Neutrosophic Sets and Systems, Vol. 80, 2025
University of New Mexico

Combine knowledge and similarity measure to solve Single valued Neutrosophic set MCDM problems

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Abstract: The Neutrosophics set have been paid attention of researchers using in many fields in the practice. It is a useful tool to deal with those complex problems. In this paper, we first investigat the knowledge measures on the Single neutrosophic set. Then, we introduce a new similarity measure of SNS that overcomes the restriction of some already existing similarity measure cases. A proposed measure-based multi-criteria decision-making (MCDM) model was constructed. In this model the knowledge measure to determine the weight of each criterion and similarity measure to rank the alternatives. This model applied to solve the agricultural land selection. Finally, the comparison results are presented to illustrate the effectiveness of the proposed method.

Keywords: SNS; similarity; MCDM; Knowledge measure

1. Introduction

In the real world, a lot of uncertainty exists to serve in decision-making problems. For instance, information gathered about a subject or the decision maker's knowledge is incomplete. To deal with such uncertain situations, fuzzy sets and intuitionistic fuzzy sets have proven as useful tools [27]. By the complexity and the continuous improvements of many fields in the practices, the fuzzy sets, intuitionistics sets cannot represent enough information. The single Neutrosophic set proposed by Smarandache [23] to overcome this limitation. In the environment of SNS, three membership $T_A(x), I_A(x), F_A(x)$ are valued in $[0,1]$ for all x in X. The SNS is the extension of fuzzy sets, intuitionistic fuzzy sets ([4], [5], [12], [20]) to deal with the uncertain information ([1], [3], [6], [7], [8], [9]). The neutrosophic set have been recognized effective tool and applied in many fields ([13], [22-24]). In addition, much attention has generalized functions and measure using Neutrosophics numbers to deal with decision making problems. Broumi and Smarandache [6] gave some similarity measures to solve MCDM problem using Hausdorff distance. Huang [10] built the distance SNS for clustering analysis problem. Kharal [14] proposed the novel score functions of SNS to deal with MCDM problems. Liu et al. [15] proposed some new aggregation operators to MCDM. Thao & Smarandache [31] pioneered introduced the divergence measure of SNS and applied to the medical diagnosis. The entropy and similarity measures are effectively function in MCDM model.

They are generalized on the SNS set and widely applied ([16], [34]). We can mention some outstanding results in [16], [21], [35-38]).

The motivation and novelties of this study: The knowledge measure of fuzzy set is used to evaluate the degree of fuzziness of the fuzzy set. If a data set having high degree of fuzziness, then the knowledge about it is low, while conversely, if the degree of fuzziness is low, then the knowledge about the data is high. Some similarity measures were proposed based on knowledge measure on intuitionistic fuzzy sets ([11], [17]). It is effective to determine the weight of criteria or rank the alternatives in MCDM model [11]. Tan and Chen [27] pointed out that there are always counter examples that demonstrate the ineffectiveness of similarity measures in some cases based on the analysis of most published studies. But, the knowledge measure of SNS is not found in any the existing works. It is a gap in the study about neutrosophic set. In the MCDM model based Single neutrosophic set the knowledge measures of SNS is using to determine the weight of each criterion.

On the other hand, neutrosophic is an extension of fuzzy sets, intuitionistic sets, so similarity measures on SNS are effective tools in MCDM problems. This motivates us to construct a new similarity measure between NSs, and providing reliable results. At the same time, to check the effectiveness, we make some comparisons with previous measures.

Population growth increases pressure on both natural and agricultural resources. This can lead to degradation of available land resources [2]. Therefore, there is a need for planning and evaluating land areas suitable for each subject and goal towards sustainable growth. If self-sufficiency in agricultural production is to be achieved in developing and transitional countries, land evaluation techniques will be necessary to develop models to predict the suitability of land for different types of agriculture. In which, multi-criteria decision-making model is one of the effective methods. This motivates us to construct an MCDM model to select agricultural land in order to illustrate our measure.

The contributions of this paper in terms of some aspects (Figure 1).

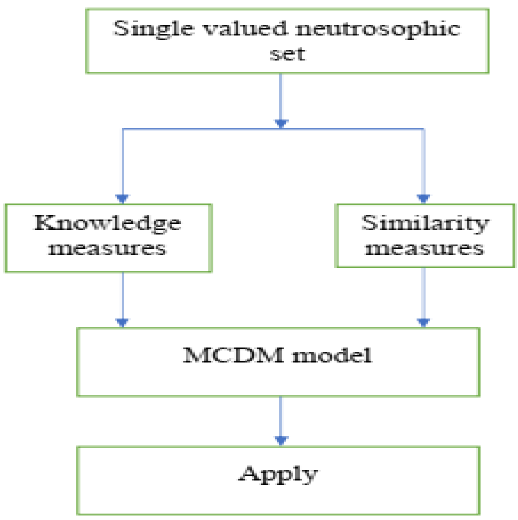

Figure 1. The flow chart of works in this study

Firstly, we construct the knowledge measure of SNS. It is used to determine the weight of the criteria. Secondly, the paper introduces a new similarity measure of the SNS set. Thirdly, we compare the proposed similarity measure to other similarity measures. Finally, we propose the TOPSIS model based on new measures to choose the best option for agricultural land selection and compare the proposed TOPSIS to some other models.

The rest of the paper is organized as follows: some concepts in SNS are introduced in section 2. The SNS's new measure (knowledge measures of SNS) is introduced in section 3. The similarity measures of SNS is proposed in section 4, in this section, we also analysis the new similarity with the existing similarity measures of SNS. The knowledge measure and new similarity measure-based TOPSIS model was applied to the agricultural land selection is shown in section 5. Next, we discuss about the ranking results of new model with other MCDM models in section 6. Finally, we give out the conclusion of this work.

2. Preliminary

In this section, the concept of SNS and their similarity measures are mentioned as follows

Definition 1. ([33]) In the universal set, a SNS A structure by three functions $T_A, I_A, F_A : X \to [0,1]$ named truth-membership, indeterminacy-membership, and falsity-membership function, respectively, such that $T_A(x)+I_A(x)+F_A(x) \le 3$ for all $x \in X$.

