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An Integrated Single-Valued Neutrosophic Combined Compromise Solution Methodology for Renewable Energy Resource Selection Problem

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Citation: Rani, P.; Ali, J.; Krishankumar, R.; Mishra, A.R.; Cavallaro, F.; Ravichandran, K.S. An Integrated Single-Valued Neutrosophic Combined Compromise Solution Methodology for Renewable Energy Resource Selection Problem. *Energies* **2021**, *14*, 4594. <https://doi.org/10.3390/en14154594>

Academic Editors: Sergio Ulgiati, Marco Casazza and Pedro L. Lomas

Received: 5 July 2021

Accepted: 26 July 2021

Published: 29 July 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Abstract: Optimal renewable energy source (RES) selection needs a strategic decision for reducing environmental pollutions, use of conventional resources, and improving economic development. In the process of RESs evaluation, several aspects like environmental, economic, social, and technical requirements play an important role. In addition, diverse factors affect the appropriate RES selection problem which adheres to uncertain and imprecise data. Thus, this selection process can be considered as a complex uncertain multi-criteria decision making (MCDM) problem. This study aims to introduce a novel integrated methodology based on Step-wise Weight Assessment Ratio Analysis (SWARA) and Combined Compromise Solution (CoCoSo) methods within single-valued neutrosophic sets (SVNSs) context, wherein the decision-makers and criteria weights are completely unknown. In the proposed approach, the criteria weights are determined by the SWARA method, and the most suitable RES alternative is determined by an improved CoCoSo method under the SVN context. Further, an illustrative case study of RES selection is considered to demonstrate the thorough execution process of the proposed method. Moreover, a comparison with existing methods is discussed to analyze the validity of the obtained result. This study performs sensitivity analysis with a various set of criteria weights to reveal the robustness of the developed approach. The strength of the proposed method is its practical applicability and ability to provide solutions under uncertain, imperfect, indeterminate, and inconsistent information.

Keywords: single-valued neutrosophic set; MCDM; SWARA; CoCoSo; renewable energy source selection



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1. Introduction

In the current era, energy has become a fundamental element for the sustainable development and well-being of any nation. Due to industrialization, population growth, and improving living standards, there has been the latest surge of concern regarding the increasing demand for energy and its related services on the one hand and increasing greenhouse gas (GHG) emissions and global climate change on the other [1]. As the limitations of fossils based energy and their unpleasant environmental effects, it is important to improve the country's living standards by providing alternative and cleaner sources

of energy. In this regard, renewable energy sources (RESs) play a vital role in securing sustainable energy with the lowest level of pollution. The continuous development of renewable energy resources has become an essential measure to meet the energy's demand, tackle climate change and satisfy the requirement of clean and sustainable development [2].

Selection of the most suitable source of renewable energy would not only improve the economic development of a country but also minimize the detrimental effects of climate change and environmental burdens. On the other hand, inappropriate RES selection might result in environmental damage and poor economic growth [3]. Thus, the selection of suitable RES alternative is the key concern for the energy companies and investors. To accomplish cleaner energy production, a variety of aspects like environmental, social, economic, technical, and institutional dimensions should be used as benchmarked decisive factors for sustainable energy planning. Because of the presence of numerous tangible and intangible evaluation factors, the selection process of an appropriate RES candidate can be treated as a multi-criteria decision-making (MCDM) problem [4–6]. In this respect, MCDM methods can be utilized to explore this problem in a better way.

Over the past few decades, MCDM has been observed as one of the most significant and omnipresent activities related to practical applications. In the literature, several efforts have been made for assessing the RESs by using a variety of MCDM approaches [7–10]. Although traditional decision-making approaches are inadequate for processing uncertain information that usually occurs in the energy planning processes. In this regard, the notion of the fuzzy set (FS) [11] has inspired researchers globally because of its flexibility and effectiveness in dealing with situations where the available information is incomplete or vague. As the generalization of FSs, Atanassov [12] pioneered the notion of the intuitionistic fuzzy set (IFS), which is more appropriate for dealing with fuzziness and uncertainty than Zadeh's proposal of FS [11].

However, the concepts of FSs and IFSs can only deal with incomplete and uncertain information but not inconsistent and indeterminate information presents in realistic situations. To manage such information more accurately, the neutrosophic set (NS) has been intended by Smarandache [13]. NS is a part of neutrosophy, which studies the origin, nature, and scope of neutralities, as well as their interactions with different ideational spectra [13], and is a powerful general formal framework, which simplifies the above mentioned sets from philosophical viewpoint. The word “neutrosophy” describes “knowledge of neutral thought” and this ‘neutral’ symbolizes the chief distinction among FSs, IFSs and their logics. NS is characterized by three independent membership functions which describe the function of truth, indeterminacy and falsity [13]. These three functions assume values lie in the nonstandard interval of $]0^-, 1^+[$. Thus, the NS has strong acceptance to develop approaches with indeterminate and inconsistent information. However, the co-domain of membership functions of a NS is real standard or nonstandard subsets of $]0^-, 1^+[$. Therefore, it is tricky to apply the NSs in practical situations from a scientific perspective. Consequently, the theory of single-valued neutrosophic set (SVNS) has been pioneered by Wang et al. [14] with some interesting and pioneering properties for better applications in real scientific and engineering areas. As an instance of NS, it consists of a truth $t_S(z_i)$, an indeterminacy $i_S(z_i)$ and a falsity $f_S(z_i)$ membership functions in the closed interval $[0, 1]$ and satisfies the condition $0 \leq t_S(z_i) + i_S(z_i) + f_S(z_i) \leq 3$. SVNSs provide us an additional potential to model uncertain, incomplete, indeterminate, and inconsistent information which occurs in practical problems [15,16].

Inspired by the concept of SVNSs, the present study develops a combined MCDM approach for managing the multi-criteria RESs evaluation problem under a single-valued neutrosophic environment. In dealing with MCDM problems, the evaluation of criteria weights and prioritization of the options are two essential and critical steps for the decision-makers (DMs). The information about the criteria weights is usually completely unknown as a consequence of the complicated decision environments and the inadequate familiarity of DMs. The stepwise weight assessment ratio analysis (SWARA) [17] approach is one of the renowned techniques, which is aimed to estimate the importance of criteria for an

MCDM problem. Unlike other weight-determining approaches, the SWARA process does not need a huge number of pairwise comparisons and has less computational complexity and high consistency. As one of the newly developed approaches, the CoCoSo (combined compromise solution) [18] method enables the DMs to rank the alternatives by means of several qualitative and quantitative criteria. It has high reliability and stability regarding the prioritization of options.

Based on the above discussions, this study extends the SWARA and the CoCoSo approaches a single-valued neutrosophic environment to introduce an integrated MCDM framework for evaluating the RES alternatives. However, few authors have combined the SWARA and the CoCoSo methods under different contexts, but no study has combined these methods under the SVN environment. Thus, this is the first study that proposes a hybrid single-valued neutrosophic-SWARA-CoCoSo (SVN-SWARA-CoCoSo) model with the combination of SWARA and CoCoSo methods from a single-valued neutrosophic (SVN) perspective.

The key contributions of this study are as follows:

- A novel decision-making methodology is originated with the combination of SWARA and CoCoSo approaches with the SVN concept.
- To determine the criteria weights, the SWARA-based procedure is discussed.
- To test the applicability of the introduced methodology, it is implemented on an empirical case study of renewable energy source selection with uncertain, indeterminate, and inconsistent information.
- Comparative and sensitivity analyses are conferred to display the reliability and robustness of the decision outcomes.

The rest part of the present article is summarized as follows: Section 2 discusses the literature of this study. Section 3 presents the basic definitions and operational laws of SVN sets. Section 4 proposes an integrated model for solving MCDM problems under SVN sets context. Section 5 presents an application of RESs assessment, which shows the practicality and capability of the present methodology. This section further presents comparative and sensitivity analyses. After a while, Section 6 concludes the whole study and recommends further study.

2. Related Works

This section briefly reviews the literature on SVN sets, the SWARA approach, the CoCoSo method, and methods for RES selection.

2.1. Single-Valued Neutrosophic Sets (SVNs)

As the FS theory [11] is more capable of reflecting human thinking about the crisp numbers, therefore, it has been received great attention in multi-criteria decision analysis. Since its appearance, several approaches and theories treating imprecision and uncertainty have been originated in the literature [19–21]. The last three decades had witnessed rapid generalizations of FS theory. The concept of IFS [12] is one of the generalized versions of FSs, which assigns to each element the degrees of membership, non-membership, and hesitancy. Thus, it offers a more effective way to manage the vagueness and uncertainty of practical circumstances. Although the concept of FS has been introduced and generalized it cannot be able to address indeterminate and inconsistent information of real-life problems. For instance, if a professional is called for their decision regarding a certain statement, then he or she may articulate that 0.5 being the “possibility that the statement is true”, 0.6 being the “possibility that the statement is false” and 0.2 being the “possibility that he or she is on the fence”. This example is excluded from the scope of FSs and IFSs, and thus, some novel concepts are required.

