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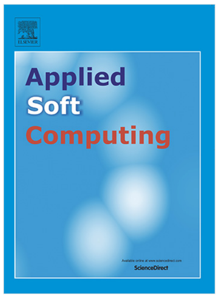

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PII: S1568-4946(21)00960-1
DOI: https://doi.org/10.1016/j.asoc.2021.108038
Reference: ASOC 108038

To appear in: *Applied Soft Computing*

Received date : 22 April 2020
Revised date : 20 July 2021
Accepted date : 19 October 2021

Please cite this article as: A.R. Mishra, P. Rani and R.S. Prajapati, Multi-criteria weighted aggregated sum product assessment method for sustainable biomass crop selection problem using single-valued neutrosophic sets, *Applied Soft Computing* (2021), doi: https://doi.org/10.1016/j.asoc.2021.108038.

Multi-criteria weighted aggregated sum product assessment method for sustainable biomass crop selection problem using single-valued neutrosophic sets

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Abstract

Determining the most optimum biomass crop alternative for biofuel production is a strategic decision due to inherent uncertainty, subjective human mind and involvement of numerous criteria. As the single-valued neutrosophic set (SVNS) is a valuable tool to tackle the uncertain, indeterminate and inconsistent information arises in real-life decision-making problems. Thus, the aim of the present work is to develop a novel weighted aggregated sum product assessment (WASPAS) framework for solving multi-criteria group decision making (MCGDM) problems with single-valued neutrosophic information. In this framework, single-valued neutrosophic subjective and objective weight integrated approach (SVN-SOWIA) is discussed to estimate the weights of criteria. This method is based on the similarity measure, aggregation operator and score value, which provides more realistic and exact weights. In this regard, new similarity measures are discussed for SVNSs with their desirable characteristics. Further, to illustrate the potentiality and feasibility of the developed approach, a case study of sustainable biomass crop alternative selection is presented under SVNSs context. The sensitivity analysis shows that the alternative 'Miscanthus' constantly obtains its top ranking in spite of how criteria weights vary. Lastly, a comparison is made to verify the robustness of the obtained outcome. The result of this work shows that the developed method can suggest more feasible performance while facing multiple influencing factors and input uncertainties, and thus, lends itself to a broader range of applications.

Keywords: Single-valued neutrosophic set; Similarity measure; Multi-criteria group decision making; Biomass crop; Weighted aggregated sum product assessment.

1. Introduction

Investigation of the suitable energy resource for continuous environmental and economic growth is of great importance worldwide. Due to increasing demand of energy, there is a future need for a certain sustainable energy resource as the fossil fuel-based energy is identified to be limited and not environmentally-sound. Ethanol has the potential to substitute the fossil fuel-based energy, therefore, essentially exploited in several nations. Recently, owing to the reduction of raw material for fossil fuels, the biomass-based energy can be seen as a shooting star amongst the most discussed alternatives from sustainable perspectives. Based on the variability of biomass resources in several nations, the assessment of optimal sustainable resource for ethanol production has become an important issue for experts [1].

India is a fastest emerging economy of the world, which requires energy to perceive its development objectives in a sustainable way. Due to improvement in living standards, population growth, economic and industrial developments, the Indian economy aspects considerable challenges in form of meeting its energy requirements in the future decade. Emergent energy needs together with inadequate conservative fuel alternatives; geo-politics of oil and ecological concern have forced the Indian government to explore renewable and sustainable energy systems. In India, biomass, wind, hydroelectric power and solar have been recognized as the main sources of renewable energy. The potency of biomass sources generally lies in the farming sector. It is estimated that 39 crop residues from 26 crops generated can be regarded for power generation and production of biofuels. India generates 686 MT gross residue biomass on annual basis, of which 234MT are anticipated as surplus for bio-energy production. The expected annual bio-energy potential from the surplus crop residue biomass is 4.15 EJ, analogous to 17% of total primary energy consumption in India. It is accounted that by 2031-2032, power generation capacity must raise to around 800 GW from the present capacity of about 183 GW, inclusive of all captive power plants to assemble the basic energy requirements of its civilians [2-3]. Realizing the prospective of bioenergy production, the ministry of new and renewable energy (MNRE), India has instigated various agendas with encouraging degree of accomplishment. India scores forth rank (after Brazil, USA and China) in the production of bioethanol from crops like sugarcane, molasses and cassava [4].

The type of the biomass crop may vary according to the geographical conditions and technological abilities. Therefore, selection of the suitable biomass crop alternative is an imperative issue in the production of ethanol [1]. Consequently, it is extremely significant to apply appropriate techniques for the determination of ideal biomass crop alternative. Sustainability, which consists of three unified and inseparable branches of economy, ecology and society, is of widespread concern in bioenergy production. The optimal crop alternative influences not only the economic practicability of ethanol production but also affects the general public and the atmosphere [5-6]. Thus, the current study focuses on biomass crop alternative selection from a sustainable view.

Due to involvement of multiple conflicting criteria, the biomass crop alternative selection process can be viewed as a difficult and uncertain multi-criteria decision-making (MCDM) problem. In this regard, the classical MCDM methods have widely been employed [7-9]. Some studies discussed that uncertain information may occur in the biomass crop assessment procedure owing to the intricacy of human cognition. In order to face with these uncertainties in the assessment of biomass crop alternatives, the doctrine of fuzzy set (FS) [10] has been pioneered in the literature [5-6,11]. In FS theory, non-belongingness degree of an element is characterized as the complement of its belongingness degree from one, but practically it is not correct. To overcome this shortcoming, several generalizations of FS theory have been introduced by the researchers. As a generalized version of FS, Atanassov [12] originated the theory of intuitionistic fuzzy set (IFS), which considers both the belongingness and non-belongingness degrees. In the recent past, IFSs have accomplished a great success in different disciplines because of its potential of managing uncertainty [13-15].

From the analysis, it is noticed that neither the FS nor IFS doctrines are proficient to cope with imprecise and incompatible information. For example, a specialist provide his/her view about a certain statement in this manner that 0.6 being the "possibility that the statement is true", 0.8 being the "possibility that the statement is false" and 0.3 being the "possibility that he or she is not sure". Thus, this example is beyond the range of FS and IFS. In order to handle such type of situation, the doctrine of Neutrosophic set (NS) [16] found to be more valuable tool. As stated by Smarandache [17], NS theory is the generalized version FS, IFS, interval-valued IFS (IVIFS), Pythagorean fuzzy set (PFS), q-rung orthopair fuzzy set (q-ROFS), picture fuzzy set (PiFS), Ternary fuzzy set (TFS), Spherical fuzzy set (SFS) and n-Hyper Spherical fuzzy set (n-HSFS). The concept of NS theory [16] is a more general framework which extends the concepts of aforementioned sets from philosophical perspective. A NS is portrayed by a truth, an indeterminacy and a falsity belongingness functions. In NS theory, these functions are absolutely independent and lie in $\left]0^{-},1^{+}\right[$. This theory provides additional functionality to take into account "knowledge of neural thought", and this additional component brings the new possibilities to model uncertain phenomena of information. In NS context, the uncertainty degree (or indeterminacy degree) is independent function and can be considered independently from the truth and falsity degrees. While in IFS, it may be noticed that the degree of hesitancy/ indeterminacy is reliant on the belongingness and non-belongingness degrees [17,18]. This presents a sense of limitation for the experts to measure the impreciseness aspects using IFS theory. Thus, with the help of NSs, the aforesaid example can be articulated as (0.6, 0.8, 0.3).

From engineering or scientific point of view, the NS and its set-theoretic operational laws need to be specified. Otherwise, it will be tricky to employ in real areas. As an instance of NS, Wang et al. [19] presented the notion of single value neutrosophic set (SVNS) for better applications in real scientific and engineering fields. In a SVNS *N*, each element has a truth belongingness value t_N, an indeterminacy belongingness value i_N and a falsity belongingness value f_N, where $0 \le t_N, i_N, f_N \le 1$ and $0 \le t_N + i_N + f_N \le 3$. SVNS gives us an additional possibility to address imprecise, uncertain, incomplete, and inconsistent data which occur in realistic problems. Thus, it would be more appropriate to express inconsistent and indeterminate information measures in real-world problems. Until now, several research efforts have been made under single-valued neutrosophic (SVN) environment [20-22].

1.1 Limitations

Based on the literature, some defects of the previously introduced methods are listed as follows:

- Some of the existing SVN-similarity measures [23-33] have counter intuitive phenomena and division by zero problems in measuring the similarity between two SVNSs.
- In studies [22,23,28,32,34-39], the authors simply focus on MCDM under SVNS context, which are basically fit for handling the decision-making problems with a single decision expert (DE) and are invalid for employing them to multi-criteria group decision-making (MCGDM) problems with SVN-information. With the increasing complexity of the problems, it is quite hard for a single DE to provide the assessment of alternatives over

multiple criteria and to make a decision. Thus, single-valued neutrosophic MCGDM is of great significance for real applications and scientific research.

- Most of the previously developed SVN-MCDM methods [21-23,28,32,36-42] have failed to derive the decision experts, which means that they have ignored the influences of the relative weights of DEs on decision results.
- The determination of criteria weights is one of the important steps of MCDM problems with multiple experts. However, in methods [23,34,35,37,38,43], the criteria weights have allocated in advance. In reality, different criteria weights will lead to varied decision outcomes. Thus, it is an essential to derive the criteria weights for accurate decision-making results.
- In the literature, several researchers have determined the optimal biomass crop alternative by applying a finite number of quantitative criteria with mathematical programming techniques but these techniques have limitations in solving uncertain biomass crop alternative selection problem with incomplete, uncertain, indeterminate and inconsistent information.

1.2 Motivations

To overcome the aforesaid limitations, this study introduces a novel MCGDM model with completely unknown information about the DEs and criteria weights under SVNS environment.

- Since the similarity measure plays a vital role in data analysis, classification, decision-making and clustering analysis, therefore, it is very interesting and noteworthy to study the similarity measure for SVNSs. This study analyzes the limitations of previously developed similarity measures using some counter intuitive cases and motivates us to introduce the new similarity measures.
- Different DEs act as diverse roles during the process of decision-making. Although, a single DE has no ability enough to handle the complex decision-making problems. For this purpose, the present work proposes a new methodology for solving MCGDM problems under uncertain environment.
- In the process of MCGDM, the weights of DEs is an important issue. However, it is quite difficult to consider an exact weight of the DE. In this regard, this study proposes a formula to derive the decision experts' weights.
- In view of the influence of diverse criteria weights in the assessment of given alternatives, this study develops a new weight-determining model to compute the weights of criteria.
- In a sustainable biomass crop selection, when we ask a DE to give his/her judgment about environmental impact of a candidate crop, he/she may say that the possibility of the statement is true is 0.6, the statement is false is 0.4 and not sure is 0.2. By means of SVNS, it can be expressed as (0.6,0.4,0.2), while it cannot be handled by IFS as sum of belongingness, non-belongingness and indeterminacy is not 1. Consequently, it is more appropriate and advantageous to employ SVNS to represent the assessment information of biomass crops. This motivates us to introduce a new MCGDM method for solving sustainable biomass crop selection problem under SVNS environment.

1.3 Contributions

On the basis of above discussions, the key contributions of this study are given by

(i) To conquer the limitations of existing similarity measures, this study develops two novel similarity measures for SVNSs.

(ii) To solve the MCGDM problems with uncertain, imprecise, indeterminate and inconsistent information, a modified Weighted Aggregated Sum Product Assessment (WASPAS) methodology is introduced from single-valued neutrosophic perspective.

(iii) In the proposed methodology, we propose a novel weighting formula to find the DEs' weights based on single-valued neutrosophic information.

(iv) To obtain the criteria weights, this study develops the single-valued neutrosophic subjective and objective weight integrated approach (SVN-SOWIA) within the context of SVNS. This approach combines the new objective-weighting procedure based on similarity measure and subjective-weighting process based on aggregation operator and score value. The developed approach can conquer the insufficiencies which arise either in an objective-weighting procedure or a subjective-weighting procedure.

(v) The proposed WASPAS method is implemented on a case study of biomass crop selection with single-valued neutrosophic information. In this study, we provide a list of economic, environmental and social aspects for biomass crop assessment from sustainability perspective.

The present work is planned as: Section 2 discusses the works related to this study. Section 3 firstly confers some basic ideas of SVNSs and then, proposes two novel similarity measures for SVNSs. Section 4 introduces a novel single-valued neutrosophic WASPAS (SVN-WASPAS) approach for solving MCGDM problems under SVNS environment. To confirm the potentiality and efficacy of the developed approach, Section 5 displays a case study of sustainable biomass crop alternative assessment problem with single-valued neutrosophic information. Further, this section confirms the strength of the proposed framework through comparative study and sensitivity investigation. Section 6 demonstrates the conclusions and further scope of the paper.

2. Related works

In the present section, we present a comprehensive review related to the work.

2.1. Single-valued neutrosophic sets (SVNSs)

Numerous doctrines and principles have been developed on FSs, but it cannot tackle the hesitancy of DEs as it is simply distinguished by a belongingness grade. To conquer the inadequacy of FSs, Atanassov [12] established the concept of IFSs. Nonetheless, IFSs can simply tackle incomplete and uncertain information but incapable to deal with inconsistent and indeterminate information occurred in realistic scenarios. To conquer these drawbacks, Smarandache [16] initially established the conception of NSs that consists of three parameters: degrees of truth, indeterminacy and falsity belongingness grades. NS is a stem of philosophy which describes the origin, nature and scope of neutralities with their interactions with diverse ideational spectra. Since its appearance, several research efforts have been made within the perspective of NSs [17,18,24].

Usually, it is hard to implement the NSs in realistic problems because the truth, indeterminacy and falsity belongingness grades lie in $]0^{-}, 1^{+}[$. To surmount this restriction, Wang et al. [19] pioneered the SVNS theory and presented the diverse properties of SVNSs. SVNS is a subclass of NS. Due to its uniqueness, SVNS [19] have strong acceptance for handling real-world problems with incomplete and indefinite information, uncertainties, predictions and so on. In the literature, Smarandache et al. [18] proposed innovative similarity measures between pairs of words, wherein words are considered as SVNSs. Luo et al. [21] studied a modified best worst method under SVNSs context. Nancy and Garg [22] developed a discrimination measure for SVNSs. Based on discrimination measure, they have suggested an enhanced Technique for Order Preference by similarity to ideal solution (TOPSIS) approach to appraise the MCDM problems with fully unknown criterion weight. In a study, Ye [23] firstly presented the correlation for SVNSs and further, employed to originate an algorithm for a MCDM method. Refaat and El-Henawy [37] gave a novel technique for evaluating quality management system audit results using SVNSs. By means of SVNSs, Zavadskas et al. [40] gave an innovative decision-making framework to solve the residential house element and material assessment problem. Later, Rani and Mishra [44] proposed an extended VlseKriterijumska Optimizcija I Kompromisno Resenje (VIKOR) technique for solving MCGDM problems with SVN-information. To model the MCGDM problems with SVN-information, Mishra and Rani [45] recommended a combined decision-making framework by integrating Combined Compromise Solution (CoCoSo) and CRiteria Importance Through Intercriteria Correlation (CRITIC) techniques with SVNS. As far as we know, there has been no research regarding the single-valued neutrosophic information based MCGDM method for biomass crop selection.