We denoted $A=\{(x,T_A(x),I_A(x),F_A(x)) \mid x \in X\}$ is a SNS A in X. The collection of SNS on X is denoted by $SNS(X)$.

For $A, B \in SNS(X)$ and for all $x \in X$, some operator is mentioned as follows:

- Complement of a SNS A: $\overline{A}=\{(x,F_A(x),1-I_A(x),T_A(x)) \mid x \in X\}$
- $A \subseteq B$ iff $T_A(x) \le T_B(x)$, $I_A(x) \ge I_B(x)$ and $F_A(x) \ge F_B(x)$ for all $x \in X$.
- $A = B$ iff $A \subseteq B$ and $B \subseteq A$.

IF $A \in SNS(X)$, then triple $(T_A(x), I_A(x), F_A(x))$ named a single valued neutrosophic number (SNN) and denoted by $a=(t_A, i_A, f_A)$.

- For $\lambda \in R^+$, we have:

$$\lambda a = \left(1-(1-t_A)^\lambda, i_A^\lambda, f_A^\lambda\right)$$

$$a^\lambda = \left(t_A^\lambda, 1-(1-i_A)^\lambda, 1-(1-f_A)^\lambda\right).$$

Now, we consider the universal set $X=\{x_1, x_2, ..., x_n\}$.

Now, we define the similarity measure on $SNS(X)$. It is often used to rank the alternatives in the MCDM problem.

Definition 2. ([6]) A function $S: SNS(X)^2 \to [0,1]$ is a similarity measure on $SNS(X)$, if it fulfills the following conditions:

(s1) $S(A,B) = S(B,A)$

(s2) $S(A,B) = 1$ iff $A = B$

(s3) If $A \subset B \subset C$ then $S(A,C) \le \min\{S(A,B), S(B,C)\}$, for all $A, B, C \in SNS(X)$.

The similarity measures are useful to handle the degree of similarity between alternatives, calculate the close alternatives and ranking to make decisions. The typical measurements are shown below.

+ Ye's similarity measures of SNSs ([35- 39]). Given $A, B \in SVNS(X)$:

- Cosine similarity measure

$$S_C(A,B) = \frac{1}{n}\sum_{i=1}^{n} \frac{T_A(x_i)T_B(x_i) + I_A(x_i)I_B(x_i) + F_A(x_i)F_B(x_i)}{\sqrt{T_A^2(x_i) + I_A^2(x_i) + F_A^2(x_i)}\sqrt{T_B^2(x_i) + I_B^2(x_i) + F_B^2(x_i)}} \tag{1}$$

- Dice similarity measure

$$S_D(A,B) = \frac{1}{n}\sum_{i=1}^{n} \frac{2(T_A(x_i)T_B(x_i) + I_A(x_i)I_B(x_i) + F_A(x_i)F_B(x_i))}{T_A^2(x_i) + I_A^2(x_i) + F_A^2(x_i) + T_B^2(x_i) + I_B^2(x_i) + F_B^2(x_i)} \tag{2}$$

- Jicard similarity measure

$$S_J(A,B) = \frac{1}{n}\sum_{i=1}^{n} \frac{T_A(x_i)T_B(x_i) + I_A(x_i)I_B(x_i) + F_A(x_i)F_B(x_i)}{\begin{bmatrix} T_A^2(x_i) + I_A^2(x_i) + F_A^2(x_i) + T_B^2(x_i) + I_B^2(x_i) + F_B^2(x_i) \\ -(T_A(x_i)T_B(x_i) + I_A(x_i)I_B(x_i) + F_A(x_i)F_B(x_i)) \end{bmatrix}} \tag{3}$$

- Cosine functions-based similarity measure

$$SCOS_1(A,B) = \frac{1}{n}\sum_{i=1}^{n} \cos\left\{\frac{\pi}{2} \max\left\{|T_A(x_i) - T_B(x_i)|, |F_A(x_i) - F_B(x_i)|, |I_A(x_i) - I_B(x_i)|\right\}\right\} \tag{4}$$

$$SCOS_2(A,B) = \frac{1}{n}\sum_{i=1}^{n} \cos\left\{\frac{\pi}{6} sum\left\{|T_A(x_i) - T_B(x_i)|, |F_A(x_i) - F_B(x_i)|, |I_A(x_i) - I_B(x_i)|\right\}\right\} \tag{5}$$

- Tangent functions -based similarity measure

$$ST_1(A,B) = 1 - \frac{1}{n}\sum_{i=1}^{n} \tan\left\{\frac{\pi}{4} \max\left\{|T_A(x_i) - T_B(x_i)|, |F_A(x_i) - F_B(x_i)|, |I_A(x_i) - I_B(x_i)|\right\}\right\} \tag{6}$$

$$ST_2(A,B) = 1 - \frac{1}{n}\sum_{i=1}^{n} \tan\left\{\frac{\pi}{12} sum\left\{|T_A(x_i) - T_B(x_i)|, |F_A(x_i) - F_B(x_i)|, |I_A(x_i) - I_B(x_i)|\right\}\right\} \tag{7}$$

- Cotangent functions -based similarity measure

$$SCOT_1(A,B) = \frac{1}{n}\sum_{i=1}^{n} \cot\left\{\frac{\pi}{4} + \frac{\pi}{4} \max\left\{|T_A(x_i) - T_B(x_i)|, |F_A(x_i) - F_B(x_i)|, |I_A(x_i) - I_B(x_i)|\right\}\right\} \tag{8}$$

$$SCOT_2(A,B)=\frac{1}{n}\sum_{i=1}^{n}\cot\left\{\frac{\pi}{4}+\frac{\pi}{12}sum\left\{\left|T_A(x_i)-T_B(x_i)\right|,\left|F_A(x_i)-F_B(x_i)\right|,\left|I_A(x_i)-I_B(x_i)\right|\right\}\right\} \quad (9)$$

+ Ye's measure ([31], [32]).

