



Analyzing Failures In Wind–Solar Hybrid Energy Systems Using a Fuzzy-Based BWM-MARCOS Approach: Challenges and Solutions

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Abstract

The reliability of hybrid renewable energy systems (HRES) depends heavily on the identification and management of potential failure modes. This study employs a fuzzy-based BWM-MARCOS approach to systematically analyze and prioritize failure modes within wind–solar hybrid systems. The model aims to prioritize the failures considering four important risk parameters: (1) severity of the failure on system, staff, and failure, (2) failure occurrence chance, (3) effort and ease of detecting the cause of the failure, and (4) economic impact of the failure. In this context, four key risk indicators were evaluated to rank failures, revealing that SP1 (cell damage), ESS1 (battery degradation), and WT11 (battery fire) are the most critical due to their potential impact on system operations. Sensitivity analysis confirmed the stability of these rankings under varying parameter weights. Additionally, cross-method validation using fuzzy TOPSIS, SAW, and MARCOS demonstrated high correlation coefficients, underscoring the reliability of the results. Tailored mitigation strategies, including advanced diagnostics, durable materials, and robust monitoring systems, are proposed to address these critical failures. While the current methodology applies to various HRES configurations, future research should incorporate real-world operational data and machine learning techniques to enhance predictive capabilities and dynamic risk management.

Keywords Wind energy · Solar energy · Failure analysis · Fuzzy set · Best–worst method · MARCOS

1 Introduction

In the face of escalating global environmental challenges, the imperative to transition toward sustainable energy sources has become more pressing than ever. The significance of RESs lies not only in their capacity to mitigate the adverse impacts of climate change but also in their pivotal role in curbing carbon emissions [1]. As the maritime sector, a major contributor to greenhouse gas emissions [2], strives to align with stringent environmental regulations, adopting renewable energy emerges as a compelling solution. Harnessing

the power of solar and wind energy presents a promising avenue to propel the maritime industry toward a greener and more sustainable future. The application of HRES in maritime operations presents a promising avenue for addressing the sector's decarbonization challenges. By leveraging the complementary nature of wind and solar energy, these systems can provide auxiliary power onboard vessels and reduce reliance on fossil fuels, particularly in emissions-intensive operations such as at-sea navigation and port activities. Moreover, integrating HRES into shore-side power systems can significantly mitigate greenhouse gas emissions during vessel berthing. However, the operational environment of maritime applications introduces unique challenges, including exposure to harsh conditions, dynamic load demands, and space limitations, which necessitate a robust failure analysis framework to ensure reliability and efficiency. In addition to these issues, the importance of energy storage in RESs is undeniably great. For instance, Ould Amrouche et al. [3] provided an overview of the pivotal role energy storage plays in RESs, emphasizing its contribution to minimizing power fluctuations and enhancing system flexibility. The

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authors' study explores various storage technologies, including hydrogen, batteries, and flywheels, with a focus on their application in photovoltaic and wind power plants. Additionally, the economic aspects of different storage technologies have been investigated. As Olabi [4] stated, researchers have categorized various factors for choosing energy storage methods, with key considerations including the accessibility of energy resources, energy demand and application, the efficiency of energy storage, the cost of energy storage, the infrastructure for energy storage, and additional factors.

The motivation for this study comes from the increasing global reliance on renewable energy systems (RES) and the critical need to ensure their reliability and efficiency. Hybrid Renewable Energy Systems (HRES), which integrate wind and solar power, are gaining prominence due to their potential to address intermittent power generation challenges. However, the complexity of these systems introduces unique challenges in terms of failure analysis and system dependability. Failures in HRES components, such as wind turbines, solar panels, and energy storage systems, not only disrupt energy production but also incur significant economic and environmental costs. While existing studies focus on individual failure modes or specific components (e.g., wind turbines or energy storage), they often lack an integrated framework that accounts for the interplay between various failure parameters under uncertain conditions. This study addresses this gap by proposing a comprehensive failure analysis methodology tailored to hybrid energy systems, integrating multi-criteria decision-making approaches with fuzzy logic to capture uncertainties systematically.

Despite the growing deployment of HRES, there remains a lack of robust methodologies that comprehensively analyze and prioritize these failures, particularly under the inherent uncertainties of such systems. Existing failure analysis approaches often fail to integrate the multi-faceted risks, such as severity, occurrence likelihood, detection difficulty, and economic impact, in a systematic and holistic manner.

This research is motivated by the urgent need for a novel framework that integrates fuzzy logic and multi-criteria decision-making (MCDM) methods to address these challenges. The proposed fuzzy-based Best–Worst Method (BWM) and Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) approach offers a sophisticated mechanism to evaluate and prioritize failures, enabling stakeholders to implement targeted mitigation strategies. By addressing the critical gap in failure analysis methodologies for HRES, this study aims to contribute to enhancing system reliability, reducing operational risks, and supporting the sustainable integration of renewable energy into power grids.

Given the growing relevance of RESs in tackling global environmental issues, it is vital to investigate the operational reliability and problems associated with these systems.

This paper aims to fill a significant gap in the literature by examining all failure parameters in wind–solar hybrid energy systems using the hybrid fuzzy BWM and fuzzy MARCOS. Applying these hybrid methods is crucial for comprehensively analyzing the myriad failure modes affecting wind–solar hybrid systems. The study emphasizes not only the identification and analysis of potential failures but also the broader operational challenges inherent in these systems. By leveraging the fuzzy BWM-MARCOS approach, this research provides a prioritized list of failures and challenges, offering a detailed and systematic solution framework. Furthermore, this paper addresses both the technical and operational challenges, proposing robust solutions that enhance the reliability and efficiency of wind–solar hybrid energy systems. This comprehensive examination and prioritization are vital for stakeholders and policymakers aiming to optimize the performance and sustainability of RESs. Thus, this research contributes significantly to the academic discourse and practical implementation of resilient and efficient hybrid renewable energy solutions.

2 Literature Review

Alternative energy sources are desperately needed since fossil fuels, which have been exploited extensively to meet current energy demands, are quickly running out. Furthermore, one major factor contributing to the phenomenon of global warming is the use of fossil fuels [5]. The most viable approach to supplying green energy to meet this global energy crisis is through renewable energy sources. It follows that renewable energy sources will likely play a major role in the power supply of the future [6]. However, it is commonly known that ambient climatic conditions have a significant impact on the output of most renewable energy sources, including photovoltaic (PV) arrays and wind turbines (WT). As a result, they generate unstable output characteristics, which is a major disadvantage of producing energy from renewable sources [7]. Thus, the constraints presented by the intermittent nature of renewable energy sources have led to the development of a variety of power converters and control systems for the management and monitoring of active and reactive power. Power grid providers seem to have serious problems with power quality, load leveling, generation dispatch control, and overall system reliability as a result of these power swings [8].

Considering these factors, it is crucial to comprehensively review of the literature to understand the various challenges associated with wind–solar hybrid systems, especially in terms of the types of failures that can occur. Wind–solar HRES, which combine photovoltaic (PV) arrays and wind turbines (WT), present unique challenges due to their reliance on variable environmental conditions, leading to



intermittent and unstable power output. These fluctuations necessitate the development of sophisticated power converters and control strategies to manage active and reactive power effectively. Power grid companies face significant issues related to power quality, load leveling, generation dispatch control, and system reliability due to these instabilities. Understanding potential failure modes and their impacts is essential, given the complexity and critical importance of maintaining reliable operations in hybrid systems. While prior research, provides insights into specific failure analysis methods like FMEA or optimization techniques for hybrid systems, these approaches are often limited in addressing multi-criteria and multi-dimensional risks comprehensively. Moreover, the lack of a holistic failure prioritization strategy that integrates operational, technical, and economic parameters remains a significant gap. This study critically evaluates and builds upon these methodologies by introducing a hybrid fuzzy BWM-MARCOS framework to provide a prioritized and actionable failure analysis.

In this context, in comparison with using solar or wind energy independently, hybrid PV/wind energy systems with battery storage have the potential to be more dependable and economical. Mahesh and Sandhu [9] highlighted a thorough assessment of hybrid PV/wind energy systems. Their paper can guide researchers to better understand how to build, analyze, and integrate these kinds of devices into the power network. Nema et al. [10] reviewed the design, operation, and control requirements of standalone PV solar–wind HRES with conventional backup sources, such as diesel or grid. The paper also highlighted potential future developments to enhance the economic attractiveness and user acceptance of these systems. Rastayesh et al. [11] assessed failures in the power stage of wind–fuel cell hybrid energy systems by using failure mode and effect analysis (FMEA) and fault tree analysis (FTA). The reliability analysis over a five-year operation period highlights the criticality of metal oxide semiconductor field effect transistors and electrolytic capacitors in the power circuit. Sinha and Chandel [12] presented an updated overview of optimization techniques used in the design and development of solar photovoltaic–wind-based hybrid energy systems. It identified promising methods for optimization and examined various techniques employed by researchers. Nazir et al. [13] examined the significance of renewable energy in attaining a carbon–neutral society, touching upon social division caused by energy initiatives and government concerns regarding ecological consequences. It highlighted the importance of acting quickly to address environmental uncertainty, showcased different renewable energy options, made comparisons with non-renewable sources, and touched on potential risks. Yin et al. [14] discussed the difficulties of unpredictable weather and conflicts in wind–solar HRES. The research suggests energy optimization models that consider risks by using the

Monte Carlo method and simulate different interferences to assess the benefits, costs, and risks of production. The outcomes show that these models are adaptable to meet the demands of decision makers while considering uncertainties and interferences. From a different aspect of view, Zhou and Yang [15] investigated the literature and ranked risks in distributed wind power by examining risk factors and experts' opinions. Using the Analytic Hierarchy Process (AHP) technique, various risks including political, economic, social, and technical risks were classified and evaluated during the distributed wind farms' entire life cycle. The findings emphasized that alterations in electricity price policy are the most crucial risk factor, emphasizing the significance of a government's long-term vision to support sustainable growth and profitability in decentralized wind initiatives. Wu and Zhang [16] evaluated the construction and operation risks of the wave–wind–solar–compressed air energy storage as a promising offshore multi-energy system. By identifying critical criteria in management, economy, and environment, a risk assessment framework was established using fuzzy evaluation methods. Results suggested that offshore HRES faced variable and complex risks, particularly in management and economy. Proposed risk response strategies aimed to facilitate resource allocation and risk aversion for decision makers. When the challenge issues in HRES systems are examined, Ueckerdt et al. [17] analyzed three major integration challenges in power systems related to incorporating wind and solar energy, including low capacity credit, reduced utilization of dispatchable plants, and over-produced generation. Using residual load duration curves, the study defined corresponding challenge variables and estimated their dependence on region, penetration, and mix of wind and solar generation. Results indicated that increasing wind and solar shares could lead to substantial impacts, which increased with penetration regardless of mix and region. Sinsel et al. [18] provided a thorough summary of the difficulties and technological solutions related to incorporating RES with fluctuating output into electrical grids. It emphasized the need to tackle these challenges to uphold power system reliability and meet decarbonization goals. Furthermore, the research created a matrix of interconnected solutions that ranked technologies according to their ability to tackle particular obstacles, improving clarity in the process of integrating renewable energy. Negro et al. [19] conducted a literature review on the challenges encountered in the development and diffusion of renewable energy technologies (RETs) in various European countries. It categorized typical systemic problems hindering RETs' progress and proposed policy recommendations to address these challenges and facilitate their diffusion and implementation. Ahmed et al. [20] reviewed the challenges associated with integrating wind energy into electricity grids and discussed proposed solution methodologies. It addressed operational, control, socioeconomic,



environmental, and market challenges, highlighting solutions such as energy storage systems, wind energy policy, and grid codes. The paper also aimed to provide a comprehensive understanding of wind energy integration challenges for both researchers and policymakers, facilitating the adoption of sustainable policies to overcome these difficulties. Shafi-ullah et al. [21] provided a survey of wind energy technology, implementation issues, and associated impacts, including environmental, social, and cost-economic aspects. It also addressed potential technical challenges and mitigation techniques for integrating large-scale wind energy into the power grid. Foxon et al. [22] years ago examined the innovation systems in the UK for various new and renewable energy technologies, identifying system failures in moving these technologies along the innovation chain. It proposed policy recommendations to address these gaps and emphasized the need for sustained investment and a stable policy framework to support the successful commercialization of sustainable technologies. From these academic studies, it is seen that the policy issue is important. Ahmed et al. [23] thoroughly analyzed hybrid wind and PV systems, with a focus on achieving stable DC bus-bar voltage by integrating with a microcontroller system via a buck-boost converter. It used a MATLAB model to examine the performance of grid-integrated hybrid systems and compare the findings to traditional fossil fuel-based power-generating methods, highlighting the necessity and usefulness of incorporating renewable energy sources into current power networks. Soudagar et al. [24] examined the integration of hybrid wind and solar energy systems, analyzing their benefits and drawbacks and stressing technical challenges such as voltage and frequency fluctuations in weak networks. It gave an overview of advances in hybrid energy systems, optimal design considerations, power electronics topologies, and control, providing vital insights for researchers, policymakers, and industry stakeholders as they transition to more sustainable and resilient energy solutions. Yang et al. [25] reviewed current structural health monitoring (SHM) approaches for offshore wind turbine (OWT) support structures, such as towers and foundations, and identified obstacles and potential future advances. The authors also examined several damage diagnosis strategies, including model-based, vibration-based, artificial intelligence, and hybrid methods, weighing their benefits and drawbacks, and gave recommendations for future study and monitoring design improvements. Feng et al. [26] employed the Fuzzy Failure Mode and Effect Analysis (FMEA) methodology to analyze and identify critical failure modes in floating offshore wind turbines, offering strategic recommendations for improving design, operation, and maintenance practices. Jain and Verma [27] offered a comprehensive assessment of reliability evaluation studies for power systems integrated with RESs, mainly wind and solar, covering peer-reviewed articles published between 2000 and 2021. Li et al. [28]

proposed a risk analysis method for condition-based maintenance (CBM) of offshore wind turbines, combining the fuzzy weighted zero inconsistency (FWZIC) technique and the DEMATEL method under a linguistic Pythagorean fuzzy environment. By identifying and analyzing 75 risk factors, the study provided valuable recommendations for implementing CBM in offshore wind turbines, validated through sensitivity and comparative analysis.

In this context, the growing integration of RESs, particularly wind and solar, into power systems presents a range of operational challenges due to their intermittent nature. Addressing these challenges requires a comprehensive understanding of the reliability and failure modes of hybrid energy systems. This literature review underscores the necessity of advanced analytical techniques and optimization strategies to enhance the performance and reliability of these systems. By comparing existing methodologies, this study highlights the limitations of conventional approaches in addressing multi-criteria risks holistically and emphasizes the novelty of the proposed framework in filling this gap. The integration of fuzzy logic with MCDM methods ensures a robust analysis that accounts for uncertainties inherent in hybrid systems, offering stakeholders a more reliable decision-making tool.

