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Picture fuzzy SWARA-based decision framework for critical spare parts identification and inventory cost assessment in renewable energy systems

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Abstract

Spare parts used in renewable energy systems vary considerably in terms of lead times, failure impacts, and production loss risks, making spare parts criticality assessment a complex decision problem. Identifying critical spare parts and evaluating their implications for inventory decisions is essential for ensuring maintenance continuity in wind and solar energy plants. To address this issue, this study proposes an integrated decision-support framework for spare parts management, focusing on determining spare parts criticality and analyzing its economic implications. In the proposed approach, uncertain expert evaluations obtained from maintenance, operation, and purchasing units are modeled using the picture fuzzy set framework, which enables experts to express acceptance, rejection, and hesitation simultaneously. The relative importance of evaluation criteria is determined using the Step-wise Weight Assessment Ratio Analysis (SWARA) method, and spare parts are evaluated according to criteria such as price, lead time, failure frequency, and production loss cost. Subsequently, the Taguchi Loss Function is employed to quantify the economic impact of deviations from target inventory levels. The results indicate that such deviations can lead to considerable economic losses, particularly for highly critical spare parts. By integrating Picture Fuzzy SWARA (PF-SWARA) with the Taguchi loss function, the proposed framework provides a structured and uncertainty-aware tool for spare parts criticality assessment and supports inventory prioritization by offering economically grounded insights.

Keywords: *spare parts management, criticality analysis, picture fuzzy swara, taguchi loss function, inventory prioritization*

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Highlights

- A novel integrated PF-SWARA–Taguchi approach is developed for spare parts analysis.
- Picture fuzzy sets capture uncertainty in expert evaluations.
- Taguchi loss quantifies economic impacts of spare parts inventory decisions.
- The proposed model ranks spare parts according to criticality levels.

1. Introduction

Recent studies indicate that maintenance activities in complex industrial systems have evolved beyond operational processes focused solely on responding to equipment failures and have increasingly become strategic decision-making activities aimed at improving equipment reliability, reducing unplanned downtime, and controlling maintenance costs. This transformation has significantly increased the importance of maintenance management, particularly in energy production facilities where operational continuity is critical [1].

In energy production systems, effective maintenance management plays a key role in ensuring operational continuity and maintaining system reliability. One of the most critical factors influencing maintenance performance is the timely availability of spare parts required during maintenance and repair activities. Previous studies emphasize that spare part availability significantly affects maintenance efficiency and therefore highlight the importance of establishing appropriate inventory control policies for spare parts [2,3].

This issue becomes even more important in renewable energy infrastructures such as wind turbines and solar power plants. Equipment failures in such systems can lead to result in substantial production losses and increased operational costs if maintenance activities are not managed effectively. Renewable energy facilities typically contain spare parts with varying characteristics: some components are relatively inexpensive and easily obtainable, whereas others have long lead times and can cause serious operational disruptions when failures occur. Consequently, identifying the criticality levels of spare parts has become an essential task for maintenance planning and inventory management. Previous studies indicate that classifying spare parts according to their criticality levels improves maintenance efficiency and supports more rational inventory management decisions [4].

Spare parts management and maintenance planning problems generally require the simultaneous evaluation of multiple and often conflicting criteria. For this reason, multi-criteria decision-making (MCDM) methods have been widely applied in spare parts criticality analysis. Existing studies show that classifying spare parts based on their criticality levels in systems with a large number of components and irregular demand patterns can significantly reduce inventory costs while improving operational efficiency [5].

Despite the growing body of literature, many existing studies address spare parts criticality analysis and inventory management separately. In particular, studies integrating uncertain expert evaluations with economic-loss-based inventory decision frameworks remain limited. Spare parts criticality assessment is inherently a complex decision-making process due to the presence of multiple evaluation criteria, a large number of spare parts, and differences in expert judgments [6]. Consequently, the need for integrated decision-support approaches that combine expert knowledge, uncertainty modeling, and economic evaluation has been emphasized in the literature [7,8].

In energy production facilities, maintenance and spare parts management decisions rely not only on quantitative operational data but also on expert knowledge and experience. Such decision environments often involve uncertainty and hesitation in expert evaluations. However, many existing studies do not adequately consider this uncertainty embedded in expert judgments [7].