$$SY_1(A,B)=1-\frac{1}{3n}\sum_{i=1}^{n}\left\{\left|T_A(x_i)-T_B(x_i)\right|+\left|F_A(x_i)-F_B(x_i)\right|+\left|I_A(x_i)-I_B(x_i)\right|\right\} \quad (10)$$

$$SY_2(A,B)=1-\frac{1}{3n}\sum_{i=1}^{n}\left\{\left|T_A(x_i)-T_B(x_i)\right|^2+\left|F_A(x_i)-F_B(x_i)\right|^2+\left|I_A(x_i)-I_B(x_i)\right|^2\right\}^{\frac{1}{2}} \quad (11)$$

$$SY_3(A,B)=\frac{1-\frac{1}{3}\sum_{i=1}^{n}\left\{\left|T_A(x_i)-T_B(x_i)\right|+\left|F_A(x_i)-F_B(x_i)\right|+\left|I_A(x_i)-I_B(x_i)\right|\right\}}{1+\frac{1}{3}\sum_{i=1}^{n}\left\{\left|T_A(x_i)-T_B(x_i)\right|+\left|F_A(x_i)-F_B(x_i)\right|+\left|I_A(x_i)-I_B(x_i)\right|\right\}} \quad (12)$$

+ Ye and Du's measure in ([38]).

$$SYD(A,B)=1-\frac{1}{n}\sum_{i=1}^{n}\max\left\{\left|T_A(x_i)-T_B(x_i)\right|,\left|F_A(x_i)-F_B(x_i)\right|,\left|I_A(x_i)-I_B(x_i)\right|\right\} \quad (13)$$

+ Thao and Smarandache ([31]).

$$S_T(A,B)=1-\frac{1}{4n}\sum_{i=1}^{n}\left[\left|T_A(x_i)-T_B(x_i)\right|+2\left|I_A(x_i)-I_B(x_i)\right|+\left|F_A(x_i)-F_B(x_i)\right|\right] \quad (14)$$

$$S_{MT}(A,B)=\frac{1}{n}\sum_{i=1}^{n}\frac{\min\left[1+\left|T_A(x_i)-T_B(x_i)\right|,1+\left|I_A(x_i)-I_B(x_i)\right|,1-\left|I_A(x_i)-I_B(x_i)\right|,1+\left|F_A(x_i)-F_B(x_i)\right|\right]}{\max\left[1+\left|T_A(x_i)-T_B(x_i)\right|,1+\left|I_A(x_i)-I_B(x_i)\right|,1-\left|I_A(x_i)-I_B(x_i)\right|,1+\left|F_A(x_i)-F_B(x_i)\right|\right]} \quad (15)$$

+ Qin and Wang's measure in ([21])

$$S_{QW}(A,B)=\frac{1}{n}\sum_{i=1}^{n}sqw(i) \quad (16)$$

where $sqw(i)=\begin{cases}1-\dfrac{\left|I_A(x_i)-I_B(x_i)\right|}{2} & \text{if } T_A(x_i)=T_B(x_i),F_A(x_i)=F_B(x_i)\\ \dfrac{2-\left|T_A(x_i)-T_B(x_i)\right|-\left|F_A(x_i)-F_B(x_i)\right|}{4} & otherwise\end{cases}$

for all $x_i\in X$.

3. Knowledge measure of SNS

Let $X=\{x_1,x_2,...,x_n\}$ be a universal set, given $A\in SNS(X)$. The knowledge measure of SNS A is determined by the Eq.(17).

$$K_{TH}(A)=\frac{2}{3n}\sum_{i=1}^{n}\left[\left|T_A(x_i)-F_A(x_i)\right|+\frac{\left|2I_A(x_i)-1\right|}{1+\left|2I_A(x_i)-1\right|}\right] \quad (17)$$

Example 1. For a SNS $A=\{(x_1,0.4,0.5,0.7),(x_2,1,0.8,0.7)\}$,

The knowledge measure of SNS A is $K_{TH}(A)=\frac{2}{3\times 2}\left[\begin{array}{l}\left(|0.4-0.7|+\frac{2|2\times 0.5-1|}{1+|2\times 0.5-1|}\right)\\+\left(|1-0.7|+\frac{2|2\times 0.8-1|}{1+|2\times 0.8-1|}\right)\end{array}\right]=0.45$.

It is easy to verify the following properties of knowledge measure of SNS:

Property 1. $K_{TH}(A)=1$ if A is crisp set.

Property 2. $K_{TH}(A)=0$ if $A=\{(x_i,T_A(x_i),0.5,T_A(x_i))\,|\,x_i\in X\}$

Property 3. $K_{TH}(A)=K_{TH}(A^C)$ for all $A\in SNS(X)$.

Theses properties are axioms to determine the knowledge measure of SNS. This is a kind of new measure on SNS. In assessing the quality of information. From the nature of knowledge measures, we see that if the information is clear, the value of knowledge measures is high, on the contrary, if the information is ambiguous, the value of knowledge measures is low. Therefore, we can use this measure to assess the weight of criteria in the MCDM model.

4. New similarity measures of SNS

In this section, we introduce a new similarity measure of SNS. Let $X=\{x_1,x_2,...,x_n\}$ be a universal set, given $A,B\in SNS(X)$. We consider a new function $S:\mathrm{SN}S(\mathrm{X})^2\to[0,1]$ by

$$S_{TH}(A,B)=1-\frac{1}{3n}\sum_{i=1}^{n}\left[|T_A(x_i)-T_B(x_i)|+\frac{2|I_A(x_i)-I_B(x_i)|}{1+|I_A(x_i)-I_B(x_i)|}+|F_A(x_i)-F_B(x_i)|\right] \quad (18)$$

for all $x_i\in X$.

Theorem 1. The Eq.(18) determine a similarity measure of two SNS sets.