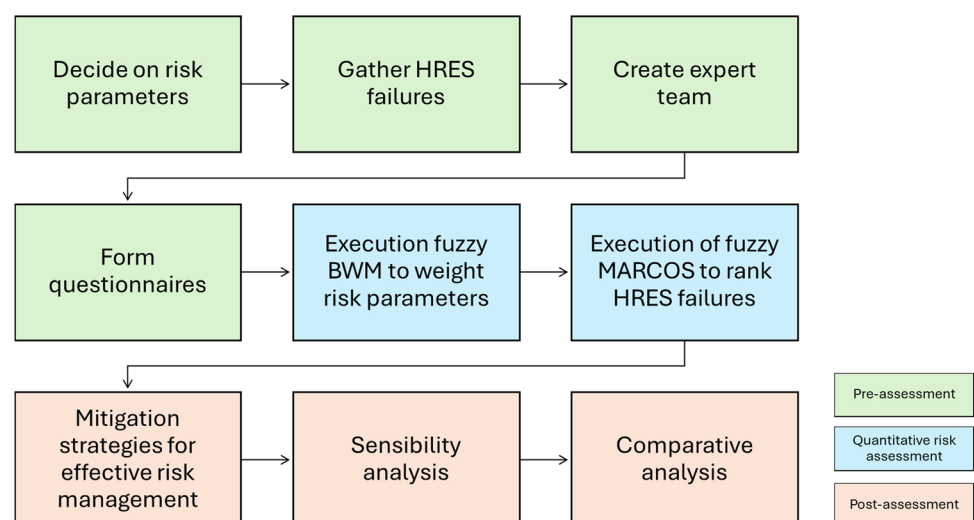
The integration of sophisticated power converters, control systems, and energy storage solutions is critical for maintaining power quality, managing load fluctuations, and ensuring overall system reliability. The proposed approach and an in-depth examination of the failures associated with wind–solar hybrid energy systems using the hybrid fuzzy BWM-MARCOS methodology are discussed in the following sections. This study aims to fill a significant gap in the literature by providing a prioritized list of failure modes and operational challenges, along with robust solutions to enhance the reliability and efficiency of these systems (Some renewable energy and fuzzy methods related studies are given in Table 1).

3 Proposed Approach

The proposed study is aimed at assessing the risks of a hybrid wind–solar energy system, which is an important HRES. This approach includes three basic phases from a bird's eye view. The first phase is the preparation before risk assessment, the second phase is the phase in which the quantitative risk analysis is carried out where the fuzzy BWM-MARCOS method is applied. The last phase is the phase in which the accuracy of the numerical results is confirmed after the risk assessment, the sensitivity and comparison analysis are executed, and planning of control measures is carried out. A general view of the proposed study is demonstrated in Fig. 1.

Table 1 A brief summary of renewable energy and fuzzy methods related studies

Area of research	Techniques	Explanation	References
Solar—Wind	Fuzzy regression	Prediction of global solar irradiance	[29]
Hybrid renewables, Solar, Wind	Fuzzy AHP, ANP	Selection of renewable energy alternatives	[30]
Hybrid	Neuro Fuzzy	Optimization of hybrid PV/wind/battery system	[31]
Solar	Neuro fuzzy	PV system failure diagnosis	[32]
Solar	SF-SWARA and FMEA	Failure analysis of solar integration	[33]
Solar	Best Worst—Fuzzy sets—TOPSIS	Optimal solar energy investment	[34]
Renewable energy	Fuzzy AHP	Challenges of renewable energy investments	[35]
Renewable energy	Fuzzy AHP-EDAS-Fuzzy FMEA	Decision analysis for renewable energy investment	[36]
Wind	FMEA-AHP	Reliable operation of wind turbines	[37]
Wind	BWM—AHP—MARCOS	Wind farm site selection	[38]
Wind	Fuzzy FMEA	Failure analysis of wind turbines	[26]
Renewable energy	FMEA—IVIF AHP	Risk assessment of renewable energy investments	[39]
Fuzzy risk assessment	BWM—MARCOS	Route selection and risk assessment model	[40]
Method based	Fuzzy MARCOS	MARCOS technique for determining performance of insurance companies	[41]
Method Based	BWM—ELECTRE	Strategic marketing information system planning	[42]

Fig. 1 General view of the proposed study

3.1 Pre-Assessment

3.1.1 Risk Parameters Used in the Assessment of Wind–Solar HRES Failures

The first pre-assessment task that needs to be performed in the risk assessment study, which has the ultimate goal of prioritizing HRES failures, is to determine which parameters will be used to define and evaluate the risk. For this purpose, three parameters are determined based on the nature of the study in the renewable energy domain as follows: (1) severity of the failure on system, staff and failure, (2) failure occurrence chance, (3) effort and ease of detecting the cause of the failure, and (4) economic impact of the failure. This selection was made by evaluating whether they may be suitable for HRES-related failure analysis among the risk parameters extracted as a result of a comprehensive literature review.

3.1.2 Potential Hybrid Renewable Energy Systems (HRES) Failures

In off-grid applications, hybrid energy systems play an especially important role in guaranteeing a constant power supply. The most widely used renewable energy sources, solar and wind power systems, are crucial to provide this steady power. Photovoltaic (PV) panels, wind turbines, a battery bank, and an AC (alternating current) to DC converter are major components of a typical solar/wind hybrid system. The schematic diagram of the system being examined is shown in Fig. 2. The generated energy is routed through a controller before being stored in the batteries. Some of the total electricity generated is lost due to the inefficiencies of the DC/DC and AC/DC converters. The primary advantage of a hybrid system is its increased reliability compared to standalone solar or wind energy systems [43, 44].

In the assessment of HRES, a comprehensive understanding of potential failures is paramount for ensuring optimal performance and reliability. The identified failure types encompass various critical elements within the HRES framework. Wind turbines (WTs), as primary components, face challenges such as blade damage and generator failures. Solar panels (SPs), another integral part of HRES, may experience issues related to cell damage or deterioration. Energy storage systems (ESSs) play a crucial role in maintaining a stable power supply but are susceptible to faults affecting overall energy storage capacity. Control and monitoring systems (CMSs), acting as the brains of the HRES, introduce risks associated with software errors or sensor malfunctions. Electricity grid integration (EGI) involves complex interactions and potential vulnerabilities that must be considered. Furthermore, human error (HE) adds another layer of risk, emphasizing the importance of proper training and operational procedures. Lastly, environmental impacts (EIs),

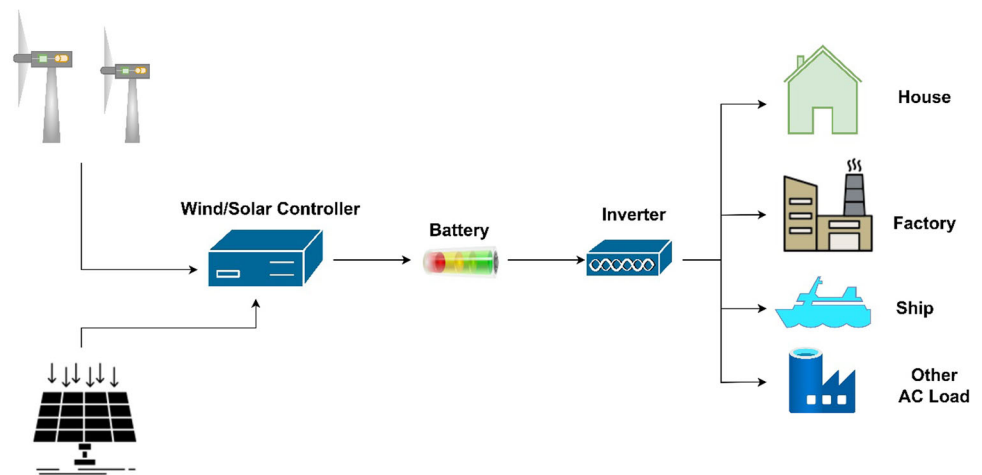
Table 2 Wind–solar HRES failures and sub-details descriptions

Failure ID	Description of the failure
WT1	Wing damage
WT2	Wind management issue
WT3	Generator fault
WT4	Bearing problem
WT5	Gearbox failure
WT6	Tower vibration
WT7	Brake and locking problem
WT8	Electrical connection problem
WT9	Sand and ice deposits
WT10	System control problem
WT11	Battery Fire
WT12	Environmental wind impact
SP1	Cell damage
SP2	Inverter failure
SP3	Shading
ESS1	Battery degradation
ESS2	Inverter problem
ESS3	Cooling problem
CMS1	Sensor failure
CMS2	Control software error
CMS3	Data connection problem
EGI1	Grid connection failure
EGI2	Frequency compatibility problem
HE1	Maintenance error
HE2	Operating error
EI1	Lightning strike
EI2	Temperature change

including extreme weather conditions or natural disasters, can pose threats to the integrity of HRES components. This section aims to delve into each failure, providing a comprehensive overview of potential challenges and uncertainties associated with the assessment of HRES. Risks are categorized in seven main headings, and twenty-seven failures considered in this study are briefly given in Table 2.

3.1.3 Expert Team and Formed Questionnaires

To evaluate the analyses to be carried out in the second part of the study, the generic outline of which is given in Fig. 1, the participation of an expert group who is experienced in the field and has spent a lot of time on these issues due to their education and age is required. Regarding the expert selection process, a panel of experts with diverse backgrounds were carefully identified to ensure a comprehensive evaluation. The panel included individuals from academia,

Fig. 2 PV-Wind hybrid system schematic

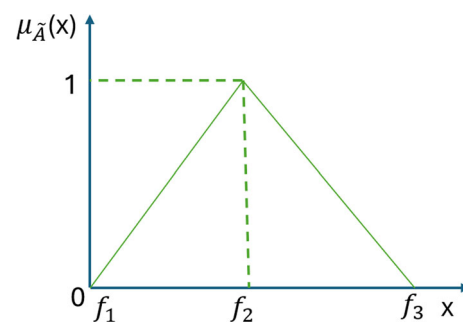
industry professionals specializing in renewable energy systems, and engineers with hands-on experience in designing and maintaining HRES. Efforts were made to achieve geographic diversity by involving experts from multiple regions (Turkey, UK, and USA) to reflect varied operational and environmental conditions, enhancing the generalizability of the findings.

To address potential biases in expert judgments, we incorporated consistency checks as part of the fuzzy BWM methodology, ensuring that all expert inputs met the required consistency thresholds. Additionally, input-based consistency analysis was conducted, confirming robust and reliable evaluations. These measures have significantly mitigated potential biases and strengthened the reliability of our analysis.

In addition, questionnaire forms are required to be designed by both fuzzy BWM and fuzzy MARCOS methodology since the data have been collected with the aid of these forms and analyzed to obtain numerical results. The surveys are designed to be user-friendly, informative about what the participating expert should do and how to do it, and prevent loss of time for the expert. The fuzzy BWM survey was prepared using macros in MS Word environment and was designed by adding various easy-to-fill buttons. Fuzzy MARCOS analysis was created in Ms Excel and has a structure that allows experts to make their evaluations easily. These surveys were administered by personally contacting the participating expert group.

3.2 Quantitative Risk Assessment

In this section, a numerical evaluation of HRES failures has been carried out. In this context, first, the relative importance weight of the four previously determined risk parameters has been determined by fuzzy BWM. Fuzzy MARCOS is then applied to rank each HRES failure. For both MCDM methods, triangular fuzzy numbers are used since they reflect the

**Fig. 3** Demonstration of a TFN

subjectivity and uncertainty well in evaluating decision makers and because of the difficulty in obtaining precise data. Therefore, the first subsection below provides a small guide on triangular fuzzy sets, the membership function of these sets, and how to perform simple arithmetic operations.

3.2.1 Preliminaries on Fuzzy Sets

A fuzzy set is a class of objects with degrees of membership. The degree of membership is an indicator of its belonging to the corresponding set. The membership function of a fuzzy number is between $[0,1]$. There are different types of fuzzy numbers in the literature. Triangular fuzzy numbers (TFNs) are the most well-known and have been successfully applied to problems in many areas. A general view of a TFN with its membership function is shown in Fig. 3. TFNs have the form $A(f_1, f_2, f_3)$. Value f_1 represents the left distribution of the confidence interval of fuzzy number A , f_2 is where the fuzzy number membership function has the maximum value—equal to 1, and f_3 represents the proper distribution of the confidence interval of TFN A [45, 46]. Moreover, A fuzzy number A on $\mathbb{R}$ is known as a triangular fuzzy number when its membership function $x \in \tilde{A}, \mu_{\tilde{A}}(x) : \mathbb{R} \rightarrow [0,1]$ is



as follows in Eq. (1):

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-f_1}{f_2-f_1} & \text{if } f_1 \leq x \leq f_2 \\ \frac{f_3-x}{f_3-f_2} & \text{if } f_2 \leq x \leq f_3 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Some arithmetic operations related to TFN are also given below (Eqs. 2–6). These are the basic operations required in modeling both fuzzy BWM and fuzzy MARCOS.

$$\begin{aligned} \text{Addition of two TFNs : } \tilde{A}_1 \oplus \tilde{A}_2 \\ = (l_{f_1} + l_{f_2}, m_{f_1} + m_{f_2}, u_{f_1} + u_{f_2}) \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Subtraction of two TFNs : } \tilde{A}_1 \ominus \tilde{A}_2 = (l_{f_1} - u_{f_2}, \\ m_{f_1} - m_{f_2}, u_{f_1} - l_{f_2}) \end{aligned} \quad (3)$$

$$\begin{aligned} \text{Multiplication of two TFNs : } \tilde{A}_1 \otimes \tilde{A}_2 \\ = (l_{f_1} l_{f_2}, m_{f_1} m_{f_2}, u_{f_1} u_{f_2}) \end{aligned} \quad (4)$$

$$\begin{aligned} \text{Division of two TFNs : } \tilde{A}_1 \oslash \tilde{A}_2 \\ = (l_{f_1}/l_{f_2}, m_{f_1}/m_{f_2}, u_{f_1}/u_{f_2}) \end{aligned} \quad (5)$$

$$\text{Reciprocal of a TFN : } \tilde{A}_1^{-1} = (1/l_{f_1}, 1/m_{f_1}, 1/u_{f_1}) \quad (6)$$

Here $\tilde{A}_1 = (l_{f_1}, m_{f_1}, u_{f_1})$ and $\tilde{A}_2 = (l_{f_2}, m_{f_2}, u_{f_2})$ refer to the two TFNs.