2.2. WASPAS method

In the past few years, lots of new decision-making methods have been proposed. Zavadskas et al. [46] proposed new utility theory-based model and named as WASPAS technique. This method has extensively been employed for several purposes. In the literature, Zavadskas et al. [34-35] designed the decision support systems using WASPAS technique on SVNSs. Further, Huang et al. [47] designed a collective linguistic Pythagorean fuzzy-based model by combining best worst method and WASPAS approach for solving energy-saving building program assessment problem. Motivated by the concepts of WASPAS and TOPSIS methods, Davoudabadi et al. [48] presented a novel last aggregation process within the context of interval-valued IFSs. In a recent study, an innovative multi-criteria WASPAS model with intuitionistic fuzzy type-2 values has been proposed by Rani et al. [49]. Mardani et al. [50] established a latest hesitant fuzzy WASPAS methodology for solving digital health interventions during COVID-19 pandemic. Rudnik et al. [51] offered a modified WASPAS technique with ordered fuzzy numbers and applied for evaluating improvement projects. To evaluate and rank the sustainable suppliers, Alrasheedi et al. [52] designed a novel MCGDM framework with the combination of WASPAS method with q-ROFSs.

2.3. Approaches for biomass crop to bioenergy production

In recent times, biomass crop selection for ethanol production is a significant issue for the environmentionalists and the government. In this respect, several authors have concentrated their studies on the innovation of novel mathematical models for biomass crop selection. In a study, Cobuloglu and Büyüktahtakın [1] proposed a novel stochastic analytic hierarchy process (AHP) for solving uncertain multi-criteria biomass crop selection problem from sustainable perspectives. Cavallaro [5] recommended an innovative Takagi-Sugeno fuzzy inference system to evaluate the sustainability indicators of biomass crop for energy production. Xiang et al. [8] provided a decision-making system to evaluate the energy potential of Miscanthus for biogas, bioethanol, electricity and pyrolysis bio-oil production. With the use of multiple criteria decision analysis, Safarian et al. [9] prioritized several bioethanol production systems fed by agricultural and waste agricultural biomass. Balezentiene et al. [10] studied a fuzzy decision support system to evaluate and rank the biomass crops. Nguyen et al. [11] suggested fuzzy geographic information system model to assess the Switchgrass-based bioenergy supply. Vicari et al. [53] designed a process model for measuring the uncertainty during lignocellulosic biomass to ethanol production. Wang et al. [54] introduced a mathematical model for biofuel production from energy crops. Achinas and Euverink [55] presented several conversion tools and methods for biomass-based ethanol production. Wang et al. [56] designed a novel dynamic technique to conduct a combined life-cycle and techno-economic assessment for three bioenergy products utilizing multiple lignocellulosic biomasses as feedstock. Leon-Olivares et al. [57] gave a mixed-integer linear programming-based framework to produce the biofuels from agricultural biomass. However, there is no study regarding the biomass crop selection using single-valued neutrosophic WASPAS methodology.

3. Single-valued neutrosophic similarity measures

This section firstly presents the basic notions related to SVNSs. Further, two innovative similarity measures are proposed to quantify the similarity between SVNSs.

3.1. Basic concepts

The notion of SVNSs originated by Wang et al. [19] is a particular form of NSs and has been applied for modeling the problems with incomplete, indeterminate and inconsistent data .

Definition 1 [19]. Let *U* be a finite discourse set and u_i be a generic element of *U*. A SVNS *N* in *U* is specified by a truth $t_N(u_i)$, an indeterminacy $i_N(u_i)$ and a falsity belongingness functions $f_N(u_i)$, where the functions $t_N(u_i)$, $i_N(u_i)$ and $f_N(u_i)$ are real subsets of $[0,1]$. Mathematically, Wang et al. [19] defined the SVNS as

$$N = \left\{ \left(u_i, t_N(u_i), i_N(u_i), f_N(u_i) \right) \middle| u_i \in U \right\},$$

where $t_N(u_i): U \to [0,1]$, $i_N(u_i): U \to [0,1]$ and $f_N(u_i): U \to [0,1]$. Additionally, the sum of $t_N(u_i)$, $i_N(u_i)$ and $f_N(u_i)$ is given as $0 \le t_N(u_i) + i_N(u_i) + f_N(u_i) \le 3$. For convenience, the triplet (t_N, i_N, f_N) is said to be a SVN number (SVNN) and denoted by $\iota = (t_N, i_N, f_N)$.

Definition 2 [19]. Let $\iota_1 = \left(t_{\iota_1}, i_{\iota_1}, f_{\iota_1}\right)$ and $\iota_2 = \left(t_{\iota_2}, i_{\iota_2}, f_{\iota_2}\right)$ be the single-valued neutrosophic numbers and $\gamma > 0$. Then, the fundamental laws for SVNSs are presented by

- $\iota_1^c = \left(f_{\iota_1}, 1 - i_{\iota_1}, t_{\iota_1}\right)$,
- $\iota_1 \subseteq \iota_2$ if $t_{\iota_1} \le t_{\iota_2}$, $i_{\iota_1} \ge i_{\iota_2}$ and $f_{\iota_1} \ge f_{\iota_2}$,
- $\iota_1 = \iota_2$ if and only if $\iota_1 \subseteq \iota_2$ and $\iota_2 \subseteq \iota_1$,
- $\iota_1 \cup \iota_2 = \left(\max\left\{t_{\iota_1}, t_{\iota_2}\right\}, \min\left\{i_{\iota_1}, i_{\iota_2}\right\}, \min\left\{f_{\iota_1}, f_{\iota_2}\right\}\right)$,
- $\iota_1 \cap \iota_2 = \left(\min\left\{t_{\iota_1}, t_{\iota_2}\right\}, \max\left\{i_{\iota_1}, i_{\iota_2}\right\}, \max\left\{f_{\iota_1}, f_{\iota_2}\right\}\right)$,
- $\iota_1 + \iota_2 = \left(t_{\iota_1} + t_{\iota_2} - t_{\iota_1} t_{\iota_2}, i_{\iota_1} i_{\iota_2}, f_{\iota_1} f_{\iota_2}\right)$,
- $\iota_1 \cdot \iota_2 = \left(t_{\iota_1} t_{\iota_2}, i_{\iota_1} + i_{\iota_2} - i_{\iota_1} i_{\iota_2}, f_{\iota_1} + f_{\iota_2} - f_{\iota_1} f_{\iota_2}\right)$,
- $\gamma \iota_1 = \left(1 - \left(1 - t_{\iota_1}\right)^{\gamma}, i_{\iota_1}^{\gamma}, f_{\iota_1}^{\gamma}\right)$,
- $\iota_1^{\gamma} = \left(t_{\iota_1}^{\gamma}, 1 - \left(1 - i_{\iota_1}\right)^{\gamma}, 1 - \left(1 - f_{\iota_1}\right)^{\gamma}\right)$.

Definition 3 [38]. For a SVNN $\iota = \left(t_\iota, i_\iota, f_\iota\right)$, the score function S is defined as

$$\mathrm{S}(\iota) = \frac{1 + t_\iota - 2i_\iota - f_\iota}{2};\ \mathrm{S}(\iota) \in [-1,1]. \tag{1}$$

Since $\mathrm{S}(\iota) \in [-1,1]$, therefore the modified score function is given by

$$\mathrm{S}^*(\iota) = \frac{3 + t_\iota - 2i_\iota - f_\iota}{4};\ \mathrm{S}^*(\iota) \in [0,1]. \tag{2}$$

Definition 4 [58]. Let $\iota_j = \left(t_j, i_j, f_j\right); j = 1(1)n$ be a group of SVNNs and $\ell = \left(\ell_1, \ell_2, \ldots, \ell_n\right)^T$ be the related weight value of ι_j, satisfying $\ell_j \in [0,1]$ and $\sum_{j=1}^{n} \ell_j = 1$. Then the SVN weighted average (SVNWA) and the SVN weighted geometric (SVNWG) operators are expressed as below:

$$SVNWA\left(\iota_1, \iota_2, \ldots, \iota_n\right) = \overset{n}{\underset{j=1}{\oplus}}\left(\ell_j \iota_j\right) = \left(1 - \prod_{j=1}^{n}\left(1 - t_j\right)^{\ell_j}, \prod_{j=1}^{n}\left(i_j\right)^{\ell_j}, \prod_{j=1}^{n}\left(f_j\right)^{\ell_j}\right), \tag{3}$$

$$SVNWG\left(\iota_1, \iota_2, \ldots, \iota_n\right) = \overset{n}{\underset{j=1}{\otimes}}\left(\ell_j \iota_j\right) = \left(\prod_{j=1}^{n}\left(t_j\right)^{\ell_j}, 1 - \prod_{j=1}^{n}\left(1 - i_j\right)^{\ell_j}, 1 - \prod_{j=1}^{n}\left(1 - f_j\right)^{\ell_j}\right). \tag{4}$$

Definition 5 [59]. Let $K, N, Q \in SVNSs(U)$. A similarity measure $S : SVNSs(U) \times SVNSs(U) \to [0, 1]$ for SVNSs is a mapping which fulfils the given postulates:

(A1). $0 \le S(K, N) \le 1$,

(A2). $S(K, N) = S(N, K)$,

(A3). $S(K, N) = 1 \Leftrightarrow K = N$, (A4). If $K \subseteq N \subseteq Q$, then $S(K,Q) \leq S(K,N)$ and $S(K,Q) \leq S(N,Q)$.

3.2. Novel similarity measures for SVNSs

In FS theory, similarity measure (SM) is a significant process to enumerate the degree of similarity between two sets. Lots of studies have been presented regarding the SMs of FS and its extensions [60-62]. In the literature, there are several studies on SMs for SVNSs. For instance, Smarandache et al. [18] pioneered new SVN-SMs between pair of words. Further, Rani and Mishra [20] originated an innovative SM for SVNSs and also conferred its efficiency over extant SMs. By means of the belongingness degree, Majumdar and Samanta [26] defined a SVN-SM and its characteristics. Based on cosine function, Ye [27] proposed a formula to measure the similarity between SVNSs. With the use of entropy, Thao and Smarandache [39] introduced some SMs for SVNSs. In a study [63], a novel procedure has developed to determine the similarity between SVNSs. Apart from the above-mentioned researches, several other studies have been presented regarding the SVN-SMs [64-66].

In this section, we firstly propose two SMs for SVNSs. Further, some examples or counter intuitive cases are discussed to prove the efficiency of proposed SVN-SMs over existing ones.

For this purpose, let $K, N \in SVNSs(U)$. Then we propose a SVN-similarity measure, given by

$$S_1(K,N) = \frac{\sum_{i=1}^{n}\left[\min\left(t_K(u_i), t_N(u_i)\right) + \min\left(\left(1-i_K(u_i)\right),\left(1-i_N(u_i)\right)\right) + \min\left(\left(1-f_K(u_i)\right),\left(1-f_N(u_i)\right)\right)\right]}{\sum_{i=1}^{n}\left[\max\left(t_K(u_i), t_N(u_i)\right) + \max\left(\left(1-i_K(u_i)\right),\left(1-i_N(u_i)\right)\right) + \max\left(\left(1-f_K(u_i)\right),\left(1-f_N(u_i)\right)\right)\right]}. \quad (5)$$

Theorem 1: The mapping $S_1(K,N)$, given in (5), is a similarity measure on SVNSs(*U*).

Proof: (A$_1$) & (A$_2$): Both are straightforward.

(A$_3$): Suppose $K, N \in SVNSs(U)$ and $K = N$, i.e., $t_K(u_i) = t_N(u_i)$, $i_K(u_i) = i_N(u_i)$, and $f_K(u_i) = f_N(u_i)$. Therefore, from Eq. (5), we obtain $S_1(K,N) = 1$.

Again, consider $S_1(K,N) = 1$. Then, from Eq. (5), we have

$$\sum_{i=1}^{n}\left[\min\left\{t_K(u_i), t_N(u_i)\right\} + \min\left\{\left(1-i_K(u_i)\right),\left(1-i_N(u_i)\right)\right\} + \min\left\{\left(1-f_K(u_i)\right),\left(1-f_N(u_i)\right)\right\}\right]$$
$$= \sum_{i=1}^{n}\left[\max\left\{t_K(u_i), t_N(u_i)\right\} + \max\left\{\left(1-i_K(u_i)\right),\left(1-i_N(u_i)\right)\right\} + \max\left\{\left(1-f_K(u_i)\right),\left(1-f_N(u_i)\right)\right\}\right]. \quad (6)$$

Since $\forall_{u_i \in U}$, $\min\left\{t_K(u_i), t_N(u_i)\right\} \leq \max\left\{t_K(u_i), t_N(u_i)\right\}$,

$$\min\left\{\left(1-i_K(u_i)\right),\left(1-i_N(u_i)\right)\right\} \leq \max\left\{\left(1-i_K(u_i)\right),\left(1-i_N(u_i)\right)\right\}$$

and $\min\left\{\left(1-f_K(u_i)\right),\left(1-f_N(u_i)\right)\right\} \leq \max\left\{\left(1-f_K(u_i)\right),\left(1-f_N(u_i)\right)\right\}$. Therefore, Eq. (6) will be true when $t_K(u_i) = t_N(u_i)$, $\left(1-i_K(u_i)\right) = \left(1-i_N(u_i)\right)$ and $\left(1-f_K(u_i)\right) = \left(1-f_N(u_i)\right)$. It implies that $K = N$.

(A₄): Let $K, N, Q \in SVNSs(U)$ and $K \subseteq N \subseteq Q$, i.e., $t_K(u_i) \le t_N(u_i) \le t_Q(u_i)$, $i_K(u_i) \ge i_N(u_i) \ge i_Q(u_i)$ and $f_K(u_i) \ge f_N(u_i) \ge f_Q(u_i)$, $\forall\, u_i \in U$.

Also, $(1-i_K(u_i)) \le (1-i_N(u_i)) \le (1-i_Q(u_i))$ and $(1-f_K(u_i)) \le (1-f_N(u_i)) \le (1-f_Q(u_i))$.