To conquer such situations, Smarandache [13] initiated the idea of NSs, which is an abstraction of the FSs and IFSs. The prominent characteristic of NS is that it is modeled by the truth-membership, indeterminacy-membership, and falsity-membership functions, which are lie in $[0^-, 1^+]$. It can describe uncertainty, imprecise, incomplete, and inconsistent

information, which the FS, IFS, Pythagorean fuzzy set, and interval-valued IFS cannot express. After the pioneering work of Smarandache [13], NSs have widely been utilized in several real applications to handle uncertainty [22–24]. Further, Wang et al. [14] revealed that NSs were problematic to employ in scientific and engineering circumstances, and then the idea of SVN has been introduced [14]. As a special case of NS, SVN is also modeled by the truth-membership, indeterminacy-membership, and falsity-membership functions; hence, it is very applicable to real applications with indeterminate and inconsistent information. Since its inception, several research efforts have been made in the literature. For instance, Chaw et al. [25] introduced the SVN relations-based decision-making model and its application to recommend the most significant aspect that affects oil prices. Vafadarnikjoo et al. [26] reviewed the customers' motives to buy reconstructed goods by means of fuzzy Delphi procedure and SVN. In a study, Luo et al. [27] presented a tangent SVN-similarity measure-based MCDM model for solving appointment registration systems problems. Garg and Nancy [28] studied an improved SVN-distance measure-based framework for handling MCDM problems. Kumar et al. [29] established a novel variational mode decomposition method based on symmetric SVN-cross entropy to diagnosis the bearing defect in the centrifugal pump. Recently, Mishra et al. [15] suggested an integrated ARAS (Additive Ratio Assessment) method to evaluate and prioritize the locations for the electric vehicle charging station. Jana and Pal [30] proposed some Dombi power operators for SVN and presented their applications in MCDM problems. In a further study, Mishra and Rani [31] developed a hybrid model by combining CRITIC (criteria importance through intercriteria correlation) and CoCoSo method for solving sustainable third-party reverse logistic provider selection problem under SVN settings.

2.2. SWARA Method

In the literature, there are several ways for evaluating the weights of criteria. In 2010, Kersulienė et al. [17] launched the concept of the SWARA approach to calculate the subjective weights of the criteria. The key characteristic of this approach is the possibility to estimate DMs' opinion about the significance ratio of the criteria in the process of their weights evaluation. As compared to AHP (analytic hierarchy process) and BWM (best-worst method), the SWARA method has less computational work, high consistency, and easy to understand [32,33]. Due to its advantages, several research efforts have been made in the literature. For instance, Rani and Mishra [16] combined the SWARA with VIKOR (Visekriterijumska optimizacija i kompromisno rešenje) technique for assessing the MCDM problems under SVN context. In a study [34], the SWARA has merged with intuitionistic fuzzy COPRAS (complex proportional assessment) to evaluate the bioenergy production processes. In a study, the integrated SWARA-CoCoSo model has been recommended for the internet of things adoption barriers in a circular economy [35]. Rani et al. [36] also combined the COPRAS and the SWARA to evaluate the sustainable supplier for Hesitant Fuzzy Sets (HFSs). To evaluate the sustainable community-based tourism in the Indian Himalayan region, He et al. [37] originated a collective decision-making framework by integrating the SWARA and the MULTIMOORA (Multiobjective optimization based on the ratio analysis plus full multiplicative form) approaches with interval-valued PFSs. Alipour et al. [38] proposed a new hybrid model by combining SWARA and CoCoSo approaches with PFSs and applied them for fuel cell and hydrogen components supplier selection. Recently, various other researchers have concentrated on the SWARA model in different environments [39–41].

2.3. CoCoSo Approach

In the literature, several MCDM approaches have been introduced for handling real decision-making problems. As one of the newly developed MCDM techniques, the CoCoSo (combined compromise solution) [18] is a powerful approach that enables DMs to rank the options by means of a range of tangible and intangible criteria. It incorporates three subordinate performance values of options through an aggregation strategy to obtain the

final compromise solution for a multiple criteria decision-making problem. This technique employs the concepts of aggregated simple additive weighting (SAW) and exponentially weighted product (EWP) models to successfully apply the merits of these two methods. In comparison with VIKOR, TOPSIS (Technique for order preference by similarity to ideal solution), and other MCDM models, the optimum solution obtained by the CoCoSo approach is not simply affected by the removal or addition of options and the changes of criteria weight distribution [33]. Thus, this method is an adaptive and robust framework, which has advantages in the stability and reliability of the decision outcomes. In view of that, a large number of researches have been carried out on the CoCoSo method for diverse MCDM problems. Ecer and Pamucar [42] designed a decision support system by integrating BWM and CoCoSo method with fuzzy sets for evaluating sustainable suppliers. To assess the performance of Waste Electrical and Electronic Equipment (WEEE) recycling partner, a hybrid decision-making model has been proposed by Rani and Mishra [43], which combines the CoCoSo method with SVNss. Lahane and Kant [44] established a novel Pythagorean fuzzy AHP-CoCoSo model to evaluate and prioritize the performance values of a circular supply chain. To assess the third-party reverse logistics providers from sustainability perspectives, Mishra and Rani [31], and Mishra et al. [45] suggested innovative CoCoSo methods under single-valued neutrosophic and hesitant fuzzy environments, respectively. Further, Liu et al. [46] offered a hybrid Pythagorean fuzzy CoCoSo method to assess the optimum medical waste treatment technology. Švadlenka et al. [47] designed an algorithm of picture fuzzy CoCoSo method for evaluating the last-mile delivery from a sustainability perspective. To assess the performance of internet of things adoption barriers, Cui et al. [35] introduced an extended Pythagorean SWARA-CoCoSo model in the context of the circular economy. However, existing studies do not combine the SWARA and the CoCoSo methods with SVNss for the selection of the most appropriate RES candidate.

2.4. Methods for Renewable Energy Source (RES) Selection

Since the process of RES selection is an imperative strategic decision-making problem for both public and private sectors, therefore, the authors have done lots of researches on this topic. In the last two decades, numerous MCDM techniques and their different extensions have been introduced about energy decision-making in the literature. For illustration, Wu et al. [4] assessed the renewable power sources with the use of cumulative prospect theory-based decision-making methods under a fuzzy environment. Kaya et al. [48] presented a review of the literature regarding fuzzy MCDM-based techniques for energy policy planning and decision-making with respect to several characteristics. Pan et al. [49] proposed a new interval type-2 fuzzy large-scale group decision-making approach to assess and select the strategic RESs in China. Ghenai et al. [8] studied a novel method using SWARA and ARAS techniques to choose and assess renewable energy systems. Rani et al. [50] discussed a fuzzy information-based MCDM method for evaluating and ranking the candidate RESs in India. Yazdani et al. [51] designed a hybrid decision-making model by integrating Shannon entropy and EDAS (Evaluation based on distance from average solution) technique for evaluating five renewable energy resources concerning diverse influencing factors. Krishankumar et al. [52] studied an integrated decision-making framework to assess and prioritize the candidate RESs within the context of the interval-valued probabilistic linguistic term set. Their study concluded that wind energy was the desirable alternative among other candidate sources. Saraswat and Digalwar [6] firstly discussed the challenges, overview, and growth of the Indian energy sector, and further, introduced a collective Shannon's entropy fuzzy MCDM methodology to address the RESs evaluation problem for sustainable development in India. In a study, Krishankumar et al. [53] proposed a q-rung orthopair fuzzy information-based MCDM framework for the systematic evaluation of RESs in Karnataka, India. However, there is no study regarding an integrated SVN-SWARA-CoCoSo methodology for the strategic evaluation and prioritization of RES alternatives under uncertain, indeterminate, and inconsistent environments.

3. Preliminary Definitions

In the current section, we present the fundamental concepts of NS and SVNS, which will be used throughout this study.

The concept of NS has been originated by Smarandache [13]. In NS theory, each element has a degree of indeterminacy besides the membership and nonmembership degrees as sometimes the DMs are not familiar with the aspects involved in the decision-making process and all the functions are independent in nature. For example, when we ask a customer for his/her opinion about a statement, he/she may say that the possibility of agreeing to a statement is 0.8 and disagreeing is 0.1 and not sure is 0.2. In a NS, it can be represented as (0.8, 0.1, 0.2) whereas it cannot be tackled by IFS as sum of membership, non-membership and hesitation value is not 1.

Definition 1 ([13]). Let $Z = \{z_1, z_2, \dots, z_n\}$ be a finite collection of elements, which is called a universal set. A neutrosophic set (NS) N in Z is a neutrosophic set that is characterized by the membership function with three dimensions/grades such as truthness grade $T_N(z_i)$, a indeterminacy grade $I_N(z_i)$ and a falsity grade $F_N(z_i)$. The functions $T_N(z_i)$, $I_N(z_i)$ and $F_N(z_i)$ are real standard or nonstandard subsets of $]0^-, 1^+[$. Mathematically, NS can be defined as

$$N = \{(z_i, T_N(z_i), I_N(z_i), F_N(z_i)) | z_i \in Z\},$$

where $T_N : Z \rightarrow]0^-, 1^+[$, $I_N : Z \rightarrow]0^-, 1^+[$ and $F_N : Z \rightarrow]0^-, 1^+[$. There is no restriction on the sum of $T_N(z_i)$, $I_N(z_i)$ and $F_N(z_i)$, so, $0 \leq \text{Sup}(T_N(z_i)) + \text{Sup}(I_N(z_i)) + \text{Sup}(F_N(z_i)) \leq 3^+$.

NS is constructed on a philosophical concept which makes it complex to process during engineering applications or to apply to real-life circumstances. Therefore, Wang et al. [1] initiated the notion of SVNSs and defined by Z an universal set consist of finite set of elements, which in the process of decision-making is considered to be subjective (Likert scale) rating values such as good, bad, normal, high, low, and so on. The membership, non-membership, and indeterminacy grades are associated with each of these rating elements within the universe of preference information for decision-making. Suppose an expert rates a painting as 'good' from the collection of elements $Z = (z_1 = \text{very bad}, z_2 = \text{bad}, z_3 = \text{neutral}, z_4 = \text{good}, z_5 = \text{very good})$ with truthness, falsity, and indeterminacy grades as 0.6, 0.5, and 0.25 for the element z_4 that characterizes the fuzziness associated with the rating given by the expert from three dimensions. Specifically, it means, the rating (element) 'good' is associated with degree of truthness as 0.6 (or 60%), degree of falsity as 0.5 (or 50%), and degree of hesitation/indeterminacy as 0.25 (or 25%).

