On Some Information Measures of Single-Valued Neutrosophic Sets and their Application in MCDM Problems

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***Abstract*: Information measures have received more attention in recent years. In this paper, the multi-criteria decision-making (MCDM) problem based on SVNS information measures is presented. Some definitions of information measures are first introduced. These include entropy, similarity measure, , cross-entropy, Aggregation operators, cosine similarity measure, subtraction operational averaging operator, correlation coefficient and projection measure. A numerical case study (metal stamping layout selection problem) is provided in which the criteria values are described in exact (crisp) values form. Firstly, the decision matrix is fuzzified and then transformed into an SVNS- decision matrix. The result of the existing methods used in this work is compared with the published results to validate the accuracy based on the same illustrative example presented in this paper and then highlights the advantages of some methods over another method. The comparative analysis demonstrates the applicability and effectiveness of the used methods.**

Keywords: Information measures -MCDM problems -SVNS Sets – Neutrophication - Metal stamping layout selection problem.

I. INTRODUCTION

A MCDM problem is the process of finding the best alternative from all of the feasible alternatives where all the alternatives can be evaluated according to several criteria. In general, the MCDM problem includes uncertainty, imprecise, incomplete, and inconsistent information that exists in the real world. IFSs and IVIFSs can handle incomplete information, however, in real decision making, decision information is often indeterminate and inconsistent; as such, it cannot be dealt with by IFSs and IVIFSs. Therefore, Smarandache [1] and [2] originally introduced the concept of neutrosophic sets (NSs), largely from a philosophical point of view. The NSs simultaneously take into account the truth membership, the indeterminacy membership, and the falsity membership, and they are independent. However, it is difficult to apply NS in the practice of science and engineering. Therefore, Wang et al. [3] presented the notion of the single-valued neutrosophic set (SVNS), which is a subclass of NSs.

From the analysis of the literature, the information measures are very useful tools to cope with uncertainty and vagueness. On the one hand, it is known that uncertainty, incomplete, and inconsistent information exist in human decision-making. Therefore, just as FSs, IFSs, and IVIFSs, research on the information measures for SVNSs remain important. On the other hand, more and more MADM methods have been developed based on SVNSs. This paper presents some handling methods for the MCDM problem under an SVNS environment using the information measures of SVNSs.

Recently, some information measures based on the SVNS set are applied to MCDM problems Ye, J. [4], [5], [6], Peng, J.J. et al [7], Liu, P.D. [8], Xiao-hui Wu1 [9].

Entropy, similarity measures, and cross-entropy are three important research topics in the fuzzy theory, which have been widely used in information fusion systems. Entropy is very important for measuring uncertain information. Since its appearance, entropy has received great attention. Majumdar et al [10] introduced an entropy function to measure the uncertainty involved in an SVNV. Similarity measures and cross-entropy are mainly used to measure the discrimination information. Up to now, a lot of research has been done about these issues based on the Jaccard, Dice, and cosine similarity measures in vector space; Ye, J. [6] proposed three vector similarity measures between SVNSs to obtain the ranking order of all alternatives in MADM problems. To overcome the drawbacks of similarity measure Ye, J. [6] and Ye, J. [11] constructed the modified cosine similarity measures for SVNSs based on the cosine function. With the help of the distance between two SVNSs, Majumdar et al [10] presented several similarity measures for SVNSs and discussed their characteristics. Under the single-valued neutrosophic environment, Ye, J. [12] proposed across-entropy to establish a MADM method. Ye, J. [4] presented the correlation coefficient of SVNSs based on the extension of the correlation coefficient of IFSs and then defined the SVNS weighted correlation coefficient between an alternative Ai and the ideal alternative A*.

The aggregation operators are important tools for aggregating fuzzy information in decision-making problems. Two of the most common operators for aggregating arguments are the weighted arithmetic average operator and the weighted geometric average operator, which have been wildly applied to decision-making problems. Ye, J. [5] extended them to

SVNS sets for aggregating neutrosophic information in decision-making problems. Then, the ranking order of alternatives is performed through the cosine similarity measure between an alternative and the ideal alternative and the best choice can be obtained according to the measure values. Haibo Wu et al [13] discussed the relationship among entropy, similarity measure and cross-entropy of SVNS sets and their application in MCDM.

As per Rui Yong et al [14], projection measure (PM) is an appropriate method for dealing with between objects evaluated. As mentioned in the existing literature, neutrosophic projection models are useful methods for solving MCDM problems. They proposed three kinds of PM (general PM, bidirectional PM, and harmonic averaging PM) in the SVNS setting**.** In the introduced multiple attribute projection methods, the ranking order of all alternatives and the best alternative can be efficiently identified by these PMs between the ideal alternative and each alternative in MCDM problems. The bigger the measured value is, the better the alternative. Regarding existing subtraction operations of SVNS number Ye, J. [15] and Shigui Du, et al [16] firstly presented an SVNS number subtraction operational weighted arithmetic averaging operator (SVNSN -SOWAAO) as a necessary complement to the existing aggregation operator of SVNS number. Next, they developed an MCDM approach based on the SVNSN -SOWAAO for the first time**.**

Due to its ability to easily reflect the ambiguous nature of subjective judgments, SVNSs are suitable for capturing imprecise, uncertain, and inconsistent information in the multi-criteria decision analysis. Therefore, the main purposes of this paper are to present some information measures of SVNSs and to demonstrate the application of the proposed decision-making methods. A numerical example is provided to illustrate the application of the proposed method s. Finally, the result of the existing methods used in this work is compared with the published results to validate the accuracy based on the same illustrative example presented in this paper and then highlights the advantages of some methods over another method. Some conclusions and future research possibilities are provided.

II. BASIC PRELIMINARIES RELATED TO SVNS SETS

In this section, some important concepts about the theory of SVNSs, and some of the recent developments related to SVNS based decision making are recapitulated, which will be utilized in the later analysis.

SVNS set model is a special case of the general NS set where the range of each of the three membership functions are in the standard unit of the interval of [0, 1], instead of the non-standard interval of] -0, 1+ [. The SVNS model is one of the most commonly used versions of the NS model, and a lot of research related to SVNS based decision making can be found in the literature. The formal definition of the SVNS is presented below, and this is followed by the definitions of some of the important concepts and set-theoretic operations of the SVNS. Let U be a universe of discourse, with a class of elements in U denoted by x.