Hence,

$$S_1(K,Q) = \frac{\sum_{i=1}^{n}\left[\min\{t_K(u_i), t_Q(u_i)\} + \min\{(1-i_K(u_i)),(1-i_Q(u_i))\} + \min\{(1-f_K(u_i)),(1-f_Q(u_i))\}\right]}{\sum_{i=1}^{n}\left[\max\{t_K(u_i), t_Q(u_i)\} + \max\{(1-i_K(u_i)),(1-i_Q(u_i))\} + \max\{(1-f_K(u_i)),(1-f_Q(u_i))\}\right]}.$$

$$S_1(K,Q) = \frac{\sum_{i=1}^{n}\left[t_K(u_i) + (1-i_K(u_i)) + (1-f_K(u_i))\right]}{\sum_{i=1}^{n}\left[t_Q(u_i) + (1-i_Q(u_i)) + (1-f_Q(u_i))\right]}. \tag{7}$$

Similarly,

$$S_1(K,N) = \frac{\sum_{i=1}^{n}\left[t_K(u_i) + (1-i_K(u_i)) + (1-f_K(u_i))\right]}{\sum_{i=1}^{n}\left[t_N(u_i) + (1-i_N(u_i)) + (1-f_N(u_i))\right]}. \tag{8}$$

From Eq. (7) and Eq. (8), we obtain

$$S_1(K,N) \ge S_1(K,Q).$$

On the similar line, we obtain $S_1(N,Q) \ge S_1(K,Q)$. [Proved]

Next, one more SVN-SM is developed based on the combination of $S_1(K,N)$ and a lattice. In general, lattice is a partially order set in which all subsets have both least upper bound (supremum) and greatest lower bound (infimum). As a result, the similarity between two sets is usually estimated based on the information of their supremum and infimum.

By considering a SVNS as a lattice notion and the subset relationship presented in Eq. (5) as a partial order, a lattice can be developed. For any two SVNSs, the supremum and infimum can be estimated from the union and intersection, respectively. In the following, a new SM for SVNSs is given by

$$S_2(K,N) = \sqrt{S_1(K,Z_{KN}) \times S_1(N,Z_{KN})}, \text{ where } Z_{KN} = K \cup N. \tag{9}$$

Theorem 2: The function $S_2(K,N)$ is a valid SM for SVNSs.

Proof: (A₁) and (A₂): Both are straightforward.

(A₃): Let $K, N \in SVNSs(U)$ and $K = N$. Also, let $Z_{KN} = K \cup N$. Therefore, $K = N = Z_{KN}$ and $S_1(K,N)$ satisfies the property (A₃). Hence, $S_2(K,N) = 1$.

Conversely, let $S_2(K,N) = 1$. This implies $S_1(K,Z_{KN}) = S_1(N,Z_{KN}) = 1$, when $Z_{KN} = K \cup N$ and $S_1(K,N)$ satisfies (A₃). Hence, $K = N = Z_{KN}$.

(A₄): Let $K,N,Q\in SVNSs(U)$ and $K\subseteq N\subseteq Q$. Then, $K\cup N=N$, $K\cup Q=Q$ and $N\cup Q=Q$.

Now, $S_2(K,Q)=\sqrt{S_1(K,Z_{KQ})\times S_1(Q,Z_{KQ})}$, which implies that $S_2(K,Q)=\sqrt{S_1(K,Q)\times S_1(Q,Q)}$. Thus, $S_2(K,Q)=\sqrt{S_1(K,Q)}$. On a similar line, we can prove that $S_2(K,N)=\sqrt{S_1(K,N)}$. As $S_1(K,N)$ holds (A_4), that is, $S_1(K,N)\geq S_1(K,Q)$, therefore, $S_2(K,N)\geq S_2(K,Q)$. Similarly, $S_2(N,Q)\geq S_2(K,Q)$.[Proved]

3.3 Comparison of different SVN-SMs

For the sake of demonstrating the advantage and reasonability of the developed SVN-SMs $S_i(K,N): i=1,2,$ we present a comparison with several previously developed SVN-SMs, which are given as: Ye [23], Broumi and Smarandache [24], Ye [25], Majumdar and Samanta [26], Ye [27], Mandal and Basu [28], Ye [29], Fu and Ye [30], Mondal et al. [31], Wu et al. [32] and Sun et al. [33]. These extant SVN-SMs are presented in Section 1 of supplementary file.

Table 1. A comparison study of SVN-similarity measures

Pairs	**Pair-1**	**Pair -2**	**Pair -3**	**Pair -4**	**Pair -5**	**Pair -6**	**Pair -7**	**Pair -8**	**Pair -9**	**Pair -10**
M	(0.5,0,0)	(0,0.5,0)	(0.3,0.2,0.3)	(0.3,0.2,0.4)	(0.4,0.2,0.3)	(1,0,0)	(1,0,0)	(1,1,1)	(1,1,1)	(0.5,0.4,0.3)
N	(0,0,0.5)	(0,0,0.5)	(0.4,0.2,0.3)	(0.4,0.2,0.3)	(0.8,0.4,0.6)	(0,1,1)	(0,0,0)	(0.6,0.5,0)	(0.8,0.5,0)	(0.5,0.4,0.3)
$S_{Y1}(M,N)$	**0.000**	**0.000**	0.9949	0.9655	1.000	0.000	**NaN**	0.8131	0.7956	1.000
$S_B(M,N)$	**0.5000**	**0.5000**	**0.9000**	**0.9000**	0.6000	0.000	**0.000**	**0.000**	**0.000**	1.000
$S_{Y2}(M,N)$	**0.6667**	**0.6667**	**0.9333**	**0.9333**	0.7000	0.000	**0.6667**	0.3667	0.4333	1.000
$S_{MS}(M,N)$	**0.000**	**0.000**	**0.8000**	**0.8000**	0.5000	0.000	**0.000**	0.3667	0.4333	1.000
$S_{Y3}(M,N)$	**0.7071**	**0.7071**	**0.9877**	**0.9877**	0.8090	0.000	**0.000**	**0.000**	**0.000**	1.000
$S_{Y4}(M,N)$	**0.8660**	**0.8660**	**0.9945**	**0.9945**	0.8910	0.000	**0.8660**	0.5446	0.6293	1.000
$S_{MB}(M,N)$	0.6781	0.5406	**0.9296**	**0.9296**	0.6495	0.000	**0.6781**	0.3219	0.3677	1.000
$S_{Y5}(M,N)$	**0.000**	**0.000**	**0.800**	**0.800**	0.500	0.000	**0.000**	0.3667	0.4333	1.000
$S_F(M,N)$	**0.5516**	**0.5516**	**0.8980**	**0.8980**	0.5900	0.000	**0.5516**	0.2578	0.3157	1.000
$S_{MP}(M,N)$	**0.7370**	**0.7370**	**0.9511**	**0.9511**	0.7655	0.000	**0.7370**	0.4507	0.5194	1.000
$S_W(M,N)$	**0.8267**	**0.8267**	**0.9930**	**0.9930**	0.8988	0.000	0.6667	0.5243	0.5660	1.000
$S_S(M,N)$	0.3258	0.8542	0.9125	0.8908	0.7175	0.000	**-0.0833**	0.8267	0.8983	1.000
$S_1(M,N)$	0.600	0.5000	0.8947	0.8421	0.6087	0.000	0.6667	0.2400	0.3200	1.000
$S_2(M,N)$	0.7746	0.7500	0.9474	0.9177	0.8041	0.000	0.8165	0.5797	0.6066	1.000

Note: Bold displays that it fails to discriminate the two pairs, therefore presents the counter intuitive cases, which flop to satisfy the axioms (A_1 and A_3) of SVN-SM. We take $p=1$ in S_{Y2}. "NaN" shows that it fails to compute the similarity degree because "the division by zero problems".

Now, we take ten pairs of SVNSs for comparing the proposed SMs $S_i(M,N): i=1,2$ with the extant ones given in supplementary file. The similarity measure outcomes generated by different formulae are presented in Table 1. By analyzing the measure outcomes, we present some interesting results, shown as follows:

- The measure $S_{Y1}(K,N)$ fails to deal with the division by zero problem, e.g., see the value of $S_{Y1}(K,N)$ when $K=(1, 0, 0)$, $N=(0, 0, 0)$(Pair-7).
- Various existing measures ($S_B(K,N)$, $S_{Y2}(K,N)$, $S_{MS}(K,N)$, $S_{Y3}(K,N)$, $S_{Y4}(K,N)$, $S_{Y5}(K,N)$, $S_F(K,N)$, $S_{MP}(K,N)$ and $S_W(K,N)$) fail to discriminate the positive and negative differences. For example, $S_B(K,N)=S_B(K_1,N_1)=0.9000$ when $K=(0.3, 0.2, 0.3)$, $N=(0.4, 0.2, 0.4)$ (Pair-

3), K_1= (0.3, 0.2, 0.4) and N_1= (0.4, 0.2, 0.3) (Pair-4). The analogous counter intuitive issues happen for $S_{Y1}(K, N)$, $S_B(K, N)$, $S_{Y2}(K, N)$, $S_{MS}(K, N)$, $S_{Y3}(K, N)$, $S_{Y4}(K, N)$, $S_{MB}(K, N)$, $S_{Y5}(K, N)$, $S_F(K, N)$, $S_{MP}(K, N)$, $S_W(K, N)$, $S_I(K, N)$. Additional counter intuitive circumstances exist when K = (0.5, 0, 0), N =(0, 0, 0.5) (Pair-1) and K_1= (0, 0.5, 0), N_1= (0, 0, 0.5) (Pair-2). For these pairs, $S_B(K, N)= S_B(K_1, N_1)$=0.5000.

- As the SM $S_S(K, N)$= −0.0833 when K = (1, 0, 0) and N = (0, 0, 0) (Pair-7) which is definitely $0 \le S_S\left(K,N\right) \le 1$, thus, it fails to satisfy the postulate (A_1). Furthermore, the postulate (A_3) is also not fulfilled by $S_{Y1}(K, N)$, $S_{MS}(K, N)$, and $S_{Y5}(K, N)$ when K = (0.5, 0, 0), N = (0, 0, 0.5) (Pair-1), K = (0, 0.5, 0), N = (0, 0, 0.5) (Pair-2), K = (0.3, 0.2, 0.3), N = (0.4, 0.2, 0.4) (Pair-3), K = (0.3, 0.2, 0.4), N =(0.4, 0.2, 0.3) (Pair-4) and K = (0.4, 0.2, 0.3), N = (0.8, 0.4, 0.6) (Pair-5) which are certainly not identical. Moreover, we observe that $S_{Y1}(K, N)= S_{MS}(K, N)= S_{Y5}(K, N)$= 0 when K = (0.5, 0, 0), N = (0, 0, 0.5) and K = (0, 0.5, 0), N = (0, 0, 0.5) (Pair-1 and Pair-2), $S_B(K, N) = S_{Y3}(K, N) = S_{MS}(K, N)= S_{Y5}(K, N)= S_B(K, N)$= 0 when K = (1, 0, 0), N = (0, 0, 0) (Pair-7), $S_B(K, N) = S_{Y3}(K, N)$ = 0 when K = (1.0, 0.0, 0.0), N = (0.6,0.5,0) and K = (1.0, 1.0, 1.0), N = (0.8,0.5,0.0) (Pair-8 and Pair-9), which are not actually opposites.

The new SVN-SMs are introduced to surmount the weaknesses of previously developed measures. The proposed measures employ the homogeneity between the truth and the falsity belongingness grades to portray the inconsistent and indeterminate data expressed by SVNNs. In addition, these SMs use the degree of indeterminacy to address the unknown of uncertainty. As such the two aspects of uncertainty of information are sufficiently expressed in this study. Moreover, it can easily be observed from Table 1 that the developed measures can avoid the counter intuitive ranking results.

This study develops two SMs for SVNSs: one is a set-theoretic measure and the other integrates the former measure and the concept of SMs on a concept lattice. The performance evaluation of the suggested SVN-SMs is twofold: evaluating how much the measures are reasonable, and signifying the accuracy when the measures are employed to feature selection, image processing, disease diagnosis, decision-making and others. Hence, the presented similarity measures $S_i\left(K,N\right): i = 1,2$ are consistent with definite pairs. In addition, these measures have no counter intuitive circumstances and results are depicted in Table 1.

4. An extended WASPAS framewrok on SVNSs

In the present section, an integrated framework is developed for solving SVN information-based MCGDM problems with unknown DEs and criteria weights, which is based on traditional WASPAS approach. In the developed framework, the SVN-SOWIA based on SVN-SM, aggregation operator and score function is presented to calculate the criteria weights. With the use of SVNSs, a group of DEs provides more flexibility in expressing their preferences under uncertain situations. The procedural structure for SVN-WASPAS framework is presented as below (see Fig. 1):

Step 1: Originate the MCGDM structure and create the decision matrix

In the process of MCGDM, let $V=\{V_1,V_2,...,V_m\}$ be a set of options and $F=\{F_1,F_2,...,F_n\}$ be set of criteria. A team of DEs $E=\{e_1,e_2,...,e_l\}$ expresses their opinions on each option V_i over the criterion F_j in form of linguistic terms (LTs). Let $M=\left(h_{ij}^{(k)}\right)$, $i=1(1)m,\ j=1(1)n$ be the linguistic matrix offered by the DEs, wherein $h_{ij}^{(k)}$ denotes the evaluation of an option V_i w.r.t. criterion F_j for k^{th} DE.

Step 2: Derive the DEs' weights

Consider that the significance degrees of the DEs is presented in LTs, which is further converted in SVNNs. Suppose $E_k=(t_k,i_k,f_k)$ be a SVNN, then weight of the k^{th} DE is presented as

$$\varpi_k=\left(\frac{\left(t_k+i_k\left(\frac{t_k}{t_k+f_k}\right)\right)}{\sum_{k=1}^{l}\left(t_k+i_k\left(\frac{t_k}{t_k+f_k}\right)\right)}\right). \tag{10}$$

Clearly, $\sum_{k=1}^{l}\varpi_k=1$ and $\varpi_k\geq 0.$

Step 3: Construct the aggregated SVN-decision matrix (A-SVN-DM).