Definition 2 ([14]). Suppose Z be a finite universal set and z_i be a generic element of Z . A SVNS S in Z is specified by a truth $t_S(z_i)$, an indeterminacy $i_S(z_i)$ and a falsity membership functions $f_S(z_i)$, where the functions $t_S(z_i)$, $i_S(z_i)$ and $f_S(z_i)$ are real subsets of $[0, 1]$. Wang et al. [14] defined the SVNS as

$$S = \{(z_i, t_S(z_i), i_S(z_i), f_S(z_i)) | z_i \in Z\},$$

where $t_S(z_i) : Z \rightarrow [0, 1]$, $i_S(z_i) : Z \rightarrow [0, 1]$ and $f_S(z_i) : Z \rightarrow [0, 1]$. Additionally, the sum of $t_S(z_i)$, $i_S(z_i)$ and $f_S(z_i)$ are in $[0, 3]$ and is given as $0 \leq t_S(z_i) + i_S(z_i) + f_S(z_i) \leq 3$. For convenience, the triplet (t_S, i_S, f_S) is defined as SVN number (SVNN) and denoted by $v = (t_S, i_S, f_S)$. For instance, there may be a situation in which an expert rates the risk in buying a stock by using SVNN and provides values as (0.5, 0.4, 0.7). This means that the expert feels that the stock is 50% risky, 40% unsure/confused of the status of the particular stock, and 70% not risky. So there is flexibility offered to the expert in expressing her/his views over the risk in buying a stock. Likewise, if we get SVNNs from three experts for a particular stock, we can label them as v_1, v_2 , and v_3 and the collection of such SVNNs forms a SVNS $S = (v_1, v_2, v_3)$.

Definition 3 ([14]). Consider $v_1 = (t_1, i_1, f_1)$ and $v_2 = (t_2, i_2, f_2)$ be two SVNNS and $\gamma > 0$, then the basic laws for SVNNS are given by

$$\begin{aligned} v_1^c &= (f_1, 1 - i_1, t_1); \\ v_1 \cup v_2 &= (\max\{t_1, t_2\}, \min\{i_1, i_2\}, \min\{f_1, f_2\}); \\ v_1 \cap v_2 &= (\min\{t_1, t_2\}, \max\{i_1, i_2\}, \max\{f_1, f_2\}); \\ v_1 \oplus v_2 &= (t_1 + t_2 - t_1 t_2, i_1 i_2, f_1 f_2); \\ v_1 \otimes v_2 &= (t_1 t_2, i_1 + i_2 - i_1 i_2, f_1 + f_2 - f_1 f_2); \\ \gamma v_1 &= (1 - (1 - t_1)^\gamma, i_1^\gamma, f_1^\gamma); \\ v_1^\gamma &= (t_1^\gamma, 1 - (1 - i_1)^\gamma, 1 - (1 - f_1)^\gamma). \end{aligned}$$

Example 1. Suppose $v_1 = (0.6, 0.4, 0.2)$ and $v_2 = (0.9, 0.3, 0.1)$ are two SVNNS, then the basic laws discussed above can be presented as

$$\begin{aligned} v_1^c &= (0.2, 1 - 0.4, 0.6) = (0.2, 0.6, 0.6); \\ v_1 \cup v_2 &= (\max\{0.6, 0.9\}, \min\{0.4, 0.3\}, \min\{0.2, 0.1\}) = (0.9, 0.3, 0.1); \\ v_1 \cap v_2 &= (\min\{0.6, 0.9\}, \max\{0.4, 0.3\}, \max\{0.2, 0.1\}) = (0.6, 0.4, 0.2); \\ v_1 \oplus v_2 &= (0.6 + 0.9 - 0.6 \times 0.9, 0.4 \times 0.3, 0.2 \times 0.1) = (0.9600, 0.1200, 0.0200); \\ v_1 \otimes v_2 &= (0.6 \times 0.9, 0.4 + 0.3 - 0.4 \times 0.3, 0.2 + 0.1 - 0.2 \times 0.1) = (0.5400, 0.5800, 0.2800); \end{aligned}$$

If $\gamma = 0.5$, then

$$\begin{aligned} \gamma v_1 &= (1 - (1 - 0.6)^{0.5}, 0.4^{0.5}, 0.2^{0.5}) = (0.3675, 0.6325, 0.4472); \\ v_1^\gamma &= (0.6^{0.5}, 1 - (1 - 0.4)^{0.5}, 1 - (1 - 0.2)^{0.5}) = (0.7746, 0.2254, 0.1056). \end{aligned}$$

Definition 4 ([54]). Let $v_1 = (t_1, i_1, f_1)$ be a SVNNS. Then the score function of v_1 can be computed in accordance with Equation (1), which as

$$\mathbb{S}(v_1) = \frac{2 + t_1 - i_1 - f_1}{3}; \mathbb{S}(v_1) \in [0, 1]. \quad (1)$$

For two SVNNS $v_1 = (t_1, i_1, f_1)$ and $v_2 = (t_2, i_2, f_2)$, then the comparison rule of score function can be presented as follows:

- (i) If $\mathbb{S}(v_1) > \mathbb{S}(v_2)$, then $v_1 > v_2$;
- (ii) If $\mathbb{S}(v_1) < \mathbb{S}(v_2)$, then $v_1 < v_2$.

Example 2. Suppose $v_1 = (0.5, 0.2, 0.6)$ and $v_2 = (0.6, 0.4, 0.2)$ are two SVNNS. Now, by using Definition 4, we obtain $\mathbb{S}(v_1) = 0.25$ and $\mathbb{S}(v_2) = 0.3$. It implies that $v_2 > v_1$, i.e., the larger the score value, the higher the SVNNS.

Definition 5 ([55]). Assume $v_i = (t_i, i_i, f_i)$; $i = 1(1)m$ be the SVNNS and $\wp = (\wp_1, \wp_2, \dots, \wp_m)^T$ be a related weight vector of v_i , satisfying $\wp_i \in [0, 1]$ and $\sum_{i=1}^m \wp_i = 1$. Then the SVN-Weighted Arithmetic (SVNWA) and SVN-Weighted Geometric (SVNWG) operators are presented as

$$\text{SVNWA}(v_1, v_2, \dots, v_m) = \bigoplus_{i=1}^m (\wp_i v_i) = \left(1 - \prod_{i=1}^m (1 - t_i)^{\wp_i}, \prod_{i=1}^m (i_i)^{\wp_i}, \prod_{i=1}^m (f_i)^{\wp_i} \right), \quad (2)$$

$$\text{SVNWG}(v_1, v_2, \dots, v_m) = \bigotimes_{i=1}^m (\wp_i v_i) = \left(\prod_{i=1}^m (t_i)^{\wp_i}, 1 - \prod_{i=1}^m (1 - i_i)^{\wp_i}, 1 - \prod_{i=1}^m (1 - f_i)^{\wp_i} \right). \quad (3)$$

Example 3. Consider $v_1 = (0.5, 0.1, 0.3)$, $v_2 = (0.4, 0.2, 0.3)$, $v_3 = (0.4, 0.3, 0.1)$ and $v_4 = (0.6, 0.1, 0.2)$ are SVNNS. Also assume that $\wp = (0.3, 0.25, 0.25, 0.2)$ be a related weight vector of v_i ($i = 1, 2, 3, 4$), then the SVNWA and SVNWG operators can be presented as

$$SVNWA(v_1, v_2, v_3, v_4) = \bigoplus_{i=1}^4 (\wp_j v_j) = \left(1 - \prod_{i=1}^4 (1 - t_i)^{\wp_i}, \prod_{i=1}^4 (i_i)^{\wp_i}, \prod_{i=1}^4 (f_i)^{\wp_i} \right) = (0.4762, 0.1565, 0.2102),$$

$$SVNWG(v_1, v_2, v_3, v_4) = \bigotimes_{i=1}^4 (\wp_j v_j) = \left(\prod_{i=1}^4 (t_i)^{\wp_i}, 1 - \prod_{i=1}^4 (1 - i_i)^{\wp_i}, 1 - \prod_{i=1}^4 (1 - f_i)^{\wp_i} \right) = (0.4638, 0.1793, 0.2344).$$

Definition 6 ([56]). Let $S, T \in SVNSS(Z)$. Then, the distance measure between the sets S and T is given by

$$D_h(S, T) = \frac{1}{3m} \sum_{i=1}^m (|t_S(z_i) - t_T(z_i)| + |i_S(z_i) - i_T(z_i)| + |f_S(z_i) - f_T(z_i)|). \quad (4)$$

For illustration, consider $S = (0.5, 0.6, 0.4)$ and $T = (0.4, 0.3, 0.2)$ be two SVNNS. With the use of Definition 5, we get $D_h(S, T) = \frac{1}{3} (|0.5 - 0.4| + |0.6 - 0.3| + |0.4 - 0.2|) = 0.2$.

4. An Integrated SVN-SWARA-CoCoSo Method

The CoCoSo method is a newly introduced MCDM approach pioneered by Yazdani et al. [18]. This method has found an extensive application in diverse fields such as the assessment of medical waste treatment technologies [46], evaluation of green growth indicators [57], WEEE recycling partner selection [43], etc. In this section, an integrated decision-making model is developed by combining the SWARA and the CoCoSo methods under a single-valued neutrosophic environment. In this model, the SWARA method is extended to the SVN context and then applied to find the subjective weights of the criteria. Also, the modified CoCoSo approach is used to evaluate and prioritize the alternatives. The procedure of the proposed model is listed in the following steps (Figure 1):

Step 1: Creating the decision matrix

To create the decision matrix, a panel of DMs $B = \{\beta_1, \beta_2, \dots, \beta_l\}$ is constructed to assess the performance of a set of options/alternatives $\{e_1, e_2, \dots, e_m\}$ with respect to attributes/criteria $\{p_1, p_2, \dots, p_n\}$. Consider that each evaluator of DMs' group gives the evaluation information of each alternative e_i by means of a criterion p_j in the form of linguistic Values (LVs). Let $\Omega = (\chi_{ij}^{(k)})$ be the required decision matrix (see Table 1), wherein $\chi_{ij}^{(k)}$ designates the evaluation information of the relative performance of an alternative e_i with respect to j th criterion given by k th DM.

Table 1. MCDM decision matrix.