Proof

For all $A,B\in SNS(X)$, we have $0\le|T_A(x_i)-T_B(x_i)|\le 1$,

$0\le\frac{2|I_A(x_i)-I_B(x_i)|}{1+|I_A(x_i)-I_B(x_i)|}\le 1$, $0\le|F_A(x_i)-F_B(x_i)|\le 1$ for all $x_i\in X$ then $0\le S_{TH}(A,B)\le 1$.

(s1) It is easy to see that $S_{TH}(A,B)=S_{TH}(A,B)$ for all $A,B\in SNS(X)$.

(s2) If $A=B$ we have $|T_A(x_i)-T_B(x_i)|=0$, $|I_A(x_i)-I_B(x_i)|=0$ and $|F_A(x_i)-F_B(x_i)|=0.$ So that $S_{TH}(A,B)=1$ if $A=B$.

(s3) For all $A,B,C\in SNS(X)$ and $A\subseteq B\subseteq C,$ we have $T_A(x_i)\le T_B(x_i)\le T_C(x_i),$ $I_A(x_i)\ge I_B(x_i)\ge I_C(x_i)$ and $F_A(x_i)\ge F_B(x_i)\ge F_C(x_i)$ for all $x_i\in X$. Because of the increased monotony of the functions $f(a)=a$ and $g(a)=\dfrac{2a}{1+a}$ (for all $a\in[0,1]$). These imply that

$$\max\{|T_A(x_i)-T_B(x_i)|,|T_B(x_i)-T_C(x_i)|\}\le|T_A(x_i)-T_C(x_i)|,$$

$$\max\left\{\frac{2|I_A(x_i)-I_B(x_i)|}{1+|I_A(x_i)-I_B(x_i)|},\frac{2|I_B(x_i)-I_C(x_i)|}{1+|I_B(x_i)-I_C(x_i)|}\right\}\le\frac{2|I_A(x_i)-I_C(x_i)|}{1+|I_A(x_i)-I_C(x_i)|},$$

$$\max\{|F_A(x_i)-F_B(x_i)|,|F_B(x_i)-F_C(x_i)|\}\le|F_A(x_i)-F_C(x_i)|$$

for all $x_i\in X$. So that

$$S_{TH}(A,C)=1-\frac{1}{3}\left[|T_A(x_i)-T_C(x_i)|+\frac{2|I_A(x_i)-I_C(x_i)|}{1+|I_A(x_i)-I_C(x_i)|}+|F_A(x_i)-F_C(x_i)|\right]$$

$$\le S_{TH}(A,B)=1-\frac{1}{3}\left[|T_A(x_i)-T_B(x_i)|+\frac{2|I_A(x_i)-I_B(x_i)|}{1+|I_A(x_i)-I_B(x_i)|}+|F_A(x_i)-F_B(x_i)|\right]$$

and

$$S_{TH}(A,C)=1-\frac{1}{3}\left[|T_A(x_i)-T_C(x_i)|+\frac{2|I_A(x_i)-I_C(x_i)|}{1+|I_A(x_i)-I_C(x_i)|}+|F_A(x_i)-F_C(x_i)|\right]$$

$$\le S_{TH}(B,C)=1-\frac{1}{3}\left[|T_B(x_i)-T_C(x_i)|+\frac{2|I_B(x_i)-I_C(x_i)|}{1+|I_B(x_i)-I_C(x_i)|}+|F_B(x_i)-F_C(x_i)|\right]$$

This means that $S(A,C)\le\min\{S(A,B),S(B,C)\}$ for all $A\subseteq B\subseteq C$. □

In general that, with $\omega=(\omega_1,\omega_2,...,\omega_n)$ is the vector weight $(\omega_i\ge0,\sum_{i=1}^{n}\omega_i=1)$ on X we obtain a general similarity measure is defined by

$$S_{TH}^{\omega}(A,B)=\sum_{i=1}^{n}\omega_i\times\left\{1-\frac{1}{3}\left[|T_A(x_i)-T_B(x_i)|+\frac{2|I_A(x_i)-I_B(x_i)|}{1+2|I_A(x_i)-I_B(x_i)|}+|F_A(x_i)-F_B(x_i)|\right]\right\}\qquad(19)$$

Theorem 2. The Eq.(19) determines a similarity measure of two SNS sets.
Proof. The proof is similar Theorem 1. □

The effectiveness of the proposed measure

To evaluate the effectiveness of the proposed measure, we compare the proposed measure with some existing measures in classification problems. Given m patterns $\{A_1, A_2, ..., A_m\}$ in the form of SNS on $X = \{x_1, x_2, ..., x_n\}$. Having C is a new SNS sample on $X = \{x_1, x_2, ..., x_n\}$.

Question: What pattern does C belong to?

To solve this problem, we first compute $S(A_i, C)$ ($i = 1, 2, ..., m$). Then, C belongs to pattern A_{i*} having $S(A_{i*}, C) = \max\{S(A_i, C) \mid i = 1, 2, ..., m\}$. We compare new similarity with some existing measures.

Example 2. First of all, we can easy that the similarity measures $S_C(A, B)$, $S_D(A, B)$ and $S_J(A, B)$ is non-determine when $A = \{(x, 0, 0, 0)\}$ and $B = \{(x, 0, 0, 0)\}$. Meanwhile, in this case, we have

$SCOS_1(A, B) = SCOS_2(A, B) = ST_1(A, B) = ST_1(A, B) = SCOT_1(A, B)$
$= SCOT_2(A, B) = SY_1(A, B) = SY_2(A, B) = SY_3(A, B) = SYD(A, B) = S_{MT}(A, B) = S_T(A, B)$
$= S_{QW}(A, B) = S_{TH}(A, B) = 1.$ It means that, in this case, the similarity measures $S_C(A, B)$, $S_D(A, B)$ and $S_J(A, B)$ are not shown the similar measure on $A = \{(x, 0, 0, 0)\}$ and $B = \{(x, 0, 0, 0)\}$, but other similarity measures (including the proposed measure) are shown that A, B are similar.