Definition 1. An SVNS set A is an object having the form $A = \{\langle x, (x), (x), (x)\rangle: x \in U\}$, where the functions $T, I, F : U \rightarrow]-0,\ 1+ [$ denote the truth, indeterminacy, and falsity membership functions,

respectively, of the element $x \in U$ concerning A. The membership functions must satisfy the condition $-0 \leq (x) + (x) + (x) \leq 3+$.

Definition 2. An SVNS set A is contained in another SVNS set B, if $TA\ (x) \leq TB\ (x)$, $(x) \geq IB\ (x)$, and $(x) \geq FB\ (x)$, for all $x \in U$. This relationship is denoted as $A \subseteq B$.

Definition 3. An SVNS A is an NS set that is characterized by a truth-membership function $TA(x)$, an indeterminacy-membership function $IA(x)$, and a falsity membership function $FA(x)$, where $TA\ (x)$, $IA(x)$, $FA\ (x) \in [0, 1]$. This set A can thus be written as

$$A = \{\langle x, TA\ (x), IA\ (x), FA\ (x)\rangle: x \in U\}$$

The sum of $TA\ (x)$, (x) and (x) must fulfill the condition

$0 \leq TA\ (x) + (x) + FA\ (x) \leq 3$. For an SVNS A in U, the triplet $((x), (x), (x))$ is called an SVN number.

A. Convert Crisp Data into SVNS Numbers (Neutrophication)

In MCDM problems, the initial information consists of the evaluations concerning the ratings of the alternatives concerning the criteria and the criterion weights. It can be presented by the decision matrix, which is the expert evaluation of the *i*th alternative by the *j*th criterion. Therefore, the decision matrix will have the following form:

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix}$$

Any datasets sourced from unverified sources may contain wrong information and this will affect the accuracy of the results obtained.

- *Step 1:* At this step, qualitative information xij is transformed into fuzzy numbers employing the vector normalization method (fuzzy decision matrix), which can be expressed as NXij:

$$NX_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} (x_{ij})^2}} \qquad (1)$$

- *Step 2:* At the neutrophication step, the fuzzy decision matrix (NX_{ij}) in the crisp form is converted into the SVNS decision matrix consisting of the degree of truthiness T, indeterminacy I, and falsehood F. Therefore, the neutrosophic decision matrix is calculated. To perform this action, the relationships between normalized values of the criteria NX_{ij} and SVNS number can be utilized. The conversion rule between NX_{ij} and SVNS numbers are shown in Table (1).

SVNS number$_{ij}$ = (F_{ij}, I_{ij}, T_{ij}) = $(NX_{ij}, 1 - NX_{ij}, 1\text{-}NX_{ij})$

Table 1. Neutrosophic conversion terms to rate the importance of the alternatives (Edmundas K. et al [17])

Crisp Normalized Terms	*SVNS Numbers*
Extremely good (EG)/1.0	*(1.00, 0.00, 0.00)*
Very very good (VVG)/0.9	*(0.90, 0.10, 0.10)*
Very good (VG)/0.8	*(0.80, 0.15, 0.20)*
Good (G)/0.7	*(0.70, 0.25, 0.30)*
Medium good (MG)/0.6	*(0.60, 0.35, 0.40)*
Medium (M)/0.5	*(0.50, 0.50, 0.50)*
Medium bad (MB)/0.4	*(0.40, 0.65, 0.60)*
Bad (B)/0.3	*(0.30, 0.75, 0.70)*
Very bad (VB)/0.2	*(0.20, 0.85, 0.80)*
Very very bad (VVB)/0.1	*(0.10, 0.90, 0.90)*
Extremely bad (EB)/0.0	*(0.00, 1.00, 1.00)*

Step 3: Normalize the SVNS decision matrix.

Since the attributes are of the cost and benefit types, then one can transform the **SVNS** decision matrix into the normalized **SVNS** decision matrix by transforming the cost attributes into the benefit attributes using the complement set. The complement of a neutrosophic set is denoted by and is defined by:

$$X = (F_{ij}, 1\text{-} I_{ij}, T_{ij}) \qquad (2)$$

B. Determine the Weights of Criteria

Due to the complexity and uncertainty of real-world decision-making problems, the information about criteria weights is usually completely unknown. Therefore, it is necessary to determine reasonable attribute weight for making a reasonable decision. Many methods are available to determine the completely unknown criteria weights in the MCDM problems under the SVNS environment namely, entropy method, maximizing deviation method, and optimization method. This work presents the entropy method.

1. Entropy Weights-Based Technique:

This method is integrated with the SVNS information measures and the MCDM methods for solving the problem and ranking the given alternatives. The main steps of this technique are summarized as follows:

Step 1: Calculation of the Entropy Values:

Based on the decision matrix, the value of the entropy for each criterion is calculated using Eqn. (3).

$$E_j = 1\text{-}1/n \sum_{i=1}^{m} (T_{ij}(X_i) + F_{ij}(X_i)) \,\left| 2(I_{ij}(X_i)) - 1 \right| \qquad (3)$$

Where E_j is the calculated entropy value for criterion j,

Step 2: Calculation of the degree of divergence:

The degree of divergence d_j of the average intrinsic information provided by the corresponding performance ratings on criterion C_j can be defined by using Equation (4) as:

$$d_j = (1 - E_j) \qquad (4)$$

Step 3: Calculation of the criteria weights:

The criteria weights are then calculated depending on the values of the entropy by Eqn. (5).

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{n}(1 - E_j)} \qquad (5)$$

C. Information Measures of SVNS Sets

Recently, some information measures based on the SVNS set are applied to MCDM problems. In this subsection, some definitions of SVNS information measures are presented.

1. Cross-Entropy Measure of SVNS Sets:

Cross entropy is used to judge the relation between two objects. Therefore, it can be defined as an SVNS cross-entropy for measuring the deviation of SVNS variables from an a priori one.

Ye, J. [5] extended the intuitionistic fuzzy cross-entropy to the SVNS set and proposed an SVNS cross-entropy measure In MCDM environments, the concept of ideal point has been used to help identify the best alternative in the deciding set. Although the ideal alternative does not exist in the real world, it does provide a useful theoretical construct against which to evaluate alternatives. Hence, an ideal benefit criterion value can be defined as:

$$\alpha_j^* = \langle T_j^*, I_j^*, F_j^* \rangle = \langle 1, 0, 0 \rangle \qquad (6)$$

$(j = 1, 2, \ldots, n)$ in the ideal alternative A^*.

