Evaluation of Wind Turbine Failure Modes Using the Developed SWARA-CoCoSo Methods Based on the Spherical Fuzzy Environment

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ABSTRACT Accurately recognizing potential failures in the early stages of providing products or services can prevent the loss of investment and time and reduce the risk of safety hazards. Failure mode and effects analysis (FMEA) is a conventional approach for detecting and prioritizing the probable failures of a product's design or production process. Nevertheless, the traditional risk priority number (RPN) method has come under criticism for its deficiencies. This paper proposes a modified FMEA method based on fuzzy Multi-Criteria Decision Making (MCDM) techniques to cope with the weaknesses of the previous methodologies and improve the primary method. The concept of spherical fuzzy sets (SFS) is utilized to address the vagueness and impreciseness of the information that allows the experts to have more freedom in making decisions by including membership, non-membership, and hesitation of fuzzy sets. Initially, the procedure of assigning weights to the RPN criteria is implemented with SFS step-wise weight assessment ratio analysis (SWARA). Then, the failure modes are ranked by the SFS combined compromise solution (CoCoSo) method. The effectiveness and practicality of the suggested approach are illustrated through a case study on the Manjil wind farm in Iran. Results show that the suggested model is more reliable and realistic to be utilized in the prioritization of failures than the common FMEA method or other integrated MCDM approaches.

INDEX TERMS CoCoSo SWARA, failure mode, multi criteria decision making, spherical fuzzy sets, wind turbines.

I. INTRODUCTION It is evident that non-renewable resources are finite, and their constant consumption prematurely ends the natural resources and leads to irreversible environmental damages. In countries like Iran, due to the lower price of fossil fuels, most of the produced energies originate from non-renewable resources that have detrimental effects on the environment and climate change. Today generating clean energy from renewable energy sources such as solar, wind, geothermal, and biomass is of major consideration for most countries. The massive extension of wind power generation during the latest decades indicates its importance in the present and future renewable energy production; thus, early identification of the probable faults and failures in wind turbines plays a prominent role in enhancing wind power technology [1].

Population growth in the world directly affects energy demand, and it is expected that electricity demand will be tripled by the year 2050 [2]. Harnessing the power of wind for electricity generation purposes was initiated in the late
19th century. Over the last three decades, as a result of the increasing interest in producing electricity from wind energy, wind farms in many windy areas around the world have been developed rapidly to meet the increasing global demand for electricity [3]. Harnessing wind power for electricity generation purposes was initiated in the late 19th century. Over the last three decades, as a result of the increasing interest in producing electricity from wind energy, wind farms in many windy areas around the world have been developed rapidly to meet the increasing global demand for electricity [3]. While non-renewable resources are becoming used up in less developed countries, producing electrical energy using wind turbines turns into being more prevalent on account of being cost-effective, environmentally friendly, and socially popular [4].

Despite the negative influence of the COVID-19 pandemic on many industries and the resultant pressure on developers, with a growth of 53%, 2020 was the best year for global wind power installations, and it has been anticipated that the wind market will experience a 4% annual increase. In other words, by 2025, over 469 GW of extra wind capacity in this promising market is expected [5]. Predicted growth in the wind energy capacity will be practicable by designing and installing new wind farms on larger scales in windy locations and upgrading older existing turbines [6]. Wind turbines have the role of converting wind’s kinetic energy to mechanical energy and then to electricity. Recently, technology advancements have significantly impacted wind turbine design to enhance their efficiency and reliability by output maximization and cost minimization. Because of the modern Wind turbines’ complex structure and design, scheduled maintenance and regular inspection would be a compulsion [7].

Modern wind turbines are cheaper, silent, and more reliable. However, they face various technical issues like wind turbine size, productivity, power-saving and transmission, system balance, safety, and fault tolerance [8]. Moreover, Wind turbines are constructed of more than 8000 different components [9], including Foundation, Tower, Blades, Hub, nacelle, Gearbox, generator, pitch system, mechanical brake, main shaft, transformer, anemometer, controller, and convertor that each element’s failure could cause a complete shutdown. Fig. 1 shows the wind turbine configuration. Unlike the traditional turbines (steam, gas, hydro), wind turbines face more failures because of their exposure to severe conditions and hard-to-reach installation locations most of the time. These failures can occur in two forms. First, failure of the components in which a replacement or repair of the specific part might be required consequently leads to noticeable economic losses, turbine shutdown, waste of produced energy, generation failure, and much longer downtimes. Second, temporary faults that probably end in shorter downtimes during energy production, turbine restarting, or shutdowns for a while [10]. On top of that, wind turbine failures not only negatively influence power output efficiency and additional cost, but also safety issues should not be underestimated [11]. There is a strong relationship between wind turbine reliability, operation and maintenance expenditure, and annual energy production [12]. Thus failure detection and elimination are essential precautions.

Generally, wind turbine failures are rooted in a combination of various causes [14]. Downtime duration is essential in assessing failure severity since this period can last from a few hours to months. On average, 38% of the assemblies cause more than 50% of the wind turbine’s failure rates and 60% of the downtime [15]. Although the hub, blades, and gearbox failures lead to the highest repair downtimes and costs, the significant replacement failure rate is so low for them [16]. Reliability analysis is playing an increasing role in today’s complex systems to detect and prevent probable failures to improve the reliability of products, processes, systems, and safety. Apart from different reliability management tools, the main goal of the failure mode and effect analysis (FMEA) is to identify and prioritize the potential failure modes before a failure arises [17]. The criticality and priority of the failure modes are assessed with risk priority number (RPN) by employing Severity (S), Occurrence (O), and Detection (D) [18].

\[
RPN = S \times O \times D
\]  

(1)

Failure modes with higher RPN are more crucial and will need prompt actions to prevent or mitigate probable risks. Regardless of the broad utilization of the FMEA method in various studies, specialists criticize it because vagueness, uncertainty, and errors are likely during decision making or entering values; moreover, all factors are considered at an equal importance level, whereas the weight of the factors can be different in various cases [19]. Several multiple criteria decision-making (MCDM)-based FMEA has been proposed to deal with such problems. MCDM methods are proved to be an efficient solution for decision-making problems that have been applied in fields such as supply chain management, supplier selection, outsourcing decisions, and performance evaluation [20], [21].