3.2.2 Procedure of FBWM

Decision makers have used traditional BWM extensively, especially in recent years, as it allows for obtaining more consistent results with fewer evaluations. The calculation procedure is based on determining the best and worst criteria and pairwise comparison of these criteria with other criteria [47, 48]. The numbers 1–9 are used in these pairwise comparisons. The decision problem is obtained by solving a linear and nonlinear mathematical model [47, 49]. The complexity of real-world problems, the limited knowledge of decision makers, and the inadequacy of using only numbers 1–9 in pairwise criteria comparisons have proposed many different BWM extensions [50]. One of the most notable extensions of BWM in this context is the FBWM suggested by Guo and Zhao [51].

Step 1: Determining the system of decision criteria. At this stage, it is determined which criteria will be evaluated. Suppose n number of decision criteria. $[c_1, c_2, \dots, c_n]$.

Step 2: The best (c_B) and the worst (c_W) risk parameters are defined. In the next stage, the best and worst criteria determined will be used in pairwise comparisons.

Step 3: Fuzzy linguistic assessment of other risk parameters with the c_B and the c_W using a 9-point triangular fuzzy linguistic scale is performed [52]. Two vectors are available for this step as follows:

$\tilde{C}_B = (\tilde{c}_{B1}, \tilde{c}_{B2}, \tilde{c}_{B3}, \dots, \tilde{c}_{Bn})$ and $\tilde{C}_W = (\tilde{c}_{W1}, \tilde{c}_{W2}, \tilde{c}_{W3}, \dots, \tilde{c}_{Wn})$. While the first is “Best to others”, the second is “Others to worst”. Also, $\tilde{c}_{Bj}$ demonstrates the fuzzy preference of the best risk parameter over the parameter j . $\tilde{c}_{iW}$ represents the fuzzy preference of the worst risk parameter over parameter j .

Step 4: Weights of risk parameters are determined. To do this, an optimization model is constructed as follows:

$$\min \xi^* \text{ s.t. } \begin{cases} |(l_B^w, m_B^w, u_B^w)/(l_j^w, m_j^w, u_j^w) - (l_{Bj}, m_{Bj}, u_{Bj})| \\ \leq (k^*, k^*, k^*) \\ |(l_j^w, m_j^w, u_j^w)/(l_W^w, m_W^w, u_W^w) - (l_{jW}, m_{jW}, u_{jW})| \\ \leq (k^*, k^*, k^*) \\ \sum_{j=1}^4 R(w_j) = 1 \\ l_j^w \leq m_j^w \leq u_j^w \\ l_j^w \geq 0 \\ j = 1, 2, 3, 4 \end{cases} \quad (7)$$

Here $\tilde{w}_B = (l_B^w, m_B^w, u_B^w)$, $\tilde{w}_j = (l_j^w, m_j^w, u_j^w)$, $\tilde{w}_W = (l_W^w, m_W^w, u_W^w)$, $\tilde{c}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$, $\tilde{c}_{jW} = (l_{jW}, m_{jW}, u_{jW})$, $\xi = (l^\xi, m^\xi, u^\xi)$, considering $l^\xi \leq m^\xi \leq u^\xi$. $\xi^* = (k^*, k^*, k^*), k^* \leq l^\xi$.

This model is solved to obtain the optimal fuzzy weights ($\tilde{w}_1^*$, $\tilde{w}_2^*$, $\tilde{w}_3^*$, $\tilde{w}_4^*$). Fuzzy weights are finally defuzzified to reach crisp weights of risk parameters using graded mean integration representation (GMIR).

3.2.3 Input-Based Consistency

BWM is a method based on two comparisons, thus allowing us to identify the inconsistency of decision makers' evaluations. If DM evaluations are not consistent, the weights determined will be unrealistic. Although many consistency calculation procedures have been proposed for BWM and its extensions, these have some shortcomings. Decision makers can calculate consistency after the evaluation and calculation steps. In this case, all calculation steps must be repeated for inconsistent evaluations. Another shortcoming is that there is no recommended threshold value for consistency. For this reason, although the decision maker calculates the consistency, they cannot compare it with the threshold values for the obtained consistency rate. For this reason, input-based consistency was proposed by Liang et al. [53].

The input-based consistency ratio CR^I is formulated as follows:

$$CR^I = \max_j CR_j^I \quad (8)$$

$$CR_j^I = \begin{cases} \frac{|a_{Bj} \times a_{jW} - a_{BW}|}{a_{BW} \times a_{BW} - a_{BW}} & a_{BW} > 1 \\ 0 & a_{BW} = 1 \end{cases} \quad (9)$$

The CR value found is compared with Table 3. If the CR is less than the threshold value in the table, it can be said that the evaluation is consistent.

3.2.4 Procedure of F-MARCOS

The MARCOS (Measurement Alternatives and Ranking according to Compromise Solution) method is a multi-criteria decision analysis method developed by Stević et al. [54]. The algorithm of this method works according to a defined relationship between the alternatives and the reference point values of these alternatives, which represent ideal and negative-ideal points. Decision making with this method is based on the utility function. The utility function represents an alternative to ideal and non-ideal solutions. The best alternative is the one closest to the ideal and at the same time, furthest from the anti-ideal reference point. The first study integrating the MARCOS method with TFN was conducted by Stanković et al. In this study, we adapt and use the algorithm of the study by Stanković et al. [55]. The fuzzy MARCOS followed in this study consists of the following application steps:

Step 1: Decision makers' judgments are gathered to evaluate the HRES failures (in general, saying "the alternatives" of the decision-making problem) concerning the four risk parameters (the evaluation criteria of the decision-making problem). These judgments are assessed by the decision-maker experts using the triangular fuzzy linguistic scale. The scale is provided in Table 4.

Thus, an initial fuzzy decision matrix consisting of m HRES failures (alternative; indicated as A) and n risk parameters (criteria; indicated as R) is constructed. A triangular fuzzy decision matrix of an expert $\tilde{A}$ can be indicated as follows:

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \cdots & \tilde{a}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{m1} & \cdots & \tilde{a}_{mn} \end{bmatrix} \quad (10)$$

Here $\tilde{a}_{ij} = \{VP, P, MP, M, MG, G, VG\}$

Step 2: A basic average in TFNs has been employed to obtain a group decision matrix consisting of the whole experts' judgments.

Table 4 Evaluation scale of HRES failures in TFNs

Linguistic term	Triangular fuzzy numbers
Very poor (VP)	(0,0, 1)
Poor (P)	(0,1, 3)
Medium poor (MP)	(1,3, 5)
Medium (M)	(3,5, 7)
Medium good (MG)	(5,7, 9)
Good (G)	(7,9, 10)
Very good (VG)	(9,10,10)

Step 3: An extended fuzzy decision matrix $\tilde{B}$ (as demonstrated in Eq. (8)) including fuzzy anti-ideal $\tilde{A}(AI)$ and fuzzy ideal solutions $\tilde{A}(ID)$ has been created. These two solutions are computed as in Eqs. (12–13).

$$\tilde{B} = \begin{bmatrix} \tilde{A}(AI) & \tilde{A}(ID) \end{bmatrix} = \begin{bmatrix} \tilde{x}_{ai1} & \tilde{x}_{ai2} & \cdots & \tilde{x}_{ain} \\ \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \\ \tilde{x}_{id1} & \tilde{x}_{id2} & \cdots & \tilde{x}_{idn} \end{bmatrix} \quad (11)$$

$$\tilde{A}(AI) = \begin{cases} \min_i \tilde{x}_{ij} & \text{if } j \text{ is a benefit criterion;} \\ \max_i \tilde{x}_{ij} & \text{if } j \text{ is a cost criterion} \end{cases} \quad (12)$$

$$\tilde{A}(ID) = \begin{cases} \max_i \tilde{x}_{ij} & \text{if } j \text{ is a benefit criterion;} \\ \min_i \tilde{x}_{ij} & \text{if } j \text{ is a cost criterion} \end{cases} \quad (13)$$

Step 4: In this step, the matrix $\tilde{B}$ has been normalized and the normalized decision matrix $\tilde{N}$ has been created. This matrix is demonstrated with $[\tilde{n}_{ij}]_{m \times n}$ and computed by Eqs. (14–15) for benefit and cost criteria, respectively.

$$\tilde{n}_{ij} = (\tilde{n}_{ij}^l, \tilde{n}_{ij}^m, \tilde{n}_{ij}^u) = \left(\frac{x_{ij}^l}{x_{id}^u}, \frac{x_{ij}^m}{x_{id}^u}, \frac{x_{ij}^u}{x_{id}^u} \right) \quad (14)$$

$$\tilde{n}_{ij} = (\tilde{n}_{ij}^l, \tilde{n}_{ij}^m, \tilde{n}_{ij}^u) = \left(\frac{x_{id}^l}{x_{ij}^u}, \frac{x_{id}^m}{x_{ij}^u}, \frac{x_{id}^l}{x_{ij}^l} \right) \quad (15)$$

Here the $(\tilde{n}_{ij}^l, \tilde{n}_{ij}^m, \tilde{n}_{ij}^u)$ and $(x_{id}^l, x_{id}^m, x_{id}^u)$ are the elements of $\tilde{B}$.

Step 5: In this step, the matrix $\tilde{N}$ The weight vector of the risk parameters has been multiplied by the weight vector, which is obtained with fuzzy BWM. To do this, a weighted normalized decision matrix $\tilde{V}$ has been created. This matrix



Table 3 Input-based threshold values [53]

Criteria								
	Scales	3	4	5	6	7	8	9
3		0.2087	0.2087	0.2087	0.2087	0.2087	0.2087	0.2087
4		0.1581	0.2352	0.2738	0.2928	0.3102	0.3154	0.3273
5		0.2111	0.2848	0.3019	0.3309	0.3479	0.3611	0.3741
6		0.2164	0.2922	0.3565	0.3924	0.4061	0.4168	0.4225
7		0.2090	0.3313	0.3734	0.3931	0.4035	0.4108	0.4298
8		0.2267	0.3409	0.4029	0.4230	0.4379	0.4543	0.4599
9		0.2122	0.3653	0.4055	0.4225	0.4445	0.4587	0.4747

is demonstrated with $\tilde{v}_{ij} = (\tilde{v}_{ij}^l, \tilde{v}_{ij}^m, \tilde{v}_{ij}^u)$ and computed by Eq. (16).

$$\tilde{v}_{ij} = \tilde{n}_{ij} \otimes \tilde{\omega}_j = (\tilde{n}_{ij}^l \times \tilde{\omega}_j^l, \tilde{n}_{ij}^m \times \tilde{\omega}_j^m, \tilde{n}_{ij}^u \times \tilde{\omega}_j^u) \quad (16)$$

Here $\tilde{\omega}_j = (\tilde{\omega}_j^l, \tilde{\omega}_j^m, \tilde{\omega}_j^u)$ represents the fuzzy weight vector of the risk parameters obtained in the fuzzy BWM stage.

Step 6: The utility degree of HRES failures ($\tilde{K}_i$) is computed by Eqs. (17–18).

$$\tilde{K}_i^- = \frac{\tilde{S}_i}{\tilde{S}_{ai}} = \left(\frac{\tilde{s}_i^l}{\tilde{s}_{ai}^l}, \frac{\tilde{s}_i^m}{\tilde{s}_{ai}^m}, \frac{\tilde{s}_i^u}{\tilde{s}_{ai}^u} \right) \quad (17)$$

$$\tilde{K}_i^+ = \frac{\tilde{S}_i}{\tilde{S}_{id}} = \left(\frac{\tilde{s}_i^l}{\tilde{s}_{id}^l}, \frac{\tilde{s}_i^m}{\tilde{s}_{id}^m}, \frac{\tilde{s}_i^u}{\tilde{s}_{id}^u} \right) \quad (18)$$

Here, $\tilde{S}_i = (s_i^l, s_i^m, s_i^u)$ indicates the sum of the elements of the weighted fuzzy matrix $\tilde{V}$. It is calculated in Eq. (19)

$$\tilde{S}_i = \sum_{j=1}^n \tilde{v}_{ij} \quad (19)$$

Step 7: The utility functions for ideal $f(\tilde{K}_i^+)$ and anti-ideal $f(\tilde{K}_i^-)$ solutions are computed. Both are calculated as in Eqs. (20–23), respectively.

$$f(\tilde{K}_i^+) = \frac{\tilde{K}_i^-}{df_{crisp}} = \left(\frac{k_i^{-l}}{df_{crisp}}, \frac{k_i^{-m}}{df_{crisp}}, \frac{k_i^{-u}}{df_{crisp}} \right) \quad (20)$$

$$f(\tilde{K}_i^-) = \frac{\tilde{K}_i^+}{df_{crisp}} = \left(\frac{k_i^{+l}}{df_{crisp}}, \frac{k_i^{+m}}{df_{crisp}}, \frac{k_i^{+u}}{df_{crisp}} \right) \quad (21)$$

$$\begin{aligned} \tilde{T}_i &= \tilde{t}_i = (t_i^l, t_i^m, t_i^u) = \tilde{K}_i^- \oplus \tilde{K}_i^+ \\ &= (k_i^{-l} + k_i^{+l}, k_i^{-m} + k_i^{+m}, k_i^{-u} + k_i^{+u}) \end{aligned} \quad (22)$$

$$\max_i \tilde{t}_i = \tilde{D} = (d^l, d^m, d^u) \quad (23)$$

$$df_{crisp} = \frac{d^l + 4d^m + d^u}{6} \quad (24)$$

Here, $\tilde{K}_i^-$, $\tilde{K}_i^+$, $f(\tilde{K}_i^-)$, $f(\tilde{K}_i^+)$ should be defuzzified.

Step 8: The utility functions of each HRES failure $f(K_i)$ are determined in Eq. (25).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}} \quad (25)$$

Step 9: The HRES failures are ranked and the one with the highest possible value of utility function is the most serious HRES failure.

3.2.5 Benefits and Main Contributions of the Proposed Comprehensive Approach

The proposed quantitative risk assessment approach employs fuzzy BWM to determine the relative importance weights of four different risk parameters. This method was chosen because it effectively addresses the challenges of uncertainty and imprecision inherent in the subjective evaluations provided by the expert group, especially through its use of triangular fuzzy numbers (TFNs). Fuzzy BWM requires fewer pairwise comparisons than other weight-determination methods, reducing cognitive load on experts while maintaining high consistency in judgments. Its robust calculation framework ensures reliable weight derivation even in uncertain or imprecise data.

For the second part of the problem, involving the prioritization of HRES failures, fuzzy MARCOS was selected due to its ability to integrate conflicting criteria into a compromise solution. Unlike fuzzy BWM, which primarily focuses on weight determination, MARCOS provides a comprehensive ranking framework by considering the distance of alternatives from both ideal and anti-ideal solutions and their relationships with reference points. This makes MARCOS particularly suitable for dynamic conditions, where changes in alternatives or criteria can significantly influence rankings.