To calculate the A-SVN-DM, each of the single decision matrices needs to be combined into one decision matrix by employing DEs' views. With the use of SVNWA operator, we create the A-SVN-DM $\square=\left(\widehat{\xi}_{ij}\right)_{m\times n}$ where

$$\widehat{\xi}_{ij}=\left(\widehat{t}_{ij},\widehat{i}_{ij},\widehat{f}_{ij}\right),=SVNWA\left(h_{ij}^{(1)},h_{ij}^{(2)},...,h_{ij}^{(l)}\right)=\left(1-\prod_{k=1}^{l}\left(1-t_{ij}^{(k)}\right)^{\varpi_k},\prod_{k=1}^{l}\left(i_{ij}^{(k)}\right)^{\varpi_k},\prod_{k=1}^{l}\left(f_{ij}^{(k)}\right)^{\varpi_k}\right). \tag{11}$$

Step 4: Normalize the A-SVN-DM

The normalized A-SVN-DM $\square=\left(\varsigma_{ij}\right)_{m\times n}$ is calculated by given expression

$$\varsigma_{ij}=\begin{cases}\widehat{\xi}_{ij}=\left(\widehat{t}_{ij},\widehat{i}_{ij},\widehat{f}_{ij}\right), & j\in F_b\\ \left(\widehat{\xi}_{ij}\right)^c=\left(\widehat{f}_{ij},1-\widehat{i}_{ij},\widehat{t}_{ij}\right), & j\in F_n\end{cases}, \tag{12}$$

where F_n and F_b are the types of cost and benefit attributes, respectively.

Step 5: Assess the criteria weights using SVN-SOWIA

Consider that each of the criteria has diverse significance value. Let $w=\left(w_1,w_2,...,w_n\right)^T$ be the weight value of a criteria set, satisfying $\sum_{j=1}^{n}w_j=1$ and $w_j\in[0,\,1]$. The developed framework for criteria weights calculation is given as follows:

Case 1: Find out the objective weight w_j^o based on the similarity measure

$$w_j^o = \frac{\sum_{i=1}^{m}\sum_{k=1,k\neq i}^{m}\left(1-S_1\left(\varsigma_{ij},\varsigma_{kj}\right)\right)}{\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1,k\neq i}^{m}\left(1-S_1\left(\varsigma_{ij},\varsigma_{kj}\right)\right)},\ \ j=1(1)n. \tag{13}$$

Case 2: Evaluate the subjective weight w_j^s for criterion.

Here, we calculate the subjective weight matrix $\left(w_j^s\right)$ for k^{th} DE, given by

$$W_j^s = \left[w_{j(k)}^s\right]_{n\times 1} = \begin{bmatrix} w_{1(k)}^s \\ w_{2(k)}^s \\ \vdots \\ w_{n(k)}^s \end{bmatrix}, \tag{14}$$

where $w_{j(k)}^s,\ j=1(1)n,\ k=1(1)l$ is the subjective weight of F_j given by the k^{th} DE and we obtain

$$w_j^s = \left(\left(w_{j(1)}^s \oplus w_{j(2)}^s \oplus \ldots \oplus w_{j(l)}^s\right)\big/ l\right). \tag{15}$$

Let $w_{j(k)}^s = \left(p_{ijk}\right)$ be the decision weight of k^{th} DE, where $p_{ijk} = \left(t_{ijk},\, i_{ijk},\, f_{ijk}\right),\ k=1(1)l$ is a SVNN. After that, we create the aggregated weight value $W_j^s = (1/l)\sum_{k=1}^{l} w_{j(k)}^s$, where

$$W_j^s = \left(1-\prod_{k=1}^{l}\left(1-t_{ijk}\right)^{\varpi_k}, \prod_{k=1}^{l}\left(i_{ijk}\right)^{\varpi_k}, \prod_{k=1}^{l}\left(f_{ijk}\right)^{\varpi_k}\right). \tag{16}$$

Here, $W_j^s = \left(t_{ij*}, i_{ij*}, f_{ij*}\right)$ is also a single-valued neutrosophic number.

Thus, the subjective weight of the j^{th} criterion is computed as

$$w_j^s = \frac{\mathrm{S}^*\left(W_j^s\right)}{\sum_{j=1}^{n}\mathrm{S}^*\left(W_j^s\right)};\ j=1(1)n. \tag{17}$$

Case 3: Determine the combined weight

By means of Eqs (13)–(17), the combined weight of criterion is given by

$$w_j = \gamma w_j^s + (1-\gamma)\, w_j^o, \tag{18}$$

where $\gamma \in [0,1]$ is the aggregation coefficient of decision precision.

Step 6: Evaluate the measures of weighted sum model (WSM) $\square_i^{(1)}$ and weighted product model (WPM) $\square_i^{(2)}$ for each option by using

$$\square_i^{(1)} = \bigoplus_{j=1}^{n} w_j\, \varsigma_{ij}. \tag{19}$$

$$\square_i^{(2)} = \bigotimes_{j=1}^{n} w_j\, \varsigma_{ij}. \tag{20}$$

Step 7: Evaluate the WASPAS or utility measure of each candidate by using

$$\square_i = \vartheta\square_i^{(1)} + (1-\vartheta)\square_i^{(2)}, \tag{21}$$

where $\vartheta \in [0,1]$ is the decision mechanism coefficient. This parameter is introduced to compute the accurateness of WASPAS measure on the basis of initial criteria precision.

Step 9: Sort the option(s) in reference to the increasing score values of $\mathbb{C}_i$.

Step 10: End.

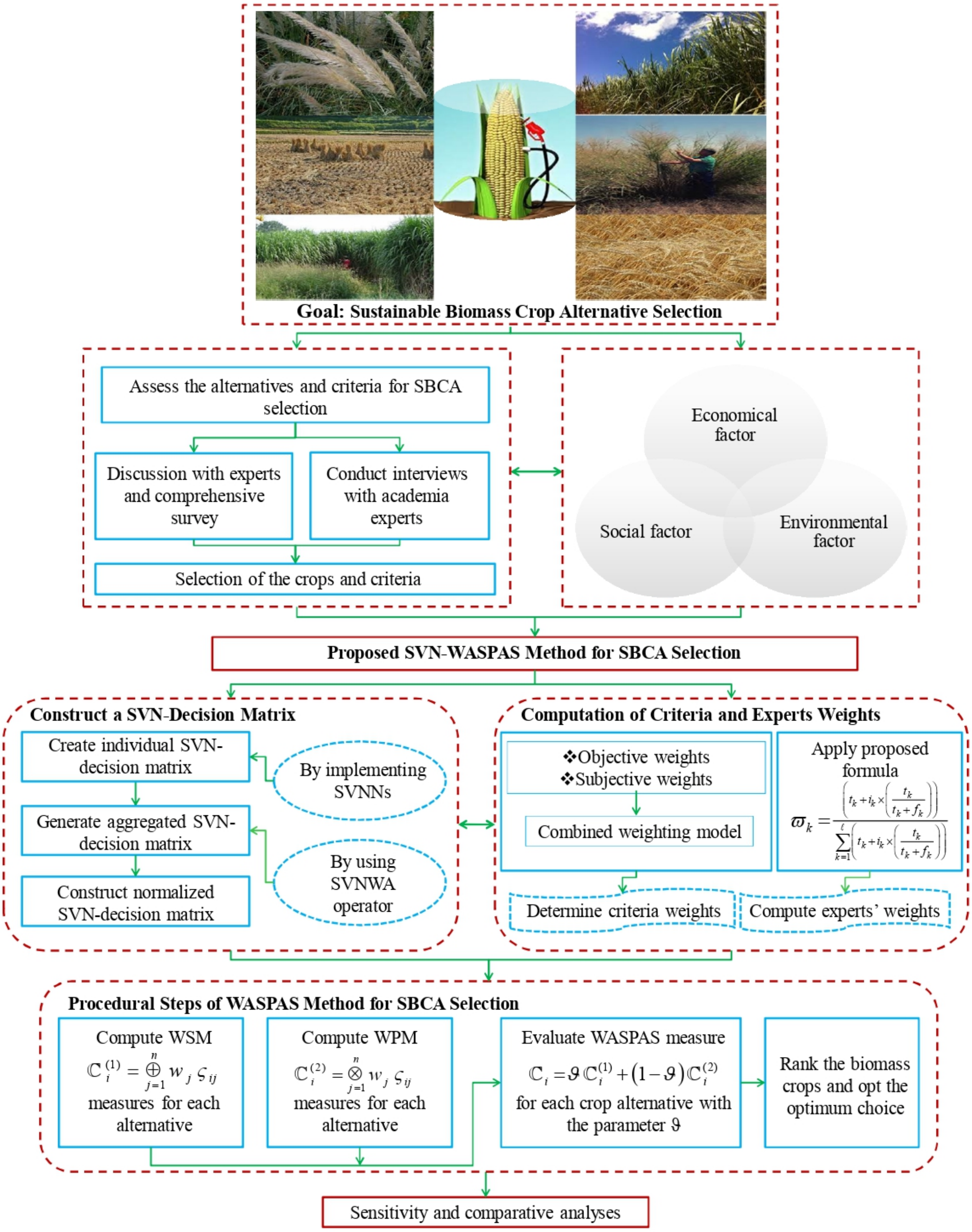

Fig.1. Flowchart of the proposed SVN-WASPAS method

Also, Algorithm 1 shows the steps involved in the proposed SVN-WASPAS approach

Algorithm 1: Pseudocode representation of SVN-WASPAS for SBCA selection

Input: m, n, l are the number of alternatives, criteria and decision experts (DEs)
Output: Rank the sustainable biomass crop alternatives (SBCAs)
Begin
Step 1: Input decision matrix and weight of each DEs in LTs
Step 2: Convert decision matrix and weight of each DEs into SVNNs
Step 3: for $k = 1$ to l
Compute ϖ_k as per Eq. (10)
end for
Step 4: Use SVNWA operaor to output A-SVN-DM $\square = \left(\hat{\xi}_{ij}\right)_{m\times n}$, $i = 1$ to m, $j = 1$ to n
Step 5: Construct normalized A-SVN-DM $\square = \left(\varsigma_{ij}\right)_{m\times n}$, $i = 1$ to m, $j = 1$ to n
Step 6: Use SVN-SOWIA with proposed similarity measure to output w_j w. r. t. decision precision parameter γ
Step 7: Use SVNWA operator to output WSM $\square_i^{(1)}$ and SVNWG operator to WPM $\square_i^{(2)}$
Step 8: Evaluate the performance of WASPAS measure $\square_i$ w. r. t. decision mechanism coefficient $\vartheta \in [0,1]$
Step 9: Rank the SBCAs according to the score values of $\square_i$
End

5. Case study: Sustainable biomass crop alternative (SBCA) assessment

In this part of the study, the introduced SVN-WASPAS method is utilized for the assessment sustainable biomass crop alternatives (SBCAs), which demonstrates the applicability of the proposed method.

5.1.Biomass crop alternatives

Biomass refers to organic material acquired from agricultural residues, energy crops, animal wastes and additional materials. Among various renewable energy resources, the energy obtained from biomass can be directly utilized for transport fuel in several developed countries. Generally, biomass can be categorized into energy crops, food crops and their agricultural residues and forest materials [1,7]. Energy crops are low cost and minimum-maintenance crops grown exclusively for bioenergy production. Food crops, basically employed for food production, are also used for bioethanol and biodiesel production. Forest residues have not been considered for this case study.

In that respect, there are some established energy crops, given as (see Fig. 2)

Switchgrass *(Panicum virgatum* L.) (V_1)

Switchgrass is the perennial tall grass that does not require to be developed every year. It can grow in poor-quality soil with low requirement of fertilizers while it provides environmental benefits such as soil conservation, greenhouse gas emissions reduction and generates high biomass yields utilized for biofuel production. Several articles have been commenced to amplify its conversion effectiveness [67].

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Miscanthus (*Miscanthusfuscus* (Roxb.) Benth) (V_2)

Miscanthus is a high yielding energy crop native to tropical and subtropical zones of southern Asia. It is a valuable crop growing on marginal land and in cool temperate climate. It has a very high yield than annual crops utilized for energy and lower carbon cost in energy production than fossil fuels [68].

Kans grass (Saccharum spontaneum L.) (V_3)

Kans grass *(Saccharum sponteneum)* is a perennial grass, growing up to three meters in height, on marginal and wetlands. It is a self-seeding, resistant to several infections and insects, tolerant to poor soils, drought and flooding; prevents erosion and enhances the soil quality because of its type of root system. It utilizes less water per gram of biomass produced than other plants. Kans grass contains a higher quantity of carbohydrate in comparison with other lignocellulosic biomasses which can be transformed to ethanol by appropriate techniques [69].

Corn (*Zea mays* L.) Sugarcane (*Saccharum officinarum* L.) Wheat (*Triticum aestivum* L.) Rice (*Oryza sativa* L.)
Kans Grass (*Saccharum spontaneum* L.) Miscanthus (*Miscanthus fuscus* (Roxb.) Benth) Switchgrass (*Panicum virgatum* L.)

Fig.2. Description of various types of biomass crop alternatives

Corn (*Zea mays* L.) (V_4)

Corn is the one of the popular and largest source of ethanol production because of its large quantity and relative easiness of conversion to ethanol. Corn grain makes a good biofuel feedstock due to its starch substance.

Sugarcane *(Saccharum officinarum* L.) (V_5)

Sugarcane is one of the main sources of biofuel production all over the world. It cultivates in a warmer climate. India is the second largest producer of sugarcane. The production of sugarcane is sensitive to transportation, fertilizers, atmosphere, irrigation and infection [1].

Wheat (*Triticumaestivum* L.) (V_6)**:**

Wheat is one of the main food crops which consists high protein substance. This crop is also employed for ethanol generation. It cultivates from its own seeds and needs seeding and irrigation each year, which enhances the production cost, while the alteration from its biomass is efficient [1].

Rice (*Oryza sativa* L.)(V_7)

Rice is a staple crop of India. Due to the farming potency of the country, the production of crop residues is also high in this country. India is not only a prime consumer of rice but also second leading manufacturer in the world. Even though, national level estimation of crop residue biomass prospective in India is accessible, state level database is limited excluding the few states [4].

5.2.Related criteria

The list of criteria presented in this section is considered from several sources to distinguish many aspects such as economic, environmental, and social facets and their characteristics for biomass crops assessment [70,71]. The detail description about the list of 20 criteria under these aspects is mentioned in Table 2.