Generally, based on inevitable uncertainty in real-life problems, solving them with effective criteria to achieve the expected results seems relatively difficult or even impracticable. Consequently, decision-makers are not able to make decisions with crisp numbers; Therefore, to deal with the uncertainty, researchers decided to use a combination of decision methods with fuzzy sets [22], [23]. For the first time, the fuzzy set theory (FST) was proposed by Zadeh et al. [24] in 1965 to cope with ambiguity and uncertainty in situations that are difficult to determine whether the crisp state is true or false is no distinct boundary for information. After that, many fuzzy sets, including Type-2 fuzzy sets [25], Neutrosophic sets [26], Intuitionistic fuzzy sets (IFS), Hesitant fuzzy sets [27], and as a generalization of IFS, Pythagorean fuzzy set (PFS) [28], [29] were introduced to develop the concept of fuzzy sets. In facing real-life problems, PFS is stronger than IFS based on the constraint that the square sum of positive and negative membership degrees is less than or equal to one [30]. Different Developed forms of PFS are used in studies to deal
with decision-making problems [31]. Finally, the Spherical fuzzy set (SFS) was established by Gündoğdu and Kahraman [32], which is the generalized form of Neutrosophic sets, Pythagorean fuzzy sets, and picture fuzzy sets.

The SFS is capable of handling the situations in which PFS and picture fuzzy sets fail [33]. The distinctive feature of the PFS compared to SFS is the neutral degree that does not exist in PFS. Even though the Picture fuzzy sets consider all neutral, positive, and negative degrees, they face difficulty when the sum of these degrees is more than 1. In such cases, SFSs are practical concepts to rely on [34]. Various studies have promoted the SFS to take advantage of it in different problems. Ashraf et al. [35] proposed an algorithm to solve decision analysis problems by introducing the SFS distance-weighted averaging (SFOWA), and SFS distance order-weighted averaging (SFDOWA), and SFS distance order-weighted average weighted averaging (SFDOWA WA) operators with the attribute weights.

Another study used a spherical fuzzy entropy measure to solve an SFS information-based group decision-making problem [36]. To solve a group decision-making problem, Ashraf et al. [37] developed another operator based on SFS numbers, called spherical linguistic fuzzy Choquet integral weighted averaging (SLFCIA) operator based on SFS numbers. Ashraf et al. [38] defined several new operational laws by Dombi t-norm and t-conorm based on SFS numbers to facilitate the decision-making. Definition of new aggregation operators has contributed to solving the real-life problems [39], [40].

With the advent of SFS theory and its application to various MCDM methods, final outputs illustrate more robust and reliable results for decision-making problems. SF-weighted aggregated sum product assessment (WASPAS) [32], SF-combinative distance-based assessment (CODAS) [41], SF-technique for order preference by similarity to ideal solution (TOPSIS) [42], SF-VIKOR [43], SF-MULTIMOORA [44], SF-analytic hierarchy process (AHP) [45], SF-PROMETHEE [46], SF-multi-objective optimization on the basis of ratio analysis (MOORA) [47]. Since the SFS provides a larger preference domain for decision-makers, DMs can make decisions more freely and assign their judgments on the membership, non-membership, and hesitancy degrees as independent parameters. By all means, it has greater space that gives greater latitudes to decision-makers. A linguistic evaluation scale based on the SFS concept gives the decision-makers the chance to make more reliable decisions and overcome their hesitancy [32], [48].

In this paper, a developed approach based on FMEA and MCDM methods in SFS to investigate and prioritize wind turbine failures is presented. The step-wise weight assessment ratio analysis (SWARA) is one of the weighting methods of MCDM that has been developed to allocate the appropriate weights of FMEA factors in an SFS. Because of this, DMs have a greater degree of freedom to express their opinions as opposed to other weighting methods. In addition, in this paper, for the first time, the combined compromise solution (CoCoSo) method in SFS is developed to rank failures. Unlike other MCDM methods, CoCoSo provides the final ranking with three different aggregation methods. Each of the aggregation methods provides a ranking score, then based on the appropriate index of the problem, the final score is obtained and the full ranking is improved. In addition,
having a higher resolution in identifying optimal alternatives is another advantage of the CoCoSo method, which has led to its selection in this paper for ranking. FMEA ranking is usually based on three common criteria: severity, detection, and occurrence. But in this paper, for more accurate results, two other effective influential factors are added to be taken into consideration since they have play a crucial role in assessing the severity of failure modes: Downtime (T) for the periods that the turbine might need a component replacement, repair, maintenance, or inspection, and Cost (C) for the extra costs that will be imposed in the case of a failure occurrence. Higher downtime duration or additional costs directly affects the system’s efficiency, performance, or total loss. Therefore, the proposed approach prevents the occurrence of failures in wind turbine systems and prevents their failure. It also saves on maintenance and repair costs of wind turbines and increases the accuracy and quality of fault detection. After recognizing the importance of each failure based on its priority, managers will be able to take the necessary measures to prevent long downtimes, large-scale failures, extra expenses, or safety issues.

The rest of the paper is organized as follows: First, a literature review on hybrid FMEA, SWARA, and CoCoSo methods is presented. Second, the preliminaries, including expressions of the concept of SFS theory, the SF-SWARA method, and the SF-CoCoSo method, are proposed and formulated. Third, the proposed methodology, case study, and implementation of the proposed method are reported to show its practicability and feasibility. Finally, conclusions and directions for future studies are addressed.