To address this limitation, this study adopts the picture fuzzy approach to represent uncertain and hesitant expert evaluations more effectively. Picture fuzzy sets (PFSs), first introduced by Cuong and Kreinovich [9], allow expert opinions to be expressed through three independent components—positive membership, negative membership, and neutral (hesitation) degrees—thereby providing a richer representation of uncertainty compared with traditional fuzzy approaches. Unlike classical fuzzy and intuitionistic fuzzy sets [10,11], PFSs enable decision experts to simultaneously express acceptance, rejection, and hesitation levels in their evaluations, allowing more realistic modeling of complex decision environments. Applications of picture fuzzy approaches in recent studies further demonstrate their effectiveness in handling uncertainty in complex decision-making problems [12,13].

Another critical aspect of spare parts criticality analysis is determining the relative importance of evaluation criteria. The reliability of the results largely depends on how effectively these criteria weights reflect expert judgments. In this study, the Step-wise Weight Assessment Ratio Analysis (SWARA) method is used to determine criteria weights based on expert evaluations. SWARA is widely applied in MCDM problems due to its ability to incorporate expert knowledge directly into the weighting process and systematically determine the relative importance of criteria [13].

Beyond ranking spare parts according to their criticality, decision experts must also evaluate the economic consequences of inventory decisions. The absence of critical spare parts leads to severe production losses and increased maintenance costs, whereas excessive inventory levels create significant capital costs for organizations [2,8]. Therefore, spare parts criticality analysis should be evaluated together with its economic implications.

To capture these economic effects, Taguchi loss functions are employed in this study to quantify the losses associated with deviations from desired spare part performance levels. The Taguchi Approach enables the economic consequences of performance deviations to be expressed quantitatively and supports the interpretation of spare parts criticality results in terms of their cost implications for inventory management decisions. Based on this perspective, this study proposes an integrated decision-support framework that combines the Picture Fuzzy SWARA (PF-SWARA) method with Taguchi loss functions to evaluate spare parts criticality in renewable energy production systems under uncertain expert evaluations, with the aim of supporting inventory prioritization decisions through economic loss-based insights.

Although SWARA-based weighting methods and Taguchi loss functions have been widely used in the literature, they are generally applied independently. However, real-world decision-making problems, particularly in spare parts management, require the simultaneous consideration of uncertainty in expert evaluations and the economic consequences of performance deviations.

In this context, the integration of PF-SWARA and the Taguchi loss function provides a distinct methodological advantage. Specifically, the proposed framework enables the systematic incorporation of uncertainty-aware criteria weights into economic loss evaluation, allowing the effects of expert uncertainty to be directly reflected in cost-based analysis. This integrated structure offers a more realistic and operationally meaningful assessment of spare parts criticality compared to approaches that treat these aspects separately.

Therefore, the proposed approach establishes a direct link between uncertainty modeling and cost-based evaluation, providing a more comprehensive and practically relevant decision-support framework.

The main contributions of this study can be summarized as follows:

1. A picture fuzzy-based decision framework is developed for spare parts criticality assessment, enabling uncertain and hesitant expert evaluations to be represented more realistically.
2. The SWARA method is employed within the picture fuzzy environment to determine the relative importance of evaluation criteria based on expert judgments.
3. The Taguchi loss function is incorporated to quantify the economic consequences of deviations in spare parts performance and inventory levels.
4. An integrated decision-support framework is proposed that links spare parts criticality evaluation with economically oriented inventory management decisions by translating criticality results into actionable implications for inventory prioritization.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on spare parts criticality analysis and inventory management. Section 3 presents the proposed methodology, including the PF-SWARA approach and the Taguchi loss functions. Section 4 describes the application of the proposed framework to spare parts criticality analysis in renewable energy production systems and includes the sensitivity analysis to examine the robustness of the obtained results. Finally, Section 5 concludes the study and outlines potential directions for future research.

2. Literature review

Spare parts management constitutes an important research area for sustaining maintenance planning, operational continuity, and reliability in production systems. In industries that require uninterrupted operations such as energy production facilities, manufacturing lines, and aviation, equipment failures lead to significant downtime and considerable economic losses. Therefore, identifying critical spare parts and developing appropriate inventory management policies for these components has become a fundamental element of maintenance and operations management.

Spare parts inventory management has long been a subject of research in the literature and is often considered a complex decision problem due to factors such as the uncertainty of spare parts demand, the stochastic nature of equipment failures, and the high costs associated with maintaining inventory. Kennedy et al. [2], in their comprehensive study on spare parts inventory systems, emphasized that spare parts demand is often irregular and that high service level requirements cause these systems to differ significantly from traditional inventory models. Similarly, Bacchetti and Saccani [7], in their extensive literature review, highlighted that demand forecasting, classification, and inventory control policies represent the major research areas in spare parts management. In a more recent study, Hu et al. [14] examined the use of operations research methods in spare parts management and noted that MCDM approaches have become an important research direction in this field.