Criteria	p_1	p_2	...	p_n
e_1	$\chi_{11}^{(1)}, \chi_{11}^{(2)}, \dots, \chi_{11}^{(l)}$	$\chi_{12}^{(1)}, \chi_{12}^{(2)}, \dots, \chi_{12}^{(l)}$...	$\chi_{1n}^{(1)}, \chi_{1n}^{(2)}, \dots, \chi_{1n}^{(l)}$
e_2	$\chi_{21}^{(1)}, \chi_{21}^{(2)}, \dots, \chi_{21}^{(l)}$	$\chi_{22}^{(1)}, \chi_{22}^{(2)}, \dots, \chi_{22}^{(l)}$...	$\chi_{2n}^{(1)}, \chi_{2n}^{(2)}, \dots, \chi_{2n}^{(l)}$
...
e_m	$\chi_{m1}^{(1)}, \chi_{m1}^{(2)}, \dots, \chi_{m1}^{(l)}$	$\chi_{m2}^{(1)}, \chi_{m2}^{(2)}, \dots, \chi_{m2}^{(l)}$...	$\chi_{mn}^{(1)}, \chi_{mn}^{(2)}, \dots, \chi_{mn}^{(l)}$

Step 2: Evaluating the weights of the DMs

To calculate the DMs' weights, let us first assume that the importance degrees of the DMs are in the form of SVNNS. For this purpose, assume that (t_k, i_k, f_k) be the importance degree of k th DM, then the process for the calculation of k th DM's weight is as below:

$$\omega_k = \frac{2 + t_k - i_k - f_k}{\sum_{k=1}^l [2 + t_k - i_k - f_k]}, \quad (5)$$

where $\omega_k \geq 0$ and $\sum_{k=1}^l \omega_k = 1$.

For example, suppose (0.60, 0.40, 0.30) (0.80, 0.30, 0.20) and (0.50, 0.50, 0.50) are importance degrees of three DMs β_1 , β_2 and β_3 , respectively. With the use of formula (5), the weights of DMs can be obtained as $\omega_1 = 0.3333$, $\omega_2 = 0.4035$ and $\omega_3 = 0.2632$.

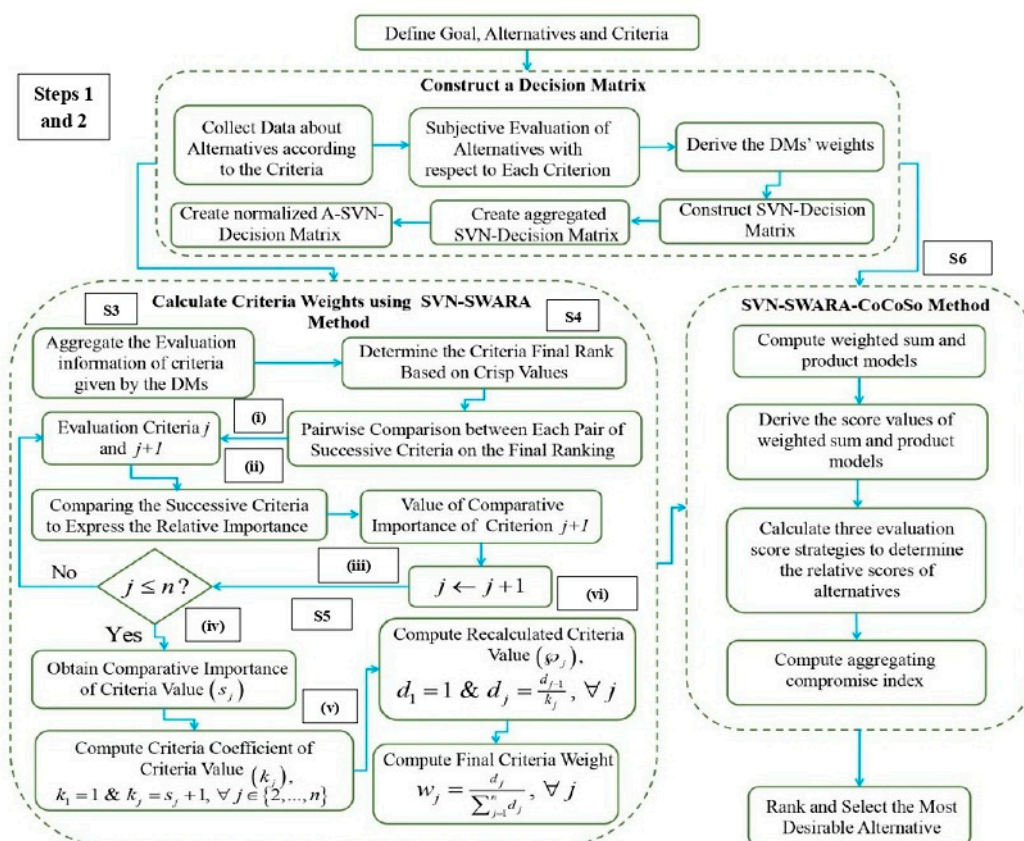


Figure 1. Flowchart of the SVN-SWARA-CoCoSo method (S3 to S6 means Step 3 to Step 6).

Step 3: Aggregation of different decision opinions

In the process of MCDM with multiple experts, it is essential to combine all the individuals' preferences of DMs into a combined opinion to construct an aggregated SVN decision matrix (A-SVN-DM). With the use of formula (3), let us consider $\tilde{N} = (\Xi_{ij})_{m \times n}$ be the A-SVN-DM, wherein

$$\Xi_{ij} = SVNWA(\Xi_{ij}^{(1)}, \Xi_{ij}^{(2)}, \dots, \Xi_{ij}^{(l)}) = \left(1 - \prod_{k=1}^l (1 - t_k)^{\omega_k}, \prod_{k=1}^l (i_k)^{\omega_k}, \prod_{k=1}^l (f_k)^{\omega_k}\right). \quad (6)$$

Step 4: Formulate the normalized aggregated decision matrix

To handle the non-beneficial and beneficial types of criteria, it is required to normalize the A-SVN-DM given by the previous step. Let $\tilde{N} = (\varsigma_{ij})_{m \times n}$ be the required normalized A-SVN-DM, where

$$\varsigma_{ij} = (\bar{t}_{ij}, \bar{i}_{ij}, \bar{f}_{ij}) = \begin{cases} \Xi_{ij} = (t_{ij}, i_{ij}, f_{ij}), & j \in p_b \\ (\Xi_{ij})^c = (f_{ij}, 1 - i_{ij}, t_{ij}), & j \in p_n, \end{cases} \quad (7)$$

wherein p_n and p_b show the types of cost and benefit criteria, respectively.

Step 5: Criteria weights calculation by SWARA method

The SWARA method involves the following steps:

Step 5-A: With the use of Equation (1), find out the score values $S(\varsigma_{kj})$ of the considered criteria.

Step 5-B: In accordance with Step 5-A, rank the criteria from most important to least important. Next, the comparative significance (s_j) of score value is determined by comparing the criteria on j^{th} and $(j-1)$ th positions.

Step 5-C: Evaluate the comparative coefficient by employing

$$k_j = \begin{cases} 1, & j = 1, \\ s_j + 1, & j > 1. \end{cases} \quad (8)$$

Step 5-D: According to Step 5-C, we evaluate the recalculated weight d_j , which as

$$d_j = \begin{cases} 1, & j = 1, \\ \frac{k_{j-1}}{k_j}, & j > 1. \end{cases} \quad (9)$$

Step 5-E: Find the subjective weight by using

$$w_j = \frac{d_j}{\sum_{j=1}^n d_j}. \quad (10)$$

Step 6: As the CoCoSo approach is developed with the combination of the simple additive weighted and exponentially weighted product models. Thus, to find the weighted sum $C_i^{(1)}$ and weighted product sequences $C_i^{(2)}$, the SVNWA and SVNWG operators can be used, and given as

$$C_i^{(1)} = \bigoplus_{j=1}^n w_j \zeta_{ij}. \quad (11)$$

$$C_i^{(2)} = \bigotimes_{j=1}^n w_j \zeta_{ij}. \quad (12)$$

Step 7: In this step, three evaluation score strategies are used to find the relative scores of the alternatives, presented as

$$Q_i^{(1)} = \frac{\mathbb{S}(C_i^{(1)}) + \mathbb{S}(C_i^{(2)})}{\sum_{i=1}^m (\mathbb{S}(C_i^{(1)}) + \mathbb{S}(C_i^{(2)}))}, \quad (13)$$

$$Q_i^{(2)} = \frac{\mathbb{S}(C_i^{(1)})}{\min_i \mathbb{S}(C_i^{(1)})} + \frac{\mathbb{S}(C_i^{(2)})}{\min_i \mathbb{S}(C_i^{(2)})}, \quad (14)$$

$$Q_i^{(3)} = \frac{\gamma \mathbb{S}(C_i^{(1)}) + (1 - \gamma) \mathbb{S}(C_i^{(2)})}{\gamma \max_i \mathbb{S}(C_i^{(1)}) + (1 - \gamma) \max_i \mathbb{S}(C_i^{(2)})}, \quad (15)$$

wherein $\gamma \in [0, 1]$ denotes the coefficient of a compromise decision mechanism. Also, $\mathbb{S}(C_i^{(1)})$ and $\mathbb{S}(C_i^{(2)})$ present the score values of $C_i^{(1)}$ and $C_i^{(2)}$, respectively.

Step 8: Based on the logical integration of three scores, the final ranking of the alternatives are evaluated via aggregating compromise index (16)

$$Q_i = (Q_i^{(1)} Q_i^{(2)} Q_i^{(3)})^{\frac{1}{3}} + \frac{1}{3} (Q_i^{(1)} + Q_i^{(2)} + Q_i^{(3)}). \quad (16)$$

The higher values of Q_i determines the better alternatives.