Example 3. Given two patterns SNSs on $X = \{x_1, x_2\}$ and two neutrosophic sets $A_1 = \{(x_1, 0.7, 0.3, 0.3), (x_2, 0.5, 0.2, 0.3)\}$, $A_2 = \{(x_1, 0.3, 0.6, 0.7), (x_2, 0.3, 0.4, 0.5)\}$. Let a new sample $C = \{(x_1, 0.5, 0.4, 0.5), (x_2, 0.4, 0.3, 0.4)\}$ on *X*. We will check which set C belong to using similarity measures.

Then, Table 1 gives the classification results based on similarity measures. In this case, we see that only the cosine similarity measure S_C having decision C belongs to pattern A_2; five similarity measures $SCOS_1$, ST_1, $SCOT_1$, SYD and S_{QW} shown that we non-determine which pattern (A_1 or A_2) that C belongs to; but our proposed measure and ten other similarity measures shown that C belongs to pattern A_1. This obtains that we can put C belongs to pattern A_1.

Table 1. The classification results

Measures	The results from C to	Classification results

	A_1	A_2	
$S_C(A_i, C)$ (in the Eq.(1))	0.9475	**0.9556**	A_2
$S_D(A_i, C)$ (in the Eq.(2))	**0.9472**	0.9460	A_1
$S_J(A_i, C)$ (in the Eq.(3))	**0.9000**	0.8983	A_1
$SCOS_1(A_i, C)$ (in the Eq.(4))	0.9694	0.9694	Non-determine
$SCOS_2(A_i, C)$ (in the Eq.(5))	**0.9768**	0.9694	A_1
$ST_1(A_i, C)$ (in the Eq.(6))	0.8815	0.8815	Non-determine
$ST_2(A_i, C)$ (in the Eq.(7))	**0.8948**	0.8815	A_1
$SCOT_1(A_i, C)$ (in the Eq.(8))	0.7903	0.7903	Non-determine
$SCOT_2(A_i, C)$ (in the Eq.(9))	**0.8107**	0.7903	A_1
$SY_1(A_i, C)$ (in the Eq.(10))	**0.8667**	0.8500	A_1
$SY_2(A_i, C)$ (in the Eq.(11))	**0.9800**	0.9750	A_1
$SY_3(A_i, C)$ (in the Eq.(12))	**0.5790**	0.5385	A_1
$SYD(A_i, C)$ (in the Eq.(13))	0.8500	0.8500	Non-determine
$S_T(A_i, C)$ (in the Eq.(14))	**0.8750**	0.8500	A_1
$S_{MT}(A_i, C)$ (in the Eq.(15))	**0.7841**	0.7424	A_1
$S_{QW}(A_i, C)$ (in the Eq.(16))	0.4250	0.4250	Non-determine
$S_{TH}(A_i, C)$ (proposed in the Eq.(18)	**0.8394**	0.8141	A_1

Example 4. Given two patterns SNSs

$A_1 = \{(x_1, 0.8, 0.8, 0.2), (x_2, 0.6, 0.6, 0.2)\}$ and $A_2 = \{(x_1, 1, 0.4, 0.4), (x_2, 0.8, 0.4, 0.4)\}$ on $X = \{x_1, x_2\}$ and the sample $C = \{(x_1, 0.6, 0.6, 0.6), (x_2, 0.8, 0.4, 0.6)\}$.

The classification results are shown in Table 2 based on measures. In this case, we see that only the similarity measure S_{MT} having decision C belongs to pattern A_1; five similarity measures $SCOS_1$, ST_1, $SCOT_1$, SYD and S_T shown that we non-determine which pattern (A_1 or A_2) that C belongs to; but our proposed measure and ten other similarity measures shown that C belongs to pattern A_2. This mean that we can put C belongs to pattern A_2.

Table 2. The classification results

Measures	The results from C to		Classification results
	A_1	A_2	
$S_C(A_i,C)$ (in the eq.(1))	0.8996	**0.9165**	A_2
$S_D(A_i,C)$ (in the eq.(2))	0.8875	**0.9115**	A_2
$S_J(A_i,C)$ (in the eq.(3))	0.7980	**0.8377**	A_2
$SCOS_1(A_i,C)$ (in the eq.(4))	0.8090	0.8090	non-determine
$SCOS_2(A_i,C)$ (in the eq.(5))	0.9135	**0.9323**	A_2
$ST_1(A_i,C)$ (in the eq.(6))	0.6751	0.6751	non-determine
$ST_2(A_i,C)$ (in the eq.(7))	0.7874	**0.8145**	A_2
$SCOT_1(A_i,C)$ (in the eq.(8))	0.5095	0.5095	non-determine
$SCOT_2(A_i,C)$ (in the eq.(9))	0.6494	**0.6880**	A_2
$SY_1(A_i,C)$ (in the eq.(10))	0.7333	**0.7667**	A_2
$SY_2(A_i,C)$ (in the eq.(11))	0.9200	**0.9267**	A_2
$SY_3(A_i,C)$ (in the eq.(12))	0.3044	**0.3636**	A_2
$SYD(A_i,C)$ (in the eq.(13))	0.6000	0.6000	non-determine
$S_T(A_i,C)$ (in the eq.(14))	0.7500	0.7500	non-determine'

$S_{MT}(A_i, C)$ (in the eq.(2))	**0.5714**	0.5000	A_1
$S_{QW}(A_i, C)$ (in the eq.(3))	0.3500	**0.4000**	A_2
$S_{TH}(A_i, C)$ (proposed in the eq.(18)	0.6889	**0.7159**	A_2

Example 5 ([27]). Given two patterns SNSs on $X = \{x_1, x_2\}$,

$A_1 = \{(x_1, 0.8, 0.8, 0.2), (x_2, 0.6, 0.8, 0.2)\}$, $A_2 = \{(x_1, 1, 0.4, 0.4), (x_2, 1, 0.2, 0)\}$ and a new sample C on X , $C = \{(x_1, 0.6, 0.6, 0.6), (x_2, 0.6, 0.2, 0.6)\}$.