Ye, J. [5] defined the following SVNS weighted cross entropy measure between each alternative and the ideal alternative $D_i(A^*, A_i)$ as the following:

$$D_i(A^*, A_i) = \sum_{j=1}^{n} W_j \left[\log_2 \frac{1}{\frac{1}{2}(1+T_{ij})} + \log_2 \frac{1}{1-\frac{1}{2}(I_{ij})} + \log_2 \frac{1}{1-\frac{1}{2}(F_{ij})}\right] + \sum_{j=1}^{n} W_j \left[T_{ij} \log_2 \frac{T_{ij}}{\frac{1}{2}(1+T_{ij})} + (1 - T_{ij}) \log_2 \frac{1-T_{ij}}{1-\frac{1}{2}(1+T_{ij})}\right] + \sum_{j=1}^{n} W_j \left[I_{ij} + (1 - I_{ij}) \log_2 \frac{1-I_{ij}}{1-\frac{1}{2}(I_{ij})}\right] + \sum_{j=1}^{n} W_j \left[F_{ij} + (1 - F_{ij}) \log_2 \frac{1-F_{ij}}{1-\frac{1}{2}(F_{ij})}\right] \qquad (7)$$

Therefore, the smaller the value of $D_i(A^*, A_i)$ is, the better the alternative A_i is. In this case, alternative A_i is close to the ideal alternative A^*. Through the weighted cross entropy D_i (A^*, A_i) (i = 1, 2, . . ., m) between each alternative and the ideal alternative, the ranking order of all alternatives can be determined and the best one can be easily identified as well.

2. Correlation Coefficients Measure of SVNS Sets

Correlation coefficients are an important tool to judge the relation between two objects. Ye, J. [4] defined the following SVNS weighted correlation coefficient between an alternative Ai and the ideal alternative A* as the following:

$$W_i(A_i,\ A^*) = \frac{\sum_{j=1}^{n} w_j\left[a_{ij}\cdot a_j^* + b_{ij}\cdot b_j^* + c_{ij}\cdot c_j^*\right]}{\sqrt{\sum_{j=1}^{n} w_j\left[a_{ij}^2 + b_{ij}^2 + c_{ij}^2\right]}\sqrt{\sum_{j=1}^{n} w_j\left[\left(a_j^*\right)^2 + \left(b_j^*\right)^2 + \left(c_j^*\right)^2\right]}} \quad (8)$$

The bigger the value of the weighted correlation coefficient W_i (A_i, A*) is, the better the alternative Ai is. Through the weighted correlation coefficient W_i (A_i, A*) between each alternative and the ideal alternative, the ranking order of all alternatives can be determined and the best one can be easily identified as well.

3. Aggregation Operators of SVNS Sets

The aggregation operators are important tools for aggregating fuzzy information in MCDM problems. Two of the most common operators for aggregating arguments are the weighted arithmetic average operator and the weighted geometric average operator, which have been wildly applied to decision-making problems. Ye, J. [5] extended them to SVNS sets for aggregating neutrosophic information in the MCDM problems. The ranking order of alternatives can be performed through the cosine similarity measure between an alternative and the ideal alternative or by score function and the best choice can be obtained according to the measure values. The bigger the measured value of cosine similarity is, the better the alternative A_i is, because the alternative A_i is close to the ideal alternative. The ranking order of alternatives can also be performed through the score function.

In summary, the decision procedure can be summarized as follows:

Step 1: Calculate the weighted arithmetic average values by using the following Equation:

$$F_w(A_1, A_2, \dots, A_n) = \left\langle 1 - \prod_{j=1}^{n}\left(1 - T_{Aj}(x)\right)^{wj},\ 1 - \prod_{j=1}^{n}\left(1 - I_{Aj}(x)\right)^{wj},\ 1 - \prod_{j=1}^{n}\left(1 - F_{Aj}(x)\right)^{wj} \right\rangle \quad (9)$$

Or the weighted geometric average values by using the following Equation:

$$G_w(A_1, A_2, \dots, A_n) = \left\langle \prod_{j=1}^{n} T_{Aj}^{wj}(x), \prod_{j=1}^{n} I_{Aj}^{wj}(x), \prod_{j=1}^{n} F_{Aj}^{wj}(x) \right\rangle \quad (10)$$

Step 2: Ranking the Alternatives

Step 2-1: Ranking by the Cosine Similarity Measure

Calculate the cosine similarity measure between SVNSs proposed by Ye, J. [4], the cosine similarity measure between each alternative and the ideal alternative can be defined as follows:

$$S_i(\alpha_i,\ \alpha^*) = \frac{t_i}{\sqrt{t_i^2 + i_i^2 + f_i^2}} \quad (11)$$

The bigger the measured value Si (α_i, α^*) is, the better the alternative Ai is, because the alternative Ai is close to the ideal alternative. Through the cosine similarity measure between each alternative and the ideal alternative, the ranking order of all alternatives can be determined and the best one can be easily identified as well.

Step 2-2: Ranking by the Score Function

Calculate the score function for each alternative, the score function for each alternative can be defined as follows:

$$S\ (a) = \frac{2 + Ta - Ia - Fa}{3} \quad (12)$$

The bigger the score function of the alternative A_i is, the better the alternative A_i is.

4. Subtraction Operational Weighted Arithmetic Averaging of SVNS Sets

Shigui Du, et al [16] firstly presented an SVNS number subtraction operational weighted arithmetic averaging operator (SVNSN -SOWAAO) as a necessary complement to the existing aggregation operator of SVNS number. Next, they developed an MCDM approach based on the SVNSN -SOWAAO for the first time**:**

Regarding the DM problem with the SVNS number, the decision steps are indicated as follows