One of the major research areas in spare parts management is spare parts criticality analysis. Since spare parts have different levels of impact on production systems, identifying critical components represents an important decision problem for maintenance planning and inventory management. Roda et al. [8], in their comprehensive literature review, identified factors such as stock-out cost, part price, lead time, demand volume, and part specificity as the most frequently used criteria in spare parts criticality analysis. Their study also indicated that certain discrepancies exist between academic models and industrial applications, particularly due to challenges related to data uncertainty, computational complexity, and subjective evaluations.

It is widely observed that MCDM methods are frequently employed in spare parts criticality analysis. Molenaers et al. [4] proposed an approach combining the Analytic Hierarchy Process (AHP) and decision diagrams to classify spare parts according to their criticality levels. In their study, criteria such as equipment criticality level, failure probability, lead time, supplier availability, and maintenance type were considered to categorize spare parts into different criticality groups. Similarly, Teixeira et al. [15] developed a multi-criteria framework for spare parts criticality analysis that can be integrated into computerized maintenance management systems. In their study, a general criticality index was established by jointly evaluating factors such as the impact of failures on production, safety and environmental risks, and logistical considerations.

Another notable study focusing on industrial applications was conducted by Stoll et al. [16]. In their work, a multi-criteria classification approach was developed to support centralized spare parts warehouse strategies in multi-facility production networks. The study combined ABC, XYZ, and VED analyses with the AHP to determine spare parts criticality levels and to propose appropriate inventory strategies for different spare parts categories. This approach demonstrated that spare parts criticality analysis should not be evaluated solely based on technical criteria but also considering logistical and cost-related dimensions.

In the aviation sector, spare parts criticality analysis has also been recognized as an important tool for maintaining operational continuity. Ayu Nariswari et al. [17] developed an AHP-based model to classify spare parts used in aircraft maintenance and repair organizations. Their study considered criteria such as operational criticality, technical characteristics, and supply attributes, and the results were reported to be highly consistent with existing classification systems. Similarly, Antosz and Ratnayake [18] proposed an AHP-based evaluation approach supported by risk analysis for prioritizing spare parts used in manufacturing systems.

Hybrid approaches that combine different MCDM techniques have also been proposed in the literature. Jajimoggala et al. [19] proposed a hybrid decision model combining Fuzzy ANP and TOPSIS methods for spare parts criticality analysis. Since many of the criteria used in spare parts criticality assessment rely on expert judgments, uncertainty and hesitation frequently arise in decision-making processes. Therefore, fuzzy logic-based approaches are widely used in the literature to model uncertainty in expert evaluations. In this context, Duran [6] developed a spare parts criticality evaluation model based on Fuzzy AHP using triangular fuzzy numbers. More recently, Sugahyer et al. [20] employed DEMATEL and AHP methods together to evaluate the criticality of spare parts used in fire and rescue vessels. In their study, DEMATEL was used to identify causal relationships among criteria, while AHP was applied to determine criteria weights and rank spare parts according to their criticality levels.

Spare parts criticality analysis is not limited to prioritizing spare parts; it is also directly associated with inventory management and related costs. Sudjatmiko and Sahroni [21] proposed a model integrating equipment criticality analysis with spare parts evaluation in order to determine appropriate safety stock levels. Their study demonstrated that factors such as lead time, service level targets, and acceptable equipment downtime are key determinants in safety stock level determination. Similarly, the SPR-C&EV method developed by Contreras et al. [22] evaluates spare parts by considering both criticality levels and economic value criteria, allowing spare parts to be categorized into different priority levels.

In recent years, spare parts criticality analysis has increasingly been considered together with inventory management and economic cost evaluations. Ilgin [23] proposed an integrated approach combining Fuzzy AHP, a simulation model, and Taguchi loss functions to evaluate economic losses resulting from deviations in spare parts performance levels. More recently, Faryani et al. [5] classified spare parts of a CO_2 compressor using a multi-criteria analysis method and conducted demand forecasting-based inventory planning for high-priority components. The results demonstrated that forecast-based inventory planning can significantly improve inventory cost performance.

When the studies in the literature are examined, it can be observed that spare parts criticality analysis is predominantly conducted using MCDM approaches. However, most existing studies focus either on criticality assessment or on inventory cost analysis separately. Studies that simultaneously integrate uncertainty modeling in expert evaluations with economic loss-based inventory assessments remain limited. This situation highlights the need for approaches that jointly consider uncertainty modeling techniques and cost-oriented inventory evaluation within spare parts criticality analysis.