5. An Application of Renewable Energy Source (RES) Selection

In this section, we implement the proposed method for the evaluation and prioritization of RESs. Here, we present an empirical case study of RESs selection in Karnataka,

India, which demonstrates the realistic use of the present SVN-SWARA-CoCoSo method. The methodical evaluation of RESs is significant in Karnataka to assure the high demand of customers and to further economic growth of the state as well as the country. Because of the uncertainty, impreciseness, and inconsistency of information with the ambiguity of the human's mind, it is quite complicated to provide exact numerical values for the criterion. Therefore, DMs' judgments of the considered evaluation criteria and their weights are usually presented in terms of linguistic values (LVs) [58]. To implement the proposed method on RES selection, a set of alternatives are considered, which are Wind energy (e_1), Solar energy (e_2), Hydroelectric energy (e_3), and Biomass energy (e_4). Next, a panel of three DMs is created to accomplish the performance score of each RES candidate. On account of preliminary scrutiny, existing literatures, and conversation with professionals, 10 criteria have been identified (Table 2 and Figure 2) for the selection of considered alternatives. In the following steps (see Figure 1), the process of the SVN-SWARA-CoCoSo methodology for the selection of suitable RES alternative is shown:

Table 2. Assessment criteria used in RESs selection.

Dimension	Criteria	Type	References
Economic	Implementation cost (p_1)	Cost	Cavallaro et al. [59], Rani et al. [5], Krishankumar et al. [53], Amer and Daim [60], Liu [9]
	Value creation (p_2)	Benefit	Buyukozkan and Karabulut [61], Colak and Kaya [62], Chen et al. [2]
Environmental	Pollutant emission (p_3)	Cost	Cavallaro et al. [59], Boran [63], Boran et al. [64], Mousavi et al. [65], Şengül et al. [3]
	Need of waste disposal (p_4)	Benefit	Mousavi et al. [65], Rani et al. [5]
	Water pollution (p_5)	Cost	Kahraman et al. [66], Cavallaro et al. [59], Mousavi et al. [65], Şengül et al. [3], Rani et al. [5]
Technical	Reliability (p_6)	Benefit	Kaya and Kahraman [67,68], Malkawi et al. [10]
	Resource density (p_7)	Benefit	Chen et al. [2], Amer and Daim [60], Buyukozkan and Karabulut [61]
Social	Compatibility with the national energy policy (p_8)	Benefit	Kahraman et al. [66], Mousavi et al. [65], Rani et al. [5]
	Public acceptance (p_9)	Benefit	Mousavi et al. [65], Chen et al. [2], Cavallaro et al. [59]
	Job creation (p_{10})	Benefit	Kaya and Kahraman [67,68], Chen et al. [2]

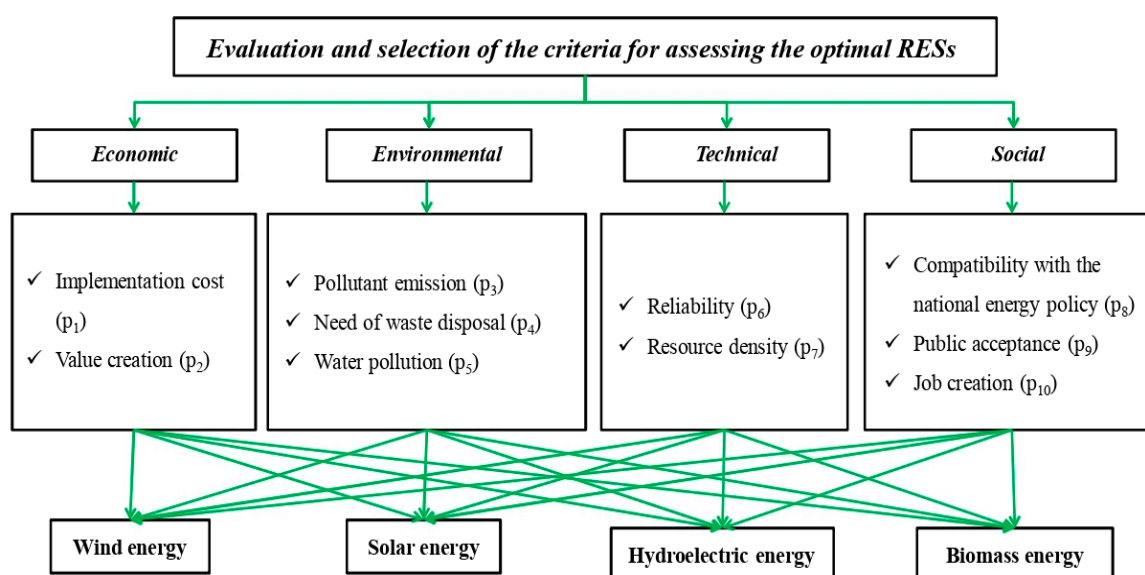


Figure 2. Hierarchical structure of selecting criteria.

Ten criteria considered in this study are cost, value creation, pollutant emission, waste disposal, pollution pertaining to water, reliability, density of resource, compatibility,

acceptance factor, creation of jobs. Criteria 1, 3, and 5 are cost types. Steps 1 and 2 cover Steps 1 to 4 in Section 4. Steps 3, 4, and 5 (denoted as S3, S4, and S5) cover Steps 5A to 5E in Section 4. Step 6 (denoted as S6) covers Steps 6 to 8 in Section 4.

Step 1–2: Tables 3 and 4 present the linguistic performance ratings and their corresponding SVNNS of the DMs and the alternatives over the considered evaluation criteria. Next, Table 5 shows the linguistic decision matrix for RESs evaluation given by the DMs. On the basis of Table 3 and Equation (5), the weights of the DMs are calculated and presented in Table 6.

Table 3. Linguistic performance ratings of the DMs.

LVs	SVNNS
Absolutely knowledgeable (AK)	(0.90, 0.10, 0.10)
More knowledgeable (MK)	(0.80, 0.30, 0.20)
Knowledgeable(K)	(0.60, 0.40, 0.30)
Average (A)	(0.50, 0.50, 0.50)
Less knowledgeable (LK)	(0.30, 0.65, 0.60)
Very less knowledgeable (VLK)	(0.20, 0.90, 0.80)

Table 4. Linguistic ratings of RESs over given criteria.

LVs	SVNNS
Absolutely good (AG)	(1.00, 0.00, 0.00)
Very very good (VVG)	(0.90, 0.10, 0.10)
Very good (VG)	(0.80, 0.15, 0.20)
Good (G)	(0.70, 0.25, 0.30)
Quite good (QG)	(0.60, 0.35, 0.40)
Medium (M)	(0.50, 0.50, 0.50)
Quite bad (QB)	(0.40, 0.65, 0.60)
bad (B)	(0.30, 0.75, 0.70)
Very bad (VB)	(0.20, 0.85, 0.80)
Very very bad (VVB)	(0.10, 0.90, 0.90)
Absolutely bad (AB)	(0.00, 1.00, 1.00)

Table 5. Linguistic decision matrix for the evaluation of RESs.

Criteria	e_1	e_2	e_3	e_4
p_1	(QB,B,B)	(M,B,QB)	(M,QB,M)	(M,QB,VB)
p_2	(VG,QG,G)	(M,VG,QG)	(QG,M,G)	(M,QG,G)
p_3	(QB,M,B)	(VB,QB,M)	(M,B,VB)	(QB,VB,QB)
p_4	(VH,H,F)	(M,VG,QB)	(M,M,QG)	(M,G,QG)
p_5	(M,QB,QB)	(VB,QB,M)	(VB,M,B)	(QB,B,QB)
p_6	(VG,G,VVG)	(G,M,G)	(M,QG,G)	(M,QG,M)
p_7	(G,QB,M)	(QB,M,QG)	(M,M,VG)	(M,G,G)
p_8	(QG,M,G)	(G,G,QB)	(QB,M,QG)	(QG,M,M)
p_9	(VG,G,M)	(VG,M,G)	(M,QG,QB)	(QG,QB,M)
p_{10}	(QG,G,QB)	(VG,QG,M)	(M,QB,G)	(M,QB,G)

Table 6. Weights of the DMs.

DMs	Linguistic Values	SVNNS	Weights
β_1	Knowledgeable (K)	(0.60, 0.40, 0.30)	0.3333
β_2	More knowledgeable (MK)	(0.80, 0.30, 0.20)	0.4035
β_3	Average (A)	(0.50, 0.50, 0.50)	0.2632

Step 3: Opinions given by three DMs are aggregated with the use of Equation (6) and then, the aggregated decision matrix is shown in Table 7.

Table 7. Aggregated decision matrix for evaluating RESs.

Criteria	e_1	e_2	e_3	e_4
p_1	(0.318, 0.715, 0.665)	(0.384, 0.631, 0.601)	(0.442, 0.556, 0.538)	(0.369, 0.639, 0.609)
p_2	(0.686, 0.242, 0.294)	(0.635, 0.280, 0.326)	(0.574, 0.370, 0.406)	(0.574, 0.361, 0.399)
p_3	(0.391, 0.607, 0.581)	(0.348, 0.663, 0.629)	(0.335, 0.677, 0.648)	(0.316, 0.724, 0.674)
p_4	(0.674, 0.253, 0.300)	(0.594, 0.330, 0.362)	(0.505, 0.455, 0.471)	(0.583, 0.344, 0.384)
p_5	(0.415, 0.596, 0.565)	(0.348, 0.663, 0.629)	(0.329, 0.690, 0.639)	(0.345, 0.689, 0.639)
p_6	(0.786, 0.166, 0.196)	(0.641, 0.286, 0.337)	(0.574, 0.361, 0.399)	(0.513, 0.433, 0.457)
p_7	(0.530, 0.441, 0.454)	(0.474, 0.497, 0.501)	(0.588, 0.364, 0.393)	(0.613, 0.315, 0.356)
p_8	(0.574, 0.370, 0.406)	(0.608, 0.321, 0.360)	(0.474, 0.497, 0.501)	(0.513, 0.444, 0.464)
p_9	(0.674, 0.253, 0.300)	(0.662, 0.279, 0.322)	(0.489, 0.464, 0.479)	(0.482, 0.494, 0.500)
p_{10}	(0.569, 0.360, 0.396)	(0.641, 0.290, 0.337)	(0.512, 0.463, 0.470)	(0.512, 0.463, 0.470)

Step 4: As the criteria p_1 , p_3 and p_5 are of cost types, and the remaining criteria are of beneficial types. To normalize the aggregated decision matrix, Equation (7) can be utilized and the required result is presented in Table 8.