Table 2. Considered criteria for SBCAs assessment

Aspect	Criteria	Meanings of Criteria	Type
Economic	Input (F_1)	Quantify the cost throughout the establishment process with land preparation, machinery, fertilizers, pesticide and labour	Cost
	Output (F_2)	Considers the harvestable quantity and productivity of biomass crop on the preferred land type	Benefit
	Production cost (F_3)	Quantify the production cost with fertilizers, herbicides, irrigation and labor cost particularly during the time between seeding and harvesting	Cost
	Storage and transportation cost (F_4)	Quantify the cost of biomass storage and and transportation requirements	Cost
	Conversion rate (F_5)	Obtained amount of gallons of ethanol per ton through biomass conversion technology	Benefit
	Sales risk (F_6)	Refers the risk of agronomists in form of sale of the biomass crop	Cost
	Equipment and knowledge (F_7)	Quantity the assessibility of the equipment throughout all the cycles and the cultivation knowledge of the agronomists about the specified crop alternative	Benefit
	Robustness (F_8)	Measures the quality of the crop alternative with respect to drought, hot and cold temparate climate, its longevity and variation in prices	Benefit
	Soil quality (F_9)	Assess the potentiality of the crop alternative on decreasing soil erosion and requiring minimum fertilization	Benefit
	Carbon emission (F_{10})	Refers the amount of total CO_2 emissions reduction and the capacity of decarbonization	Benefit
	Usage of chemicals (F_{11})	Measures the negative consequences on the soil quality during the process of energy production	Cost
Environmental	Water quality/requirement (F_{12})	Measures the potentiality of the biomass crop alternative with respect to water efficiency	Benefit

Social	Biodiversity and wildlife (F_{13})	Quantify the impacts of biomass farming on biodiversity and wildlife including bird and insect populations	Benefit
	Land type (F_{14})	Measures the effect of biomass generation on a certain land type; cropland, grassland, and marginal land	Benefit
	Invasiveness (F_{15})	Evaluates risk and control cost of the biomass crop option related with a high dispersal rate and the harmful impacts	Cost
	Technological development (F_{16})	Refers the potential technological developments needed for ethanol conversion rate and the productivity on farms	Benefit
	Workforce requirement (F_{17})	Refers to increment in employment rate and gain of the workforce	Benefit
	Contribution to welfare (F_{18})	Evaluates the potentiality of the increment in wealth of the society and economic development as a result of biomass generation	Benefit
	Sustainable energy (F_{19})	Evaluates the ability of altering the fossil fuel	Benefit
	Compete for food (F_{20})	Quantify the changes of the food security by measuring the proper allocation of cropland	Benefit

5.3.Implementation of proposed SVN-WASPAS method

In this part, the SVN-WASPAS framework is implemented to prioritize the biomass crop alternatives from sustainability perspective. For this, a panel of three DEs $\{e_1, e_2, e_3\}$ is formed to process the proposed methodology on the present application and to identify the most suitable candidate among a set of SBCAs. All the DEs are from different areas and also they have more than 20 years of work experience in their domain. According to the DEs' opinions and earlier studies, the considered alternatives are estimated under 20 criteria, presented in Table 2. Next, Table 3 and Table 4 (adopted from [20,40,45]) present the LTs to compute the relative importance of three DEs and the performance ratings for assessing the SBCAs over considered factors, and then expressed in terms of SVNNs. Based on Table 3 and Eq. (10), the DEs' weights are determined and shown in Table 5. Table 6 describes the individual decision preferences for each crop candidate V_i concerning the considered evaluation factors. In accordance with Eq. (11), an aggregated decision matrix is estimated and shown in Table 7. Since some evaluation factors are of cost-type and the others are of benefit-type, so, the normalized A-SVN-DM is evaluated using Eq. (12) and depicted in Table 8.

Table 3. LTs for rating the DEs performances

LTs	SVNNs
Extremely qualified (EQ)	(0.90, 0.10, 0.10)
Very very qualified (VVQ)	(0.75, 0.25, 0.20)
Very qualified (VQ)	(0.60, 0.35, 0.40)
Qualified (Q)	(0.50, 0.45, 0.50)
Less qualified (LQ)	(0.25, 0.75, 0.70)
Very less qualified (VLQ)	(0.10, 0.90, 0.90)

Table 4. Performance ratings of the SBCAs in terms of LTs

LTs	SVNNs
Extremely high (EH)	(1.00, 0.00, 0.00)
Very very high (VVH)	(0.90, 0.10, 0.10)
Very high (VH)	(0.80, 0.15, 0.20)
High (H)	(0.70, 0.25, 0.30)
Moderately high (MH)	(0.60, 0.35, 0.40)

Fair (F)	(0.50, 0.50, 0.50)
Moderately low (ML)	(0.40, 0.65, 0.60)
Low (L)	(0.30, 0.75, 0.70)
Very low (VL)	(0.20, 0.85, 0.80)
Very very low (VVL)	(0.10, 0.90, 0.90)
Extremely low (EL) / 0 grades	(0.00, 1.00, 1.00)

Table 5. Weights of the DEs for rating the SBCAs

DEs	LVs	SVNNs	Weights
e_1	Q	(0.50, 0.45, 0.50)	0.2092
e_2	VVQ	(0.75, 0.25, 0.20)	0.4210
e_3	VQ	(0.60, 0.35, 0.40)	0.3698

Table 6. Evaluation of sustainable biomass crop alternatives in terms of LTs given by three DEs

	V_1	V_2	V_3	V_4	V_5	V_6	V_7
F_1	(ML, VL,VL)	(L,ML,VL)	(MH, ML,F)	(MH,MH,F)	(F,F,ML)	(MH,F,MH)	(F,ML,MH)
F_2	(H,VH,H)	(VH,VH,VH)	(F,MH,F)	(VH,MH,VH)	(VH,H,H)	(F,L,MH)	(F,MH,F)
F_3	(ML,L,F)	(VL,L,VL)	(ML,F,MH)	(MH,H,F)	(F,F,ML)	(L,ML,ML)	(VL,L,F)
F_4	(F,MH,ML)	(F,H,H)	(ML,MH,F)	(L,ML,VL)	(ML,F,ML)	(L,F,ML)	(H,MH,ML)
F_5	(MH,H,F)	(VH,H,VH)	(ML,MH,L)	(VH,MH,ML)	(MH,MH,H)	(VH,H,VH)	(H,MH,MH)
F_6	(L, L,VL)	(L,VL,VL)	(H,MH,F)	(L,MH,F)	(L,F,ML)	(H,L,F)	(L,F,H)
F_7	(MH,L,F)	(L,L,VL)	(MH,F,H)	(VH,H,F)	(VVH,F,MH)	(F,MH,H)	(F,VL,VL)
F_8	(H,VH,MH)	(MH,VH,VH)	(F,MH,L)	(MH,F,L)	(F,ML,MH)	(L,F,VVL)	(VL,L,F)
F_9	(F,VH,MH)	(VVH,VH,H)	(MH,H,F)	(VL,ML,L)	(ML,VL,ML)	(MH,H,L)	(VL,H,F)
F_{10}	(VVH,H,MH)	(H,H,VH)	(ML,ML,F)	(VVL,ML,L)	(MH,H,VH)	(H,F,VVH)	(H,ML,F)
F_{11}	(L, ML,VL)	(L,L,VL)	(MH, F,L)	(ML,L,F)	(F,L,ML)	(L,H,ML)	(H,F,ML)
F_{12}	(ML,L,F)	(L,ML,VL)	(VH,F,ML)	(ML,MH,VH)	(VH,H,VVH)	(F,ML,H)	(F,F,VL)
F_{13}	(VVH,MH,H)	(H,MH,VH)	(MH,ML,F)	(MH,VH,L)	(F,ML,MH)	(L,MH,L)	(L,VVL,F)
F_{14}	(F,H,MH)	(H,H,VVH)	(VH,MH,F)	(VVL,VL,L)	(ML,F,MH)	(F,ML,MH)	(H,VH,VH)
F_{15}	(L, VL,L)	(L,VL,VL)	(ML,H,F)	(VL,VVL,L)	(F,VL,VVL)	(F,H,ML)	(F,MH,VH)
F_{16}	(H,MH,F)	(VH,H,MH)	(H, VH,F)	(ML,MH,F)	(H,F,ML)	(F,H,VH)	(F,MH,ML)
F_{17}	(ML,F,F)	(ML,ML,VL)	(ML,F,MH)	(VH,MH,VL)	(H,H,MH)	(F,L,VH)	(F,ML,ML)
F_{18}	(VH,H,VVH)	(VH,H,VH)	(F,L,F)	(VH,L,F)	(F,L,MH)	(VH,L,ML)	(L,ML,F)
F_{19}	(F,H,MH)	(H,VVH,H)	(ML,H,F)	(L,MH,ML)	(VL,F,ML)	(VH,F,ML)	(H,H,ML)
F_{20}	(F,H,F)	(VH,F,VH)	(ML,VVL,F)	(ML,VL,L)	(VH,F,L)	(L,H,MH)	(H,VL,H)

Table 7. A-SVN-DM for sustainable biomass crop alternative selection

	V_1	V_2	V_3	V_4	V_5	V_6	V_7
F_1	(0.250, 0.786, 0.736)	(0.278, 0.740, 0.689)	(0.474, 0.498, 0.502)	(0.533, 0.393, 0.430)	(0.435, 0.545, 0.531)	(0.537, 0.401, 0.436)	(0.478, 0.492, 0.498)
F_2	(0.703, 0.206, 0.257)	(0.769, 0.150, 0.200)	(0.502, 0.436, 0.459)	(0.717, 0.207, 0.261)	(0.703, 0.215, 0.266)	(0.454, 0.520, 0.529)	(0.502, 0.436, 0.459)
F_3	(0.381, 0.630, 0.600)	(0.215, 0.810, 0.760)	(0.478, 0.481, 0.490)	(0.571, 0.346, 0.385)	(0.435, 0.545, 0.531)	(0.343, 0.678, 0.628)	(0.327, 0.682, 0.652)
F_4	(0.471, 0.475, 0.487)	(0.612, 0.306, 0.348)	(0.474, 0.471, 0.484)	(0.278, 0.740, 0.689)	(0.405, 0.588, 0.560)	(0.377, 0.613, 0.585)	(0.544, 0.388, 0.420)
F_5	(0.571, 0.346, 0.385)	(0.740, 0.182, 0.233)	(0.413, 0.538, 0.541)	(0.595, 0.334, 0.373)	(0.605, 0.314, 0.364)	(0.740, 0.182, 0.233)	(0.601, 0.317, 0.368)
F_6	(0.245, 0.781, 0.731)	(0.215, 0.819, 0.769)	(0.571, 0.356, 0.396)	(0.450, 0.491, 0.507)	(0.377, 0.613, 0.585)	(0.494, 0.477, 0.490)	(0.503, 0.449, 0.467)
F_7	(0.450, 0.526, 0.533)	(0.245, 0.781, 0.731)	(0.578, 0.359, 0.397)	(0.649, 0.270, 0.315)	(0.691, 0.278, 0.291)	(0.578, 0.348, 0.389)	(0.289, 0.728, 0.697)
F_8	(0.511, 0.445, 0.479)	(0.717, 0.192, 0.245)	(0.444, 0.498, 0.512)	(0.444, 0.514, 0.523)	(0.478, 0.492, 0.498)	(0.289, 0.682, 0.668)	(0.327, 0.682, 0.652)

F_9	(0.622, 0.281, 0.328)	(0.785, 0.157, 0.186)	(0.571, 0.346, 0.385)	(0.282, 0.737, 0.686)	(0.317, 0.720, 0.670)	(0.521, 0.395, 0.430)	(0.474, 0.448, 0.472)
F_{10}	(0.734, 0.213, 0.239)	(0.707, 0.212, 0.263)	(0.408, 0.597, 0.565)	(0.256, 0.749, 0.710)	(0.682, 0.233, 0.286)	(0.729, 0.242, 0.255)	(0.517, 0.451, 0.462)
F_{11}	(0.278, 0.740, 0.689)	(0.245, 0.781, 0.731)	(0.444, 0.514, 0.523)	(0.381, 0.630, 0.600)	(0.377, 0.636, 0.603)	(0.463, 0.471, 0.482)	(0.514, 0.445, 0.457)
F_{12}	(0.381, 0.630, 0.600)	(0.278, 0.740, 0.689)	(0.568, 0.383, 0.406)	(0.610, 0.318, 0.359)	(0.793, 0.160, 0.186)	(0.525, 0.441, 0.454)	(0.380, 0.595, 0.583)
F_{13}	(0.736, 0.218, 0.243)	(0.682, 0.241, 0.293)	(0.474, 0.498, 0.502)	(0.574, 0.325, 0.369)	(0.478, 0.492, 0.498)	(0.386, 0.561, 0.565)	(0.303, 0.704, 0.690)
F_{14}	(0.574, 0.342, 0.383)	(0.767, 0.185, 0.210)	(0.619, 0.307, 0.351)	(0.191, 0.830, 0.793)	(0.478, 0.481, 0.490)	(0.478, 0.492, 0.498)	(0.740, 0.174, 0.225)
F_{15}	(0.249, 0.787, 0.737)	(0.249, 0.819, 0.769)	(0.517, 0.414, 0.434)	(0.191, 0.834, 0.801)	(0.261, 0.742, 0.725)	(0.514, 0.418, 0.437)	(0.630, 0.295, 0.341)
F_{16}	(0.571, 0.356, 0.396)	(0.674, 0.240, 0.293)	(0.619, 0.285, 0.330)	(0.474, 0.471, 0.484)	(0.514, 0.445, 0.457)	(0.660, 0.259, 0.305)	(0.471, 0.475, 0.487)
F_{17}	(0.439, 0.540, 0.527)	(0.310, 0.709, 0.659)	(0.478, 0.481, 0.490)	(0.555, 0.365, 0.410)	(0.633, 0.279, 0.330)	(0.565, 0.394, 0.422)	(0.405, 0.602, 0.569)
F_{18}	(0.793, 0.160, 0.186)	(0.740, 0.182, 0.233)	(0.413, 0.584, 0.569)	(0.551, 0.411, 0.435)	(0.454, 0.520, 0.529)	(0.523, 0.447, 0.462)	(0.381, 0.622, 0.591)
F_{19}	(0.574, 0.342, 0.383)	(0.758, 0.176, 0.197)	(0.517, 0.414, 0.434)	(0.416, 0.535, 0.538)	(0.352, 0.636, 0.609)	(0.568, 0.383, 0.406)	(0.435, 0.545, 0.531)
F_{20}	(0.542, 0.384, 0.411)	(0.698, 0.237, 0.284)	(0.334, 0.676, 0.660)	(0.282, 0.754, 0.704)	(0.546, 0.402, 0.427)	(0.530, 0.385, 0.422)	(0.555, 0.399, 0.436)

