis [20], etc.

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Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

References

1. Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353
2. Zadeh LA (1978) Fuzzy sets as a basis for a theory of possibility. Fuzzy Sets and Syst 1:3–28
3. Dubois D, Prade H (1988) Possibility theory. New York, London
4. Kovalerchuk B (2017) Relationships between probability and possibility theories. In: Kreinovich V (ed) Uncertainty modeling, studies in computational intelligence, Springer vol 6, no 83, pp 97–122
5. Mladenovic N, Hansen P (1997) Variable neighborhood search. Comput Oper Res 24:1097–1100
6. Hansen P, Mladenovic N (2001) Variable neighborhood search: Principles and applications. Eur J Oper Res 130(3):449–467
7. Hansen P, Mladenovic N, Perez J (2008) Variable neighborhood search: Methods and applications. Ann Oper Res 175(1):367–407
8. Dash P, Hore S (2016) Moving towards an optimal sample using VNS algorithm. Hacet J Math Stat 45(5):1519–1524
9. Hore S (2017) Variable neighborhood search algorithm to achieve optimal allocation design for known covariates. Biostat Biometrics Open Access J 4(1):555627
10. Hwang CL, Yoon K (1981) Multiple attribute decision making methods and applications. Springer, Berlin
11. Chen SJ, Hwang CL (1992) Fuzzy multiple attribute decision making: Methods and applications. Springer, Berlin
12. Das S, Shil B, Pramanik S (2021) SVPNS-MADM strategy based on GRA in SVPNS environment. Neutrosophic Sets Syst 47:50–65
13. Majumder P, Das S, Das R, Tripathy BC (2021) Identification of the most significant risk factor of covid-19 in economy using cosine similarity measure under svpns-environment. Neutrosophic Sets Syst 46:112–127
14. Mondal K, Pramanik S (2014) Intuitionistic fuzzy multi-criteria group decision making approach to quality-brick selection problem. J Appl Quant Methods 9(2):35–50
15. Mukherjee A, Das R (2020) Neutrosophic bipolar vague soft set and its application to decision making problems. Neutrosophic Sets Syst 32:410–424
16. Pramanik P, Mukhopadhyaya D (2011) Grey relational analysis based intuitionistic fuzzy multi criteria group decision-making approach for teacher selection in higher education. Internat J of Comput Appl 34(10):21–29
17. Das R, Mukherjee A, Tripathy BC (2021) Application of Neutrosophic Similarity Measures in Covid-19. Ann Data Sci 8(4):55–70. https://doi.org/10.1007/s40745-021-00363-8
18. Das R, Tripathy BC (2022) Separation axioms on spatial topological space and spatial data analysis. Ann Data Sci. https://doi.org/10.1007/s40745-022-00393-w
19. Olson DL, Shi Y (2007) Introduction to business data mining. McGraw-Hill/Irwin, New York
20. Shi Y, Tian YJ, Kou G, Peng Y, Li JP (2011) Optimization based data mining: theory and applications. Springer, Berlin
21. Tien JM (2017) Internet of things, real-time decision making, and artificial intelligence. Ann Data Sci 4(2):149–178
22. Shi Y (2022) Advances in big data analytics: theory, algorithm and practice. Springer, Singapore

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