Table 8. Normalized A-SVN-DM for RESs selection.

Criteria	e_1	e_2	e_3	e_4
p_1	(0.665, 0.285, 0.318)	(0.601, 0.369, 0.384)	(0.538, 0.444, 0.442)	(0.609, 0.361, 0.369)
p_2	(0.686, 0.242, 0.294)	(0.635, 0.280, 0.326)	(0.574, 0.370, 0.406)	(0.574, 0.361, 0.399)
p_3	(0.581, 0.393, 0.391)	(0.629, 0.327, 0.348)	(0.648, 0.323, 0.335)	(0.674, 0.276, 0.316)
p_4	(0.674, 0.253, 0.300)	(0.594, 0.330, 0.362)	(0.505, 0.455, 0.471)	(0.583, 0.344, 0.384)
p_5	(0.565, 0.404, 0.415)	(0.629, 0.337, 0.348)	(0.639, 0.310, 0.329)	(0.639, 0.311, 0.345)
p_6	(0.786, 0.166, 0.196)	(0.641, 0.286, 0.337)	(0.574, 0.361, 0.399)	(0.513, 0.433, 0.457)
p_7	(0.530, 0.441, 0.454)	(0.474, 0.497, 0.501)	(0.588, 0.364, 0.393)	(0.613, 0.315, 0.356)
p_8	(0.574, 0.370, 0.406)	(0.608, 0.321, 0.360)	(0.474, 0.497, 0.501)	(0.513, 0.444, 0.464)
p_9	(0.674, 0.253, 0.300)	(0.662, 0.279, 0.322)	(0.489, 0.464, 0.479)	(0.482, 0.494, 0.500)
p_{10}	(0.569, 0.360, 0.396)	(0.641, 0.290, 0.337)	(0.512, 0.463, 0.470)	(0.512, 0.463, 0.470)

Step 5: The DMs play an important role in the assessment of criteria weights by the SWARA process. In this process, firstly each DM assumes the importance of each criterion. Then, score values of each criterion are computed (see Table 9). In accordance with score values, rank the criteria from most significant to less significant (see Table 10). After that, the comparative significances, comparative coefficients, and recalculated weights are calculated based on Equations (7)–(9) and given in Table 10. With the use of Equation (10), the final weights of the criteria are presented as

$$w_j = (0.1013, 0.0986, 0.0971, 0.1068, 0.1034, 0.1132, 0.1088, 0.0916, 0.0880).$$

Table 9. Weights of criteria demonstrated by DMs for RESs selection.

Criteria	β_1	β_2	β_3	Aggregated SVNns	Score Values
p_1	QG	M	G	(0.574, 0.370, 0.406)	0.599
p_2	M	QG	QG	(0.540, 0.394, 0.431)	0.572
p_3	G	M	QB	(0.535, 0.425, 0.442)	0.556
p_4	QB	M	QG	(0.474, 0.497, 0.501)	0.492
p_5	VG	QG	QB	(0.623, 0.311, 0.353)	0.653
p_6	G	QG	M	(0.589, 0.344, 0.385)	0.620
p_7	QG	G	VG	(0.677, 0.244, 0.297)	0.712
p_8	G	QG	G	(0.641, 0.286, 0.337)	0.672
p_9	QG	QB	M	(0.482, 0.494, 0.500)	0.496
p_{10}	QB	M	M	(0.442, 0.546, 0.531)	0.455

Table 10. Obtained outcomes by SWARA technique for RESs assessment.

Criteria	Score Values	Comparative Significance of Criteria Value (s_j)	Coefficient (k_j)	Recalculated Weight (d_j)	Criteria Weight (w_j)
p_7	0.712	-	1.000	1.000	0.1132
p_8	0.672	0.040	1.040	0.9615	0.1088
p_5	0.653	0.019	1.019	0.9436	0.1068
p_6	0.620	0.033	1.033	0.9135	0.1034
p_1	0.599	0.021	1.021	0.8947	0.1013
p_2	0.572	0.027	1.027	0.8712	0.0986
p_3	0.556	0.016	1.016	0.8575	0.0971
p_9	0.496	0.060	1.060	0.8090	0.0916
p_4	0.492	0.004	1.004	0.8058	0.0912
p_{10}	0.455	0.37	1.037	0.7770	0.0880

Steps 6–8: Through the use of Equations (11) and (12), the values of weighted sum $C_i^{(1)}$ and weighted product $C_i^{(2)}$ sequences are computed for the different RESs under various considered criteria. Further, the outcomes of the SVN-SWARA-CoCoSo method are determined by employing Equations (13)–(16) and are mentioned in Table 11. Corresponding to the assessment value Q_i , the preference order of RESs is $e_1 \succ e_2 \succ e_3 \succ e_4$, and thus, the wind energy (e_1) is the ideal option over different RES alternatives.

Table 11. Overall compromise ranking outcomes of different companies.

Options	$C_i^{(1)}$	$C_i^{(2)}$	$S(C_i^{(1)})$	$S(C_i^{(2)})$	$Q_i^{(1)}$	$Q_i^{(2)}$	$Q_i^{(3)}$	Q_i	Ranking
e_1	(0.583, 0.366, 0.393)	(0.539, 0.434, 0.438)	0.608	0.556	0.2731	2.3442	1.0143	2.0764	1
e_2	(0.545, 0.401, 0.427)	(0.514, 0.455, 0.460)	0.572	0.533	0.2593	2.2266	0.9496	1.9636	2
e_3	(0.490, 0.477, 0.487)	(0.473, 0.504, 0.503)	0.509	0.489	0.2340	2.0102	0.8570	1.7725	3
e_4	(0.491, 0.471, 0.484)	(0.471, 0.512, 0.507)	0.512	0.484	0.2336	2.0066	0.8556	1.7694	4

6. Analysis and Results Discussion

This study presents an integrated SVN-SWARA-CoCoSo methodology for assessing the RESs in Karnataka, India. The outcomes of the considered case study suggest some important insights about the evaluation criteria and optimum RES candidate. The criteria weight outcomes show that Resource density (0.1132) is the most significant criterion, followed by the Compatibility with the national energy policy (0.1088), Water pollution (0.1068), Reliability (0.1034), and others, whereas Job creation (0.0880) is the least important criterion for RESs assessment in the considered case study. The findings of the results conclude that the wind energy is the optimum RES alternative in Karnataka. To validate the feasibility and robustness of the introduced method, comparison with previously developed methods and sensitivity analysis are demonstrated in this section.

6.1. Comparative Study

In the present section, comparisons with different approaches are discussed to certify the robustness of the proposed method. For comparative study, we have selected three important SVN information-based methods from existing studies, which are TOPSIS [69], VIKOR [16], and WASPAS (an integration of Weighted sum model (WSM) and Weighted product model (WPM)) [70].

6.1.1. SVN-TOPSIS Method

The procedural steps of the SVN-TOPSIS model are given as

Steps 1–5: Analogous to SVN-SWARA-CoCoSo approach.

Step 6: Ideal and anti-ideal solutions are calculated in terms of SVNNS, given as

$$\iota^+ = \{(0.318, 0.715, 0.665), (0.686, 0.242, 0.294), (0.316, 0.724, 0.674), (0.674, 0.253, 0.300), (0.329, 0.690, 0.639), (0.786, 0.166, 0.196), (0.613, 0.315, 0.356), (0.608, 0.321, 0.360), (0.674, 0.253, 0.300), (0.641, 0.290, 0.337), \}$$

$$\iota^- = \{(0.442, 0.556, 0.538), (0.574, 0.370, 0.406), (0.391, 0.607, 0.581), (0.505, 0.455, 0.471), (0.415, 0.596, 0.565), (0.513, 0.433, 0.457), (0.474, 0.497, 0.501), (0.474, 0.497, 0.501), (0.482, 0.494, 0.500), (0.512, 0.463, 0.470), \}$$

Step 7: Determine the distance between each candidate's RES and ideal solution, and anti-ideal solution, respectively.

Step 8: Relative closeness index (CC_i) of each RES option is enumerated in Table 12.

Table 12. Results of SVN-TOPSIS framework for RES selection.

Options	$D_h(\zeta_{ij}, \iota^+)$	$D_h(\zeta_{ij}, \iota^-)$	CC_i	Ranking
e_1	0.041	0.113	0.737	1
e_2	0.058	0.096	0.625	2
e_3	0.117	0.037	0.241	4
e_4	0.097	0.057	0.367	3

Hence, the desirable RESs alternative wind energy (e_1) is the best choice.

Step 9: In accordance with the relative closeness coefficient, the preference order of the RES options can be determined (see Table 12).

6.1.2. SVN-VIKOR Method

Step 1–6: Similar to the proposed approach.

Step 7: The Group Utility Measure (GUM), Individual Regret Measure (IRM) and Compromise Measure (CM) of each RES candidate are evaluated in Table 13.

Table 13. The values of GUM, IRM, and CM for RESs selection.

RESs	GUM	Ranking	IRM	Ranking	CM	Ranking
e_1	0.398	1	0.097	1	0.039	1
e_2	0.368	2	0.113	3	0.300	2
e_3	0.760	4	0.124	4	1.000	4
e_4	0.553	3	0.103	2	0.355	3

Step 8: Determine the preference order the options. The minimum value of CM decides the optimum alternative.

The whole computational steps of the SVN-VIKOR framework are presented in Table 13. Thus, wind energy (e_1) is the best option.