Table 8. Normalized A-SVN-DM for biomass crop evaluation process

	V_1	V_2	V_3	V_4	V_5	V_6	V_7
F_1	(0.736, 0.214, 0.250)	(0.689, 0.260, 0.278)	(0.502,0.502, 0.474)	(0.430, 0.607, 0.533)	(0.531,0.455, 0.435)	(0.436,0.599, 0.537)	(0.498, 0.508, 0.478)
F_2	(0.703, 0.206, 0.257)	(0.769, 0.150, 0.200)	(0.502, 0.436, 0.459)	(0.717, 0.207, 0.261)	(0.703, 0.215, 0.266)	(0.454, 0.520, 0.529)	(0.502, 0.436, 0.459)
F_3	(0.600, 0.370, 0.381)	(0.760, 0.190, 0.215)	(0.490,0.519, 0.478)	(0.385, 0.654, 0.571)	(0.531,0.455, 0.435)	(0.628,0.322, 0.343)	(0.652, 0.318, 0.327)
F_4	(0.487, 0.525, 0.471)	(0.348, 0.694, 0.612)	(0.484,0.529, 0.474)	(0.689, 0.260, 0.278)	(0.560,0.412, 0.405)	(0.585,0.387, 0.377)	(0.420, 0.612, 0.544)
F_5	(0.571, 0.346, 0.385)	(0.740, 0.182, 0.233)	(0.413, 0.538, 0.541)	(0.595, 0.334, 0.373)	(0.605, 0.314, 0.364)	(0.740, 0.182, 0.233)	(0.601, 0.317, 0.368)
F_6	(0.731, 0.219, 0.245)	(0.769, 0.181, 0.215)	(0.396,0.644, 0.571)	(0.507, 0.509, 0.450)	(0.585,0.387, 0.377)	(0.490,0.523, 0.494)	(0.467, 0.551, 0.503)
F_7	(0.450, 0.526, 0.533)	(0.245, 0.781, 0.731)	(0.578, 0.359, 0.397)	(0.649, 0.270, 0.315)	(0.691, 0.278, 0.291)	(0.578, 0.348, 0.389)	(0.289, 0.728, 0.697)
F_8	(0.511, 0.445, 0.479)	(0.717, 0.192, 0.245)	(0.444, 0.498, 0.512)	(0.444, 0.514, 0.523)	(0.478, 0.492, 0.498)	(0.289, 0.682, 0.668)	(0.327, 0.682, 0.652)
F_9	(0.622, 0.281, 0.328)	(0.785, 0.157, 0.186)	(0.571, 0.346, 0.385)	(0.282, 0.737, 0.686)	(0.317, 0.720, 0.670)	(0.521, 0.395, 0.430)	(0.474, 0.448, 0.472)
F_{10}	(0.734, 0.213, 0.239)	(0.707, 0.212, 0.263)	(0.408, 0.597, 0.565)	(0.256, 0.749, 0.710)	(0.682, 0.233, 0.286)	(0.729, 0.242, 0.255)	(0.517, 0.451, 0.462)
F_{11}	(0.689, 0.260, 0.278)	(0.731, 0.219, 0.245)	(0.523,0.486, 0.444)	(0.600, 0.370, 0.381)	(0.603,0.364, 0.377)	(0.482,0.529, 0.463)	(0.457, 0.555, 0.514)
F_{12}	(0.381, 0.630, 0.600)	(0.278, 0.740, 0.689)	(0.568, 0.383, 0.406)	(0.610, 0.318, 0.359)	(0.793, 0.160, 0.186)	(0.525, 0.441, 0.454)	(0.380, 0.595, 0.583)
F_{13}	(0.736, 0.218, 0.243)	(0.682, 0.241, 0.293)	(0.474, 0.498, 0.502)	(0.574, 0.325, 0.369)	(0.478, 0.492, 0.498)	(0.386, 0.561, 0.565)	(0.303, 0.704, 0.690)
F_{14}	(0.574, 0.342, 0.383)	(0.767, 0.185, 0.210)	(0.619, 0.307, 0.351)	(0.191, 0.830, 0.793)	(0.478, 0.481, 0.490)	(0.478, 0.492, 0.498)	(0.740, 0.174, 0.225)

F_{15}	(0.737, 0.213, 0.249)	(0.769, 0.181, 0.249)	(0.434,0.586, 0.517)	(0.801, 0.166, 0.191)	(0.725,0.258, 0.261)	(0.437,0.582, 0.514)	(0.341, 0.705, 0.630)
F_{16}	(0.571, 0.356, 0.396)	(0.674, 0.240, 0.293)	(0.619, 0.285, 0.330)	(0.474, 0.471, 0.484)	(0.514, 0.445, 0.457)	(0.660, 0.259, 0.305)	(0.471, 0.475, 0.487)
F_{17}	(0.439, 0.540, 0.527)	(0.310, 0.709, 0.659)	(0.478, 0.481, 0.490)	(0.555, 0.365, 0.410)	(0.633, 0.279, 0.330)	(0.565, 0.394, 0.422)	(0.405, 0.602, 0.569)
F_{18}	(0.793, 0.160, 0.186)	(0.740, 0.182, 0.233)	(0.413, 0.584, 0.569)	(0.551, 0.411, 0.435)	(0.454, 0.520, 0.529)	(0.523, 0.447, 0.462)	(0.381, 0.622, 0.591)
F_{19}	(0.574, 0.342, 0.383)	(0.758, 0.176, 0.197)	(0.517, 0.414, 0.434)	(0.416, 0.535, 0.538)	(0.352, 0.636, 0.609)	(0.568, 0.383, 0.406)	(0.435, 0.545, 0.531)
F_{20}	(0.542, 0.384, 0.411)	(0.698, 0.237, 0.284)	(0.334, 0.676, 0.660)	(0.282, 0.754, 0.704)	(0.546, 0.402, 0.427)	(0.530, 0.385, 0.422)	(0.555, 0.399, 0.436)

Table 9. Criteria weights obtained by a group of DEs

Criteria	e_1	e_2	e_3	Aggregated SVNNs	Score values	Weight
F_1	MH	F	VH	(0.630, 0.304, 0.347)	0.669	0.0649
F_2	F	H	MH	(0.574, 0.342, 0.383)	0.627	0.0610
F_3	F	MH	MH	(0.537, 0.388, 0.427)	0.583	0.0567
F_4	F	ML	MH	(0.478, 0.492, 0.498)	0.499	0.0485
F_5	MH	H	H	(0.637, 0.276, 0.326)	0.690	0.0671
F_6	VH	F	MH	(0.622, 0.313, 0.356)	0.660	0.0642
F_7	VL	ML	L	(0.282, 0.737, 0.686)	0.281	0.0273
F_8	MH	F	ML	(0.471, 0.491, 0.497)	0.498	0.0484
F_9	ML	L	VL	(0.278, 0.749, 0.699)	0.270	0.0262
F_{10}	H	VH	H	(0.703, 0.206, 0.257)	0.759	0.0737
F_{11}	F	ML	ML	(0.405, 0.602, 0.569)	0.408	0.0397
F_{12}	ML	F	MH	(0.478, 0.481, 0.490)	0.507	0.0493
F_{13}	ML	F	F	(0.439, 0.540, 0.527)	0.458	0.0445
F_{14}	MH	ML	MH	(0.511, 0.443, 0.467)	0.539	0.0524
F_{15}	ML	ML	VL	(0.310, 0.709, 0.659)	0.308	0.0299
F_{16}	VH	MH	L	(0.574, 0.350, 0.392)	0.620	0.0603
F_{17}	VL	ML	F	(0.356, 0.645, 0.615)	0.363	0.0353
F_{18}	ML	MH	ML	(0.442, 0.513, 0.514)	0.475	0.0462
F_{19}	H	F	L	(0.489, 0.466, 0.481)	0.519	0.0505
F_{20}	ML	F	H	(0.525, 0.431, 0.446)	0.554	0.0539

To estimate the objective criteria weights, Eqs (5) and (13) are used and shown as $w_j^o =$ (0.0430, 0.0445, 0.0447, 0.0429, 0.0363, 0.0502, 0.0607, 0.0469, 0.0623, 0.0605, 0.0389, 0.0603, 0.0555, 0.0644, 0.0619, 0.0322, 0.0431, 0.0550, 0.0473, 0.0494).

To estimate the subjective criteria weights, Eqs (14)–(17) are employed and shown as (see Table 9)

$w_j^s =$ (0.0649, 0.0610, 0.0567, 0.0485, 0.0671, 0.0642, 0.0273, 0.0484, 0.0262, 0.0737, 0.0397, 0.0493, 0.0445, 0.0524, 0.0299, 0.0603, 0.0353, 0.0462, 0.0505, 0.0539).

By means of objective and subjective weights, the combined weights of criteria is calculated using Eq. (18) ($\gamma = 0.5$) and thus, we get

$w_j =$ (0.0539, 0.0527, 0.0507, 0.0457, 0.0517, 0.0572, 0.0440, 0.0476, 0.0442, 0.0671, 0.0393, 0.0548, 0.0500, 0.0584, 0.0459, 0.0462, 0.0392, 0.0506, 0.0489, 0.0517).

Using Eqs (19)-(21), the WSM $\left(\square_i^{(1)}\right)$, WPM $\left(\square_i^{(2)}\right)$ and WASPAS $\left(\square_i\right)$ measures of each alternative and their score values $\mathrm{S}\left(\square_i^{(1)}\right)$ and $\mathrm{S}\left(\square_i^{(2)}\right)$ are computed and shown in Table 10. As a consequence, the ranking order of the given SBCAs is $V_2 \succ V_1 \succ V_5 \succ V_6 \succ V_4 \succ V_3 \succ V_7$ and hence, V_2, i.e., Miscanthus is the most suitable crop alternative from sustainability perspective.

Table 10. Computed results of the developed method

Alternative	WSM measure		WPM measure		WASPAS measure	Ranking
	$\square_i^{(1)}$	$\mathrm{S}^*\left(\square_i^{(1)}\right)$	$\square_i^{(2)}$	$\mathrm{S}^*\left(\square_i^{(2)}\right)$	$\square_i$	
V_1	(0.631, 0.311, 0.339)	0.668	(0.602, 0.349, 0.368)	0.529	0.651	2
V_2	(0.684, 0.250, 0.288)	0.724	(0.619, 0.346, 0.351)	0.535	0.684	1
V_3	(0.492, 0.474, 0.474)	0.518	(0.480, 0.498, 0.487)	0.515	0.508	6
V_4	(0.519, 0.438, 0.448)	0.549	(0.460, 0.526, 0.507)	0.526	0.512	5
V_5	(0.582, 0.371, 0.389)	0.613	(0.552, 0.414, 0.420)	0.524	0.594	3
V_6	(0.547, 0.411, 0.423)	0.576	(0.521, 0.446, 0.447)	0.522	0.561	4
V_7	(0.482, 0.488, 0.489)	0.504	(0.453, 0.534, 0.519)	0.516	0.485	7

5.4. Sensitivity investigation

In the current section, sensitivity investigation is used to confirm the steadiness of developed SVN-WASPAS approach and also, eradicate any possible entity opinion biases which may manipulate the results [20,72]. Sensitivity investigation can be performed in two ways, by varying the criteria weights computed by SVN-SOWIA and by altering the decision mechanism coefficient values. In first two cases, we analyze the use of DEs opinions in subjective weights while providing the significance value of each criterion and also by structure of data in objective weights of SBCAs with the variation of parameter $\gamma \in [0,1]$.

Case-1. The first case determines the criteria weights by considering only objective weight-determining approach (at $\gamma = 0.0$) instead of incorporated weighting technique. Therefore, the performance values and rank of the alternatives are calculated and shown in Tables 11-12. The performance of the crop candidates is shown in the first column of Table 12 and the ranking order is given as $V_2 \succ V_1 \succ V_5 \succ V_6 \succ V_4 \succ V_3 \succ V_7$, whereas the objective criteria weights are presented in the first column of Table 11.

Case-2. The second case computes the weights by considering the subjective weight-determining approach (at $\gamma = 1.0$) rather than incorporated weighting technique. Thus, the performance values and rank of the alternatives are presented in Tables 11-12. The performance of alternative values is given in the last column of Table 12 and the preference order is obtained in the following way: $V_2 \succ V_1 \succ V_5 \succ V_6 \succ V_4 \succ V_3 \succ V_7$ wherein the subjective weights are given in the last column of Table 11.

On the basis of the above-mentioned sensitivity analysis, we have obtained the following results: (i) the preferences of the alternatives in Case-1 demonstrate the structure of criteria with respect to their alternatives; and (ii) the preference order of the alternatives in Case-2 illustrates the DEs significance about the criteria with respect to their consideration. These two cases explain that the prioritization order of the SBCAs is equivalent in each case while changing the weights of the criteria. However, the objective weighting model evaluates the criteria weights through computational procedures without any consideration of the DEs' opinions, whilst the subjective-weighting model evaluates the criteria weights simply based on the consideration of DEs' preferences. Moreover, the SVN-SOWIA can conquer the drawbacks which occur either in an objective weighting approach or a subjective-weighting approach. Thus, we can strongly recommend the SVN-SOWIA to determine the criteria weights for SBCA assessment. The outcomes of the sensitivity investigation with anticipated weights are presented in Fig. 3 and Fig. 4.

Case-3. Altering the values of $\vartheta \in [0,1]$ can assist us to evaluate the sensitivity investigation of the present methodology moving from WSM to WPM. The WSM measure (when $\vartheta = 1.0$) is calculated which consider only the integrated weights (when $\gamma = 0.5$ in Table 11). The performances of alternative values are given in first column of Table 13 and the preference order is obtained as $V_2 \succ V_1 \succ V_5 \succ V_6 \succ V_4 \succ V_3 \succ V_7$ when the integrated weights are given in Table 11 ($\gamma = 0.5$). Similarly, the WPM measure (when $\vartheta = 0.0$) is calculated which consider only the integrated weights (when $\gamma = 0.5$ in Table 11). The performances of alternative values are given in last column of Table 13 and the preference order is obtained as $V_2 \succ V_1 \succ V_5 \succ V_6 \succ V_4 \succ V_3 \succ V_7$ when the integrated weights are given in Table 11 ($\gamma = 0.5$). Thus, the proposed method has an adequate stability over the diverse parameter $\vartheta \in [0,1]$ values. Along with Fig. 5, sustainable biomass crop type alternative (V_2) has the first rank, V_1 has the second rank, while V_7 has worst rank.

Case-4. To reflect diverse sets of DEs' preferences and sensitivity investigation, four different weighting approaches are considered and sensitivity investigation of alternatives ranking under the weights of attributes is analyzed. Weighting approaches are as

(a) Holistic framework: Equal preference weights to all criteria,

(b) Economic framework: Strong emphasis on economic costs and other financial considerations,

(c) Social framework: Preference toward actions involving the highest social benefits, and

(d) Environmental framework: Dominance of environmental criteria.

Holistic approach weights are calculated with Eq. (22) for the different scenarios; preference weights of the preferred criteria groups are estimated through Eq. (23) and for other criteria groups' weights, Eq. (24) are used.

$$w_e = \frac{1}{n}, \tag{22}$$

$$w_p = \frac{\text{maximum weight}}{n_p}, \tag{23}$$

$$w_o = \frac{1 - \text{maximum weight}}{n_o}, \tag{24}$$

wherein n is the total number of criteria; e is equal; p is preferred; o is other; maximum weight is 0.9 [73] weights of criteria are calculated.