Step 1: From the SVNS decision matrix, the j^{th} SVNS positive ideal solution can be determined by:

$$a_j^+ = < \max (T_{ij}), \min (I_{ij}), \min (F_{ij}) > \quad (13)$$

While the j^{th} SVNSN negative ideal solution can be determined by:

$$a_j^- = < \min (T_{ij}), \max (I_{ij}), \max (F_{ij}) > \quad (14)$$

Step 2: Two collective values d_i^+ and d_i^- • for each alternative can be obtained by the SVNS-SOWAA operator:

$$d_i^+ = \langle 1 - \prod_{j=1}^{n}\left(1 - T_{c_{ij}^+}\right)^{w_j}, \prod_{j=1}^{n}\left(I_{c_{ij}^+}\right)^{w_j}, \prod_{j=1}^{n}\left(F_{c_{ij}^+}\right)^{w_j}\rangle \quad (15)$$

$$d_i^- = \langle 1 - \prod_{j=1}^{n}\left(1 - T_{c_{ij}^-}\right)^{w_j}, \prod_{j=1}^{n}\left(I_{c_{ij}^-}\right)^{w_j}, \prod_{j=1}^{n}\left(F_{c_{ij}^-}\right)^{w_j}\rangle \quad (16)$$

Where w_j (j = 1, 2, …, n) is the attribute weight for $w_j \in [0, 1]$ and $\sum_{j=1}^{n} W_j = 1$, and the components in the SV-NNs C_{ij}^+ and C_{ij}^- contain the following forms:

$$T_{c_{ij}^+} = \begin{cases} \frac{T_{a_j^+} - T_{a_{ij}}}{1 - T_{a_{ij}}}, if\ T_{a_j^+} \geq T_{a_{ij}}\ and\ T_{a_{ij}} \neq 1 \\ 0, otherwise \end{cases} \quad (17)$$

$$I_{c_{ij}^+} = \begin{cases} \frac{I_{a_j^+}}{I_{a_{ij}}}, if\ I_{a_j^+} \leq I_{a_{ij}}\ and\ I_{a_{ij}} \neq 0 \\ 1, otherwise \end{cases} \quad (18)$$

$$F_{c_{ij}^+} = \begin{cases} \frac{F_{a_j^+}}{F_{a_{ij}}}, if\ F_{a_j^+} \leq F_{a_{ij}}\ and\ F_{a_{ij}} \neq 0 \\ 1, otherwise \end{cases} \quad (19)$$

$$T_{c_{ij}^-} = \begin{cases} \frac{T_{a_j^+} - T_{a_j^-}}{1 - T_{a_j^-}}, if\ T_{a_j^-} \leq T_{a_{ij}}\ and\ T_{a_j^-} \neq 1 \\ 0, otherwise \end{cases} \quad (20)$$

$$I_{c_{ij}^-} = \begin{cases} \frac{I_{a_{ij}}}{I_{a_j^-}}, if\ I_{a_j^-} \geq I_{a_{ij}}\ and\ I_{a_j^-} \neq 0 \\ 1, otherwise \end{cases} \quad (21)$$

$$F_{c_{ij}^-} = \begin{cases} \frac{F_{a_{ij}}}{F_{a_j^-}}, if\ F_{a_j^-} \geq F_{a_{ij}}\ and\ F_{a_j^-} \neq 0 \\ 1, otherwise \end{cases} \quad (22)$$

Step 3: For (d_i^+) and (d_i^-) calculate the score function using Eq. (12)

Step 4: The relative closeness degree of each alternative concerning the ideal solution is calculated by:

$$RCD_i = \frac{s(d_i^-)}{s(d_i^-) + s(d_i^+)} \quad for\ C_i \epsilon\ [0,1] \quad (23)$$

The larger value of C_i reveals that an alternative is closer to the ideal solution and farther from the negative ideal solution simultaneously. Therefore, all the alternatives can be ranked in descending order according to the values of C_i. The alternative with the largest value is chosen as the best one.

5. Ranking of the Alternatives Based on Projection Measure:

Rui Yong et al [14] proposed three kinds of PM (general PM, bidirectional PM, and harmonic averaging PM) in the SVNS setting**.** In the introduced multiple attribute projection methods, the ranking order of all alternatives and the best alternative can be efficiently identified by these PMs between the ideal alternative and each alternative in MCDM problems. The bigger the measured value is, the better the alternative. We can rank all alternatives and easily select the best one according to the measured values.

By applying Eq. (24) or Eq. (25) the weighted bidirectional PM or weighted harmonic averaging PM between the ideal alternative *A** and an alternative *Ai* are given, respectively, by

$$\text{BProjw}\ (S_i, S^*) = \frac{\|S_i\|_w \cdot \|S^*\|_w}{\|S_i\|_w \cdot \|S^*\|_w + \left| \|S_i\|_w - \|S^*\|_w \right| (S_i \cdot S^*)_w} \quad (24)$$

$$P_w(S_i \cdot S^*) = \frac{2(S_i \cdot S^*)_w}{\|S_i\|_w + \|S^*\|_w} \quad (25)$$

$$Where\ \ \|S_i\|_w = \sqrt{\sum_{j=1}^{n} w_j^2 \left(T_{ij}^2 + I_{ij}^2 + F_{ij}^2\right)}\ and\ \ \|S^*\|_w = \sqrt{\sum_{j=1}^{n} w_j^2 \left[\left(T_j^*\right)^2 + \left(I_j^*\right)^2 + \left(F_j^*\right)^2\right]},\ and\ \ (S_i \cdot S^*)_w = \sqrt{\sum_{j=1}^{n} w_j^2 \left(T_{ij}T_j^* + I_{ij}I_j^* + F_{ij}F_j^*\right)}\ \ for\ \ SVNSs$$

III. CASE STUDY ILLUSTRATION

In this section, a metal stamping layout selection problem is used to illustrate the validity and effectiveness of the developed method. The following case study is adapted from Singh et al [18]. They presented a strip-layout selection methodology using the digraph and matrix approach. They considered an annual production of 400,000 numbers of a blank, shown in Figure 1. Six alternative strip-layouts, shown in Figure 2, are synthesized. Five strip-layout selection attributes are identified relevant to the case, and these are: economical material utilization, die cost, stamping operational cost, required production rate, and job accuracy. Table (2) presents the alternative strip-layout data

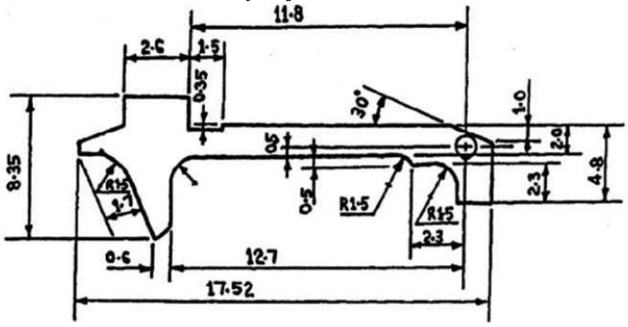

Fig. 1, Blank profile (from reference [18])