Table 3 gives the classification results based on similarity measures. In this case, we see that having thirteen similarity measures S_C, S_D, S_J , $SCOS_1$, $SCOS_2$, ST_1 , ST_2 , $SCOT_1$, $SCOT_2$, SY_1 , SY_2 , SY_3 , SYD shown that C would not belong to pattern A_1 or A_2; only S_{QW} having decision C belongs to pattern A_1; but our proposed measure and two other similarity measures shown that C belongs to pattern A_2. This mean that we can put C belongs to pattern A_2. It also indicates the effectiveness of the proposed similarity measure.

Table 3. The classification results

Measures	The results from C to		Classification results
	A_1	A_2	
$S_C(A_i, C)$ (in the Eq.(1))	0.8122	0.8122	non-determine
$S_D(A_i, C)$ (in the Eq.(2))	0.8056	0.8056	non-determine
$S_J(A_i, C)$ (in the Eq.(3))	0.6850	06850	non-determine
$SCOS_1(A_i, C)$ (in the Eq.(4))	0.6984	0.6984	non-determine
$SCOS_2(A_i, C)$ (in the eq.(5))	0.8898	0.8898	non-determine
$ST_1(A_i, C)$ (in the Eq.(6))	0.5828	0.5828	non-determine
$ST_2(A_i, C)$ (in the Eq.(7))	0.7598	0.7598	non-determine

$SCOT_1(A_i, C)$ (in the Eq.(8))	0.4172	0.4172	non-determine
$SCOT_2(A_i, C)$ (in the Eq.(9))	06134	0.6134	non-determine
$SY_1(A_i, C)$ (in the Eq.(10))	0.7000	0.7000	non-determine
$SY_2(A_i, C)$ (in the Eq.(11))	0.8733	0.8733	non-determine
$SY_3(A_i, C)$ (in the Eq.(12))	0.2500	0.2500	non-determine
$SYD(A_i, C)$ (in the Eq.(13))	0.5000	0.5000	non-determine
$S_T(A_i, C)$ (in the Eq.(14))	0.6750	**0.7500**	A_2
$S_{MT}(A_i, C)$ (in the Eq.(2))	0.4107	**0.5982**	A_2
$S_{QW}(A_i, C)$ (in the Eq.(3))	**0.3750**	0.3000	A_1
$S_{TH}(A_i, C)$ (proposed in the Eq.(18)	0.6528	**0.6778**	A_2

The above four examples have demonstrated the feasibility of the proposed new measure. Specifically, as in Example 2, the new measure is better than the ones (such as those in Eq.(4), Eq.(6), Eq.(8), Eq.(13), and Eq.(16)). In Example 3, the new measure is better than the ones (such as those in Eq.(4), Eq.(6), Eq.(8), Eq.(13), Eq.(14), and Eq.(15)). In Example 4, the new measure has superiority over the previous ones (such as those in Eq.(1) - (13)).

In the next section, we apply this new measure to build a TOPSIS model to solve the MCDM problem, then we also compare the proposed method with some existing methods.

5. The proposed knowledge and similarity measures-based TOPSIS model for agricultural land selection

In MCDM problem, we have to determine an optimal option from set of m alternatives $A = \{A_1, A_2, ..., A_m\}$ based on n criteria $C = \{C_1, C_2, ..., C_n\}$. In this problem, we consider each A_i is a SNS on C, i.e. $A_i = \{(C_j, D_{ij}) \mid C_j \in C\}$ where $D_{ij} = (T_{ij}, I_{ij}, F_{ij})$ in which $T_{ij} = T_{ij}(C_j), I_{ij} = I_{ij}(C_j), F_{ij} = F_{ij}(C_j)$ for all $i = 1, 2, ..., m,\ j = 1, 2, ..., n$. So that, we a SNS decision matrix $D = [D_{ij}]_{m \times n}$.

The proposed TOPSIS model based on similarity measure of SNSs is presented as in Algorithm 1. Figure 2 displays the flow chart of new similarity-based SNS TOPSIS model.

Algorithm 1. New similarity-based SNS TOPSIS model

***Input**: a SNS decision matrix.*

Output: *ranking of* $A=\{A_1,A_2,...,A_m\}$.

Step 1. Determine the weight ω_j of each criteria C_j (the decision maker can choose the weight ω_j of each criteria C_j), for all $j=1,2,...,n$.

$$\omega_j=\frac{K_{C_j}(A_i)}{\sum_{j=1}^{n}K_{C_j}(A_i)} \qquad (20)$$

where $K_{C_j}(A_i)$ is the knowledge measure of criteria C_j for all $j=1,2,...,n$

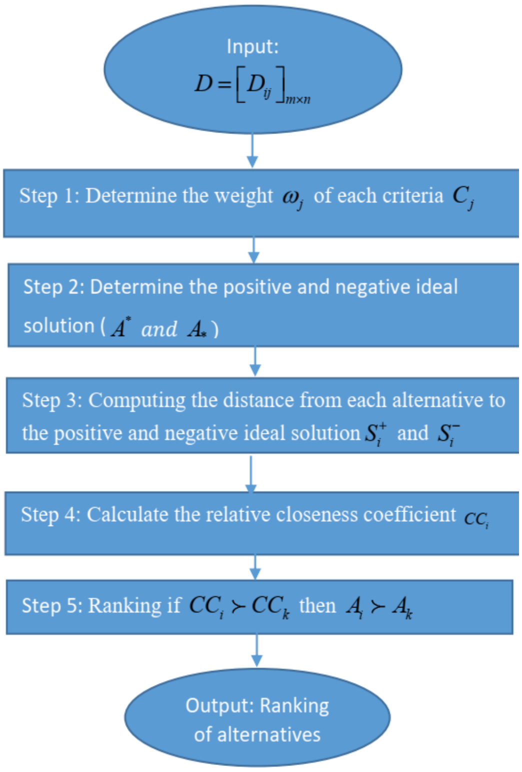

Fig 2*. A*lgorithm diagram of ***new similarity-based SNS TOPSIS model***

Step 2. Compute the SNS best solution A^* and the SNS worst solution A_* as follow