The performance of SBCAs is given in Fig. 6. In this case, Miscanthus (V_2) is the best SBCA by using the proposed SVN-WASPAS framework, holistic, economic, environmental and social frameworks of criteria weighting (see Fig. 6), while Rice (V_7) is determined as the worst SBCA. To attain better insight from the SVN-WASPAS method on SBCA assessment, we compute the score values of diverse crop alternatives on each criterion, as shown in Fig. 6. As Miscanthus (V_2) has significantly maximum score for holistic, economic, environmental and social aspects of criteria, therefore, it is preferred as the most suitable crop alternative for ethanol production from sustainable perspective. Owing to its minimum scores in sales risk and carbon emissions, rice is the least favorable candidate, based on the considered factors.

According to the aforementioned discussion, it can be noticed that by considering the varied parameters values and different weighting procedures will improve the strength of the proposed SVN-WASPAS model.

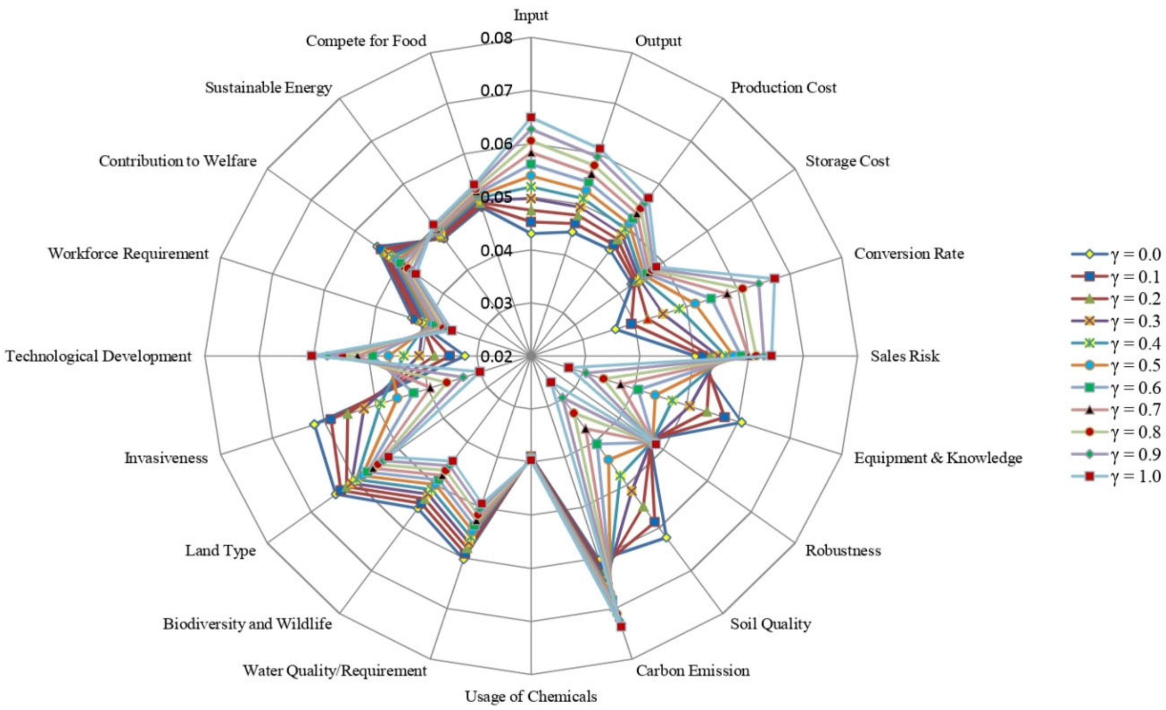

Fig.3. Sensitivity investigation results regarding various values of (γ).

Table 11. Computational assessment of proposed SVN-WASPAS method

	$\gamma = 0.0$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
F_1	0.0430	0.0452	0.0474	0.0496	0.0518	0.0539	0.0561	0.0583	0.0605	0.0627	0.0649
F_2	0.0445	0.0462	0.0478	0.0494	0.0511	0.0527	0.0544	0.0560	0.0577	0.0594	0.0610
F_3	0.0447	0.0459	0.0471	0.0483	0.0495	0.0507	0.0519	0.0531	0.0543	0.0555	0.0567
F_4	0.0429	0.0435	0.0440	0.0446	0.0451	0.0457	0.0463	0.0468	0.0474	0.0479	0.0485
F_5	0.0363	0.0394	0.0425	0.0455	0.0486	0.0517	0.0548	0.0579	0.0609	0.0640	0.0671
F_6	0.0502	0.0516	0.0530	0.0544	0.0558	0.0572	0.0586	0.0600	0.0614	0.0628	0.0642
F_7	0.0607	0.0574	0.0540	0.0507	0.0473	0.0440	0.0407	0.0373	0.0340	0.0306	0.0273
F_8	0.0469	0.0470	0.0472	0.0473	0.0475	0.0476	0.0478	0.0479	0.0481	0.0483	0.0484
F_9	0.0623	0.0587	0.0551	0.0515	0.0479	0.0442	0.0406	0.0370	0.0334	0.0298	0.0262
F_{10}	0.0605	0.0618	0.0631	0.0645	0.0658	0.0671	0.0684	0.0697	0.0711	0.0724	0.0737
F_{11}	0.0389	0.0390	0.0391	0.0391	0.0392	0.0393	0.0394	0.0395	0.0395	0.0396	0.0397
F_{12}	0.0603	0.0592	0.0581	0.0570	0.0559	0.0548	0.0537	0.0526	0.0515	0.0504	0.0493
F_{13}	0.0555	0.0544	0.0533	0.0522	0.0511	0.0500	0.0489	0.0478	0.0467	0.0456	0.0445
F_{14}	0.0644	0.0632	0.0620	0.0608	0.0596	0.0584	0.0572	0.0560	0.0548	0.0536	0.0524

F_{15}	0.0619	0.0587	0.0555	0.0523	0.0491	0.0459	0.0427	0.0395	0.0363	0.0331	0.0299
F_{16}	0.0322	0.0350	0.0378	0.0406	0.0434	0.0462	0.0491	0.0519	0.0547	0.0575	0.0603
F_{17}	0.0431	0.0423	0.0415	0.0408	0.0400	0.0392	0.0384	0.0376	0.0369	0.0361	0.0353
F_{18}	0.0550	0.0541	0.0532	0.0524	0.0515	0.0506	0.0497	0.0488	0.0480	0.0471	0.0462
F_{19}	0.0473	0.0476	0.0479	0.0483	0.0486	0.0489	0.0492	0.0495	0.0499	0.0502	0.0505
F_{20}	0.0494	0.0498	0.0503	0.0508	0.0512	0.0517	0.0521	0.0525	0.0530	0.0535	0.0539

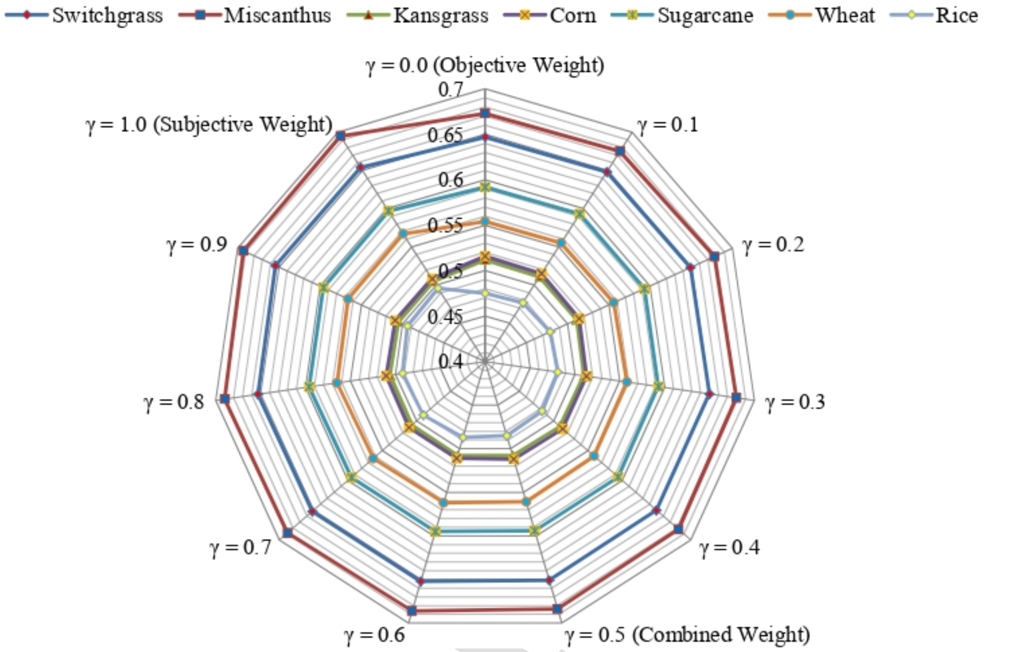

Fig.4. Comparison of degree of relative significance of biomass crops to various parameter (γ) values.

Table 12. Preference order of biomass crops with SVN-WASPAS method for various parameter γ values

	$\gamma = 0.0$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
V_1	0.647	0.648	0.649	0.650	0.650	0.651	0.652	0.652	0.653	0.654	0.654
V_2	0.673	0.675	0.678	0.680	0.682	0.684	0.686	0.688	0.690	0.693	0.695
V_3	0.512	0.511	0.511	0.510	0.509	0.508	0.508	0.507	0.506	0.505	0.505
V_4	0.516	0.515	0.514	0.513	0.513	0.512	0.511	0.511	0.510	0.509	0.508
V_5	0.592	0.593	0.593	0.593	0.594	0.594	0.595	0.595	0.596	0.596	0.597
V_6	0.554	0.555	0.556	0.558	0.559	0.561	0.562	0.563	0.565	0.566	0.567
V_7	0.475	0.477	0.479	0.481	0.483	0.485	0.487	0.490	0.492	0.494	0.496

Table 13. Preference order of biomass crops with SVN-WASPAS method for various parameter ϑ values

	$\vartheta = 0.0$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
V_1	0.634	0.637	0.641	0.644	0.648	0.651	0.654	0.658	0.661	0.664	0.668
V_2	0.644	0.652	0.660	0.668	0.676	0.684	0.692	0.700	0.708	0.716	0.724
V_3	0.499	0.501	0.503	0.505	0.507	0.508	0.510	0.512	0.514	0.516	0.518
V_4	0.475	0.482	0.490	0.497	0.505	0.512	0.519	0.527	0.534	0.542	0.549
V_5	0.576	0.580	0.583	0.587	0.591	0.594	0.598	0.602	0.605	0.609	0.613
V_6	0.545	0.548	0.551	0.554	0.558	0.561	0.564	0.567	0.570	0.573	0.576
V_7	0.467	0.470	0.474	0.478	0.482	0.485	0.489	0.493	0.497	0.501	0.504

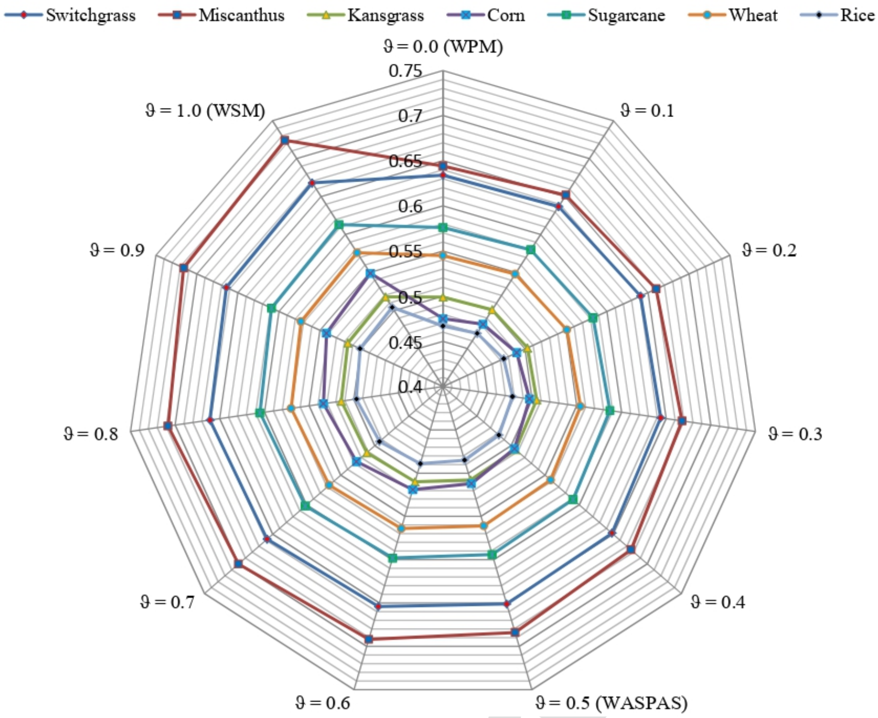

Fig.5. Relative significance degrees of biomass crops with various values of (ϑ).

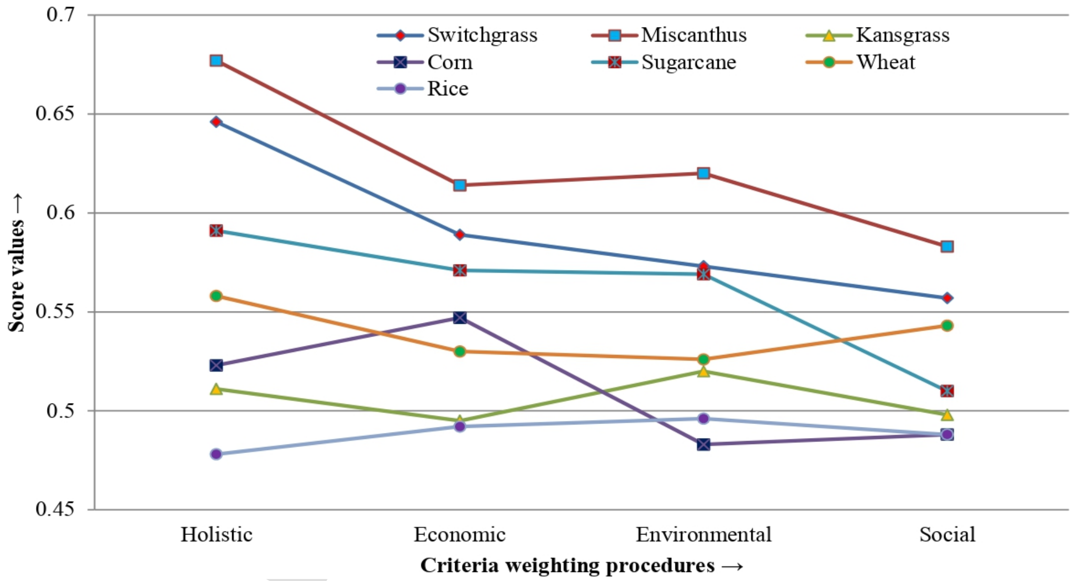

Fig.6. Weighted scores of SBCAs under different criteria procedures.