2.1. Research gap

Table 1 presents a comparative overview of studies conducted in the field of spare parts criticality analysis and inventory management. As observed in the literature, most studies focus on identifying and prioritizing spare parts based on their criticality levels using MCDM approaches such as AHP, DEMATEL, and various hybrid approaches [4,15–20]. However, these studies generally concentrate on criticality classification and rarely integrate criticality assessment with the economic evaluation of inventory-related consequences.

Another limitation of the existing literature is the insufficient consideration of uncertainty in expert evaluations. Although several studies employ fuzzy logic-based approaches, classical fuzzy models are limited in their ability to fully capture hesitation and ambiguity in expert judgments. In this context, picture fuzzy sets (PFSs) provide a more flexible representation of uncertainty [9,12,13].

Consequently, there is a need for integrated decision-support approaches that simultaneously address spare parts criticality assessment, uncertainty in expert evaluations, and the economic implications of inventory decisions. To fill this research gap, this study develops an integrated framework that models expert uncertainty using PFSs, determines criteria weights through the SWARA method, and evaluates the economic impacts of spare parts performance using Taguchi loss functions.

Table 1. Comparative overview of related studies.

References	Method / Approach	Sector / Application Area	Criticality Analysis	Inventory Cost Analysis	Uncertainty Modelling
Jajimoggala et al. [19]	Fuzzy ANP + TOPSIS	Steel manufacturing	✓	✗	✓
Molenaers et al. [4]	AHP + Decision Diagram	Petrochemical industry	✓	✗	✗
Duran [6]	Fuzzy AHP	Manufacturing	✓	✗	✓
Stoll et al. [16]	AHP + Decision Tree (ABC/XYZ/VED)	Automotive manufacturing	✓	✓	✗
Sudjatmiko and Sahroni [21]	Criticality-based safety stock model	Manufacturing	✓	✓	✗
Sughayer et al. [20]	DEMATEL + AHP hybrid approach	Maritime rescue vessels	✓	✗	✗
Teixeira et al. [15]	Multi-criteria framework integrated with CMMS	Maintenance management systems	✓	✗	✗
Antosz and Ratnayake [18]	Risk analysis + AHP	Manufacturing systems	✓	✗	✗
Ayu Nariswari et al. [17]	AHP-based classification model	Aviation maintenance	✓	✗	✗
Ilgin [23]	Fuzzy AHP + Simulation + Taguchi loss function	Manufacturing	✓	✓	✓
Contreras et al. [22]	SPR-C&EV classification method	Industrial systems	✓	✓	✗
Faryani et al. [5]	MCDM + demand forecasting	Petrochemical industry	✓	✓	✗
This Study	**PF-SWARA + Taguchi Loss Function**	**Renewable energy systems**	**✓**	**✓**	**✓**

3. Methodology

This study proposes an integrated decision framework to determine the criticality levels of spare parts and evaluate their corresponding inventory cost implications in renewable energy systems. The proposed methodology consists of two main stages that combine a MCDM approach with a cost-based optimization perspective.

In the first stage, the PF-SWARA method is employed to determine the relative importance weights of the evaluation criteria. Considering that expert assessments inherently involve uncertainty and hesitation, PFSs are used to represent expert judgments through membership, non-membership, and neutrality degrees. Expert evaluations expressed with picture fuzzy linguistic terms are first aggregated and then processed through the SWARA procedure to obtain the final weights of the criteria. This stage allows the identification of the relative criticality structure of spare parts based on expert knowledge.

In the second stage, the Taguchi loss function is used to analyze the inventory cost implications of deviations from target stock levels. The Taguchi approach enables quantifying the quality loss arising from inventory deviations and provides a systematic way to evaluate the economic impact of different stock-level decisions.

By integrating the results from the PF-SWARA weighting process with the Taguchi loss-based cost analysis, the proposed framework supports the evaluation of spare parts criticality together with their economic implications and provides a basis for inventory prioritization decisions. The overall research framework of the proposed methodology is illustrated in Figure 1, and the detailed mathematical formulations for each stage are presented in the following subsections.