Additionally, its stability and robustness, demonstrated by its insensitivity to the removal of the worst-ranked alternative (e.g., [56]), further justify its application.

While alternative methods such as LBWA, FUCOM, MABAC, MAIRCA, and VIKOR were considered, they were not selected for specific reasons related to the nature of our study. Fuzzy BWM simplifies the decision-making process by requiring experts to compare the "best" criterion with all others and all others with the "worst." This approach reduces the number of pairwise comparisons needed compared to traditional methods, making it more time-efficient and less cognitively demanding for decision makers. In contrast, Fuzzy LBWA employs a hierarchical framework that assesses criteria across multiple levels, linking relationships and offering detailed insights into complex, multi-layered problems. However, this method can be more demanding, requiring greater effort from decision makers to establish these relationships comprehensively. Fuzzy BWM is particularly robust in maintaining consistency, supported by its well-defined consistency index. Its streamlined comparison process ensures reliable results, especially for straightforward decision problems. Meanwhile, Fuzzy LBWA is highly valued for its stability in dynamic and hierarchical systems, as it effectively captures interdependencies between levels, making it suitable for more complex decision structures. Given the scope of our problem, which does not encompass a highly complex hierarchical structure, Fuzzy BWM aligns better with our problem-solving requirements and was thus chosen as the preferred method.

Fuzzy MARCOS performs well under uncertain conditions and maintains ranking stability even when alternatives are modified. For example, removing the worst alternative does not affect the ranking of others, ensuring robustness in decision making. Unlike MABAC or MAIRCA, MARCOS explicitly considers both ideal and anti-ideal solutions while analyzing the relationships between alternatives and reference points [57], differs from others in that it has a simpler algorithm that does not become more complex as the number of criteria or alternatives increases [58]. This feature ensures a balanced evaluation of conflicting criteria [59]. While VIKOR struggles with vague or imprecise input, the fuzzy version of MARCOS seamlessly integrates uncertainty, making it more suitable for problems where data precision is challenging [60]. It was chosen for its ability to balance conflicting criteria, capture uncertainty, and provide a robust compromise solution tailored to the study's requirements. By leveraging fuzzy MARCOS, the study ensures a comprehensive and balanced approach to prioritizing alternatives, addressing limitations of MABAC, MAIRCA, and VIKOR while capitalizing on MARCOS's strengths.

3.3 Post-Assessment

The first post-assessment study is to propose mitigation plans for prioritized HRES failures. It is generally not possible to eliminate the risk here. The aim is to reduce the negative effects of risk to a reasonable level. Here, of course, economic factors, and managerial and personnel-oriented factors are effective in taking these actions. However, in our study, the urgency and scope of these measures are decided by looking at the score and final ranking of the failure. A second post-assessment study is sensitivity analysis. As in many MCDM studies, determining the effect of the change in the weights of the four risk parameters in this study on the final HRES failures score and ranks defines the sensitivity analysis. Here, unlike the literature, some extreme scenarios have been tested, and the results of the effects of possible major changes in the risk parameter weights that may occur in the future are given in detail. Finally, the comparison study includes testing the HRES failure rankings determined by fuzzy MARCOS in this study with other equivalent MCDM methods and mutually benchmarking the results.

4 Application Case

A wind turbine's mechanical, electrical, and software components are only a few of the systems and parts on which risk analysis can be performed. Determining the causes of failure for every component is essential to creating a maintenance plan that works. An intricate collection of mechanical and electrical components, such as pitch, yaw, brakes, frequency converter, gearbox, generator, and blades, make up a wind turbine. Figure 4 shows the wind turbine system's configuration. These parts are subjected to harsh environmental conditions, and proper operational practices are essential for enhancing reliability and prolonging the wind turbine's lifespan [37].

4.1 Design of Questionnaires

The first of the pre-assessment tasks was to determine the parameters that contribute to the numerical assessment of risk in the study. In this context, four basic parameters have been determined. These are given in the section where the methodology is explained. Next, determining the final list of HRES failures was another pre-assessment task. Regarding it, 27 different failure modes were identified under seven main headings. The other two elements are the composition of the expert group and the design of the evaluation surveys. In this context, six experts who are competent in their field were determined. The identities of these experts are not given in the article, but they are coded as ZE, TG, AK, DB, ZA, and HIS. Two questionnaires were designed for both fuzzy



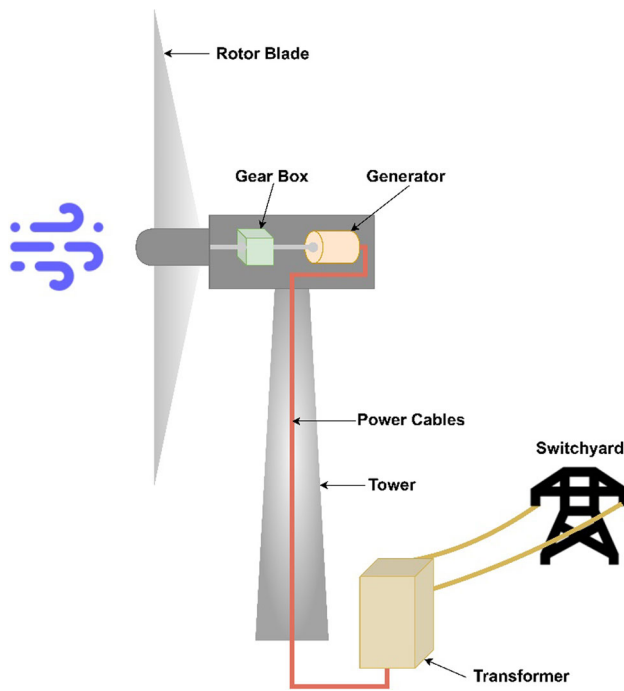


Fig. 4 Basic wind turbine system configuration

BWM and fuzzy MARCOS. You can find the full version of these surveys in the Supplementary file.

4.2 Execution of Fuzzy BWM to Determine Risk Parameters' Weights

The importance weights of four risk parameters have been determined in pairwise comparisons of six experts. The "best" and "worst" parameters corresponding with the first two steps of fuzzy BWM are selected and assessed by the fuzzy linguistic scale given in fuzzy BWM steps. Table 5 demonstrates the preferences of each expert on four risk parameters. The best and worst choices by each expert are also included in the tables. Each expert's pairwise comparisons have been solved as separate mathematical programming models (as given in FBWM step 4) and solved in Lingo. Results for risk parameter weights in an interval plot are provided in Table 6 and visualized in Fig. 5.

The fuzzy BWM mathematical model of #ZE is presented in Eq. 26. The model was solved in the Lingo 20.0 program, and the solution was reached in 24 iterations using the QP model class. The decision maker was asked to determine the best criterion in the first step of creating the mathematical model. The decision maker determined the best criterion as R4. Then, he was asked to compare R4 with R1, R2 and R3, respectively. Başhan et al. 2022's scale was used in the comparison. Then, the decision maker was asked to choose the least important parameter. The least important parameter was determined as R2. Similarly, R2 was compared pairwise

with R1 and R3 using Başhan et al. 2022's scale. The fuzzy numbers obtained were crisped using the GMIR procedure [51], and the weights of the risk parameters were calculated.

$$\begin{aligned}
 & \text{Min } k^* \\
 & l_4 - (2/3)u_1 \leq k^*u_1; \quad l_4 - (2/3)u_1 \geq -k^*u_1 \\
 & m_4 - (1)m_1 \leq k^*m_1; \quad m_4 - (1)m_1 \geq -k^*m_1 \\
 & u_4 - (3/2)l_1 \leq k^*l_1; \quad u_4 - (3/2)l_1 \geq -k^*l_1 \\
 & l_4 - (2)u_2 \leq k^*u_2; \quad l_4 - (2)u_2 \geq -k^*u_2 \\
 & m_4 - (2.5)m_2 \leq k^*m_2; \quad m_4 - (2.5)m_2 \geq -k^*m_2 \\
 & u_4 - (3)l_2 \leq k^*l_2; \quad u_4 - (3)l_2 \geq -k^*l_2 \\
 & l_4 - (5/6)u_3 \leq k^*u_3; \quad l_4 - (5/6)u_3 \geq -k^*u_3 \\
 & m_4 - (1)m_1 \leq k^*m_1; \quad m_4 - (1)m_1 \geq -k^*m_1 \\
 & u_4 - (5/4)l_3 \leq k^*l_3; \quad u_4 - (5/4)l_3 \geq -k^*l_3 \\
 & l_1 - (5/6)u_2 \leq k^*u_2; \quad l_1 - (5/6)u_2 \geq -k^*u_2 \\
 & m_1 - (1)m_2 \leq k^*m_2; \quad m_1 - (1)m_2 \geq -k^*m_2 \\
 & u_1 - (5/4)l_2 \leq k^*l_2; \quad u_1 - (5/4)l_2 \geq -k^*l_2 \\
 & l_3 - (2/3)u_2 \leq k^*u_2; \quad l_3 - (2/3)u_2 \geq -k^*u_2 \\
 & m_3 - (1)m_2 \leq k^*m_2; \quad m_3 - (1)m_2 \geq -k^*m_2 \\
 & u_3 - (3/2)l_2 \leq k^*l_2; \quad u_3 - (3/2)l_2 \geq -k^*l_2 \\
 & \text{s.t.} \\
 & 1/6 * l_1 + 1/6 * 4 * m_1 + 1/6 * u_1 \\
 & + 1/6 * l_2 + 1/6 * 4 * m_2 + 1/6 * u_2 + \\
 & 1/6 * l_3 + 1/6 * 4 * m_3 + 1/6 * u_3 + 1/6 * l_4 \\
 & + 1/6 * 4 * m_4 + 1/6 * u_4 = 1 \\
 & l_1 \leq m_1 \leq u_1 \\
 & l_2 \leq m_2 \leq u_2 \\
 & l_3 \leq m_3 \leq u_3 \\
 & l_4 \leq m_4 \leq u_4 \\
 & l_1 \geq 0; \quad l_2 \geq 0; \quad l_3 \geq 0 \\
 & k \geq 0
 \end{aligned} \tag{26}$$

From Fig. 5, it has been seen that the risk parameter with the highest degree of importance was "Economic impact of the failure-R4" with 0.3151. This was followed by "Severity of the failure on system, staff and failure-R1" and "Effort and ease of detecting the cause of the failure-R3" with 0.2591 and 0.2427. The risk parameter with the lowest level of importance was "Failure occurrence chance-R2" with a value of 0.1831. An important finding here is that all parameters have relatively close importance values. The final stage of FBWM is the calculation of consistency ratios. In this context, input-based consistency computation has been employed which is suggested by Liang et al. (2020) as in Fig. 6. It has been confirmed that there are evaluations that do not exceed the threshold value calculated for each expert (0.199, 0.1994, 0.1994, 0.2457, and 0.1529, respectively). Thus, all evaluations were obtained under a robust consistency analysis.

Table 5 Fuzzy evaluations of the best and worst risk parameters by linguistic terms

#ZE (Best: R ₄ ; Worst: R ₂)	Risk parameter			
	R ₁	R ₂	R ₃	R ₄
Best to others	3	6	2	1
Others to worst	2	1	3	6
#TG (Best: R ₁ ; Worst: R ₂)	R ₁	R ₂	R ₃	R ₄
Best to others	1	5	2	3
Others to worst	5	1	3	2
#AK (Best: R ₄ ; Worst: R ₂)	R ₁	R ₂	R ₃	R ₄
Best to others	2	5	3	1
Others to worst	3	1	2	5
#DB (Best: R ₁ ; Worst: R ₃)	R ₁	R ₂	R ₃	R ₄
Best to others	1	4	5	2
Others to worst	5	2	1	4
#ZA (Best: R ₄ ; Worst: R ₂)	R ₁	R ₂	R ₃	R ₄
Best to others	4	6	2	1
Others to worst	3	1	3	6
#HIS (Best: R ₄ ; Worst: R ₂)	R ₁	R ₂	R ₃	R ₄
Best to others	2	4	2	1
Others to worst	2	1	2	4

Table 6 Weights of risk parameters by each expert including average values

Expert ID	w1	w2	w3	w4
ZE	0.2348	0.1735	0.2439	0.3478
TG	0.2978	0.1432	0.2824	0.2766
AK	0.2551	0.1902	0.2428	0.3120
DB	0.3254	0.1976	0.1795	0.2975
ZA	0.1920	0.1797	0.2582	0.3701
HIS	0.2495	0.2146	0.2495	0.2864
Average	0.2591	0.1831	0.2427	0.3151

4.3 Execution of Fuzzy MARCOS to rank HRES Failures

First, HRES failures are evaluated concerning the four different risk parameters by six experts. The linguistic scale within TFN given in Table 2 has been used here. Due to space constraints, expert evaluations (with linguistic terms) are presented in the Supplementary file. The given linguistic values are converted into relevant TFNs, averaged, and the initial aggregated decision matrix is created. Table 7 shows this decision matrix.

Then, by employing the application steps of the Fuzzy MARCOS algorithm one by one (from Eq. 8 to Eq. 21), the values given in Table 8 are obtained. In the table, indices from 1 to 27 represent the HRES failures from ID codes WT1 to EI2, respectively. It should be noted here that among the four

risk parameters, R3 is a cost-oriented criterion, while R1, R2, and R4 are benefit-oriented criteria.

After defuzzification of the $\tilde{K}_i^-$, $\tilde{K}_i^+$, $f(\tilde{K}_i^-)$, $f(\tilde{K}_i^+)$ values, the utility functions of each HRES failure $f(K_i)$ are determined using Eq. (22). The results are given in Table 9.

At the final scene, the ranking of HRES failures is ordered (Fig. 7). Preliminary results show that less than half of HRES failures have an $f(K_i)$ value above average. These correspond to 12 HRES failures in total. The remaining failure modes are below average. Of course, the high value of $f(K_i)$ indicates the seriousness and riskiness of the failure mode. In this context, it seems that the three most risky failures are SP1, ESS1, and WT11. These are related to cell damage, battery degradation, and battery waste, respectively.