5.5.Comparison with extant methods

Throughout the present section, we aim to compare the outcomes of the suggested SVN-WASPAS technique with the results of SVN-TOPSIS method [22], Cobuloglu and Buyuktahtakın [1], Baušys et al. [74] and Peng and Dai [75].

For this, firstly we present the structure of SVN-TOPSIS approach, which as

Steps 1-5: Follow the SVN-WASPAS method

Step 6: Compute single-valued neutrosophic ideal and anti-ideal solutions

Let $\widehat{\Box} = \left(\widehat{\xi}_{ij}\right)_{m\times n}$ be an A-SVN-DM that describes the normalized performance of option V_i in terms of criterion F_j. In the SVN-TOPSIS framework, the determination of single-valued neutrosophic ideal and anti-ideal solutions of each criterion is a significant issue for the experts. Let κ_j^+ and κ_j^- denote the ideal and anti-ideal solutions in terms of SVNNs, respectively, and computed by

$$\kappa_j^+ = \left(t_j^+, i_j^+, f_j^+\right) = \begin{cases} \left(\max\limits_i \widehat{t}_{ij}, \min\limits_i \widehat{i}_{ij}, \min\limits_i \widehat{f}_{ij}\right), & j \in F_{\max} \\ \left(\min\limits_i \widehat{t}_{ij}, \max\limits_i \widehat{i}_{ij}, \max\limits_i \widehat{f}_{ij}\right), & j \in F_{\min}, \end{cases} \tag{25}$$

$$\kappa_j^- = \left(t_j^-, i_j^-, f_j^-\right) = \begin{cases} \left(\min\limits_i \widehat{t}_{ij}, \max\limits_i \widehat{i}_{ij}, \max\limits_i \widehat{f}_{ij}\right), & j \in F_{\max} \\ \left(\max\limits_i \widehat{t}_{ij}, \min\limits_i \widehat{i}_{ij}, \min\limits_i \widehat{f}_{ij}\right), & j \in F_{\min}, \end{cases} \tag{26}$$

where $F_{\max}$ and $F_{\min}$ are the beneficial and non-beneficial types of attributes, respectively.

Step 7: Estimate the separation degrees of the options from single-valued neutrosophic ideal and anti-ideal solutions, given by

$$J_w\left(\widehat{\xi}_{ij}, \kappa_j^+\right) = \frac{1}{\left(\sqrt{2}-1\right)} \sum_{i=1}^{n} w_j \begin{bmatrix} \left(\dfrac{\left(\widehat{t}_{ij}\right)^2 + \left(t_j^+\right)^2}{2}\right)^{1/2} - \dfrac{\widehat{t}_{ij} + \left(t_j^+\right)}{2} \\ + \left(\dfrac{\left(\widehat{i}_{ij}\right)^2 + \left(i_j^+\right)^2}{2}\right)^{1/2} - \dfrac{\widehat{i}_{ij} + \left(i_j^+\right)}{2} \\ + \left(\dfrac{\left(\widehat{f}_{ij}\right)^2 + \left(f_j^+\right)^2}{2}\right)^{1/2} - \dfrac{\widehat{f}_{ij} + \left(f_j^+\right)}{2} \end{bmatrix}, \tag{27}$$

$$J_w\left(\widehat{\xi}_{ij}, \kappa_j^-\right) = \frac{1}{\left(\sqrt{2}-1\right)} \sum_{i=1}^{n} w_j \begin{bmatrix} \left(\dfrac{\left(\widehat{t}_{ij}\right)^2 + \left(t_j^-\right)^2}{2}\right)^{1/2} - \dfrac{\widehat{t}_{ij} + \left(t_j^-\right)}{2} \\ + \left(\dfrac{\left(\widehat{i}_{ij}\right)^2 + \left(i_j^-\right)^2}{2}\right)^{1/2} - \dfrac{\widehat{i}_{ij} + \left(i_j^-\right)}{2} \\ + \left(\dfrac{\left(\widehat{f}_{ij}\right)^2 + \left(f_j^-\right)^2}{2}\right)^{1/2} - \dfrac{\widehat{f}_{ij} + \left(f_j^-\right)}{2} \end{bmatrix}. \tag{28}$$

Step 8: Calculate the closeness degree

Now, we assess the relative closeness degree of each candidate, which as

$$C_i = \frac{J_w\left(\hat{\xi}_{ij}, \kappa_j^-\right)}{J_w\left(\hat{\xi}_{ij}, \kappa_j^-\right) + J_w\left(\hat{\xi}_{ij}, \kappa_j^+\right)},\ C_i \in [0, 1]. \tag{29}$$

The higher degree of C_i means the better option.

Step 9: End.

Along with Table 7 and Eq. (25)-Eq. (26), the κ_j^+ and κ_j^- are estimated and presented as $\kappa_j^+ = \{$(0.430, 0.607, 0.533), (0.769, 0.150, 0.200), (0.385, 0.654, 0.571), (0.348, 0.694, 0.612), (0.740, 0.182, 0.233), (0.396,0.644, 0.571), (0.649, 0.270, 0.291), (0.717, 0.192, 0.245), (0.785, 0.157, 0.186), (0.734, 0.212, 0.239), (0.457, 0.555, 0.514), (0.793, 0.160, 0.186), (0.736, 0.218, 0.243), (0.767, 0.174, 0.210), (0.341, 0.705, 0.630), (0.674, 0.240, 0.293), (0.633, 0.279, 0.330), (0.793, 0.160, 0.186), (0.758, 0.176, 0.197), (0.698, 0.237, 0.284)$\}$,
$\kappa_j^- = \{$(0.736, 0.214, 0.250), (0.454, 0.520, 0.529), (0.760, 0.190, 0.215), (0.689, 0.260, 0.278), (0.413, 0.538, 0.541), (0.769, 0.181, 0.215), (0.245, 0.781, 0.731), (0.289, 0.682, 0.668), (0.282, 0.737, 0.686), (0.256, 0.749, 0.710), (0.731, 0.219, 0.245), (0.278, 0.740, 0.689), (0.303, 0.704, 0.690), (0.191, 0.830, 0.793),(0.801, 0.166, 0.191), (0.474, 0.475, 0.487), (0.310, 0.709, 0.659), (0.381, 0.622, 0.591), (0.352, 0.636, 0.609), (0.282, 0.754, 0.704)$\}$. Now, the results of the SVN-TOPSIS model are shown in Table 14. By Eq. (27)-Eq. (29), we calculate the relative closeness degree of SBCA and are shown in Table 14. Table 14 displays the ranking outcomes of the seven biomass crop alternatives as obtained by the mentioned approach. Thus, the candidate V_2 (Miscanthus) is the first choice for the considered sustainable biomass crop alternatives.

Table 14. Preference order of biomass crop alternatives based on SVN-TOPSIS method

SBCA	$J_w\left(\hat{\xi}_{ij}, \kappa_j^+\right)$	$J_w\left(\hat{\xi}_{ij}, \kappa_j^-\right)$	C_i	Ranking
V_1	0.189	0.231	0.550	3
V_2	0.159	0.261	0.622	1
V_3	0.200	0.221	0.525	5
V_4	0.250	0.170	0.405	7
V_5	0.195	0.227	0.537	4
V_6	0.178	0.243	0.577	2
V_7	0.227	0.194	0.461	6

In comparison with SVN-TOPSIS [22], Cobuloglu and Buyuktahtakın [1], Baušys et al. [74] and Peng and Dai [75], the merits of the presented approach are listed as follows (comparison results are shown in Table 15):

- For the TOPSIS [22,75] model, it is compulsory to assess the divergences between each alternative on each criterion and that of the ideal solution, which is a lengthy process and reduces the accuracy of the results, while SVN-COPRAS [74] method can be originated from the correlation of complex relationships between elements of a SVN-decision matrix using SVNWA operator. The TOPSIS and COPRAS methods suffer from two significant shortcomings: (a) the non-meaningfulness of the resulting rankings in mixed data contexts (i.e. the rankings of alternatives may change under possible transformations of the initial attribute values, in the measurement-theoretic sense of the term); and (b) rank reversals or ranking irregularities (i.e. the rankings of alternatives may alter if a new option added to the considered set of options or an previous one is erased from it or replaced it). In the current study, we develop the SVN-WASPAS method which combines the WPM and WSM to acquire the benefits of both the models. The overall computational procedure of the SVN-WASPAS technique is effortless, and the reliability and accuracy of the outcomes are higher.

- In [1], the AHP is applied for determining the attribute weights. For this purpose, the total $n(n-1)/2$ pairwise comparisons of attributes are essential. However, it is complicated to carry out fully consistent pairwise comparisons if the number of attributes is large. While in SVN-COPRAS [74], the authors have assumed the criteria weights. In [22], the authors have calculated only the criteria objective weights based on divergence measure-based technique. In the proposed method, a novel SVN-SOWIA is utilized for determining the criteria weights due to its effortlessness and lesser number of computation steps, which confirms the flexibility and effectiveness of the proposed approach.
- The SVNSs enhance the elicitation of linguistic knowledge when a group of DEs hesitates among various values to evaluate the sustainable biomass crop alternative problem. The use of SVNSs offers a more flexible process to describe DEs' evaluations. As a consequence, a structured framework is developed to integrate DEs knowledge and experiences for choosing the desirable biomass crop option.
- The WASPAS model, one of the renowned utility principle-based models for MCDM, selects a candidate which has the utmost utility; whereas the extant methods choose a candidate which is closest to the ideal solution.
- The presented methodology in this study could suggest the more accurate decision under uncertain context due to the estimation criteria and DEs' weights. In addition, two other models, WSM and WPM, are assessed as main features in the procedure of the SVN-WASPAS approach lead the computational outcomes to a consistent solution. These features comprise the last aggregation approach to evade the loss of data and to modify the SVN-WASPAS model based on SVNSs information.

Table 15. Comparative discussion of different methodologies with various aspects

Aspects	**Peng and Dai [75]**	**Nancy and Garg [22]**	**Baušys et al. [74]**	**Cobuloglu and Buyuktahtakın [1]**	**Proposed Framework**
Approaches	TOPSIS and MABAC methods	TOPSIS method	COPRAS method	AHP-based LLSM	WASPAS methodology
Alternatives/criteria assessment	SVNSs	SVNSs	SVNSs	FSs	SVNSs
Aggregation process	Geometric	Not considered	Arithmetic	Arithmetic, Geometric	Arithmetic, Geometric
Theme of prioritization	Compromise solution	Compromise solution	Compromise solution	outranking method	Utility theory
Criteria weights	Similarity measure	divergence measure	Assumed	AHP method	New method based on

	procedure	procedure			similarity measure
MCDM process	Single	Single	Single	Group	Group
Involvement of additional data overhead for weight calculation	Excluded	Excluded	Included	Included	Included
Does the ranking approach consider nature of criteria	No	No	No	Yes	Yes
Expert weights	Not considered	Not considered	Not considered	Computed	Computed (Using scoring model)
Normalization type	Vector	Vector	Linear	Linear	Linear, vector
Optimal SBCA	V_2	V_2	V_3	V_1, V_6	V_2

In the following, we present the limitations of the introduced MCGDM methodology:

- In the developed SVN-WASPAS technique, all criteria are considered to be independent. However, in realistic circumstances, there are interrelationships among the criteria.
- A realistic complexity is that decision experts must be instructed with the preference style to properly utilize the flexibility and potential of single-valued neutrosophic sets.
- As environmental problems become increasingly serious, more dimensions of sustainability should be considered in the assessment of biomass crops for ethanol production.

6. Conclusions

The main objective of this work is to create a hybrid methodology for evaluating and ranking the sustainable biomass crops under uncertain, imprecise, indeterminate and inconsistent environment. To acquire the significant criteria to assess the biomass crops, a comprehensive review of the current literature has been carried out. The present study addressed the five main concerns under SVNS environment. First, two new similarity measures have been introduced for SVNSs as this measure has proven to be an imperative topic in the study of uncertainty. Second, the weights of the DEs have been calculated to avoid the subjective randomness in making a decision. Third, the criteria weights have been assessed through SVN-SOWIA by incorporating the subjective weights obtained by the DEs and the objective weights achieved from a new SVN-similarity measure based approach. Fourth, an integrated single-valued neutrosophic WASPAS (SVN-WASPAS) technique has been proposed to solve the MCGDM problems from SVN perspective. Finally, a case study of sustainable biomass crop selection has been given to demonstrate the practicability and usefulness of the developed technique. The calculation result shows that the sustainable biomass crop V_2 (Miscanthus) should be preferred as the most favorable alternative based on the highest WASPAS measure score. Further, sensitivity investigation and comparison with extant techniques have been presented to prove the robustness and stability of the suggested SVN-WASPAS approach. The outcomes indicate that the sustainable biomass crop V_2 (Miscanthus) is always scores the highest rank no matter how the variations of criteria weights. Thus, the developed method not only provides the ranking orders of the crop alternatives but also investigates the criteria performances in the assessment of crop alternatives.

The future research should be directed toward the implementation of the present method for solving other MCGDM scenarios namely low carbon supplier selection, water distillation selection as well as the assessment of the appropriate sustainable biomass crop in various countries or regions. Moreover, one of the future research directions should be the extension of proposed WASPAS model in a bipolar and interval-valued neutrosophic environment. In addition, the directions of future work involves the development of other classical group decision-making methods such as Gained and Lost Dominance Score (GLDS), Double Normalization-based Multiple Aggregation (DNMA), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) and the star additive utility method (UTASTAR) under single-valued neutrosophic environment.

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- **Highlights**

1. Novel similarity measures are developed for SVNSs.
2. A modified WASPAS method is developed to solve the single-valued neutrosophic MCGDM problems.
3. New procedures are discussed to evaluate the weights of the decision experts and the criteria.
4. Case study of biomass crop selection is presented to show the applicability of the developed method.

Arunodaya Raj Mishra: Conceptualization, Formal analysis, Revision, Proofread, Visualization, Methodology, Resources, Writing - Original Draft, References, Review & Editing.

Pratibha Rani: Conceptualization, Methodology, Proofread, Revision, Validation, Writing - Original Draft, Comparative Study and Sensitivity Analysis.

Ravi Sundar Prajapati: Formal analysis, Proofread, Validation, Sensitivity Analysis, Writing - Review & Editing.

Conflict of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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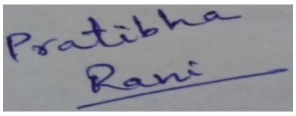
Corresponding author signed on behalf of all coauthors:

Sincerely



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Journal Pre-proof