II. LITERATURE REVIEW

In this section, related literature is reviewed in three subsections. In the first part, applications of the FMEA method and combined approaches based on this method in different fields are examined. The second and third sections present the application of the SWARA and CoCoSo techniques.

A. HYBRID FMEA APPROACH

Failure modes and effects analysis (FMEA) is a systematic approach broadly used in various research fields and industries to assess potential failures in a product’s design or process [49]. Due to the traditional FMEA method’s deficiencies, studies show that combining the FMEA method with MCDM techniques can be more reliable and practicable. Wang et al. [50] introduced a new FMEA method in combination with the interval-valued intuitionistic fuzzy Analytic Network Process (IVIF-ANP) and IVIF-Complex Proportional Assessment (COPRAS) for the identification and prioritization of the hospital service risk factors. Lo and Liou [51] proposed an integrated risk assessment model where the best-worst method (BWM) was used to obtain the weights of RPN elements, and the grey interval linguistic variables were used to manage information uncertainty. In another study, they suggested a hybrid MCDM-based FMEA model for identifying the critical failures in manufacturing. First, they employed the Decision making trial and evaluation laboratory (DEMATEL) technique to determine the weights of the risk factor. Then, they ranked the failure modes using four different MCDM methods (SAW, VIKOR, GRA, and COPRAS) based on the TOPSIS method to cope with the problem of different priority ranking results from different MCDM methods [52].

Ghoushchi et al. [53] used the fuzzy BWM to measure the weights of the RPN factors and prioritized the failures using MOORA based on the Z-number theory. Ghoushchi et al. [54] presented a hybrid approach based on Z-SWARA and Z-MOORA with an extended FMEA method to prioritize the failure modes of an automotive supplier firm. Boral and Chakraborty [55] presented an integrated interval type-2 fuzzy sets (IT2F)-MCDM-based FMEA approach to detect and prioritize the potential failure modes of CNC machines due to human errors. For this purpose, The IT2F-AHP was adopted to calculate the weights of the risk factors; then, to model the causal interactions among different errors IT2F-decision-making trial and evaluation laboratory (DEMATEL) was used. In the last section, the IT2F-Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS) was extended to rank the risk factors.

Wang et al. [56] utilized the probabilistic hesitant fuzzy linguistic term sets (PHFLTSs) to overcome the existing uncertainty problem and after exploiting the social network analysis (SNA), maximizing consensus method (MCM), and BWM to assign the weights to RPN factors, finally, the risk ranking of failure modes were obtained using the TOPSIS technique. Rahmati et al. [57] discussed a new methodology which is a combination of Z-SWARA and Z-WASPAS techniques with the FMEA method to evaluate the priority of risk factors of financial measurement for the management control system of production companies. Ghoushchi et al. [58] proposed an extended FMEA method based on the BWM-COPRAS approach to assess health safety and environmental risk in the fuzzy environment using the G-number theory.

B. SWARA METHOD

Keršuliene and Turskis [59] introduced the step-wise weight assessment ratio analysis (SWARA) approach to assigning appropriate weights to the criteria. In this method, experts have a significant role in evaluating the weights. At first, each DM ranks the criteria from the most important to the least significant one, according to their experience and knowledge. Then the overall ranks are obtained based on the mediocre value of ranks [60]. The main feature of this method is that DMs’ opinions about the importance ratio of the criteria are estimated through the weights determination process. SWARA is an uncomplicated methodology used in many complicated MCDM problems, such as supplier selection, machine tool selection, packaging design, personnel selection, reverse logistic problems, occupational health, and
safety risk assessment, manufacturing, and waste elimination process.

Moreover, SWARA is a useful method in a situation where problem priorities are already defined based on policies of companies or countries and criteria evaluation is not required anymore, while other weighting methods, like AHP and ANP, are highly related to the criteria evaluations. Zolfani and Bahrami [61] recommended a SWARA-COPRAS method for prioritizing investments in high-tech industries. To solve a location selection problem for a marine current energy production plant in turkey, an integrated SWARA-WASPAS has been suggested [62].

Most of the time the judgment of experts is not definite due to hesitancy and vagueness of their opinion or lack of information, consequently, to cope with this problem, researchers have applied MCDM methods in the fuzzy environment [63]. Zarbakhshnia et al. [64] proposed a hybrid method of fuzzy SWARA and COPRAS to evaluate and select the sustainable third-party reverse logistic provider. In another study, a Pythagorean fuzzy SWARA-VIKOR approach has been recommended to select the solar panel performance evaluation [65]. He et al. [66] suggested an extended interval-valued Pythagorean fuzzy SWARA-MULTIMOORA to investigate the status of sustainable community-based tourism in the Indian Himalayan region. Ghousechi et al. [67] used an integrated SWARA-WASPAS approach in the spherical fuzzy environment to solve the landfill site selection for medical waste.

C. CoCoSo METHOD

CoCoSo was developed by Yazdani et al. [68] in 2019 as a new MCDM method that combines simple additive weighting and an exponentially weighted product model. It is one of the recent multi-criteria decision-making methods based on compromise solutions and a helpful technique in ranking or selecting multiple alternatives. However, MCDM approaches have been widely criticized for diverse ranking results and optimal alternatives in the same decision-making problem. The solution obtained by CoCoSo is more reliable and stable. The CoCoSo has been used in different research fields as an effective method for ordering the criteria. For sustainable supplier selection problems, Zolfani et al. [69] suggested a BWM-CoCoSo. A hybrid MCDM model has been proposed based on the fuzzy SWARA and CoCoSo method [70]. Torkayesh et al. [71] used CoCoSo to evaluate the healthcare performance after assessing the weights of the healthcare indicators by applying the best-worst method (BWM) and level-based weight assessment (LBWA). To solve the distribution location selection problem of perishable agricultural products, a hybrid SFS Hierarchy process (AHP) and CoCoSo method have been utilized [72]. Adar et al. [73] prioritized the management of industrial wastewater criteria based on the AHP-CoCoSo approach.