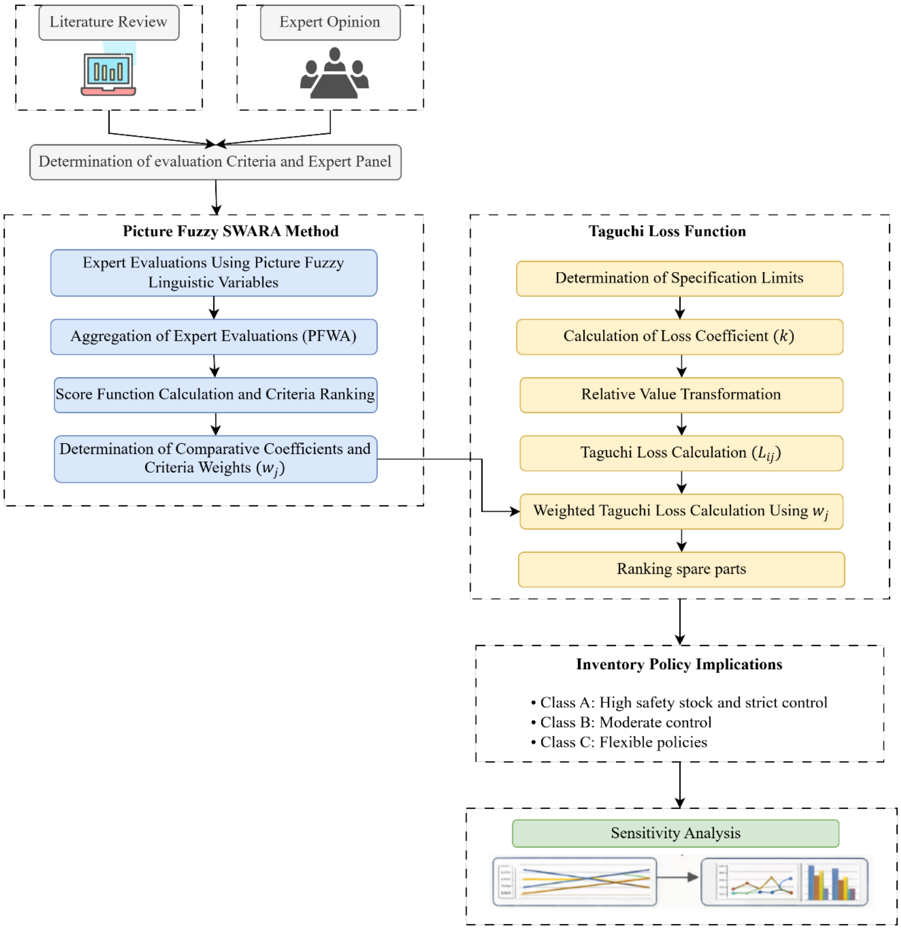

Figure 1. Framework of the proposed methodology

3.1. Picture fuzzy sets

Definition 1 [12]: Let U be a universal set. A PFS A defined on U can be expressed as follows:

$$A = \{(u, \mu_A(u), I_A(u), v_A(u)) \mid \; u \in U\} \tag{1}$$

In a PFS A defined on the universe U, each element $u \in U$ is described by three independent parameters: the positive membership degree $\mu_A(u)$, the neutral (indeterminacy) degree $I_A(u)$, and the non-membership degree $v_A(u)$. These parameters take values within the interval [0,1]. To ensure the consistency of the representation, the sum of these three degrees must satisfy the condition $0 \leq \mu_A(u) + I_A(u) + v_A(u) \leq 1$ for every element u. The remaining portion of the unit interval corresponds to the refusal degree, which is defined as $\pi_A(u) = 1 - (\mu_A(u) + I_A(u) + v_A(u))$.

Definition 2 [12]: Let A and B be two PFSs. The basic operations between these sets are defined as follows:

$$A \oplus B \; = \{\mu_A + \mu_B - \mu_A\mu_B, I_A I_B, v_A v_B\} \tag{2}$$

$$A \otimes B \; = \{\mu_A\mu_B, I_A I_B, v_A + v_B - v_A v_B\} \tag{3}$$

$$\lambda A \; = \{(1 - (1 - \mu_A)^\lambda), I_A^\lambda, v_A^\lambda\} \quad \lambda > 0 \tag{4}$$

$$A^\lambda \; = \{\mu_A^\lambda, I_A^\lambda, (1 - (1 - v_A)^\lambda)\} \quad \lambda > 0 \tag{5}$$

Definition 3 [24]: Picture fuzzy numbers (PFNs) obtained from different criteria or experts must be aggregated in order to derive a single representative evaluation. For this purpose, weighted aggregation operators can be employed. Among the commonly used operators in picture fuzzy environments are the

Picture Fuzzy Weighted Geometric (PFWG) operator and the Picture Fuzzy Weighted Averaging (PFWA) operator.