To show how the values regarding fuzzy MARCOS are obtained, a small example of demonstrating the computational steps is considered useful. To employ fuzzy MARCOS



Fig. 5 Weights of four risk parameters by five experts in an interval plot

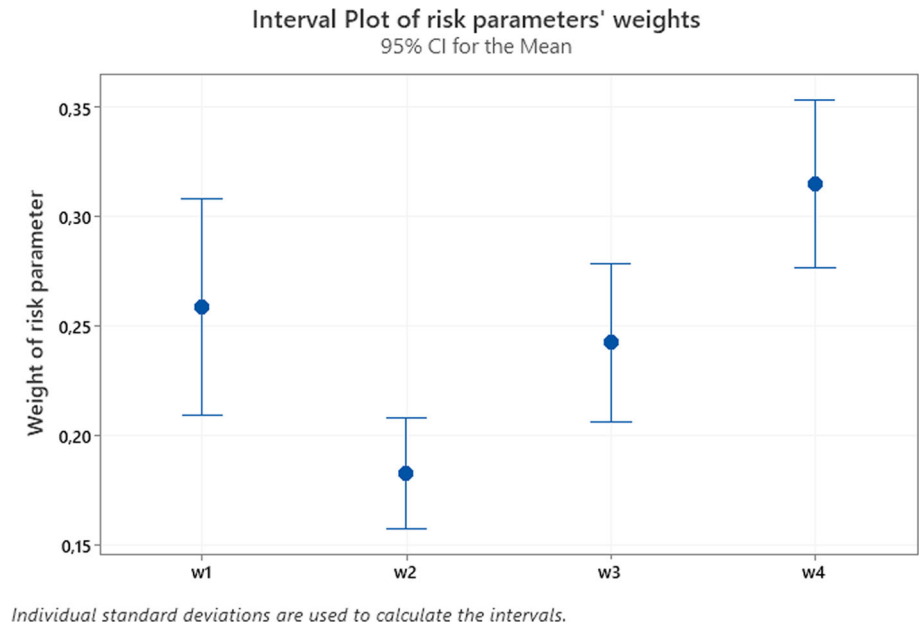
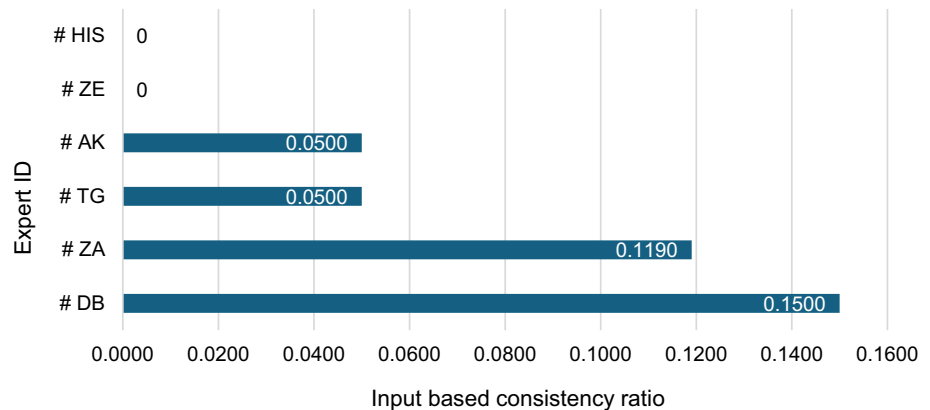


Fig. 6 Input-based consistency ratios for each expert



regarding ranking of HRES failures, decision makers' judgments are gathered with respect to the four risk parameters. These judgments are assessed by the decision-maker experts using the triangular fuzzy linguistic scale in Table 3. For example, the aggregated value of WT1 failure "Wing damage" with respect to the R1 ($\tilde{a}_{11}$) is computed by averaging the values of six experts. Thus, $\tilde{a}_{11} = \{M, M, MP, MP, M, MP\}$. Here the lower value the fuzzy aggregated is computed as $\frac{3+3+1+1+3+1}{6} = 2$. Similarly, the medium and upper values of the fuzzy aggregated $\frac{5+5+3+3+5+3}{6} = 4$ and $\frac{7+7+5+5+7+5}{6} = 6$, respectively. Thus, $\tilde{a}_{11} = (2, 4, 6)$ as summarized in Table 6. Secondly, by taking similar averaging operation in remaining of the matrices, a group decision matrix consisting of the whole experts' judgments have been formed as in Table 6.

Thirdly, for the extended fuzzy decision matrix $\tilde{B}$, $\tilde{A}(AI)$ and $\tilde{A}(ID)$ are computed. To make these computations, it should be noted that R1, R2 and R4 are beneficial criteria while the R3 is a cost-based criterion. $\tilde{A}(AI)$ is computed by

making maximum of the values in R1, R2 and R4 columns and minimum of the values in R3 column for the fuzzy element's low, medium and high values. On the other hand, $\tilde{A}(ID)$ is computed by making minimum of the values in R1, R2 and R4 columns and maximum of the values in R3 column for low, medium and high values of the fuzzy element.

Thus, $\tilde{A}(AI)$ values for R1, R2, R3 and R4 are computed as follows, respectively: $\{(7.333, 9.167, 10), (4, 6, 7.833), (0.833, 2.333, 4.333), (6.667, 8.5, 9.667)\}$. With a similar form, $\tilde{A}(ID)$ values for R1, R2, R3 and R4 are computed as follows, respectively: $\{(0.333, 1.667, 3.667), (0, 0.667, 2.333), (7.667, 9.333, 10), (0.5, 1.833, 3.667)\}$.

Then in the fourth step, normalization is carried out and a normalized decision matrix is formed. As an example for this step's computation, $\tilde{n}_{11} = (\tilde{n}_{11}^l, \tilde{n}_{11}^m, \tilde{n}_{11}^u) = \left(\frac{x_{11}^l}{x_{id}^l}, \frac{x_{11}^m}{x_{id}^m}, \frac{x_{11}^u}{x_{id}^u} \right) = \left(\frac{2}{10}, \frac{4}{10}, \frac{6}{10} \right) = (0.2, 0.4, 0.6)$. Then, we proceed to obtain the weighted

Table 7 The averaged initial fuzzy decision matrix

Failure ID	R1	R2	R3	R4
WT1	(2,4,6)	(2.167,4,5.833)	(5,7,8.667)	(4,6,8)
WT2	(0.333,1.667,3.667)	(0.667,2,4)	(2.5,4.333,6.167)	(1.167,3,5)
WT3	(3.667,5.667,7.667)	(1.5,3.333,5.333)	(5.333,7.333,8.833)	(3.333,5.333,7.333)
WT4	(3,5,7)	(1.167,3,5)	(2.333,4.333,6.333)	(4,5.833,7,5)
WT5	(5,7,8.833)	(1.333,3,5)	(3.667,5.667,7.667)	(6.333,8.167,9,5)
WT6	(1.667,3.333,5.333)	(0,0.667,2.333)	(2.833,4.667,6,5)	(2.333,4.333,6.333)
WT7	(2.833,4.667,6.667)	(0.833,2.667,4.667)	(5,7,8.667)	(1.167,3,5)
WT8	(2,4,6)	(1,2.333,4.333)	(5.667,7.667,9)	(2,5,4.333,6.333)
WT9	(1.833,3.333,5.167)	(2,3.667,5,5)	(2.667,4.667,6.667)	(1.167,3,5)
WT10	(3,5,7)	(2.667,4.667,6.667)	(3.667,5.667,7.667)	(1.833,3.667,5.667)
WT11	(7.333,9.167,10)	(0.333,1.667,3.667)	(7.333,9,9.833)	(6.667,8,5,9.667)
WT12	(1.667,3.333,5.333)	(0.167,1.167,3)	(3,5,7)	(0,5,1.833,3.667)
SP1	(7.333,9.167,10)	(4,6,7.833)	(7.667,9.333,10)	(6.667,8,5,9.667)
SP2	(4.333,6.333,8)	(2.333,4.333,6.167)	(4.667,6.667,8,5)	(2.667,4.667,6.667)
SP3	(1.667,3,4.833)	(1.167,2.333,4.167)	(2.667,4.667,6,5)	(1.167,3,5)
ESS1	(6,8,9,5)	(3.667,5.667,7,5)	(6.333,8.333,9.667)	(6,7.833,9,333)
ESS2	(3.667,5.667,7,5)	(2,4,5.833)	(3,5,7)	(4,6,7.833)
ESS3	(3,5,7)	(1.5,3.333,5.333)	(4,6,8)	(3.667,5.667,7.667)
CMS1	(4.667,6.667,8,5)	(3.333,5.333,7.333)	(2.167,4,6)	(3,5,6.833)
CMS2	(2.167,4,6)	(0.667,1.833,3.667)	(3.833,5.667,7.667)	(2,4,6)
CMS3	(1.667,3.333,5.333)	(0.167,1.167,3)	(4.833,6.667,8.333)	(2.167,4,6)
EG11	(3.333,5.333,7)	(0.167,1.167,3)	(6.833,8,8,5)	(3.833,5.667,7.667)
EG12	(3,5,5.333,7.167)	(0.333,1,5,3.333)	(5.333,7.333,8.833)	(3,5,5.333,7.333)
HE1	(3,5,7)	(3,5,5.333,7.333)	(0.833,2.333,4.333)	(3.333,5.333,7.333)
HE2	(2,5,4.167,6)	(3.167,5,7)	(3.667,5.667,7.667)	(2,5,4.167,6)
EI1	(3,5,5.167,7)	(0.333,1,5,3.333)	(5.667,7.667,9.167)	(3.833,5.667,7,5)
EI2	(0.833,2,5,4.333)	(0.167,1.333,3.333)	(4.333,6.333,8.167)	(1,2.667,4.667)

normalized values ($\tilde{v}_{ij}$). Within the same manner, $\tilde{v}_{11} = \tilde{n}_{11} \otimes \tilde{\omega}_1 = (\tilde{n}_{11}^l \times \tilde{\omega}_1^l, \tilde{n}_{11}^m \times \tilde{\omega}_1^m, \tilde{n}_{11}^u \times \tilde{\omega}_1^u) = (0.2 \times 0.2591, 0.4 \times 0.2591, 0.6 \times 0.2591) = (0.052, 0.104, 0.155)$. Here the weight of R1 comes from fuzzy BWM as 0.2591. Following the same formulas $\tilde{v}_{12} = (0.051, 0.094, 0.136)$, $\tilde{v}_{13} = (0.023, 0.029, 0.040)$, and $\tilde{v}_{14} = (0.130, 0.196, 0.261)$.

Then, the utility degrees of WT1 failure “Wing damage” is computed. For this, the sum of the elements of the weighted fuzzy matrix ($\tilde{S}_1$) is obtained as follows:

$\tilde{S}_1 = (0.052 + 0.051 + 0.023 + 0.130, 0.104 + 0.094 + 0.029 + 0.196, 0.155 + 0.136 + 0.040 + 0.261) = (0.256, 0.422, 0.593)$. The whole version of this calculation is provided in Table 7. Also, $\tilde{S}_{ai} = (0.547, 0.741, 1.000)$ and $\tilde{S}_{id} = (0.045, 0.140, 0.295)$ are computed. The utility degree $\tilde{K}_1^- = \frac{\tilde{S}_1}{\tilde{S}_{ai}} = \left(\frac{\tilde{s}_1^l}{\tilde{s}_{ai}^l}, \frac{\tilde{s}_1^m}{\tilde{s}_{ai}^m}, \frac{\tilde{s}_1^u}{\tilde{s}_{ai}^u} \right) = \left(\frac{0.256}{0.295}, \frac{0.422}{0.140}, \frac{0.593}{0.045} \right) = (0.867, 3.007, 13.132)$ and $\tilde{K}_i^+ = \frac{\tilde{S}_1}{\tilde{S}_{id}} = \left(\frac{\tilde{s}_1^l}{\tilde{s}_{id}^l}, \frac{\tilde{s}_1^m}{\tilde{s}_{id}^m}, \frac{\tilde{s}_1^u}{\tilde{s}_{id}^u} \right) =$

$\left(\frac{0.256}{1.000}, \frac{0.422}{0.741}, \frac{0.593}{0.547} \right) = (0.256, 0.569, 1.083)$ are then obtained as provided in Table 7. The utility functions for ideal $f(\tilde{K}_1^+)$ and anti-ideal $f(\tilde{K}_1^-)$ solutions are then computed as follows:

$$\begin{aligned} \tilde{T}_1 &= \tilde{t}_1 = \left(t_1^l, t_1^m, t_1^u \right) = \tilde{K}_1^- \oplus \tilde{K}_1^+ \\ &= \left(k_1^{-l} + k_1^{+l}, k_1^{-m} + k_1^{+m}, k_1^{-u} + k_1^{+u} \right) \\ &= (0.867 + 0.256, 3.007 + 0.569, 13.132 + 1.083) \\ &= (1.123, 3.576, 14.215) \end{aligned}$$

$$\max_i \tilde{t}_i = \tilde{D} = \left(d^l, d^m, d^u \right) = (2.285, 5.738, 20.004)$$

$$df_{crisp} = \frac{2.285 + 4 * 5.738 + 20.004}{6} = 7.540$$



Table 8 Computed $\tilde{S}_i$, $\tilde{K}_i^-$, $\tilde{K}_i^+$ and $\tilde{T}_i$ values