Additionally, CoCoSo has been applied in fuzzy environments to deal with uncertain issues in decision-making problems. A novel method integrating PF-SWARA and PF-CoCoSo has been suggested to rank organizations in the manufacturing sector [74]. Yazdani et al. [68] recommended an integrated F-FMEA-CoCoSo algorithm through triangular fuzzy hesitant sets (TFHS) for outsourcing risk analysis. Liu et al. [75] studied a novel Pythagorean fuzzy (PF) CoCoSo to assess medical waste treatment technology. In another study, Lahane and Kant [76] suggested an integrated PF-AHP and PF-CoCoSo method to evaluate and order the performance outcomes of a circular supply chain. Table 1 presents some of the hybrid FMEA approaches that have been developed based on MCDM methods.

III. PRELIMINARIES

This paper presents a hybrid integrated decision-making approach based on SF theory for evaluating and prioritizing failure modes of the wind turbine. Therefore, the fundamentals of the theory used in the proposed approach are discussed in this section.

A. SPHERICAL FUZZY SET THEORY

Spherical fuzzy set theory is one of the latest fuzzy sets introduced by Kutlu Gündoğdu and Kahraman [77] in 2019. This section presents some of the properties, arithmetic operations, and principles of SFSs.

Definition 1 ([77]): According to the Ref. SFS Z of the universe of discourse X is given by:

\[ Z = \{(x, \mu_z(x), \nu_z(x), \pi_z(x)) | x \in X\} \]  \hspace{1cm} (2)
where $\mu_x : X \rightarrow [0, 1], v_x : X \rightarrow [0, 1], \pi_x : X \rightarrow [0, 1]$ represent the degrees of membership, non-membership, and hesitance for every $x \in X$ in the SFS $Z$, respectively.

$$0 \leq (\mu_x(x))^2 + (v_x(x))^2 + (\pi_x(x))^2 \leq 1 \quad (3)$$

**Definition 2 ([78]):** Let $Z_1 = [\mu_{11}, v_{11}, \pi_{11}]$ and $Z_2 = [\mu_{21}, v_{21}, \pi_{21}]$ be two SF numbers and $k$ to be a constant number greater than $0$. The basic mathematical operations of these two SF numbers are as follows:

$$Z_1 \oplus Z_2 = \left[\sqrt{\mu_{11}^2 + \mu_{21}^2 - \mu_{11}^2 \mu_{21}^2}, v_{11}, \pi_{11}\right]$$

$$Z_1 \otimes Z_2 = \left[\frac{\sqrt{v_{11}^2 + v_{21}^2 - v_{11}^2 v_{21}^2}}{v_{11}}, \frac{\sqrt{1 - \mu_{11}^2 - \pi_{11}^2}, \frac{1}{\pi_{11}}\right]$$

$$Z_1 \ominus Z_2 = \left[\sqrt{(1 - v_{11}^2)\pi_{11}^2 + (1 - \mu_{11}^2)\pi_{21}^2 - \pi_{11}^2 \pi_{21}^2}, v_{11}, \pi_{11}\right]$$

$$kZ = \left[\sqrt{(1 - (1 - k^2)^2)^2}, v_{11}, \pi_{11}\right]$$

$$Z^k = \mu_{11}^k \left[\sqrt{(1 - \pi_{11}^2)^2}, v_{11}, \pi_{11}\right]$$

**Definition 3 ([45], [67]):** For these SFS $Z_1 = [\mu_{11}, v_{11}, \pi_{11}]$ and $Z_2 = [\mu_{21}, v_{21}, \pi_{21}]$. The following rules under the condition $k, k_1, k_2 > 0$, are valid.

$$Z_1 \oplus Z_2 = Z_2 \oplus Z_1 \quad (8)$$

$$Z_1 \otimes Z_2 = Z_2 \otimes Z_1 \quad (9)$$

$$k(Z_1 \oplus Z_2) = kZ_1 \oplus kZ_2 \quad (10)$$

$$k_1Z_1 + k_2Z_2 = (k_1 + k_2)Z_1 \quad (11)$$

$$Z_1 \otimes Z_2 = \left[Z_1^{k_1} \otimes Z_2^{k_2}\right] \quad (12)$$

$$Z_1^{k_1} \otimes Z_1^{k_2} = Z_1^{k_1 + k_2} \quad (13)$$

**Definition 4 ([78]):** Let $Z = \mu_x v_x \pi_x$ represents an SF number. The score value and accuracy function of the number $Z$ is calculated as follows:

$$\text{Score}(Z) = (\mu_x - \pi_x)^2 - (v_x - \pi_x)^2 \quad (14)$$

$$\text{Accuracy}(Z) = \mu_x^2 + v_x^2 + \pi_x^2 \quad (15)$$

Note that: $Z_1 < Z_2$ if and only if

1. $\text{score}(Z_1) < \text{score}(Z_2)$ or
2. $\text{score}(Z_1) = \text{score}(Z_2)$ and $\text{Accuracy}(Z_1) < \text{Accuracy}(Z_2)$

**Definition 5 ([45]):** Single-valued Spherical Weighted Arithmetic Mean (SWAM) with respect to $w = (w_1, w_2, \ldots, w_n)w_i \in [0, 1]$, $\sum_{i=1}^{n} w_i = 1$, is computed as follows:

$$\text{SWAM}_w(Z_1 \cdots Z_n) = w_1Z_1 + w_2Z_2 + \cdots + w_nZ_n$$

$$= \left[1 - \sum_{i=1}^{n} (1 - \mu_i^2)w_i\right]^2 \sum_{i=1}^{n} \mu_i w_i$$

$$\times \left[1 - \sum_{i=1}^{n} (1 - \mu_i^2, w_i - \pi_i^2)w_i\right]^2 \quad (17)$$