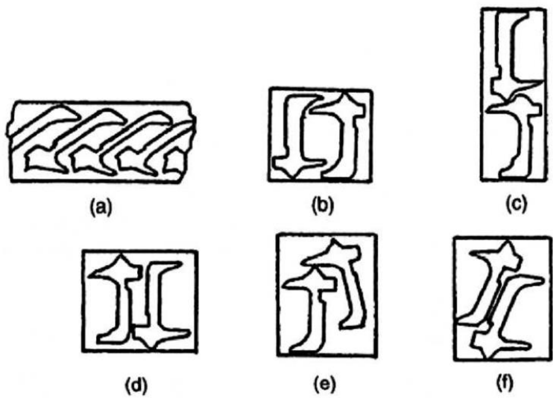

Fig. 2, Six alternative strip-layouts (from Singh and Sekhon [18])

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Table 2. Alternative strip-layout data from (Singh and Sekhon [18]; reprinted with permission from Elsevier)

Layout	C1	C2	C3	C4	C5
A1	0.26	25000	130	80	4
A2	0.4	28560	138	120	3
A3	0.33	31109	90	150	3
A4	0.32	31702	150	125	2
A5	0.31	32390	160	110	2
A6	0.31	32663	116	108	2

C1: economical material utilization, C2:die cost, C3: stamping operational cost , C4: required production rate , and C3: job accuracy.

A. Solving the Case Study (Ranking Order of the Alternatives)

1. Convert crisp Data into SVNS Numbers (Neutrosophical)

Due to high volume computing, only the final values are listed and all computations are cared out with the Microsoft Excel.

Step 1. Normalization of the decision matrix

The crisp decision matrix Table (2) needs to be converted into SVNS numbers is performed applying a vector normalization approach by using Equation (1).

Step 2. The obtained normalized decision matrix is converted into the SVNS numbers using the relationships between normalized values and SVNS numbers as presented in Table (1).

Step 3. Normalizing SVNS Decision Matrix

Since the criteria C2 and C3 are of the cost types, one can transform the SVNS decision matrix into the normalized SVNS decision matrix by transforming the cost attributes into the benefit attributes using Eq. (2).
The normalized SVNS decision matrix is listed in Table (3).

Table 3. Normalized SVNS Decision Matrix

LaLayout	C_1	C_2	C_3
A_1	(0.3273, 0.7227, 0.6727)	(0.6638, 0.2862, 0.3362)	(0.6000, 0.3500, 0.4000)
A_2	(0.5035, 0.4965, 0.4965)	(0.6159, 0.3341, 0.3841)	(0.5753, 0.3747, 0.4247)
A_3	(0.4154, 0.6346, 0.5846)	(0.5816, 0.3684, 0.4184)	(0.7230, 0.2270, 0.2270)
A_4	(0.4028, 0.6472, 0.5972)	(0.5737, 0.3763, 0.4263)	(0.5384, 0.4616, 0.4616)
A_5	(0.3902, 0.6598, 0.6098)	(0.5644, 0.3856, 0.4356)	(0.5076, 0.4924, 0.4924)
A_6	(0.3902, 0.6598, 0.6098)	(0.5607, 0.3893, 0.4393)	(0.6430, 0.3070, 0.3570)

Layout	C_4	C_5
A_1	(0.2782, 0.7718, 0.7218)	(0.5898, 0.3602, 0.4102)
A_2	(0.4173, 0.6327, 0.5827)	(0.4423, 0.6077, 0.5577)
A_3	(0.5216, 0.4784, 0.4784)	(0.4423, 0.6077, 0.5577)
A_4	(0.4347, 0.6153, 0.5653)	(0.2949, 0.7551, 0.7051)
A_5	(0.3825, 0.6675, 0.6175)	(0.2949, 0.7551, 0.7051)
A_6	(0.3756, 0.6744, 0.6244)	(0.2949, 0.7551, 0.7051)

2. Determine the Weights of Criteria using Entropy Weights Method

For the normalized **SVNS** decision matrix, the entropy value of criterion C1 can be calculated with the help of Eqn. (3):

E_1=1-(1/6)((0.3273+0.6727)│2(0.7227)-1│+ (0.5035+ 0.4965) │2 (0.4965) - 1│+ (0.4154+ 0.5846) │2 (0.6346)-1│+ (0.4028+0.5972) │2 (0.6472)-1│+(0.3902+0.6098)│2(0.6598)-1│+ (0.3902+0.6098)│2(0.6598)-1│= 06690.

The degree of divergence d_1 of the average intrinsic information provided by the corresponding performance ratings on criterion C_1 can be defined by using Equation (4) as:

$d_1 = (1 - E_1) = (1 - 0.6690)$

The same calculation steps can be performed for all criteria

$d_2 = (1 - 0.6559)$, $d_3 = (1 - 0.6850)$, $d_4 = (1 - 0.6467)$ and $d_5 = (1 - 0.5518)$

Then the entropy weight of the C_1 can be calculated with the help of Equation (5) as follows:

W_1= (1-0.6690) / ((1-0.6690) + (1-0.6559) + (1-0.6850) + (1-0.6467) + (1-0.5518)) = 0.1848

The same calculation steps can be performed for all criteria

Therefore, the weight vector of the criteria is

(W_1= 0.1848, W_2 = 0.1921, W_3 = 0.1758, W_4= 0.1972 and

W_5 = 0.2502)

3. Applying the Information Measures - Based Technique:

In this stage, some information measures are applied for solving the case study based on the normalized SVNS numbers.

1. Ranking the Alternatives Based on Cross-Entropy Measure (CEM):

With the help of Eq. (7), the cross-entropy values between an alternative A_i and the ideal alternative A* can be calculated. Due to high volume computing, only the final values are listed as follows:

CEM $_1$(A*; A_1) = 1.9652, CEM $_2$(A*, A_2) =1.8730, CEM $_3$(A*, A_3) =1.7759, CEM $_4$(A*, A_4) = 2.2575, CEM $_5$(A*, A_5) =2.3599 and CEM $_6$(A*, A_6) =2.2552

The smaller the value of CEM_i (A^*, A_i) is, the better the alternative A_i is. In this case, the alternative A_i is close to the ideal alternative A^*.

According to the cross-entropy values, thus the ranking order of the alternatives is A_3, A_2, A_1, A_6, A_4, and A_5. Hence, the best alternative is A_3 and the worst alternative is A_5.