$\tilde{S}_i$	(s_i^l, s_i^m, s_i^u)	$\tilde{K}_i^-$	$\tilde{K}_i^+$	$\tilde{T}_i$
$\tilde{S}_{ai}$	(0.045,0.14,0.295)	$\tilde{k}_i^-$	$\tilde{k}_i^+$	$\tilde{t}_i$
		$(k_i^{-l}, k_i^{-m}, k_i^{-u})$	$(k_i^{+l}, k_i^{+m}, k_i^{+u})$	(t_i^l, t_i^m, t_i^u)
$\tilde{S}_1$	(0.256,0.422,0.593)	$\tilde{k}_1^-$	$\tilde{k}_1^+$	$\tilde{t}_1$
$\tilde{S}_2$	(0.095,0.234,0.432)	$\tilde{k}_2^-$	$\tilde{k}_2^+$	$\tilde{t}_2$
$\tilde{S}_3$	(0.262,0.426,0.6)	$\tilde{k}_3^-$	$\tilde{k}_3^+$	$\tilde{t}_3$
$\tilde{S}_4$	(0.267,0.436,0.629)	$\tilde{k}_4^-$	$\tilde{k}_4^+$	$\tilde{t}_4$
$\tilde{S}_5$	(0.394,0.553,0.711)	$\tilde{k}_5^-$	$\tilde{k}_5^+$	$\tilde{t}_5$
$\tilde{S}_6$	(0.15,0.287,0.471)	$\tilde{k}_6^-$	$\tilde{k}_6^+$	$\tilde{t}_6$
$\tilde{S}_7$	(0.154,0.31,0.485)	$\tilde{k}_7^-$	$\tilde{k}_7^+$	$\tilde{t}_7$
$\tilde{S}_8$	(0.179,0.326,0.499)	$\tilde{k}_8^-$	$\tilde{k}_8^+$	$\tilde{t}_8$
$\tilde{S}_9$	(0.163,0.313,0.501)	$\tilde{k}_9^-$	$\tilde{k}_9^+$	$\tilde{t}_9$
$\tilde{S}_{10}$	(0.226,0.394,0.577)	$\tilde{k}_{10}^-$	$\tilde{k}_{10}^+$	$\tilde{t}_{10}$
$\tilde{S}_{11}$	(0.436,0.576,0.687)	$\tilde{k}_{11}^-$	$\tilde{k}_{11}^+$	$\tilde{t}_{11}$
$\tilde{S}_{12}$	(0.092,0.214,0.395)	$\tilde{k}_{12}^-$	$\tilde{k}_{12}^+$	$\tilde{t}_{12}$
$\tilde{S}_{13}$	(0.521,0.676,0.784)	$\tilde{k}_{13}^-$	$\tilde{k}_{13}^+$	$\tilde{t}_{13}$
$\tilde{S}_{14}$	(0.278,0.448,0.612)	$\tilde{k}_{14}^-$	$\tilde{k}_{14}^+$	$\tilde{t}_{14}$
$\tilde{S}_{15}$	(0.14,0.273,0.461)	$\tilde{k}_{15}^-$	$\tilde{k}_{15}^+$	$\tilde{t}_{15}$
$\tilde{S}_{16}$	(0.458,0.619,0.758)	$\tilde{k}_{16}^-$	$\tilde{k}_{16}^+$	$\tilde{t}_{16}$
$\tilde{S}_{17}$	(0.301,0.476,0.653)	$\tilde{k}_{17}^-$	$\tilde{k}_{17}^+$	$\tilde{t}_{17}$
$\tilde{S}_{18}$	(0.258,0.426,0.606)	$\tilde{k}_{18}^-$	$\tilde{k}_{18}^+$	$\tilde{t}_{18}$
$\tilde{S}_{19}$	(0.33,0.511,0.708)	$\tilde{k}_{19}^-$	$\tilde{k}_{19}^+$	$\tilde{t}_{19}$
$\tilde{S}_{20}$	(0.163,0.313,0.49)	$\tilde{k}_{20}^-$	$\tilde{k}_{20}^+$	$\tilde{t}_{20}$
$\tilde{S}_{21}$	(0.142,0.274,0.446)	$\tilde{k}_{21}^-$	$\tilde{k}_{21}^+$	$\tilde{t}_{21}$
$\tilde{S}_{22}$	(0.239,0.375,0.531)	$\tilde{k}_{22}^-$	$\tilde{k}_{22}^+$	$\tilde{t}_{22}$
$\tilde{S}_{23}$	(0.235,0.375,0.541)	$\tilde{k}_{23}^-$	$\tilde{k}_{23}^+$	$\tilde{t}_{23}$
$\tilde{S}_{24}$	(0.315,0.515,0.835)	$\tilde{k}_{24}^-$	$\tilde{k}_{24}^+$	$\tilde{t}_{24}$
$\tilde{S}_{25}$	(0.247,0.396,0.57)	$\tilde{k}_{25}^-$	$\tilde{k}_{25}^+$	$\tilde{t}_{25}$
$\tilde{S}_{26}$	(0.245,0.38,0.539)	$\tilde{k}_{26}^-$	$\tilde{k}_{26}^+$	$\tilde{t}_{26}$
$\tilde{S}_{27}$	(0.083,0.215,0.389)	$\tilde{k}_{27}^-$	$\tilde{k}_{27}^+$	$\tilde{t}_{27}$
$\tilde{S}_{id}$	(0.547,0.741,1)			

$$f(\tilde{K}_1^+) = \frac{\tilde{K}_1^-}{df_{crisp}} = \left(\frac{k_1^{-l}}{df_{crisp}}, \frac{k_1^{-m}}{df_{crisp}}, \frac{k_1^{-u}}{df_{crisp}} \right) = \left(\frac{0.867}{7.540}, \frac{3.007}{7.540}, \frac{13.132}{7.540} \right) = (0.115, 0.399, 1.742)$$

$$f(\tilde{K}_1^-) = \frac{\tilde{K}_1^+}{df_{crisp}} = \left(\frac{k_1^{+l}}{df_{crisp}}, \frac{k_1^{+m}}{df_{crisp}}, \frac{k_1^{+u}}{df_{crisp}} \right) = \left(\frac{0.256}{7.540}, \frac{0.569}{7.540}, \frac{1.083}{7.540} \right) = (0.034, 0.075, 0.144)$$

After these computations, $\tilde{K}_1^-$, $\tilde{K}_1^+$, $f(\tilde{K}_1^-)$, $f(\tilde{K}_1^+)$ are defuzzified and $\tilde{K}_1^- = 4.338$, $\tilde{K}_1^+ = 0.602$, $f(\tilde{K}_1^-) = 0.575$, and $f(\tilde{K}_1^+) = 0.080$ are obtained. Finally, the utility function of WT1 failure “Wing damage” $f(K_1)$ are determined as.

$$f(K_1) = \frac{K_1^+ + K_1^-}{1 + \frac{1-f(K_1^+)}{f(K_1^+)} + \frac{1-f(K_1^-)}{f(K_1^-)}} = \frac{0.602 + 4.338}{1 + \frac{1-0.080}{0.080} + \frac{1-0.575}{0.575}} = 0.373.$$



Table 9 Results of fuzzy MARCOS method

Failure ID	K_i^-	K_i^+	$f(K_i^+)$	$f(K_i^-)$	$f(K_i)$
WT1	4.338	0.602	0.575	0.080	0.373
WT2	2.764	0.358	0.367	0.048	0.137
WT3	4.389	0.609	0.582	0.081	0.382
WT4	4.549	0.629	0.603	0.083	0.409
WT5	5.476	0.779	0.726	0.103	0.622
WT6	3.184	0.426	0.422	0.056	0.189
WT7	3.352	0.452	0.445	0.060	0.212
WT8	3.492	0.475	0.463	0.063	0.233
WT9	3.431	0.461	0.455	0.061	0.222
WT10	4.130	0.567	0.548	0.075	0.333
WT11	5.522	0.800	0.732	0.106	0.646
WT12	2.528	0.328	0.335	0.043	0.114
SP1	6.403	0.934	0.849	0.124	0.889
SP2	4.545	0.635	0.603	0.084	0.413
SP3	3.082	0.410	0.409	0.054	0.176
ESS1	5.999	0.864	0.796	0.115	0.764
ESS2	4.847	0.677	0.643	0.090	0.473
ESS3	4.409	0.610	0.585	0.081	0.384
CMS1	5.228	0.730	0.693	0.097	0.553
CMS2	3.385	0.457	0.449	0.061	0.217
CMS3	3.030	0.406	0.402	0.054	0.171
EGI1	3.880	0.539	0.515	0.071	0.296
EGI2	3.909	0.541	0.519	0.072	0.299
HE1	5.705	0.769	0.757	0.102	0.640
HE2	4.127	0.571	0.547	0.076	0.335
EI1	3.936	0.547	0.522	0.073	0.305
EI2	2.504	0.325	0.332	0.043	0.112

4.4 Mitigation Strategies for Effective Risk Management and Recommendations

Wind–solar HRESs must be highly reliable and efficient for reliable and sustainable energy generation. Due to these systems' complex architecture, which combine solar and wind energy, many failure mechanisms and operational difficulties may occur. A complete strategy including routine maintenance, sophisticated monitoring, sturdy design, and efficient management techniques is needed to address these problems. The discovered system components categorize failure modes in the following sections, and mitigation strategies are shown in Fig. 8, which also offer technological mitigation measures to improve system longevity and performance.

4.4.1 Wind Turbine (WT) Issues

Considering wing damage (WT1), using drones and high-resolution imaging technologies to conduct routine maintenance schedules and inspections to identify early indicators of turbine blade wear and tear looks like that will be used soon. To increase the blades' longevity, using high-strain fatigue resistance modern composite materials is highly recommended. For bearing problems (WT4), it is advised to use vibration analysis and oil particle detection in real-time condition monitoring systems to continuously evaluate the health of the bearings. It is recommended to employ predictive maintenance methods that employ machine learning algorithms to anticipate bearing failures and plan for prompt replacements. Considering gearbox failures (WT5), it is advisable to employ high-precision gear manufacturing techniques and advanced lubrication systems to reduce wear and tear. Integrating continuous torque monitoring and thermal imaging to detect early signs of gearbox issues and



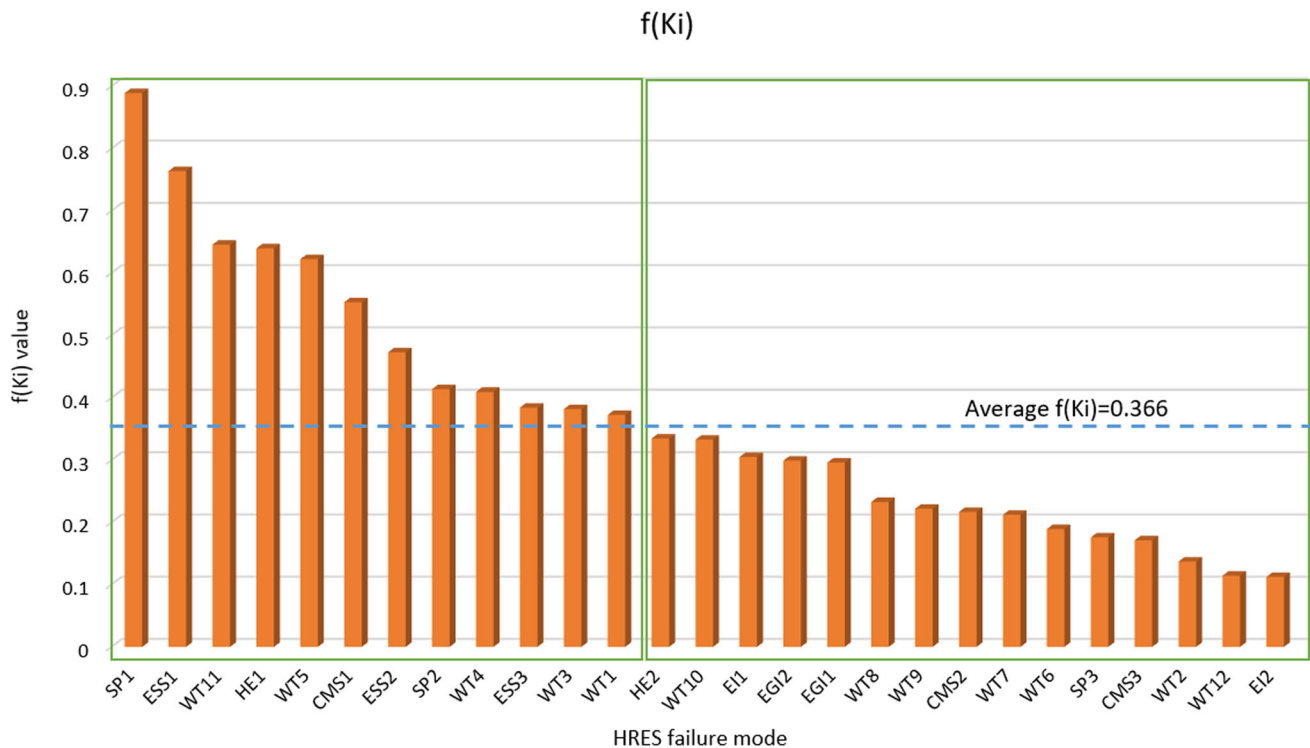


Fig. 7 Final fuzzy MARCOS values of HRES failures (showing their rankings)

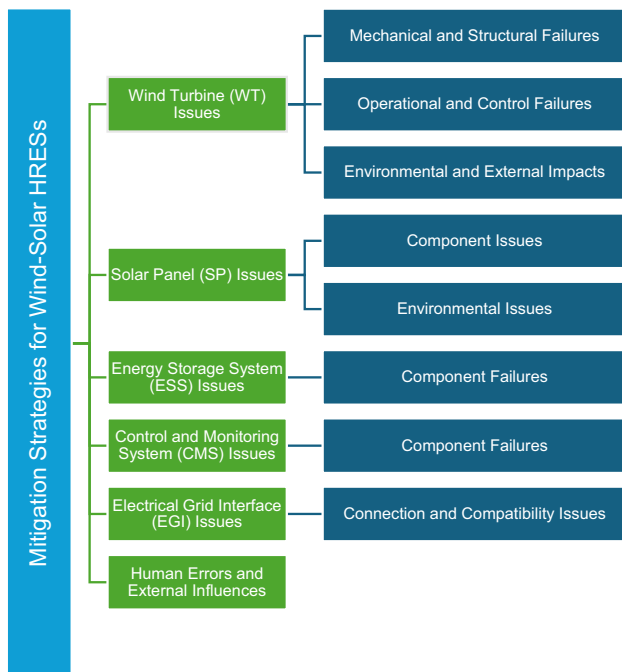


Fig. 8 Mitigation strategies for wind–solar hybrid RESs

perform maintenance before critical failures occur is also recommended. One of the mitigation strategies for WT is tower vibration (WT6), it is advised to install active control systems and vibration dampers to lessen tower oscillations.

It is also recommended to do a modal analysis during the design phase to optimize the tower construction and lessen its vulnerability to vibrations brought on by wind loads.

If we look into operational and control failures, and wind management issues (WT2), developing and implementing advanced control algorithms for yaw and pitch systems to optimize wind capture efficiency is recommended. Using real-time wind speed and direction sensors to adjust turbine orientation dynamically is also advised. Besides, for mitigation strategies of generator faults (WT3), integrating thermal management systems to prevent overheating and employing redundant generator systems to ensure continuous operation is recommended. Utilizing real-time electrical monitoring to detect anomalies and perform preventive maintenance is also advised. In addition, brake and locking problems (WT7) can be examined and it is recommended to use high-reliability braking systems with fail-safe mechanisms. Conducting regular functional tests and implementing remote monitoring to ensure brake systems are operating correctly is also advised. Even if all of these aspects are working properly, there may be a problem with the control systems. For eliminating system control problems (WT10) employing robust and validated control software with redundancy features is recommended. Regularly updating and testing control algorithms to address emerging issues and improve system stability is also advised.

In the environmental and external impacts group, electrical connection problems (WT8) come to the fore. In this



context, using corrosion-resistant materials and sealed connectors to prevent environmental damage is recommended. Implementing regular inspections and maintenance of electrical connections, particularly in harsh marine environments or dirty land facilities, is also advised. In terms of sand and ice deposits (WT9) provided that the permits and limits of the manufacturing companies regarding these issues are carefully examined, applying anti-icing and anti-soiling coatings on turbine blades and key components is recommended. Using de-icing systems and heated blades to mitigate the impact of ice formation is also advised. In case of overheating and battery-related fires (WT11), it is advised to install fire detection and suppression systems in control cabinets and nacelles. It's also advisable to regularly conduct fire safety drills and inspections and to use fire-retardant materials in high-risk areas. Furthermore, environmental wind impact (WT12) should be considered. Developing adaptive control systems that can adjust turbine operations based on real-time environmental conditions is recommended. Using aerodynamic blade designs to reduce the impact of extreme wind events is also advised. This situation is also important in terms of exergy efficiency.