**Definition 6 ([45]):** Spherical Weighted Geometric Mean (SWGM) with respect to $w = (w_1, w_2, \ldots, w_n)w_i \in [0, 1]$, $\sum_{i=1}^{n} w_i = 1$, is computed as follows:

$$\text{SWGM}_w(Z_1, \cdots, Z_n) = Z_1^w + Z_2^w + \cdots + Z_n^w$$

$$= \prod_{i=1}^{n} \mu_i^w [1 - \prod_{i=1}^{n} (1 - \mu_i^2)w_i]^2$$

$$\times \prod_{i=1}^{n} (1 - v_i^2)w_i^2$$

$$\times \prod_{i=1}^{n} (1 - \pi_i^2)w_i^2 \quad (18)$$

**B. SF-SWARA**

Assigning weights to criteria is one of the critical stages in MCDM problems. The SWARA method was introduced by Zavadskas et al. [59] in 2010, which can rank and determine the weight of criteria. In this method, a group of experts shares their opinions about the options while a researcher takes notes and, based on them, determines the relative weights by ranking them [79]. The SF-SWARA is used in this study to assess the weights of RPN factors considering the probable uncertainty in decision-makers’ views. The steps of SF-SWARA are described as follows:

**Step 1:** Preference ranking of the criteria based on the SF-SWARA. In this step, the evaluation criteria are sorted from maximum preference to a minimum according to the DM’s opinions and linguistic variables.

**Step 2:** Making a decision matrix with SF numbers. At this step, the linguistic variables expressed by the DMs are changed to Spherical Fuzzy numbers with Table 2.

**Step 3:** Calculating the weight of DMs and building the aggregated Decision matrix. The preferences of each DM are aggregated using the SWAM or SWGM operator, as shown in Equation 17 and 18.

**Step 4:** Evaluating the comparative significance of score value. It is started from the criteria in the second place which is a score between 0 and 1 allocated by DMs to the factor $j$ in relation to the previous criterion ($j - 1$). After applying this process to all the criteria the comparative importance of score value ($s_j$) is obtained.
Step 5: calculating the comparative coefficient. The comparative coefficient \((k_j)\) is computed from the Eq. 19:

\[
k_j = \begin{cases} 
1 & j = 1 \\
\frac{s_j}{s_j + 1} & j > 1 
\end{cases} 
\] (19)

Step 6: Estimating the spherical fuzzy weight. The fuzzy weight \((p_j)\) is calculated from the Eq. 20:

\[
p_j = \begin{cases} 
1 & j = 1 \\
\frac{k_j - 1}{s_j} & j > 1 
\end{cases} 
\] (20)

Step 7: Estimating the relative weights of the evaluation criteria. In this step, to estimate the relative weights of the evaluation criteria Eq. 21 is used, in which \(w_j\) represents the comparative weight of criterion \(j\) and \(n\) is the number of criteria.

\[
w_j = \frac{p_j}{\sum_{j=1}^{n} p_j} 
\] (21)

C. SF-CoCoSo
For the first time, the Combined Compromised Solution (CoCoSo) method was proposed by Yazdani et al. [68] in 2019. The suggested hybrid approach integrates simple additive weighting and exponentially weighted product models. In this study, CoCoSo is extended to SF-CoCoSo, which provides more reliable results to cope with the real-world state of vagueness and uncertainty. After specifying the alternatives and the related criteria, the steps of the proposed SF-CoCoSo are as follows:

Step 1: Determination of the initial decision matrix. The first step in MCDM methods is the construction of a decision matrix as shown below. Let \(D = \{d_1, d_2, \ldots, d_m\}\) be the set of choices, \(C = \{C_1, C_2, \ldots, C_j, \ldots, C_n\}\) set of assumed criteria and \(W = \{w_1, w_2, \ldots, w_n\}\) set of weights with respect to \(w_j \in [0, 1]\). Here \(X\) is the evaluation of choice \(M\) based on criteria \(n\) by decision-maker number \(K\), which has been shown by \(S = (S_{ij})_{m \times n}\) matrix and it is formed on linguistic terms.

\[
S = (C_j(d_i))_{m \times n} = \begin{bmatrix} 
S_{11} & \cdots & S_{1n} \\
\vdots & \ddots & \vdots \\
S_{m1} & \cdots & S_{mn} 
\end{bmatrix} 
\] (22)

Step 2: Linguistic variables Conversion into SF numbers. In the second step, the determined linguistic variables from step 1 transform to SF numbers using Table 2, and the decision matrix is built according to Eq. 23

\[
S = (C_j(d_i))_{m \times n} = \begin{bmatrix} 
\mu_{11}v_{11}\pi_{11} & \cdots & \mu_{1n}v_{1n}\pi_{1n} \\
\vdots & \ddots & \vdots \\
\mu_{m1}v_{m1}\pi_{m1} & \cdots & \mu_{mn}v_{mn}\pi_{mn} 
\end{bmatrix} 
\] (23)

Step 3: Aggregated Decision Matrix Construction. In this step experts’ views are integrated considering the assigned weight for each. Afterward, The aggregated decision matrix with the utilization of the Spherical Weighted Arithmetic Mean (SWAM) or Spherical Weighted Geometric Mean (SWGM) operator, which is shown in Eq. 17 and 18.

Step 4: Score function calculation. Using Eq. 14, Score Value for each SF number is calculated and the matrix of \(S^* = (s_{ij}^*)_{m \times n}\) is formed.