2. Ranking the Alternatives Based on Weighted Correlation Coefficient (WCC)

By using Equation (8), one can obtain the value of the weighted correlation coefficient for each alternative as shown:

$WCC_1(A_1,A^*)$ = 0.5436 , $WCC_2(A_2,A^*)$ = 0.4399 , $WCC_3(A_3,A^*)$ = 0.6023 , $WCC_4(A_4,A^*)$ = 0.4656 , $WCC_5(A_5,A^*)$ = 0.4380 and $WCC_6(A_6,A^*)$ = 0.4649

The bigger the value of WCC_i (A_i, A^*) is, the better the alternative A_i is. In this case, the alternative A_i is connected to the ideal alternative A^*.

Therefore, the ranking order of the alternatives is A_3, A_1, A_4, A_6, A_2, and A_5. Clearly, amongst them, A_3 is the best alternative and the worst alternative is A_5.

3. Ranking by Weighted Cosine Similarity Measure (WCSM)

By applying Equation (11), one can give the value of WCSM for all alternatives

WCSM (A_1, A*) = 0.5835 , WCSM(A_2,A^*) = 0.5854 , WCSM(A_3,A^*) = 0.6150 , WCSM(A_4,A^*) = 0.4849 , WCSM(A_5,A^*) = 0.4561 and WCSM (A_6, A^*) = 0.4914

The bigger the value of WCC_i (A_i, A^*) is, the better the alternative A_i is.

Therefore, the ranking order of the alternatives is A3, A1, A4, A6, A2, and A5. Obviously, amongst them, A3 is the best alternative and the worst alternative is A5.

4. Ranking of the Alternatives Based on Aggregation Operators

The proposed method is applied to solve this problem according to the following computational procedure:

4-a . Weighted Arithmetic Average Operator

Step 1: The Weighted Arithmetic Average Operator (WAAO) for Ai can be calculated with the help of Equation (9):

$WAAO_{A1}$ = α1= (0.5186, 0.5419, 0.5320), $WAAO_{A2}$ = α2 = (0.5115, 0.5128, 0.5002), $WAAO_{A3}$ = α3 = (0.5433, 0.4944, 0.4810), $WAAO_{A4}$ = α4= (0.4484, 0.6064, 0.5741), $WAAO_{A5}$= α5 = (0.4277, 0.6251, 0.5926), $WAAO_{A6}$ = α6 = (0.4571, 0.6061, 0.5774)

Step 2- Ranking the Alternative

The ranking order of alternatives can be performed through the cosine similarity measure between an alternative and the ideal alternative or by score function and the best choice can be obtained according to the measure values.

Step 2- 1 - Ranking by Weighted Cosine Similarity Measure (WCSM):

By applying Equation (11), one can compute WCSM between an alternative A_i and the ideal alternative as follows:

$WCSM_1$ (α_1, α^*) = 0.5639, WCSM $_2$(α_2, α^*) = 0.5811, WCSM $_3$(α_3, α^*) = 0.6187, WCSM $_4$(α_4, α^*) = 0.4731, WCSM $_5$(α_5, α^*) = 0.4447 and WCSM $_6$(α_6, α^*) = 0.4792

The bigger the value of WCSM $_i$ (A_i, A^*) is, the better the alternative A_i is.

Therefore the ranking order of six alternatives is A_3, A_2, A_1, A_6, A_4, and A_5. It can be seen that the alternative A_3 is the best choice among all the alternatives.

Step 2- 2- Ranking by Score Function (SF):

With the help of Equation (12), the SF for alternative A_i can be computed as follow:

SF_1 = (2 + 0.5185 - 0.5419 - 0.5320)/ 3 = 0.4816

SF_2 = 0.4995, SF_3 = 0.5226, SF_4 = 0.4226, SF_5 = 0.4033, and SF_6 = 4245

The bigger the value of SF_i is, the better the alternative A_i is.

From the SF, the ranking order of six alternatives is A_3, A_2, A_1, A_6, A_4, and A_5. Therefore, it can be seen that the alternative A_3 is the best choice among all the alternatives.

4-b Weighted Geometric Average Operator

On the other hand, one can also utilize the Weighted Geometric Average Operator (WGAO). The WGAO for A_i can be computed by applying Equation (10):

$WGAO_{A1}$ (α_1) = (0.4680, 0.4532, 0.4814)

$WGAO_{A2}$ (α_2) = (0.4998, 0.4831, 0.4885)

$WGAO_{A3}$ (α_3) = (0.5190, 0.4464, 0.4567)

$WGAO_{A4}$ (α_4) = (0.4259, 0.5655, 0.5516)

$WGAO_{A5}$ (α_5) = (0.4074, 0.5860, 0.5723)

$WGAO_{A6}$ (α_6) = (0.4226, 0.5414, 0.5429)

With the help of Equation (11), the WCSM for alternative A_i can be used as a ranking method and computed as follows:

$WCSM_1$ (α_1, α^*) = 0.5777, $WCSM_2$ (α_2, α^*) = 0.5883, $WCSM_3$ (α_3, α^*) = 0.6307, $WCSM_4$ (α_4, α^*) = 0.4746, $WCSM_5$ (α_5, α^*) = 0.4453 and $WCSM_6$ (α_6, α^*) = 0.4827

Thus, the ranking order of six alternatives is A_3, A_2, A_1, A_6, A_4, and A_5. Accordingly, it can be seen that alternative A_3 is still the best choice among all the alternatives.

With the help of Equation (12), the score function for alternative A_i can be can be used as a ranking method and computed as following:

SF_1 = (2 + 0.4680 - 0.4532 - 0.4814)/ 3 = 0.5111, SF_2 = 0.5094, SF_3 = 0.5386, SF_4 = 0.4363, SF_5 = 0.4164 and SF_6 = 0.4461

The greater the value of SF_i (A_i, A^*) is, the better the alternative A_i is.

From the SF, the ranking order of six alternatives is A_3, A_1, A_2, A_6, A_4, and A_5. Therefore, it can be seen that the alternative A_3 is the best choice among all the alternatives.

It can be seen that the above two kinds of ranking orders and the best alternative are the same.

5. Ranking of the Alternatives Based on Subtraction Operational Aggregation Operators:

Due to high volume computing, only the final values are listed.