Let $w = (w_1, w_2, \ldots., w_n)$ denote the weight vector associated with the evaluation criteria, where $w_j \in [0,1]$ and $\sum_{j=1}^{n} w_j = 1$. These operators combine the membership, non-membership, and indeterminacy degrees of PFNs while considering the relative importance of each criterion in the aggregation process.

The PFWG operator is defined as:

$$PFWG_w(A_1, \ldots \ldots, A_n) = \left\{\prod_{j=1}^{n} \mu_{A_j}^{w_j}, \prod_{j=1}^{n} I_{A_j}^{w_j}, 1 - \prod_{j=1}^{n} (1 - v_{A_j})^{w_j}\right\} \quad (6)$$

Similarly, the PFWA operator can be expressed as:

$$PFWA_w(A_1, \ldots \ldots, A_n) = \left\{1 - \prod_{j=1}^{n} \left(1 - \mu_{A_j}\right)^{w_j}, \prod_{j=1}^{n} I_{A_j}^{w_j}, \prod_{j=1}^{n} v_{A_j}^{w_j}\right\} \quad (7)$$

These aggregation operators allow multiple picture fuzzy evaluations to be combined into a single PFN while preserving the influence of the associated criterion weights.

Definition 4 [24]: For decision-making applications, PFNs must be converted into scalar values in order to enable comparison and ranking of alternatives. This transformation is generally performed using score functions and accuracy functions, which provide crisp numerical measures representing the relative preference of PFNs.

The score functions used to evaluate the relative desirability of PFNs can be defined as follows:

$$SC_1 = Score_1(\mathrm{A}) = \frac{1}{2}\left(1 + 2\mu_{\mathrm{A}} - v_{\mathrm{A}} - \frac{I_{\mathrm{A}}}{2}\right) \quad (8)$$

$$SC_2 = Score_2(\mathrm{A}) = \left(2\mu_{\mathrm{A}} - v_{\mathrm{A}} - \frac{I_{\mathrm{A}}}{2}\right) \quad (9)$$

$$SC_3 = Score_3(\mathrm{A}) = (\mu_{\mathrm{A}} - v_{\mathrm{A}}) \quad (10)$$

In addition to the score functions, an accuracy function can be used to further discriminate between PFNs that have identical score values. The accuracy function is calculated as:

$$Accuracy(\mathrm{A}) = \mu_{\mathrm{A}} + v_{\mathrm{A}} + I_{\mathrm{A}} \quad (11)$$

Based on these measures, the ranking of two PFNs A and B is determined as follows:

$\widetilde{A_p} < \widetilde{B_p}$ if and only if

$$Score(\mathrm{A}) < Score(\mathrm{B}), \text{ or} \quad (12)$$

$$Score(\mathrm{A}) = Score(\mathrm{B}) \text{ and } Accuracy(\mathrm{A}) < Accuracy(\mathrm{B}) \quad (13)$$

3.2. Picture fuzzy SWARA (PF-SWARA)

SWARA is a MCDM method proposed by Keršulienė et al. [25] to determine the weights of criteria based on expert judgments. In this method, experts first rank the criteria according to their perceived importance and subsequently determine the relative importance differences through sequential comparisons. A notable advantage of the SWARA method is that expert opinions are directly incorporated into the weighting process while requiring fewer pairwise comparisons than many traditional weighting approaches.

However, expert evaluations in MCDM problems often involve uncertainty and hesitation. To better represent such situations, PFSs are employed. PFSs enable a more comprehensive representation of experts' assessments by simultaneously considering the degrees of membership, non-membership, and neutrality.

In this study, the PF-SWARA approach is adopted to determine the criterion weights. This approach integrates the stepwise weighting structure of the SWARA method with the uncertainty modeling capability of PFNs. Accordingly, expert evaluations are expressed using picture fuzzy linguistic variables and aggregated before applying the SWARA procedure to obtain the final weights of the criteria. The application steps of the PF-SWARA method are presented below [13].

Step 1. Experts evaluate each criterion using predefined linguistic terms presented in Table 2. These linguistic assessments are then expressed as PFNs to represent the membership, neutrality, and non-membership degrees associated with each evaluation.

Table 2. Linguistic scale and corresponding PFNs used for expert evaluations [13].

Linguistic Variables	**PFNs (μ, I, v)**
Very Low (VL)	(0.05, 0.45, 0.50)
Low (L)	(0.10, 0.40, 0.45)
Medium-Low (ML)	(0.15, 0.35, 0.40)
Medium (M)	(0.30, 0.35, 0.35)
Medium-High (MH)	(0.40, 0.20, 0.15)
High (H)	(0.45, 0.15, 0.10)
Very High (VH)	(0.50, 0.10, 0.05)

Step 2. The picture fuzzy evaluations obtained from the experts are aggregated using the PFWA operator to obtain the collective assessment of each criterion.