Step 5: Normalization of decision matrix. Generally, normalization is applied to all the MCDM methods. In this step, with respect to the relations shown below, the decision matrix is normalized according to Eq. 24 for positive variables and Eq. 25 for negative variables. \(s_{ij}^*\) and \(s_{ij}^-\) are the highest and lowest values of each column of variables respectively.

\[
S = \frac{S_{ij}}{S_{ij}^*} \quad \text{if } j \in B 
\] (24)

\[
S = \frac{s_{ij}^-}{s_{ij}^*} \quad \text{if } j \in C 
\] (25)

where

\[
s_{ij}^* = \min \{s_{ij}\} \quad \text{and} \quad s_{ij}^* = \max \{s_{ij}\} 
\] (26)

Step 6: Calculating the power weight of comparability and sum of weighted comparability sequences. In this step, the power weight of comparability \((P_i)\) and the sum of weighted comparability \((S_i)\) sequences for each alternative are calculated. \(W\) is the weight of variables which is an input of CoCoSo method. \(S_i\) and \(P_i\) values are originated from the SAW and WASPAS methods, respectively.

\[
P_i = \sum_{j=1}^{n} (S_{ij})^W 
\] (27)

\[
S_i = \sum_{j=1}^{n} W_jS_{ij} 
\] (28)

Step 7: Determination of appraisal score based on three strategies. In this part, the score of the alternatives based on three appraisal strategies are obtained using Formulas 29 - 31. Eq. 29 defines the arithmetic mean of the scores of WSM and WPM while Eq. 30 expresses the relative scores of WSM and WPM compared to the best. Eq. 31 is a balanced compromise of WSM and WPM. In Eq. 31, \(\lambda\) is assigned by an expert, although in the case of \(\lambda = 0.5\) is more flexible.

\[
k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)} 
\] (29)

\[
k_{ib} = \frac{S_i}{\min_i S_i + P_i} 
\] (30)

\[
k_{ic} = \frac{\lambda S_i + (1 - \lambda)P_i}{\lambda \max_i S_i + (1 - \lambda) \max_i P_i}, \quad 0 \leq \lambda \leq 1 
\] (31)

Step 8: Determination of final score and ranking of the options. In this section, based on Eq. 32 the final score is determined, in fact, it depicts the summation of arithmetic
mean and Geometric mean of the previous three strategies, hence, the best options are with the higher $k_i$ score.

$$k_i = \sqrt[3]{k_{ia}k_{ib}k_{ic}} + \frac{k_{ia} + k_{ib} + k_{ic}}{3} \quad (32)$$

**IV. ANALYSIS**

In this section, explanations about the case study are provided and the proposed approach step-by-step is implemented based on the introduced formulas. In addition, the results of the proposed approach are examined and analyzed for sensitivity.

**A. PROPOSED APPROACH**

In this study, an integrated framework of FMEA-SWARA-CoCoSo under the SF environment is developed to evaluate and prioritize the potential failures of wind turbines to reduce extra costs and long-term downtimes while improving its performance for more clean energy generation. Concerning
the advantages of SFSs that have been applied in this study, the vagueness of the DMs’ views is diminished; therefore, results are more reliable and applicable in real-life cases. This methodology is presented in three main phases. In the first phase, FMEA experts specify the potential failures of wind turbines concerning each failure mode’s severity (S), occurrence (O), detection (D), Downtime (T), and Cost (C). In the next phase, using the SF-SWARA, weights are assessed for all five factors of the FMEA approach. In the final phase, all the failures that have been specified in phase 1 are ranked via the developed SF-CoCoSo method based on the criteria weights obtained from phase 2. The implementation process of the proposed method is shown in Fig. 2.

B. CASE STUDY

This section aims to reveal the feasibility and potentiality of the proposed method, and it is implemented to rank the potential failures of the wind turbines in Manjil, which is located in Gilan province in the north of Iran and well known as Iran’s city of wind turbines. The first experience of Iran in installing and using modern wind turbines dates back to 1994. Manjil, with high wind potential, also known as the windy city of Iran, is located about 220 km northeast of Tehran and 80 km south of the Caspian Sea in Gilan province. Due to the mountainous geographical situation of the Manjil wind farm and constant high-speed winds, it is one of the best locations in the world to produce electricity by harnessing wind energy.

Wind turbines have been constructed of about 8000 components, and a failure of each can lead to turbine shutdowns, performance disorders, long downtimes, and a high cost of repair or replacement of the components. Overall, the main parts of a wind turbine include the foundation, tower, nacelle, anemometer, blades, gearbox, yaw system, pitch system, hub, rotor, low-speed shaft, main shaft bearing, high-speed shaft, generator, controller, mechanical brake. A wind turbine uses the aerodynamic force from the rotation of the blades to convert wind energy into electricity, which is the same as a helicopter. The pressure difference between the blades’ sides leads to drag and lift forces. The rotor starts to spin because of the stronger lift force compared to the drag force. The rotor is connected to the generator, responsible for producing electricity from wind energy. In this study, a list of 18 potential failures of the wind turbines in Manjil have been investigated with the help of 3 FMEA experts based on five factors: severity (S), occurrence (O), detection (D), Downtime (T), and Cost (C), all are presented in the Table 3. In this paper, three professional and experienced specialists familiar with new energy development and technology have been used. Specialists have at least ten years of work in air filtration, HEPA filter testing, and test, adjust, and balance work.

C. RESULTS

In this section, the results of the proposed research approach in evaluating the failure modes of wind turbines are examined. This study aims to introduce a new approach using MCDM methods in an environment of uncertainty. According to the first step of the proposed approach, experts first express the importance of each of the criteria according to Table 4 in linguistic terms using Table 2.

The linguistic variables expressed by the experts are then converted to spherical fuzzy numbers according to Table 2. Using the Equations 17 and 18 and the weight of the specialists, which are 0.5, 0.3 and 0.2, respectively, the aggregated decision matrix is formed (see Table 5).