4.4.2 Solar Panel (SP) Issues

For cell damage (SP1), it is recommended to regularly inspect and clean solar panels using automated cleaning robots to prevent and identify damage early. Employing high-durability materials for solar cells to withstand environmental stresses is also advised. Inverter failure of solar panels (SP2), implementing advanced diagnostics and real-time monitoring systems for inverters to predict and prevent failures is recommended. Using redundant inverters and providing efficient cooling solutions to maintain operational stability is also advised. Besides, one of the important environmental issues is shading regarding solar panels. For the shading problem (SP3), it is recommended to optimize panel placement and use shading analysis tools (i.e., HOMER Pro, SAM, etc.) during the design phase to minimize shading effects. Implementing bypass diodes in solar panels to mitigate the impact of partial shading on overall system performance is also advised.

4.4.3 Energy Storage System (ESS) Issues

In the component failures part, battery degradation (ESS1) is crucial. From the open-source literature and best of our knowledge, utilizing battery management systems to monitor and optimize battery health and lifespan is recommended. Implementing regular cycling and temperature management protocols to prolong battery life is also important and should be taken into attention. Another problem of ESS is the inverter problem, and regularly testing and maintaining

inverters to ensure reliable performance is recommended. Using advanced power electronics that are robust and efficient in energy conversion and management is also advised by manufacturers. Another problem of the ESS is cooling (ESS3). For cooling problems, incorporating advanced cooling systems, such as liquid cooling or phase change materials, to maintain optimal operating temperatures for batteries and inverters is recommended.

4.4.4 Control and Monitoring System (CMS) Issues

Regarding sensor failures (CMS1), it is recommended to implement redundant sensors and robust calibration protocols to ensure accurate data collection. Additionally, using self-diagnosing sensors that can alert operators to potential failures are advised, enhancing the reliability of the monitoring systems. In the literature, it is noted that control software errors (CMS2) are common. In this regard, thorough testing and validation of control software to minimize errors is recommended. Regularly updating and patching software to address vulnerabilities and improve performance should also be considered to maintain system stability and security. Sometimes data connection problems (CMS3) are also encountered. Establishing secure and reliable data communication channels with failover mechanisms to prevent connectivity issues is recommended. It is also advisable to use multiple communication pathways to ensure continuous data flow, thereby enhancing system robustness.

4.4.5 Electrical Grid Interface (EGI) Issues

One of the important problems in connection and compatibility issues is grid connection failures (EG11). Designing and implementing robust grid connection protocols to handle variable loads and ensure seamless integration is recommended. The use of smart grid technologies to enhance connectivity and reliability is also advised. On the other hand, frequency compatibility problems (EG12) are common. In these cases, utilizing advanced power electronics to manage frequency compatibility and synchronization with the grid is recommended. Implementing dynamic frequency regulation systems to stabilize grid operations should also be considered.

4.4.6 Human Errors (HE) and External Influences (EI)

Maintenance error (HE1), operating error (HE2), and external influences such as lightning strikes (EI1) and temperature change (EI2) are in these groups of failures. Providing comprehensive training and certification programs for maintenance staff is crucial. Implementing standardized procedures and checklists to minimize human error during operations



and maintenance is also advised and it should even be mandatory. For HE2, implementing robust operational protocols and continuous training programs for operators is necessary. The use of automated systems where possible to reduce the likelihood of human error is also advised. Besides, for EI1, installing lightning protection systems and surge protectors to safeguard against lightning strikes is important. Regularly inspecting and maintaining these systems to ensure functionality is also fundamentally needed. For EI2, designing systems with temperature resilience in mind, including the use of temperature-tolerant materials and components, is beneficial. Implementing environmental monitoring systems to provide early warnings of extreme temperature changes is also important.

A multi-faceted strategy that incorporates reliable design, cutting-edge monitoring, and efficient management techniques is needed to address the numerous problems and difficulties that arise in wind–solar HRESs. These systems may be made far more reliable and efficient by methodically detecting and resolving possible problems. The suggested hybrid fuzzy BWM and fuzzy MARCOS methodologies for thorough failure analysis, ranking difficulties, and presenting strong remedies to enhance the resilience and functionality of HRESs are thoroughly examined in this article.

4.5 Sensitivity Analysis

We performed a sensitivity analysis to explore how modifying the four risk parameter weights would affect the final ranking of HRES failures. We systematically varied each variable (weight of risk parameter) during this analysis, increasing and decreasing it from 10 to 90%. We ensured that these adjustments were made in proportion to the weight of each variable, maintaining a total of 1 for the weights. Table 10 shows the scenarios created to employ sensibility. Sensitivity analysis results are presented in two separate ways (a) and (b) of Fig. 9. To avoid harming the readability of the graphs, 72 scenarios are presented in two separate graphs. Each 3D surface plot also shows that the results are sensitive to changes in the weights of the four risk parameters. Because the order of HRES failures is largely preserved in each scenario. Changes were observed in the priorities of some failure modes that remained in the middle of the ranking, provided they were not too many. SP1, ESS1, and WT11, mostly prioritized in the as-is scenario, remain in the top three. Therefore, the enactment of prevention and mitigation axioms that can be planned for these failure modes is also confirmed and strongly approved.

4.6 Comparative Study

The same problem was solved with alternative fuzzy MCDM methods for the second stage to strengthen the study results,

where the priority scores of HRES failures were determined. The results are shown in Fig. 10. The results show that the trend of the rankings obtained by all three methods is largely the same. In Fig. 11, the Pearson correlation analysis has also confirmed a higher correlation (98.4%, 91.7% and 89.5%) between the results of fuzzy MARCOS, fuzzy TOPSIS and fuzzy SAW.

4.7 Discussion on Top-Ranked Failures and Recommendations

The prioritization of failure modes highlights critical vulnerabilities in HRES, with SP1 (cell damage), ESS1 (battery degradation), and WT11 (battery fire) emerging as the most significant. These failures were prioritized due to their high severity, economic impact, and potential to disrupt system operations. SP1 is associated with reduced energy generation efficiency and long-term performance degradation, necessitating the use of advanced diagnostic tools to detect early signs of cell wear and robust maintenance protocols to extend panel lifespan. ESS1 is critical due to its direct influence on the stability and reliability of energy storage systems, emphasizing the need for high-quality, durable battery materials and improved battery management systems to minimize degradation. Similarly, WT11 poses a significant safety and operational risk, requiring the installation of comprehensive fire detection and suppression systems alongside regular system inspections to mitigate catastrophic outcomes. From an economic perspective, a cost–benefit analysis underscores the importance of addressing these failures. For instance, the upfront investment in advanced monitoring and maintenance for SP1 can significantly outweigh the economic losses associated with reduced energy efficiency and replacement costs. Likewise, mitigating ESS1 and WT11 can prevent substantial downtime and safety liabilities, ensuring sustained operation and compliance with industry regulations. Future studies could provide a detailed quantification of these cost–benefit scenarios to further support stakeholders in decision making. Actionable recommendations for various stakeholders are as follows:

- Focusing on real-time monitoring and predictive maintenance using advanced diagnostics to promptly identify and address critical failures is crucial. Establishing regular training programs to enhance awareness of potential risks and emergency protocols are also needed.
- Incorporating redundancy and fail-safe mechanisms into the design of HRES components to reduce system vulnerability is indispensable. Prioritizing the integration of durable materials and advanced technologies in energy generation, storage, and control systems are also needed.
- For policymakers, developing regulatory frameworks and incentive programs to encourage the adoption of robust

Table 10 Scenario setting

Scenario ID	Description	R1	R2	R3	R4	Scenario ID	Description	R1	R2	R3	R4
#0	Base scenario (as-is)	0.259	0.183	0.243	0.315	#37	Increase w3 by 50%:	0.218	0.154	0.364	0.265
#1	Increase w1 by 10%:	0.285	0.177	0.234	0.304	#38	Decrease w3 by 50%:	0.301	0.212	0.121	0.366
#2	Decrease w1 by 10%:	0.233	0.190	0.251	0.326	#39	Increase w4 by 50%:	0.199	0.141	0.187	0.473
#3	Increase w2 by 10%:	0.253	0.201	0.237	0.308	#40	Decrease w4 by 50%:	0.319	0.225	0.299	0.158
#4	Decrease w2 by 10%:	0.311	0.018	0.292	0.379	#41	Increase w1 by 60%:	0.415	0.145	0.192	0.249
#5	Increase w3 by 10%:	0.251	0.177	0.267	0.305	#42	Decrease w1 by 60%:	0.104	0.222	0.294	0.381
#6	Decrease w3 by 10%:	0.267	0.189	0.218	0.325	#43	Increase w2 by 60%:	0.224	0.293	0.210	0.273
#7	Increase w4 by 10%:	0.247	0.175	0.232	0.347	#44	Decrease w2 by 60%:	0.294	0.073	0.275	0.357
#8	Decrease w4 by 10%:	0.271	0.192	0.254	0.284	#45	Increase w3 by 60%:	0.209	0.148	0.388	0.254
#9	Increase w1 by 20%:	0.311	0.170	0.226	0.293	#46	Decrease w3 by 60%:	0.309	0.218	0.097	0.376
#10	Decrease w1 by 20%:	0.207	0.196	0.260	0.337	#47	Increase w4 by 60%:	0.188	0.133	0.176	0.504
#11	Increase w2 by 20%:	0.247	0.220	0.232	0.301	#48	Decrease w4 by 60%:	0.331	0.234	0.310	0.126
#12	Decrease w2 by 20%:	0.271	0.147	0.254	0.329	#49	Increase w1 by 70%:	0.440	0.138	0.183	0.238
#13	Increase w3 by 20%:	0.242	0.171	0.291	0.295	#50	Decrease w1 by 70%:	0.181	0.202	0.268	0.348
#14	Decrease w3 by 20%:	0.276	0.195	0.194	0.335	#51	Increase w2 by 70%:	0.218	0.311	0.205	0.266
#15	Increase w4 by 20%:	0.235	0.166	0.220	0.378	#52	Decrease w2 by 70%:	0.300	0.055	0.281	0.365
#16	Decrease w4 by 20%:	0.283	0.200	0.265	0.252	#53	Increase w3 by 70%:	0.201	0.142	0.413	0.244
#17	Increase w1 by 30%:	0.337	0.164	0.217	0.282	#54	Decrease w3 by 70%:	0.317	0.224	0.073	0.386
#18	Decrease w1 by 30%:	0.181	0.202	0.268	0.348	#55	Increase w4 by 70%:	0.176	0.124	0.165	0.536
#19	Increase w2 by 30%:	0.242	0.238	0.226	0.294	#56	Decrease w4 by 70%:	0.343	0.242	0.321	0.095
#20	Decrease w2 by 30%:	0.277	0.128	0.259	0.336	#57	Increase w1 by 80%:	0.466	0.132	0.175	0.227
#21	Increase w3 by 30%:	0.234	0.166	0.316	0.285	#58	Decrease w1 by 80%:	0.052	0.234	0.311	0.403
#22	Decrease w3 by 30%:	0.284	0.201	0.170	0.345	#59	Increase w2 by 80%:	0.213	0.330	0.199	0.259
#23	Increase w4 by 30%:	0.223	0.158	0.209	0.410	#60	Decrease w2 by 80%:	0.306	0.037	0.286	0.372



Table 10 (continued)

Scenario ID	Description	R1	R2	R3	R4	Scenario ID	Description	R1	R2	R3	R4
#24	Decrease w4 by 30%:	0.295	0.208	0.276	0.221	#61	Increase w3 by 80%:	0.193	0.136	0.437	0.234
#25	Increase w1 by 40%:	0.363	0.158	0.209	0.271	#62	Decrease w3 by 80%:	0.326	0.230	0.049	0.396
#26	Decrease w1 by 40%:	0.155	0.209	0.277	0.359	#63	Increase w4 by 80%:	0.164	0.116	0.153	0.567
#27	Increase w2 by 40%:	0.236	0.256	0.221	0.287	#64	Decrease w4 by 80%:	0.354	0.251	0.332	0.063
#28	Decrease w2 by 40%:	0.282	0.110	0.264	0.343	#65	Increase w1 by 90%:	0.492	0.125	0.166	0.216
#29	Increase w3 by 40%:	0.226	0.160	0.340	0.275	#66	Decrease w1 by 90%:	0.026	0.241	0.319	0.414
#30	Decrease w3 by 40%:	0.292	0.207	0.146	0.355	#67	Increase w2 by 90%:	0.207	0.348	0.194	0.252
#31	Increase w4 by 40%:	0.211	0.149	0.198	0.441	#68	Decrease w2 by 90%:	0.311	0.018	0.292	0.379
#32	Decrease w4 by 40%:	0.307	0.217	0.287	0.189	#69	Increase w3 by 90%:	0.184	0.130	0.461	0.224
#33	Increase w1 by 50%:	0.389	0.151	0.200	0.260	#70	Decrease w3 by 90%:	0.334	0.236	0.024	0.406
#34	Decrease w1 by 50%:	0.130	0.215	0.285	0.370	#71	Increase w4 by 90%:	0.152	0.107	0.142	0.599
#35	Increase w2 by 50%:	0.230	0.275	0.216	0.280	#72	Decrease w4 by 90%:	0.366	0.259	0.343	0.032
#36	Decrease w2 by 50%:	0.288	0.092	0.270	0.350						

HRES designs and proactive maintenance practices is needed. Promoting industry standards for safety and reliability to minimize the risks associated with critical failure modes should also be considered.

By deepening the understanding of these prioritized failure modes and offering targeted strategies, this study not only advances the academic discourse on HRES reliability but also provides a practical roadmap for stakeholders to enhance system resilience, operational efficiency, and long-term sustainability.

4.8 Scalability and Future Research Directions

The proposed methodology is inherently scalable to other hybrid systems, such as solar–hydro or wind–battery configurations, as it employs a generalized multi-criteria decision-making framework. By modifying the input parameters to reflect the specific components and interactions of these systems, the approach can effectively prioritize failure modes in diverse hybrid configurations. For larger installations, the

methodology remains applicable with the inclusion of additional criteria or expert inputs to account for the increased complexity and interdependencies. Integrating real-time monitoring data and machine learning techniques represents a promising avenue for future research. Real-time data can enhance the accuracy and timeliness of failure detection, allowing for dynamic updates to risk assessments. Machine learning algorithms can uncover patterns and predict failure probabilities by analyzing historical and real-time data, offering a predictive dimension to failure management. These advancements would complement the existing methodology, enabling proactive and adaptive decision making for HRESs across various scales and configurations.