Step 3. The aggregated PFN of each criterion is transformed into a crisp score value for ordering purposes. The score function is calculated as:

$$S_j' = \frac{\mu_j + I_j - v_j + 1}{2} \quad (14)$$

Where μ_j, I_j, v_j represent the components of the aggregated PFN of criterion j.

Step 4. Criteria are ranked from the most important to the least important according to their score values.

Step 5. The difference between the scores of consecutive criteria is used to determine the relative importance of each criterion.

Step 6. Based on these differences, the comparative coefficients are computed as:

$$k_j = \begin{cases} 1 & j = 1 \\ S_j + 1 & j > 1 \end{cases} \tag{15}$$

Step 7: The recalculated weight values are obtained as:

$$q_j = \begin{Bmatrix} 1 & j = 1 \\ \frac{q_{j-1}}{k_j} & j > 1 \end{Bmatrix} \tag{16}$$

Step 8: Finally, the normalized weights of the criteria are calculated as:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{17}$$

where n denotes the number of criteria.

3.3. Taguchi loss function

The Taguchi loss function approach is an important quality engineering method developed to quantitatively express the economic losses that arise when the performance of a product or system deviates from its target value. Unlike traditional quality perspectives that consider performance acceptable as long as it remains within specification limits, the Taguchi approach assumes that any deviation from the target value results in a quality loss. Accordingly, the economic loss associated with the system increases as the performance characteristic moves further away from its target value [26].

Within the Taguchi framework, performance characteristics are generally categorized into three types: Lower-is-Better (LB), Higher-is-Better (HB), and Nominal-is-Best (NB). For LB criteria, smaller values are preferred, whereas HB criteria aim to maximize the performance measure. In the NB case, the objective is to achieve a value as close as possible to a predefined target. The evaluation process based on the Taguchi loss function consists of the following steps [27,28]:

Step 1: Determination of Specification Limits

In order to apply the Taguchi loss function, specification limits must first be determined for each evaluation criterion. These limits represent the acceptable performance boundary for the related criterion and serve as reference values in the loss calculations.

Step 2. Calculation of Loss Coefficients

After determining the specification limits, the loss coefficient for each criterion is calculated. The Taguchi loss coefficient is obtained using Eq. (18).

$$k = \frac{A}{\Delta^2} \tag{18}$$

where k represents the loss coefficient, A denotes the acceptable loss when the specification limit is reached, and Δ represents the tolerance interval between the target value and the specification limit.

For criteria with different performance characteristics, the tolerance interval is defined to Eq. (19).

$$\Delta = \begin{cases} 1 - SL, & \text{for HB} - \text{type criteria} \\ SL, & \text{for LB} - \text{type criteria} \end{cases} \tag{19}$$

where SL represents the specification limit defined for the corresponding criterion.

Step 3. Relative Value Transformation

Since the criteria are expressed in different measurement units, a Relative Value (RV) transformation is applied to ensure comparability among criteria.

For LB criteria, the RV is calculated using Eq. (20).

$$RV_{ij} = \left(\frac{x_{ij} - x_j^{min}}{x_j^{min}}\right) \times 100 \tag{20}$$

where x_{ij} represents the observed value of alternative i with respect to criterion j, and x_j^{min} denotes the minimum value among all alternatives for criterion j. This formulation reflects the relative deviation of each alternative from the best (minimum) observed value.

For HB criteria, the RV is obtained using Eq. (21).

$$RV_{ij} = \frac{x_{ij}}{x_j^{max}} \times 100 \tag{21}$$

where x_j^{max} denotes the maximum observed value for criterion j. In this case, larger observed values yield higher relative values, preserving the preference structure of HB-type criteria.

Step 4. Calculation of Taguchi Loss Values

After obtaining the relative values, Taguchi loss values are calculated for each criterion. For LB criteria, the loss value is computed using Eq. (22).

$$L_{ij} = k_j y_{ij}^2 \tag{22}$$

where L_{ij} represents the Taguchi loss value of alternative i with respect to criterion j, y_{ij} denotes the calculated relative value for that criterion, and k_j is the loss coefficient associated with criterion j.

For HB criteria, the loss value is calculated according to Eq. (23).

$$L_{ij} = k_j \frac{1}{y_{ij}^2} \tag{23}$$

Step 5: Weighted Taguchi Loss Calculation

In the final stage, the Taguchi loss values are weighted according to the relative importance of the criteria in order to incorporate the significance of each criterion into the evaluation process. The weighted loss value is calculated as:

$$WL_{ij} = w_j L_{ij} \tag{24}$$

where WL_{ij} represents the weighted loss value of alternative i for criterion j and w_j denotes the weight of criterion j.