+ $A^*=\left\{\left(C_j,T_j^*,I_j^*,F_j^*\right)|C_j\in C\right\}$

where

$$T_j^*=\begin{cases}\min\limits_{i=1,...,m} T_{ij} \text{ if } C_j \text{ is non-benifite}\\ \max\limits_{i=1,...,m} T_{ij} \text{ if } C_j \text{ is benifite}\end{cases}$$

$$I_j^* = \begin{cases} \max\limits_{i=1,\dots,m} \mathrm{I}_{ij} \text{ if } C_j \text{ is non-benifit} \\ \min\limits_{i=1,\dots,m} I_{ij} \text{ if } C_j \text{ is benifite} \end{cases}$$

$$F_j^* = \begin{cases} \max\limits_{i=1,\dots,m} F_{ij} \text{ if } C_j \text{ is non-benifit} \\ \min\limits_{i=1,\dots,m} F_{ij} \text{ if } C_j \text{ is benifite} \end{cases} \tag{21}$$

+ $A_* = \left\{ \left(C_j, T_j^{'}, I_j^{'}, F_j^{'} \right) | C_j \in C \right\}$

where

$$T_j^{'} = \begin{cases} \max T_{ij} \text{ if } C_j \text{ is non-benifite} \\ \min\limits_{i=1,\dots,m} T_{ij} \text{ if } C_j \text{ is benifite} \end{cases}$$

$$I_j^{'} = \begin{cases} \min\limits_{i=1,\dots,m} \mathrm{I}_{ij} \text{ if } C_j \text{ is non-benifite} \\ \max\limits_{i=1,\dots,m} I_{ij} \text{ if } C_j \text{ is benifite} \end{cases}$$

$$F_j^{'} = \begin{cases} \min\limits_{i=1,\dots,m} F_{ij} \text{ if } C_j \text{ is non-benifite} \\ \max\limits_{i=1,\dots,m} F_{ij} \text{ if } C_j \text{ is benifite} \end{cases} \tag{22}$$

Step 3. Using the eq.(3) to determine S_i^+ and S_i^- are the similarity measures from A_i to A^* and A_*, respectively, in detail as follows:

$$S_{TH}^{\omega}(A_i, A^*) = \sum_{j=1}^{n} \omega_j \times \left\{ 1 - \frac{1}{3} \left[\left| T_{ij}(C_j) - T_j^*(C_j) \right| + \frac{2\left| I_{ij}(C_j) - I_j^*(C_j) \right|}{1 + 2\left| I_{ij}(C_j) - I_j^*(C_j) \right|} + \left| F_{ij}(C_j) - F_j^*(C_j) \right| \right] \right\} \tag{23}$$

$$S_{TH}^{\omega}(A_i, A_*) = \sum_{j=1}^{n} \omega_j \times \left\{ 1 - \frac{1}{3} \left[\left| T_{ij}(C_j) - T_j^{'}(C_j) \right| + \frac{2\left| I_{ij}(C_j) - I_j^{'}(C_j) \right|}{1 + 2\left| I_{ij}(C_j) - I_j^{'}(C_j) \right|} + \left| F_{ij}(C_j) - F_j^{'}(C_j) \right| \right] \right\} \tag{24}$$

Step 4. Determine the relative closeness coefficient of $A_i, (i = 1, 2, \dots, m)$ as

$$CC_i = \frac{S_i^+}{S_i^+ + S_i^-} \tag{25}$$

for all $i = 1, 2, \dots, m.$

Step 5. Ranking: if $CC_i \succ CC_k$ then $A_i \succ A_k$ for all $i, k = 1, 2, \dots, m.$

Now, we use Algorithm 1 to solve a support decision problem to select the agricultural land as follows:

Example 6 ([3]). A trader wants to invest in the agricultural sector and find suitable land. He/she has to choose the optimal alternative in a set of five alternatives $A = \{A_1, A_2, A_3, A_4, A_5\}$ depend on the set of five criteria $C = \{C_1, C_2, C_3, C_4, C_5\}$ (where C_1: location, C_2: climate, C_3: fertility, C_4: price,

C_5:water availability). In which, the criteria C_2 (climate) and C_4 (price) are the cost criteria, and other are benefit criteria. The relationship between the alternatives and criteria shown in the Table 4.

Table 4. SNS decision matrix (Ashraf and Abdullah, 2020)

	C_1	C_2	C_3	C_4	C_5
A_1	(0.5,0.3,0.4)	(0.3,0.2,0.5)	(0.2,0.2,0.6)	(0.4,0.2,0.3)	(0.3,0.3,0.4)
A_2	(0.7,0.1,0.3)	(0.3,0.2,0.7)	(0.6,0.3,0.2)	(0.2,0.4,0.6)	(0.7,0.1,0.2)
A_3	(0.5,0.3,0.4)	(0.4,0.2,0.6)	(0.6,0.1,0.2)	(0.3,0.1,0.5)	(0.6,0.4,0.3)
A_4	(0.7,0.3,0.2)	(0.2,0.2,0.7)	(0.4,0.5,0.2)	(0.2,0.2,0.5)	(0.4,0.5,0.4)
A_5	(0.4,0.1,0.3)	(0.2,0.1,0.5)	(0.4,0.1,0.5)	(0.6,0.3,0.4)	(0.3,0.2,0.4)

We use Algithm1 to solve this* agricultural land selection problem as follows*:

Step 1. By considering that, each criterion is a SNS on the set of alternative sets $A = \{A_1, A_2, A_3, A_4, A_5\}$. Using the Eq.(21), we compute the weight vector of $C = \{C_1, C_2, C_3, C_4, C_5\}$ is $\omega = (0.203, 0.2437, 0.2081, 0.1929, 0.1523)$.

Step 2. Determine SNS best solution A^* and the SNS worst solution A_* by using the Eq.(21) and Eq.(22) (see Table 5).