The score values of spherical fuzzy numbers are obtained using Eq. 14 and the matrix S is formed in the next step. Then, according to the value of the score function, the criteria are arranged in descending order, and and are obtained using the Equations 19 and 20. Finally, which is the final weight of the criteria, is calculated by Equation 21. As shown in Table 6, we find that the severity criterion with weight (0.259) takes precedence over the other criteria.

The SF-CoCoSo method is then used to rank failure modes. According to this method’s first step, the decision matrix is first formed by the FMEA team with spherical fuzzy linguistic terms.

Then decision matrices based on spherical fuzzy variables are converted to spherical fuzzy numbers using Table 2. And according to the next step, the aggregated matrix is formed based on the weight of the specialists and using Equation 17 (see Table 8).

Then, the matrix S is formed using Equation 14 and normalization is performed using Equations 24 and 25 based on the type of criteria. Table 9 presents the normalized matrix. In this study, according to the nature of the problem, the criteria of severity, probability of occurrence, Cost, and time are positive and the criterion of detection is negative.

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**TABLE 4. The importance of criteria in the form of spherical fuzzy linguistic variables.**

| Criteria | DM1 | DM2 | DM3 |
|----------|-----|-----|-----|
| Severity | HI  | VHI | HI  |
| Occurrence | SLI | LI  | SLI |
| Detection | LI  | VLI | VLI |
| Cost     | SMI | EI  | SLI |
| Time     | LI  | VLI | ALI |

**TABLE 5. Aggregated spherical fuzzy decision matrix based on SWAM.**

| Criteria | S | O | D | T | C | W | P |
|----------|---|---|---|---|---|---|---|
| Severity | 0.19798 | - | I | I | I | 0.259044 |
| Occurrence | 0.00296 | 0.200954 | 1.200954 | 0.832671 | 0.215699 |
| Detection | 0.05503 | 0.052062 | 1.052062 | 0.791466 | 0.205025 |
| Cost | 0.28311 | 0.220170 | 1.220170 | 0.644475 | 0.166948 |
| Time | -0.37224 | 0.089135 | 1.089135 | 0.591731 | 0.153284 |
TABLE 7. Evaluation of failure modes based on spherical fuzzy linguistic variables.

| Failure modes | Severity | Occurrence | Detection | Cost | Time |
|---------------|----------|------------|-----------|------|------|
|               | DM1 | DM2 | DM3 | DM1 | DM2 | DM3 | DM1 | DM2 | DM3 | DM1 | DM2 | DM3 |
| FM1           | HÍ | SÍ | MÍ | HÍ | VÍ | SÍ | HÍ | VÍ | SÍ | HÍ | SÍ | MÍ |
| FM2           | SÍ | VÍ | HÍ | SÍ | VÍ | HÍ | SÍ | HÍ | VÍ | SÍ | HÍ | SÍ |
| FM3           | MÍ | VÍ | VÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM4           | HÍ | HÍ | VÍ | VÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ |
| FM5           | VÍ | HÍ | HÍ | HÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM6           | HÍ | VÍ | VÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM7           | HÍ | VÍ | VÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM8           | HÍ | VÍ | VÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM9           | SÍ | HÍ | MÍ | HÍ | VÍ | SÍ | HÍ | VÍ | SÍ | HÍ | SÍ | MÍ |
| FM10          | HÍ | VÍ | HÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM11          | SÍ | HÍ | SÍ | MÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM12          | SÍ | HÍ | SÍ | MÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM13          | HÍ | HÍ | VÍ | VÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ |
| FM14          | VÍ | HÍ | VÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM15          | HÍ | SÍ | MÍ | HÍ | VÍ | SÍ | HÍ | VÍ | SÍ | HÍ | SÍ | MÍ |
| FM16          | HÍ | SÍ | MÍ | HÍ | VÍ | SÍ | HÍ | VÍ | SÍ | HÍ | SÍ | MÍ |
| FM17          | HÍ | VÍ | HÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |
| FM18          | HÍ | VÍ | HÍ | SÍ | VÍ | HÍ | HÍ | VÍ | HÍ | VÍ | SÍ | VÍ |

The values of the power weight of comparability ($P_i$) and the sum of weighted comparability ($S_i$) are calculated using Equations 27 and 28, respectively, for each failure mode.

In this step, the weights obtained from the SWARA method are used. (See Table 10)

Finally, $k_{1a}$, $k_{1b}$ and $k_{1c}$ are calculated using Equations 29–31. In the mentioned Eq, the value of $\lambda$ for equilibrium is

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FIGURE 3. Comparison of failure mode rankings with different $\lambda$.

TABLE 11. Comparison of CoCoSo method ranking with MOORA and COPRAS methods.

| Failure mode | RPN | SF-CoCoSo | SF-MOORA | SF-COPRAS |
|--------------|-----|-----------|----------|-----------|
| FM1          | 13  | 18        | 18       | 18        |
| FM2          | 11  | 14        | 17       | 16        |
| FM3          | 11  | 16        | 16       | 17        |
| FM4          | 4   | 7         | 8        | 8         |
| FM5          | 2   | 1         | 1        | 1         |
| FM6          | 9   | 9         | 7        | 7         |
| FM7          | 8   | 12        | 11       | 10        |
| FM8          | 6   | 8         | 9        | 9         |
| FM9          | 10  | 10        | 10       | 11        |
| FM10         | 3   | 3         | 5        | 5         |
| FM11         | 13  | 15        | 15       | 15        |
| FM12         | 12  | 17        | 14       | 14        |
| FM13         | 5   | 5         | 4        | 4         |
| FM14         | 1   | 2         | 2        | 2         |
| FM15         | 8   | 13        | 13       | 12        |
| FM16         | 9   | 11        | 12       | 13        |
| FM17         | 1   | 4         | 3        | 3         |
| FM18         | 7   | 6         | 6        | 6         |

considered equal to 0.5. And using these 3 values, the final score of each failure mode, $k_i$, based on Equation 32 is obtained. And the ranking is based on the final score. According to Table 10, we find that FM5 with a score of 4.238 has a higher priority than other failure modes. FM14 and FM10 with a score of 4.035 and 3.848 are in the second and third priority, and FM1 with score 1.355 is in the last priority. Therefore, based on this prioritization, specialists can take preventive and corrective measures to avoid the negative effects of these failures.