Step 1: The SVNS positive ideal solution and negative ideal solution can be determined using decision matrix Table (3) and Equations (13) and (14):

PIS = [(0.5035, 0.4965, 0.4965), (0.6638, 0.2862, 0.3362), (0.7230, 0.2270, 0.2770), (0.5216, 0.4784, 0.4784), (0.5898, 0.3602, 0.4102)]

NIS = [(0.3273, 0.7227, 0.6727), (0.5607, 0.3893, 0.4393), (0.5076, 0.4924, 0.4924), (0.2782, 0.7718, 0.7218), (0.2949, 0.7551, 0.7051)]

Step 2: The two collective values for the first alternative d1+, d1- can be obtained by using the Equations (15) and (16) as the following:

- The components of Equations (15) and (16) can be calculated using the forms (17-22) as follows:

$T_{C1}^{+} = 0.2620$, $I_{C1}^{+} = 0.6870$, $F_{C1}^{+} = 0.7380$, $T_{C1}^{-} = 0.0$

$I_{C1}^{-} = 1.0$, $F_{C1}^{-} = 1.0$

Substituting these components in Equations (15) and (16), the two collective values for the first alternative d_1^+, d_1^- can be obtained as the following:

$T\ d_1^+ = 0.1828$, $I\ d_1^+ = 0.7867$, $F\ d_1^+ = 0.8172$

$T\ d_1^- = 0.2002$, $I\ d_1^- = 0.7377$, $F\ d_1^- = 0.7998$

Hens, $d_1^+ = (0.1828, 0.7867, 0.8172)$ and $d_1^- = (0.2002, 0.7377, 0.7998)$

Step 3: By applying Equation (12), the score values of the first alternative S (di+) and S (di-) can be calculated as the following:

$S(d_1^+) = (2 + 0.1828 - 0.7867 - 0.8172) /3 = 0.1930$

$S(d_1^-) = (2 + 0.2002 - 0.7377 - 0.7998) /3 = 0.2209$

Step 4: By using Equation (23), the relative closeness degree of the first alternative RCD1 can be calculated as the following:

$RCD_1 = 0.2209 / (0.2209+0.1930) = 0.5337$

The same calculation steps can be performed to obtain the RCD for each alternative as shown:

$RCD_2 = 0.4756$, $RCD_3 = 0.6127$, $RCD_4 = 0.2074$, $RCD_5 = 0.1247$ and $RCD_6 = 0.2610$

Since the ranking order of the relative closeness degrees is RCD_3, RCD_1, RCD_2, RCD_6, RCD_4, and RCD_5, the ranking order of all alternatives is A_3, A_1, A_2, A_6, A_4, and A_5. Hence the best alternative is A_3.

6. Ranking of the Alternatives Based on Projection Measure:

The bidirectional PM ($BProj_w(A_1, A^*)$) and harmonic averaging PM ($P_w(A_1, A^*)$) are applied to solve the case study.

First, from the normalized SVNS decision matrix Table (3), the following ideal alternative can be determined:

A^* {(0.9, 0.1, 0.2), (0.85, 0.1, 0.1), (0.9, 0.1, 0.1), (0.85, 0.1, 0.1), (0.9, 0.1, 0.2)}.

Second, based on Eq. (24) and (25), the measure values between an alternative A_i and the ideal alternative A* can be calculated. For example, the calculations for A_1 are as follows:

$$BProj_w(A_1, A^*) = \frac{(0.4088*0.3713)}{(0.4088*0.3713)+|(0.4088-0.3713)|*0.1459} = 0.9652$$

$$Pw(A1, A^*) = \frac{(2*0.1459)}{0.4088+0.3713} = 0.3740$$

Where;

(A₁ . A*) = [(0.1848^2) * (0.3273*0.5035 + 0.7227*0.4965 + 0.6727*0.4965)+ (0.1921^2)*(0.6638*0.6638 + 0.2862*0.2862 +0.3362*0.4393)+(0.1758^2)*(0.6000*0.7230+0.3500*0.2270 +0.4000*0.2770)+(0.1972^2)*(0.2782*0.5216+0.7718*0.4784 +0.7218*0.4784)+(0.2502^2)*(0.5898*0.5898+0.3602*0.3602 + 0.4102*0.4102)]^0.5 = 0.1459

||A*||w = (0.1848^2)*(0.5035^2 + 0.4965^2 + 0.4965^2) +(0.1921^2)*(0.6638^2+0.2862^2+0.3362^2)+(0.1758^2)*(0.7230^2 + 0.2270^2 + 0.2770^2) + (0.1972^2)*(0.5216^2 + 0.4784^2 + 0.4784^2) + (0.2502^2)*(0.5898^2 + 0.3602^2 + 0.4102^2)]^0.5 = 0.3713

||A₁||w = [(0.1848^2)*(0.3273^2 + 0.7227^2 + 0.6727^2) + (0.1921^2)*(0.6638^2+0.2862^2+0.3362^2)+(0.1758^2)*(0.6000^2 + 0.3500^2 + 0.4000^2) + (0.1972^2)*(0.2782^2 + 0.7718^2 + 0.7218^2) + (0.2502^2)*(0.5898^2 + 0.3602^2 + 0.4102^2) ^0.5 = 0.4088

Thus, all the measure values between an alternative A_i and the ideal alternative A^* are obtained by similar calculations and shown in Table (4). The bigger the measured value, the better the alternative. One can rank all alternatives and easily select the best one according to the measured values.

Table 4. Decision Results of two PMs

	A1	A2	A3	A4	A5	A6	Ranking
$BProj_w$	0.9652	0.9735	0.9745	0.9486	0.9441	0.9461	A3>A2>A1>A4>A6>A5
Pw	0.3740	0.3721	0.3742	0.3677	0.3672	0.3703	A3>A1>A2>A6>A4>A5

IV. COMPARATIVE ANALYSIS

This section presents and performs a brief comparative analysis of the results that are conducted in this work and achieved using ten SVNS- information measures to solving the metal stamping layout selection problem. The result of the existing methods used in this work is compared with the published results to validate the accuracy based on the same

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illustrative example presented in this paper and then highlights the advantages of some methods over another method. The same case study is considered by Rao [19] with some traditional MCDM methods (GTMA, SAW, WPM, AHP, TOPSIS, and modified TOPSIS). Das and Srinivas [20] is demonstrated the same problem with traditional TOPSIS combined with the AHP method. The same case study is considered by Nirmal Nital [21] with three SVNS-information measures The ranking order obtained is compared with the ranking order published in the literature, and the result is shown in Table (5).