Table 5. The values of A^* and A_*

	C_1	C_2	C_3	C_4	C_5
A^*	(0.7,0.1,0.2)	(0.2,0.2,0.7)	(0.6,0.1,0.2)	(0.2,0.4,0.6)	(0.7,0.1,0.2)
A_*	(0.4,0.3,0.4)	(0.4,0.1,0.5)	(0.2,0.5,0.6)	(0.6,0.1,0.3)	(0.3,0.5,0.4)

Step 3. Using the Eq.(23) and the Eq.(24), we get S_i^+ and S_i^- from A_i to A^* and A_*, respectively (see Table 6).

Table 6. The results of S_i^+ and S_i^-

	A_1	A_2	A_3	A_4	A_5
$S(A_i, A^*)$	0.7569	0.9620	0.8499	0.8417	0.8172
$S(A_i, A_*)$	0.8967	0.6985	0.8135	0.8219	0.8427

Step 4. Determine CC_i of $A_i, (i = 1, 2, ..., 5)$ by using the Eq.(25) (see Table 7)

Table 7. The values of $CC_i, (i = 1, 2, ..., 5)$ and ranking

	A_1	A_2	A_3	A_4	A_5
CC_i	0.4577	0.5794	0.5109	0.5059	0.4923

Ranking	5	**1**	2	3	4

Step 5. Ranking (in Table 7) $A_2 \succ A_3 \succ A_4 \succ A_5 \succ A_1$. Thus A_2 is the best alternative.

6. Discussion

In this section, we compare result when using our proposed method with some methods as: SVNFWA, SVNWG, SVNOWG, SVNOWA and SVNWA [18], [19], L-SVNHWA and L-SVNHWG [3], TS-MCDM [31]. Raking results shown that $A_2 \succ A_3 \succ A_4 \succ A_5 \succ A_1$. It means that A_2 is the best alternative and A_1 is the worst alternative (see Fig. 3).

Moreover, the above methods have more computational steps and are more complex than the proposed new method. The methods SVNFWA, VNWG, SVNOWG, SVNOWA, and SVNWA, L-SVNHWA and L-SVNHWG used either the aggregation operator and the score function or the outranking relation matrix to rank the alternatives. Even the L-SVNHWA and L-SVNHWG methods also use trigonometric aggregation operators under the NSN environment. Therefore, the implementation steps of the above methods are not less than 7 steps, while the new method proposed here only needs 5 calculation steps. This proves that the proposed new method has simpler calculation steps, but the efficiency of the method is still achieved as the above methods.

It is evident that this presentation confirms the reasonable and applicability of the proposed similarity-based SNS TOPSIS model under SNS environments.

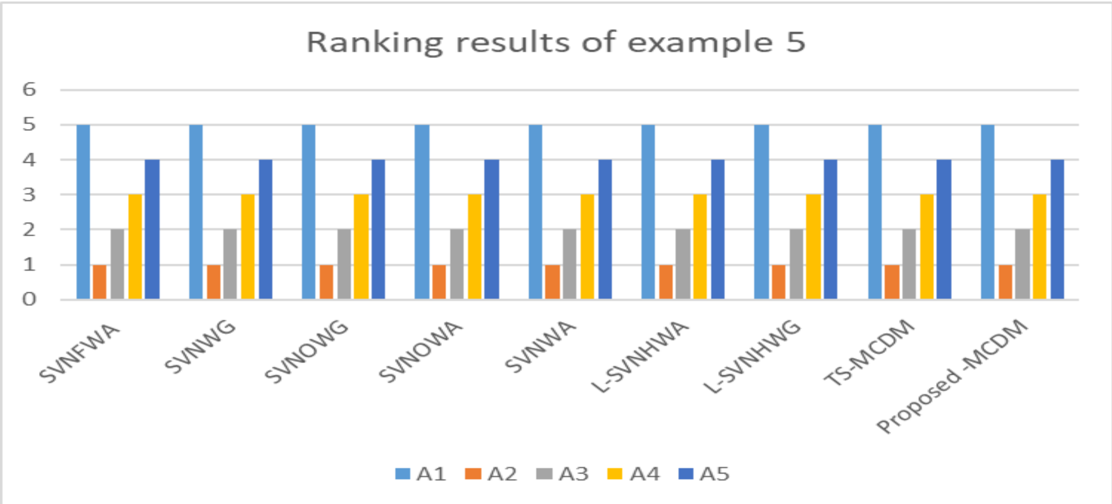

Fig. 3: Raking results of Example 5 when using some different ranking methods

7. Conclusion

In this paper, we construct the knowledge measure of SNS. It is a new measure of SNSs. This is a new main contribution of this paper. The knowledge measures allowed us to determine the weights of criteria in the MCDM model. In the same time, we also proposed a new similarity measure for SNSs. Comparing results shows the benefit of the new measure can overcome a lot of the limitations encountered in some cases of already existing similarity measures. Next, the knowledge measures and new similarity measure based-MCDM is introduced to apply to the problem of agricultural land selection. The new model is simple easy to use and efficiency. To demonstrate the feasibility of the proposed method, we also compared to some other decision-making methods in the agricultural land selection: the rating using the suggested method is also in line with the rating results using some of the existing ranking methods.

The disadvantage of this method is that it has not yet given the relationship between the knowledge measure of SNS with other measures of SNS. This is also something that needs to be expanded in the direction of future research. In the future, the connection of the knowledge and similarity measure need to study. Moreover, we will continue to work to find other metrics on SNS as dissimilarity measures shown in [9], divergence measures in [27] and the extended Neutrosophic sets, rough fuzzy set, or rough standard neutrosophic set. At the same time, they apply them to solving real-world problems, and other problem classes such as pattern recognition problem, cluster analysis problem, and other MCDM models as in [9], [38].

Acknowledgement. The authors gratefully acknowledge the financial support from the Banking Academy of Vietnam.

Data availability: Adopted datasets using in Example 5 come from the paper: *Ashraf, S., & Abdullah, S. (2020). Decision Support Modeling For Agriculture Land Selection Based On Sine Trigonometric Single Valued Neutrosophic Information. International Journal of Neutrosophic Science (IJNS) Vol.9, 60-73.*

Conflicts of Interest: The authors declare no conflict of interest.

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Received: Oct 10, 2024. Accepted: Jan 16, 2025