6.1.3. SVN-WASPAS Method

The structure of the SVN-WASPAS approach is given by

Step 1–6: Same as a preceding approach

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

$$P_i = \vartheta C_i^{(1)} + (1 - \vartheta) C_i^{(2)},$$

where $\vartheta \in [0, 1]$ is the coefficient of the decision mechanism. This parameter is introduced to compute the accurateness of the WASPAS measure based on initial criteria precision. Also, the values of $C_i^{(1)}$ and $C_i^{(2)}$ are calculated based on Equations (11) and (12).

Step 8: Sort the option(s) in reference to the decreasing score values of P_i .

Using the WSM $(C_i^{(1)})$, WPM $(C_i^{(2)})$ and WASPAS (P_i) measures of each alternative and their score values $S(C_i^{(1)})$ and $S(C_i^{(2)})$ are computed and shown in Table 14. As a consequence, the ranking order of the given RESs is $e_1 \succ e_2 \succ e_3 \succ e_4$ and hence, e_1 , i.e., wind energy is the most suitable RES alternative from a sustainability perspective.

Table 14. Computed results of SVN-WASPAS method.

RES	Weighted Sum Model (WSM)		Weighted Product Model (WPM)		WASPAS Measure (P_i)	Ranking
	$C_i^{(1)}$	$S(C_i^{(1)})$	$C_i^{(2)}$	$S(C_i^{(2)})$		
e_1	(0.583, 0.366, 0.393)	0.608	(0.539, 0.434, 0.438)	0.556	0.582	1
e_2	(0.545, 0.401, 0.427)	0.572	(0.514, 0.455, 0.460)	0.533	0.5525	2
e_3	(0.490, 0.477, 0.487)	0.509	(0.473, 0.504, 0.503)	0.489	0.499	3
e_4	(0.491, 0.471, 0.484)	0.512	(0.471, 0.512, 0.507)	0.484	0.498	4

The outcomes of comparative study verify that the wind energy is the most optimal candidate among other alternative RESs. Moreover, the prioritization order of RESs analyzed by the present SVN-SWARA-CoCoSo framework is equivalent and consistent with the ranking obtained by SVN-WSM, SVN-WPM and SVN-WASPAS approaches, whereas slightly different from SVN-TOPSIS and SVN-VIKOR methods. The ranking results obtained by the proposed and existing methods are depicted in Figure 3. In comparison with the SVN-TOPSIS, SVN-VIKOR, SVN-WSM, SVN-WPM and SVN-WASPAS methods, the SVN-SWARA-CoCoSo approach has the following advantages:

- The present SVN-SWARA-CoCoSo model uses a comparability structure and then the weights are merged with the SAW and EWP models. To verify the preference order, relative scores based on three different aggregation measures of each candidate are computed. Finally, logical integration of relative scores is presented to find the ranking results. The existing methods SVN-TOPSIS, SVN-VIKOR [16], SVN-WSM [70], SVN-WPM [70] and SVN-WASPAS [70] don't support these types of combination.
- In the process of the SVN-TOPSIS [69] model, the computation of distance measures from each option to the ideal and anti-ideal solutions, respectively, are essential which makes this model lengthy and decreases the precision of the decision results. While, in the present technique, a compromise solution based on three evaluation aggregation strategies can be determined, which makes the CoCoSo model simpler and enhances the consistency and accuracy of the outcomes.
- The proposed approach employs both linear and vector normalization to eliminate the different units of criterion functions. However, the SVN-TOPSIS [69] and SVN-VIKOR [70] use only vector and linear normalization, respectively, to eliminate the different units of criterion functions. As a consequence, the present approach is simpler, accurate, reliable, and flexible than existing approaches.

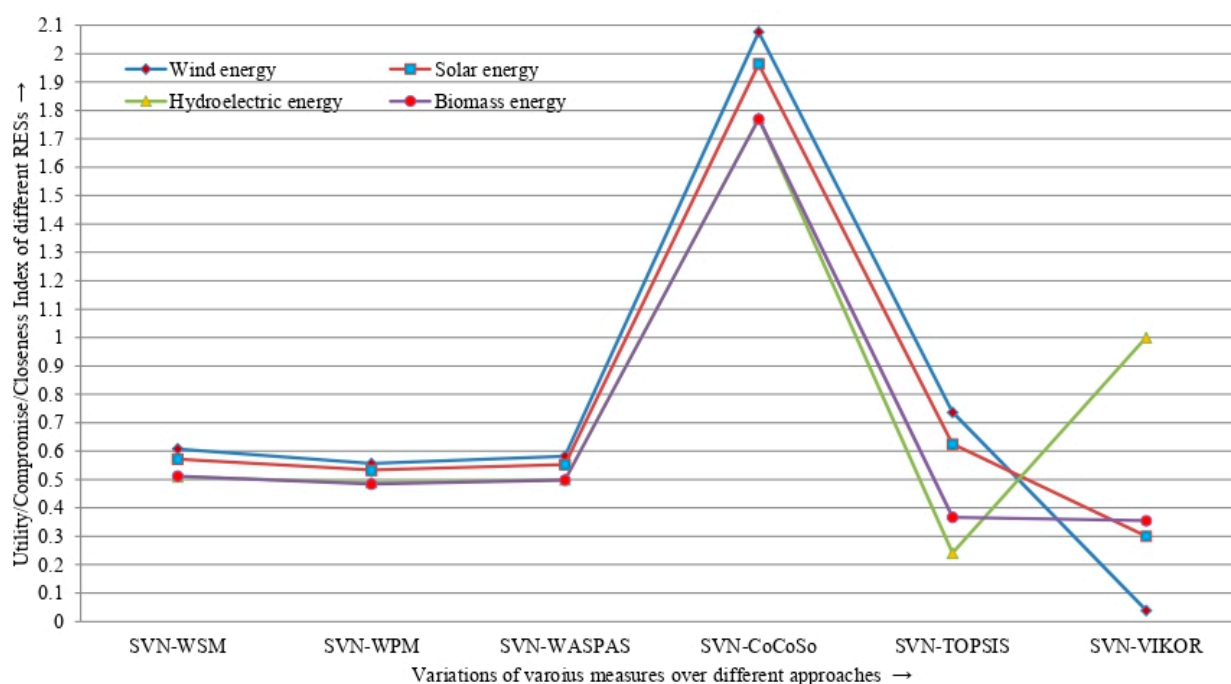


Figure 3. Comparison of proposed with extant methods for RESs selection.

6.2. Sensitivity Analysis (SA)

To verify the robustness of the present SVN-SWARA-CoCoSo model, we perform a SA with respect to various values of parameter ' γ '. This procedure also eliminates the possible human judgmental biases which may influence the decision results [16,31]. In reference to the varying values of ' γ ', the relative scores and assessment values of the RES candidates are estimated. And thus, it can easily be scrutinized that the prioritization ordering of the candidate RESs is equivalent in each set (see Table 15). Also, the optimum RES alternative is wind energy (e_1), whereas the worst alternative is biomass energy (e_4) in that region.

Table 15. Assessment values of RESs over different values of γ .

RESs	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
e_1	2.0860	2.0840	2.0821	2.0802	2.0783	2.0764	2.0746	2.0728	2.0710	2.0693	2.0676
e_2	1.9691	1.9680	1.9669	1.9658	1.9647	1.9636	1.9626	1.9616	1.9606	1.9596	1.9586
e_3	1.7862	1.7834	1.7806	1.7778	1.7751	1.7725	1.7698	1.7673	1.7647	1.7622	1.7598
e_4	1.7786	1.7767	1.7748	1.7730	1.7712	1.7694	1.7677	1.7660	1.7643	1.7627	1.7610

Figure 4 demonstrates the graphical structure of the compromise values of RESs. The outcomes of SA proved that the wind energy constantly secures its top ranking despite how the compromise coefficient ' γ ' vary. Thus, the introduced model has adequate stability with respect to varied values of ' γ '. Last but not least, we can observe from SA that the present method is independent of any biases and the acquired decision outcomes are robust.

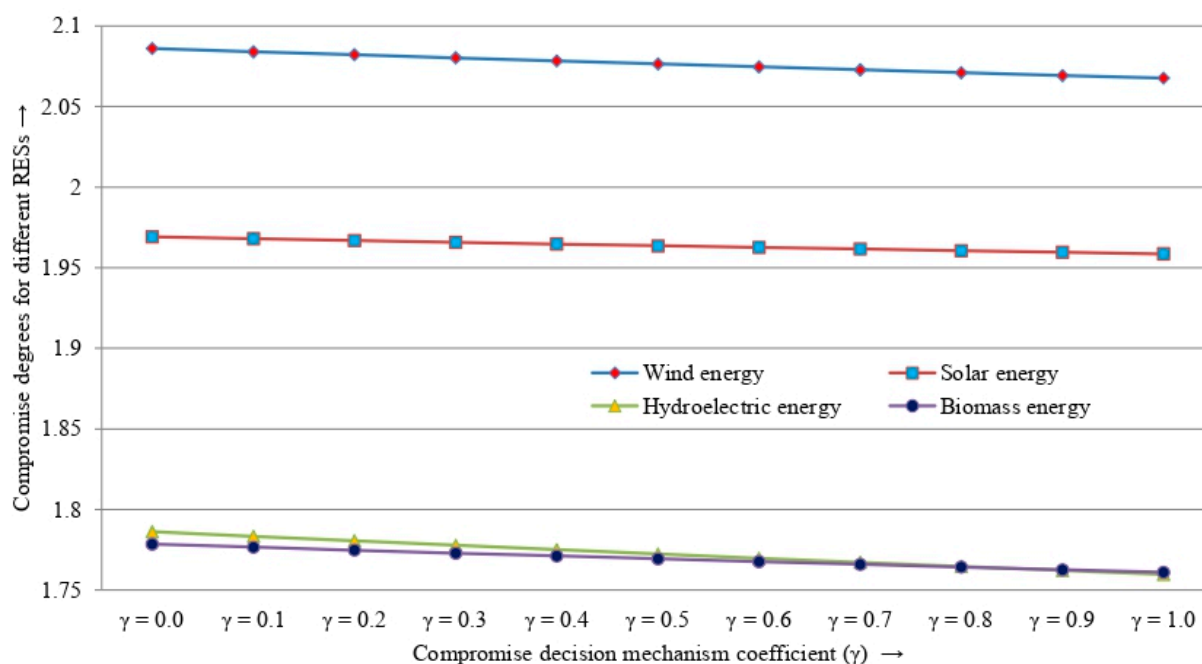


Figure 4. Compromise degrees of RESs concerning various values of γ .