The result comparisons presented in the Table show that the results obtained by the proposed methods used in this work are relatively similar to the results reported in the literature. All methods suggested alternative A_3 is the first choice and alternative A_5 is the poorest choice except in the TOPSIS obtained by Rao [19] where alternative A_6 outranks alternative A_5.

The results show that the two top-ranked alternatives A_3 and A_2 remain unchanged in almost all the methods applied except in the WCC and Pw methods where alternative A2 outranks alternative A1 as compared to the other methods.

In Table 5, all the ranking orders of the sex alternatives given by the three different SVNS information measures applied by Nirmal Nital [21] are identical, and two methodologies (i) alternative weight and (ii) advance correlation coefficient function of alternative, work without calculating attribute weight among three proposed methodology, whereas entropy weight of alterative works with calculating attribute weight.

It can be seen that the ranking largely remains unchanged especially among the first 2 ideal alternatives and the last 2 poorest choices. The comparative analysis, therefore, confirms that no matter the changes made to the MCDM methods (crisp and/or SVNS) and weights of the criteria (traditional and/or SVNS-entropy weight method), alternatives A_5 and A_2 remains the best alternatives in the selection problems, but it is reflecting on the ranking order of alternatives. However, since the ultimate aim of the decision-making framework is to select the best alternative, changes occurring outside the best alternative are not of utmost importance.

However, it is noticed that one alternative outranks another alternative obtained by another approach. The main reason is that the one approach determines a solution that is the closest to the positive ideal solution (PIS), while the other approach determines a solution with the shortest distance from the PIS and the farthest from the NIS.

It shows that the weight criteria make a change in rank position in further ranking results, but it holds well for the first ranking purpose. Minor change occurs due to entropy weight criteria and due to different weight criteria calculation/ assumption/ expert opinion. Some methodologies work without calculating any kind of relative importance of attributes among the other methodology. Whereas all methods work with calculating attribute weight. Some methodologies work with minimum calculations. These methods show also gives better result for the last ranking solution.

From the result of the existing information measures used in this work, it is noted that:

(1) Some existing approaches used the information measures based technique proposed an SVNS weighted arithmetic average operator, subtraction operational aggregation operator, and an SVNS weighted geometric average operator, these methods need to perform an aggregation on the input SVNS arguments, which may increase the computational complexity and therefore lead to the loss of information. In contrast, some approaches do not need to perform such an aggregation but directly deal with the input SVNS arguments; thereby can retain the original decision information as much as possible.

(2) Some existing approaches proposed the similarity measures between each alternative and the ideal alternative to establishing an MCDM method. In contrast, some approaches utilize the score function. Although the same ranking results are obtained here, some information measures have less calculation and it is more flexible and more sustainable for the MCDM with SVNS information. The score function has extremely important for the process of MCDM.

Table 5. Ranking Obtained using Existing Methods

Ranking of alternatives		
Information Measures		**Ranking from Existing Methods**
CE		$A_3 > A_2 > A_1 > A_6 > A_4 > A_5$
WCC		$A_3 > A_1 > A_4 > A_6 > A_2 > A_5$
WCS		$A_3 > A_2 > A_1 > A_6 > A_4 > A_5$
WA AO	**WCS**	$A_3 > A_2 > A_1 > A_6 > A_4 > A_5$
	SF	$A_3 > A_2 > A_1 > A_6 > A_4 > A_5$
WG AO	**WCS**	$A_3 > A_2 > A_1 > A_6 > A_4 > A_5$
	SF	$A_3 > A_1 > A_2 > A_6 > A_4 > A_5$
Sub.AO		$A_3 > A_1 > A_2 > A_6 > A_4 > A_5$
Projection	**BProjw**	$A_3 > A_2 > A_1 > A_4 > A_6 > A_5$
	Pw	$A_3 > A_1 > A_2 > A_6 > A_4 > A_5$
Ranking collected from (Rao [19])		
GTMA		$A_3 > A_2 > A_1 > A_6 > A_4 > A_5$
SAW		$A_3 > A_2 > A_1 > A_4 > A_6 > A_5$
WPM		$A_3 > A_2 > A_1 > A_4 > A_6 > A_5$
AHP		$A_3 > A_2 > A_1 > A_4 > A_6 > A_5$
TOPSIS		$A_3 > A_2 > A_1 > A_4 > A_5 > A_6$
Modified TOPSIS		$A_3 > A_2 > A_1 > A_4 > A_6 > A_5$
Ranking collected from Das and Srinivas [20]		
W of Ai		$A_3 > A_2 > A_1 > A_5 > A_6 > A_4$
E.W of Ai		$A_3 > A_2 > A_1 > A_5 > A_6 > A_4$
ACC of Ai		$A_3 > A_2 > A_1 > A_5 > A_6 > A_4$
Ranking collected from Nirmal Nital [21]		
TOPSIS combined with the AHP		$A_3 > A_2 > A_1 > A_5 > A_6 > A_4$

CE: Cross Entropy, WCC: Weighted Correlation Coefficient, WCS: Weighted Cosine Similarity, WAAO: Weighted Arithmetic Average Operator, WGAO: Weighted Geometric Average Operator, SF: Score Function, Sub.AO:

Subtraction Operational Aggregation Operator, $BProj_w$: bidirectional PM, Pw: harmonic averaging PM.

V. CONCLUSIONS

SVNSs can be utilized to solve the indeterminate and inconsistent information that exists in the real world but which FSs and IFSs cannot deal with. Considering the advantages of SVNSs, several methods of SVNSs are put forward and used to solve MCDM problems.

However, there are existing information measures as discussed in the kinds of literature to solve the MCDM problems. In this paper, the main contributions are to solve a numerical case study (metal stamping layout selection problem) in which the criteria values are described in exact (crisp) values form and to use some existing information measures to rank the alternatives. Firstly, the decision matrix is fuzzified and then transformed into an SVNS- decision matrix the result of the existing methods used in this work is compared with the published results to validate the accuracy based on the same illustrative example presented in this paper and then highlights the advantages of some methods over another method. The comparative analysis demonstrates the applicability, effectiveness, and rationality of the used methods.

In the future, according to the different requirements in the real-world applications, how to optimize some information measures could form the scope of discussion and further detailed study.

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