4.9 Limitations and Ethical Considerations

In this study, ethical considerations have been thoroughly addressed, particularly regarding the environmental impacts of failures and the fairness of expert selection. The environmental impact of failures, such as damage to ecosystems caused by malfunctions in wind turbines or energy storage systems, has been implicitly incorporated into the failure

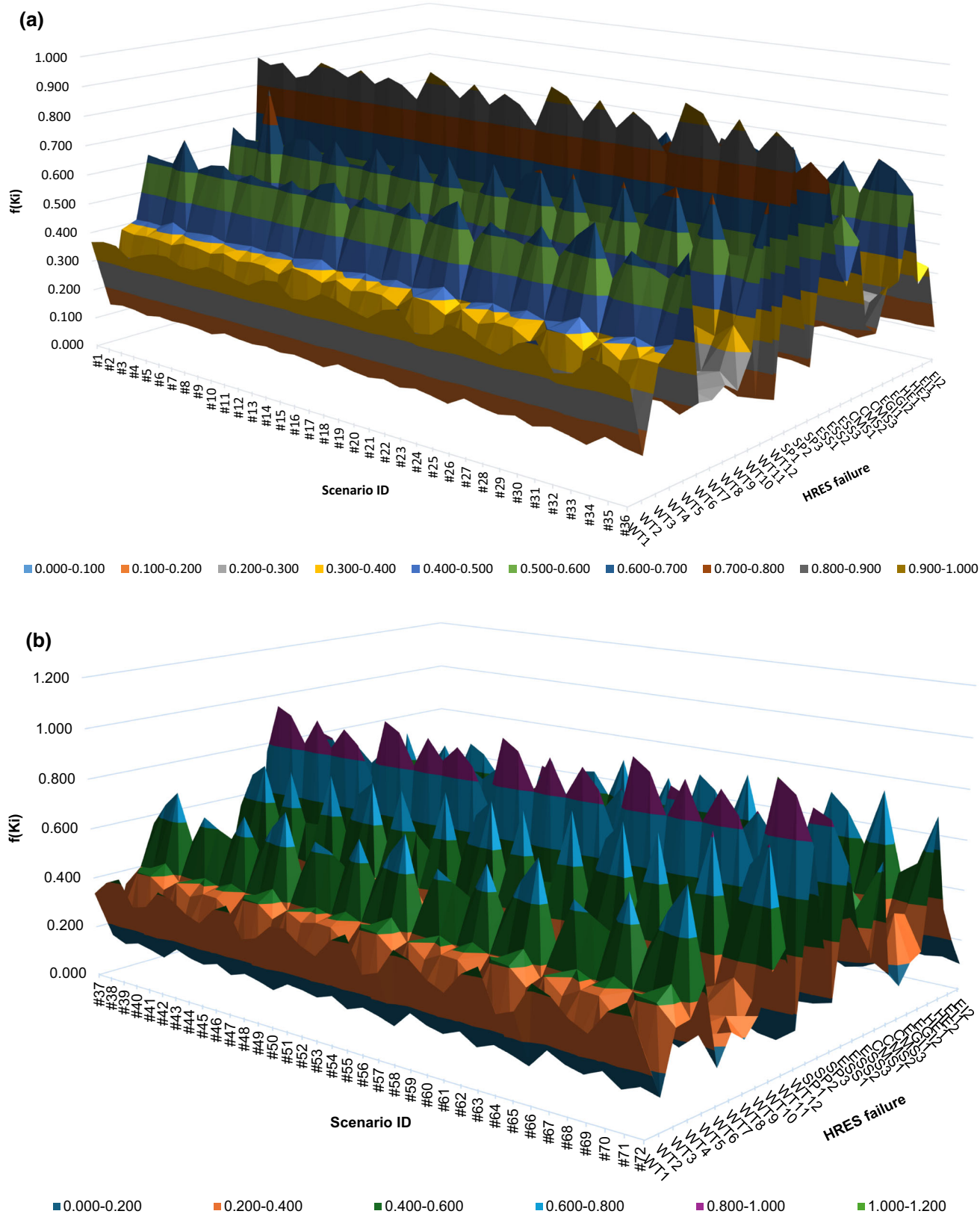


Fig. 10 Results of comparative analysis

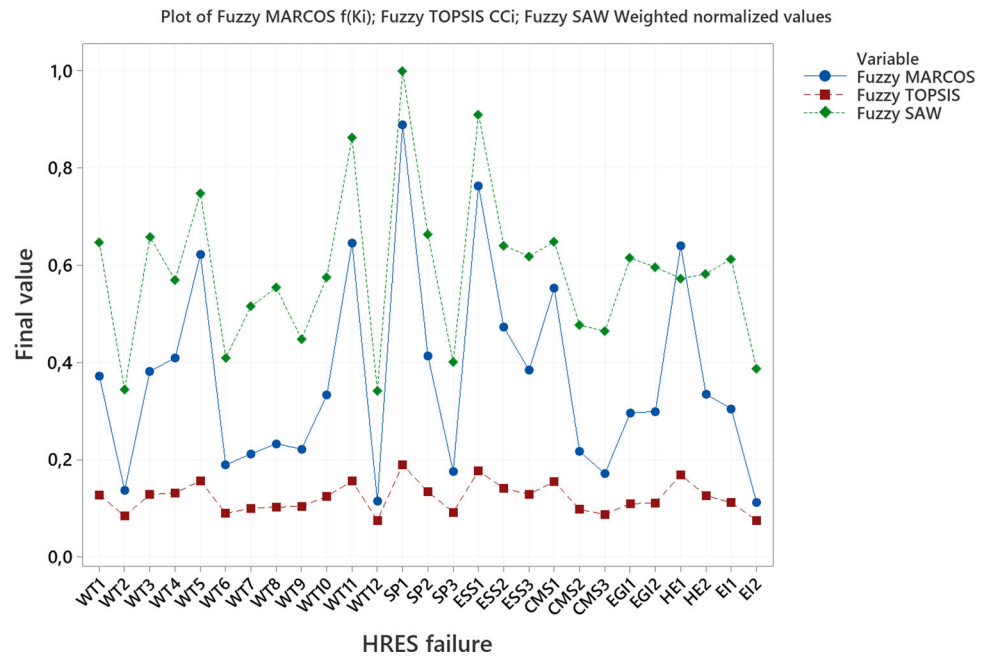
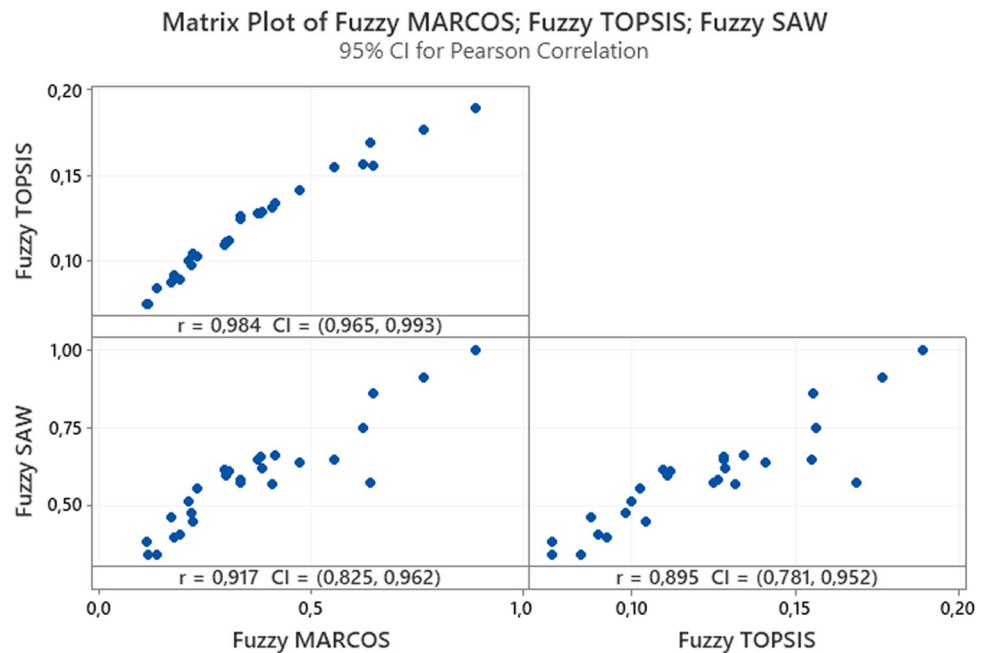


Fig. 11 Results of correlation analysis



analysis framework. By evaluating the environmental sensitivity of each failure mode, we have ensured that the potential ecological consequences of system failures are given due consideration. This approach aligns with the core objective of HRESs, which is sustainability.

Regarding the fairness of expert selection, careful attention was given to selecting experts with diverse backgrounds, including varying industry experience, geographical representation, and areas of expertise. This diversity was critical to ensure a comprehensive and unbiased assessment of failure modes across different contexts. Furthermore, efforts

were made to minimize any potential bias in expert judgments, including the use of consensus-building techniques and consistency checks in the evaluation process. These measures have contributed to the integrity and reliability of the study's results, ensuring that ethical standards were maintained throughout the research.



5 Conclusion

The complex nature of system dependability and failure management in the context of HRES calls for a thorough and systematic approach. To guarantee stable and dependable energy system operations, possible failure modes within HRES must be analyzed and prioritized. This study does this by applying sophisticated fuzzy multi-criteria decision-making (MCDM) techniques. Our investigation has identified and ranked the failure modes of HRES, highlighting that less than half of the identified failures exhibit an $f(K_i)$ value above average, indicating their higher risk and criticality. Specifically, the three most critical failures: SP1 (cell damage), ESS1 (battery degradation), and WT11 (battery fire) were consistently prioritized across different analysis scenarios. These failure modes present significant risks due to their potential to severely disrupt system operations and degrade system performance. In this context, we performed a sensitivity analysis by methodically changing the weights of the four important risk indicators to confirm the validity of our conclusions. This analysis demonstrated that while the overall ranking of failure modes remained largely stable, there were notable shifts in the prioritization of failure modes that ranked in the middle. Crucially, in every scenario, the top three failure modes (SP1, ESS1, and WT11) remained critical, highlighting the need for focused mitigation approaches. Further validation of our results was achieved by applying alternative fuzzy MCDM methods such as fuzzy MARCOS, fuzzy TOPSIS, and fuzzy SAW. The consistency of the rankings produced by these methods, confirmed by high Pearson correlation coefficients (98.4%, 91.7%, and 89.5%), underscores the reliability of our prioritization process. This robust cross-method agreement validates the identified failure modes and their prioritization, lending confidence to the proposed mitigation strategies. Mitigation strategies tailored to the critical failure modes are essential for enhancing the resilience and reliability of HRES. For SP1 (cell damage), the implementation of advanced diagnostic tools and robust maintenance protocols is recommended to detect and mitigate cell failures promptly. For ESS1 (battery degradation), the use of high-quality, durable battery materials and advanced battery management systems is advised to extend battery life and prevent degradation. For WT11 (battery fire), the installation of comprehensive fire detection and suppression systems is essential to mitigate the risk of catastrophic fires. In addition to these specific strategies, the study emphasizes the importance of continuous monitoring and adaptive management to address the dynamic and evolving nature of HRES failures. The integration of real-time monitoring systems, predictive analytics, and preventive maintenance can significantly enhance system reliability and performance.

On the other hand, the results of this study provide system designers and engineers with actionable insights for enhancing the reliability and efficiency of HRES. The prioritization of failure modes, such as SP1 (cell damage), ESS1 (battery degradation), and WT11 (battery fire), highlights critical areas requiring immediate attention. For instance, addressing SP1 involves implementing advanced diagnostic tools and robust maintenance protocols, while ESS1 and WT11 emphasize the need for durable materials, smart battery management systems, and comprehensive fire prevention strategies. These findings guide engineers in focusing on high-impact issues to ensure safer and more resilient system operations.

Furthermore, the sensitivity analysis and cross-method validation underscore the robustness and adaptability of the rankings, demonstrating their relevance across different operational scenarios. For engineers in the field, this means adopting a proactive risk management approach, utilizing real-time monitoring systems, and regularly updating strategies to accommodate evolving system conditions. By leveraging these insights, system designers can make informed decisions to optimize resource allocation, enhance system resilience, and support sustainable energy integration goals. This research thus serves as a practical roadmap for mitigating risks and improving the long-term performance of HRES.

All things considered, this work offers a thorough and organized methodology for locating, evaluating, and ranking HRES failure modes. The results provide significant perspectives and practical suggestions for interested parties seeking to maximize the development, functioning, and upkeep of HRESs. Stakeholders can contribute to the larger objective of sustainable and dependable renewable energy integration by strengthening the resilience and efficiency of HRES through the implementation of the suggested mitigation techniques.

Summary of key findings of this study:

- **Critical Failures Identified:** The top three critical failures are SP1 (cell damage), ESS1 (battery degradation), and WT11 (battery fire), which require immediate and focused mitigation efforts due to their high risk and impact on system operations.
- **Analysis of Sensitivity Confirmation:** Sensitivity analysis was used to verify the robustness of the failure rankings, demonstrating consistency in the important failure modes' prioritizing despite changes in risk parameter weights.
- **Validation Using Alternative Methods:** High correlation coefficients were used to confirm the agreement between various methods, and the use of alternative fuzzy MCDM methods confirmed the consistency and dependability of the prioritized outcomes.



- **Proposed Mitigation Strategies:** Targeted mitigation strategies for each critical failure mode were proposed, emphasizing advanced diagnostics, durable materials, and comprehensive monitoring and management systems.
- **Continuous Improvement:** The study underscores the necessity of continuous monitoring and adaptive management to address evolving failure modes and enhance overall system reliability.

Consequently, this research offers a strategic roadmap for enhancing the resilience and operational efficiency of HRESs, making a substantial contribution to the understanding and management of failure modes in these systems. For stakeholders, the recommendations are an invaluable resource that directs the development and application of strong and efficient risk-reduction and HRES performance-enhancing methods.

Although the study is a guide for the operational efficiency of HRESs, it has some limitations. These issues can be summarized more succinctly as follows. First, the fact that the HRES considered does not consider specific geography and extreme climatic conditions limits the effect of the results obtained. Developments in the wind and solar energy sector may cause the validity of the results to be questioned. Since historical data are not kept systematically and the parameters affecting the system cannot be fully modeled, using entropy-based methods, which are objective assessment methods, is not possible. Validation of the proposed model is a process that requires a lot of resources. All these limitations can be addressed in future studies.

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Declarations

Conflict of interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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