6.3. Complexity Analysis and Computational Time—Proposed Model

The proposed work integrates SWARA-CoCoSo methods for rational ranking of renewable energies. SWARA as discussed elaborately in Section 4, is used for weight assessment and CoCoSo method is used for ranking energy options. It would be interesting to readers to understand the complexity of the framework.

In Section 4, Steps 1 to 4 are referred as data preparation steps, which takes $(k+1)O(mn) + O(kn)$ where k is the number of DMs, m is the number of energy options, and n is the number of criteria. Specifically, data matrix construction has complexity of $kO(mn)$, followed by criteria weight calculation matrix with complexity $O(kn)$ and data aggregation with complexity $O(mn)$. Adding these entities gives the complexity as $kO(mn) + O(kn) + O(mn) = (k+1)O(mn) + O(kn)$.

Step 5 of Section 4 deals with weight calculation by acquiring rating from DMs' as input. Initially, the score values are determined and the sorting is done with complexity $2O(kn)$. Later, for determining significance, coefficients, and recalculation the complexity is given by $3O(n^2)$. Weight calculation yields $O(n)$ as complexity. Hence, weight calculation by using SWARA has complexity of $2O(kn) + 3O(n^2) + O(n)$.

As discussed earlier, CoCoSo approach is used for ranking energy options. Steps 6 to 8 deal with the formulation. Clearly, the complexity is given by $O(mn) + 3O(m) + O(m) = O(mn) + 4O(m)$. Based on the discussion, the complexity of the framework is given by $(k+1)O(mn) + O(kn) + 2O(kn) + 3O(n^2) + O(n) + O(mn) + 4O(m) = (k+2)O(mn) + 3O(kn) + 3O(n^2) + O(n) + 4O(m)$.

Based on Figure 5 (In X axis 1 is 100, 2 is 300, 3 is 500, 4 is 1000, 5 is 3000, and 6 is 5000) it is clear that the proposed model takes higher time for implementation compared to the counterpart methods. This is understood from the formulation of SVN-CoCoSo, which has three stages of score to determine ranking of energy sources by considering both the arithmetic and geometric weighted preferences. These steps add to the execution time, but with the recent advancement in the hardware setting, the execution is achievable and there is higher degree of estimation in the proposed work that adds to the rationality of ranking, which is lacking in the counterpart methods. As a result, though the method is computationally complex, it has a systematic and rational grading of energy alternatives.

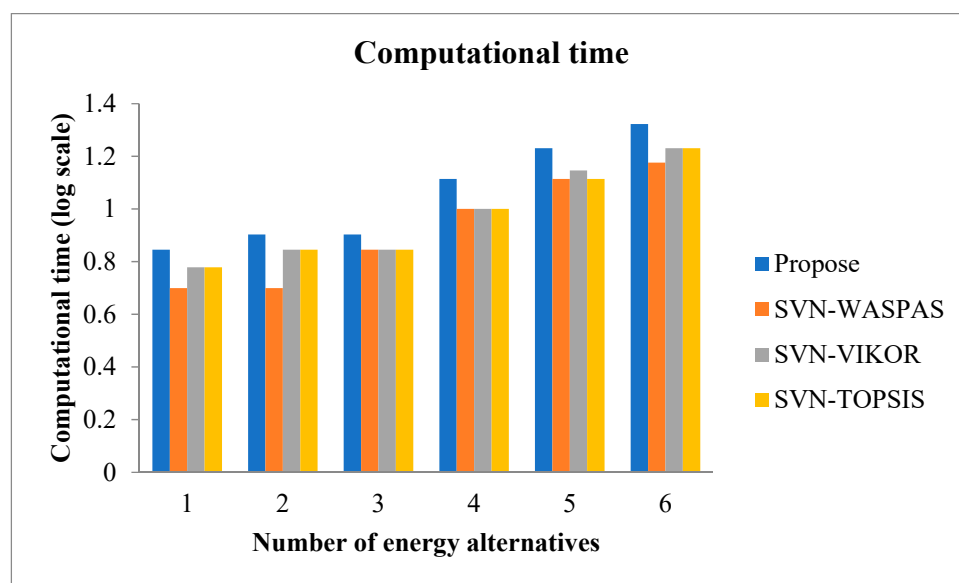


Figure 5. Time taken by different ranking models.

7. Conclusions

The objective of this study is to establish an MCDM model for selecting more appropriate RES in Karnataka, India. In this regard, an integrated method has been developed by combining SWARA and CoCoSo methods within the context of SVNS. In this method, the SWARA process has been operated to compute the subjective weights of the criteria and to model the uncertainty associated with the DMs' opinions and preferences within the SVNSs context. The CoCoSo approach has been presented to prioritize the options. To confirm the usefulness and feasibility of the present method, a case study of the RES selection problem with multiple qualitative and quantitative criteria has been presented under the SVNSs environment. The obtained results verify that the present method can successfully tackle the RES evaluation problem with inconsistent and indeterminate information. Comparison with previous models has been discussed to confirm the potentiality of the acquired results. In addition, SA with respect to various values of compromise parameters has been carried out to certify the robustness of the present decision-making model. In the future, we will extend our study by developing an integrated weighting model based on the combination of objective and subjective criteria weights under SVNSs environment and combined with several other MCDM approaches. Plans are also made to try the process with different criteria and experts. In addition, we will use the introduced methodology with excitement to other realistic decision-making problems with energy options such as fossil fuels/clean energies/nuclear energy.

Author Contributions: Contributions of all authors are presented below. All authors have read the paper and agree for its submission to the journal. Conceptualization—P.R., J.A. and R.K.; prototype creation—P.R. and R.K., A.R.M.; preparing the working model—P.R., J.A., R.K. and A.R.M.; data collection—J.A. and A.R.M.; testing of code—P.R. and R.K.; document drafting—P.R., J.A., R.K. and K.S.R.; literature review preparation—A.R.M. and F.C.; presentation enhancement—F.C. and K.S.R.; language edit—F.C. and K.S.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

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

Nomenclature

Abbreviation	Full Form	Variables/ Parameters	Meaning
A-SVN-DM	Aggregated single-valued neutrosophic decision matrix	Z	Universal set
AHP	Analytic hierarchy process	z_i	Element of universal set
ARAS	Additive Ratio Assessment	S	Single-valued neutrosophic set
BWM	Best worst method	$t_S(z_i)$	Truth membership function
CRITIC	Criteria importance through intercriteria correlation	$i_S(z_i)$	Indeterminacy membership function
CoCoSo	Combined compromise solution	$f_S(z_i)$	Falsity membership function
CM	Compromise Measure (CM)	v	Single-valued neutrosophic number
COPRAS	Complex proportional assessment	$\mathbb{S}(\cdot)$	Score function
DMs	Decision makers	$\wp = (\wp_1, \wp_2, \dots, \wp_m)^T$	Related weight vector of SVN v_i
EDAS	Evaluation based on distance from average solution	$D_h(S, T)$	Distance measure between the SVN S and T
EWP	Exponentially weighted product	$B = \{\beta_1, \beta_2, \dots, \beta_l\}$	A panel of decision makers
FS	Fuzzy set	$\{e_1, e_2, \dots, e_m\}$	Set of alternatives
GHG	Greenhouse gas	$\{p_1, p_2, \dots, p_n\}$	Set of criteria
GUM	Group Utility Measure	Ω	Decision matrix
IFS	Intuitionistic fuzzy set	$\chi_{ij}^{(k)}$	Evaluation information of i^{th} alternative over j^{th} criteria given by k^{th} decision maker
IRM	Individual Regret Measure	ω_k	Weight of k^{th} decision maker
LVs	Linguistic values	$\mathbb{N} = (\Xi_{ij})_{m \times n}$	Aggregated Single-valued neutrosophic decision matrix
MCDM	Multi-criteria decision making	$\bar{\mathbb{N}} = (\zeta_{ij})_{m \times n}$	Normalized decision matrix
MULTIMOORA	Multiobjective Optimization based on the Ratio Analysis plus Full Multiplicative Form	s_j	Comparative significance
NS	Neutrosophic set	k_j	Comparative coefficient
RES	Renewable energy source	d_j	Recalculated weight
SWARA	Step-wise Weight Assessment Ratio Analysis	w_j	Subjective weight of j^{th} criterion
SVNS	Single-valued neutrosophic set	p_n	Types of cost criteria
SVN	Single-valued neutrosophic	p_b	Types of benefit criteria
SVN-SWARA-CoCoSo	Single-valued neutrosophic-SWARA-CoCoSo	$\mathbb{C}_i^{(1)}$ and $\mathbb{C}_i^{(2)}$	Weighted sum and weighted product models
SVN-TOPSIS	Single-valued neutrosophic TOPSIS	$\gamma \in [0, 1]$	Coefficient of compromise decision mechanism
SVN-VIKOR	Single-valued neutrosophic VIKOR	$Q_i^{(1)}, Q_i^{(2)}, Q_i^{(3)}$	Three evaluation score strategies
SVN-WASPAS	Single-valued neutrosophic WASPAS	Q_i	Aggregating compromise index
SAW	Simple additive weighting	ι^+	Ideal solution
TOPSIS	Technique for order preference by similarity to ideal solution	ι^-	Anti-ideal solution
WEEE	Waste Electrical and Electronic Equipment	CC_i	Relative closeness index
WSM	Weighted sum model	P_i	WASPAS measure
WPM	Weighted product model	$\theta \in [0, 1]$	Decision mechanism coefficient in WASPAS measure
WASPAS	Weighted aggregated sum product assessment		
VIKOR	Visekriterijumska optimizacija i Kompromisno resenje		

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