D. SENSITIVITY ANALYSIS

In the proposed approach, the final ranking is based on the $\lambda$ parameter, which originates from the CoCoSo method. In this section, by changing the $\lambda$ parameter, we examine its effect on the ranking results. Several scenarios have been defined for this purpose. Fig. 3 shows the different $\lambda$ values and ranking results. Based on the results, we find that with the change of $\lambda$, there is no significant change in the results. The ranking is the same in all scenarios, and $\lambda$ change does not have a serious impact on the ranking because FM5 in all scenarios is identified with high priority. However, depending on the nature of the data and the subject matter, experts can make serious decisions about the value of $\lambda$. However, experts can make a serious decision about the value of $\lambda$, depending on the nature of the data and the issue.

E. COMPARISON ANALYSIS

Finally, to show the validity and effectiveness of the proposed CoCoSo method, the ranking process has been done with other methods such as conventional FMEA, MOORA, and COPRAS. According to Table 11, by comparing the results it is clear that in the conventional FMEA, FM14 and FM17 are jointly in the first place. FM7 and FM15 are jointly in the 8th rank. Moreover, simultaneous examination of the RPN illustrates that in the final results, the failure modes are in 13 categories instead of 18. This indicates that not only prioritization based on the traditional RPN method is incomplete, but also is segregation not possible. Therefore, the decision-maker might be confused and probably not be able to take appropriate preventive and corrective measures. This incomplete ranking can be derived from not assigning different weights to the criteria or not considering uncertainty. In CoCoSo, MOORA, and COPRAS methods, FM5 has been identified with high priority, but other rankings have been changed. By reviewing the results of all 4 methods, it can be seen that the critical priorities are the same, so it can be concluded that the results obtained from the proposed
method are valid. Furthermore, to show the superiority of CoCoSo method, a correlation test was performed between these 3 methods with FMEA. Based on the results of this test in Fig. 4 the CoCoSo method with Spearman correlation degree (0.925) is superior to the MOORA and COPRAS methods with correlations (0.897) and (0.910) respectively.

V. CONCLUSION
Although in Iran, wind turbines are the source of a very low portion of the produced electricity, only 0.04%, there is a promising future for generating electrical energy from the clean energy of wind, according to the governors. Manjil has been identified as the best location for this goal; nevertheless, only 51 wind turbines have been installed in Manjil. This region and other locations in Iran have considerable potential for installing new and modern wind turbines to increase the rate of electricity production from renewable energies. In this paper, an integrated approach based on FMEA, SWARA, and CoCoSo methods for assessing wind turbine failures is presented. Also, due to the uncertainty in real-world problems, the SFS has been used to give more freedom to DMs to express their ideas. In this study, two factors of time and cost were added to the factors and the SWARA method was used to assign appropriate weights. Also, due to the use of three different aggregation methods to present the results, the CoCoSo method was developed in this paper as a ranking method for the first time in an SFS. The failures identified by the FMEA team were then ranked and the results showed that Generator fault and Mechanical brake fault are critical priorities. Therefore, preventive and corrective measures should be taken by the relevant managers to deal with them. Also, new scenarios were created by changing the λ parameter to prove the validity and accuracy of the results. Comparing the ranking results based on the created scenarios shows that λ change has not made any significant changes to the ranking. Also, finally, the proposed method was compared with other MCDM methods such as MOORA and COPRAS, and the critical priorities were the same in all three methods. Then, to show the superiority of the SF-CoCoSo method, Spearman correlation degree test was performed and SF-CoCoSo with correlation degree 0.925 was preferred to other methods.

This paper, like other papers, is not without its limitations. Usually, in all real-world decision-making issues, there are direct or indirect relationships between the criteria of the issue in question that affect the ranking. One of the main limitations of this paper is the issue of relationships between criteria, which has not been considered. In addition, another limitation of this paper is access to the required data and information. In this paper, 3 experts in this field have been used to collect data, and it is likely that with increasing the number of experts, the results will change to some extent. Also, the SFS linguistic variables used to express the opinions of experts are in the form of 9 scales. Therefore, to increase the degree of freedom of experts and increase confidence and certainty, it is better to increase the scale of language variables. In future research, it is suggested to use the Choquet integral or fuzzy cognitive map to examine the relationships between criteria to examine and evaluate the relationships between criteria to obtain more reliable and accurate results. Also, to increase the certainty of the results and opinions of experts, two fuzzy numbers can be used, so the proposed approach can be developed with theories of D-number or Z-number theory. In addition, in future research, it is possible to add more relevant criteria by examining the subject more broadly and to use more experts in this field. Also, Other MCDM methods that were not involved in this study can be used, such as BWM, OPA, BCM WASPAS, VIKOR, SECA, and MARCOS in the SFS environment.

AUTHOR CONTRIBUTION
Saeid Jafarzadeh Ghoushchi: conceptualization, validation, writing-rev and editing; Sepideh Miralizadeh Jalalat: writing—original draft, methodology, software, investigation; Ali Memarpour Ghiaci: writing—original draft, conceptualization, investigation, methodology; Shabnam Rahnmanay Bonab: formal analysis, conceptualization, writing-rev and editing, and validation; Gholamreza Haseli: data curation, formal analysis, writing-rev and editing; and Hana Tomaskova: validation, investigation, visualization. All authors have read and agreed to the published version of the manuscript.
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