Finally, the total loss value for each alternative is obtained by summing the weighted losses across all criteria:

$$TL_i = \sum_{j=1}^{n} WL_{ij} \tag{25}$$

where TL_i denotes the total loss value associated with alternative i.

4. Case study: criticality analysis of spare parts in the energy sector

In this section, an application is conducted on spare parts used in the energy sector in order to demonstrate the applicability of the proposed PF-SWARA–Taguchi integrated approach. The proposed framework consists of two main stages. In the first stage, the PF-SWARA method is employed to determine the weights of the criteria used in the spare part criticality analysis. In the second stage, the Taguchi loss function is applied to evaluate the economic impacts of deviations in stock levels and to determine appropriate inventory levels for critical spare parts.

The evaluation criteria used in the study were determined based on a comprehensive literature review and the opinions of experts with experience in maintenance and spare parts management in the energy sector. In this context, criteria frequently used in spare part criticality analysis in the literature were examined, and a set of criteria was established by considering the technical, operational, and economic factors affecting spare parts management in energy production facilities.

Accordingly, a total of ten criteria were identified: price, demand quantity, lead time, number of suppliers, failure frequency, maintenance plan, critical equipment impact, production loss cost, supplier distance, and repair time. These criteria were selected to comprehensively evaluate the operational importance of spare parts used in energy production facilities and their impacts on inventory management decisions. The criteria used in the study are presented in Table 3.

Table 3. Evaluation criteria used in the spare part criticality analysis.

Code	Criteria	Description	References
C1	Price	Acquisition cost of the spare part affecting inventory investment	[8,15]
C2	Demand Quantity	Frequency of spare part usage in maintenance operations	[8,15]
C3	Lead Time	Time required to procure the spare part from suppliers	[4,8]
C4	Number of Suppliers	Availability of alternative suppliers for procurement	[4,15]
C5	Failure Frequency	Frequency of component failure requiring replacement	[15,17]
C6	Maintenance Plan	Whether the spare part is included in preventive maintenance plans	[4,18]
C7	Critical Equipment Impact	Impact of component failure on critical equipment operation	[15,21]
C8	Production Loss Cost	Economic loss caused by production downtime	[8]
C9	Supplier Distance	Distance between supplier and facility affecting logistics	[15]
C10	Repair Time	Time required to restore equipment after replacement	[18]

The evaluations used in this study were obtained from experts with professional experience in maintenance management, spare parts planning, and inventory management in the energy sector. Expert selection was based on criteria such as years of industry experience, technical expertise, and involvement in maintenance-related decision-making processes. Accordingly, three experts working in energy production facilities with substantial experience in maintenance planning and spare parts management were included in the study.

The experts evaluated the identified criteria using linguistic assessments. To incorporate the relative importance of expert judgments, expert weights were determined within the picture fuzzy framework. Each expert's importance was represented by PFNs reflecting their expertise levels, following [13]. Accordingly, the representations were defined as {(0.56,0.12,0.20), (0.47,0.33,0.10), (0.62,0.15,0.23)}, ensuring consistency with picture fuzzy constraints and capturing differences in expert knowledge. These values were then defuzzified using the score function given in Eq. (14) and normalized to obtain the final expert weights. Accordingly, the normalized weights were calculated as 0.314, 0.360, and 0.326, respectively.

4.1. Weighting of criteria using PF-SWARA

In this stage, the weights of the criteria used in the spare part criticality analysis were determined using the PF-SWARA method. Within the PF-SWARA framework, experts first evaluated the identified criteria according to their relative importance by using the linguistic variables defined in Table 2.

Based on the assessments provided by the experts, a picture fuzzy decision matrix was constructed. This matrix represents the linguistic evaluations of the experts regarding the importance levels of the criteria. The resulting picture fuzzy decision matrix obtained from expert evaluations is presented in Table 4.

Table 4. Picture fuzzy decision matrix based on expert evaluations.

Criteria	Expert 1	Expert 2	Expert 3
C1	VH	MH	M
C2	M	ML	L
C3	VH	VH	MH
C4	M	VL	ML
C5	VH	H	H
C6	M	M	MH
C7	H	MH	M
C8	VH	H	MH
C9	MH	ML	ML
C10	ML	L	VL

Table 5. Aggregated picture fuzzy decision matrix for the criteria.

Criteria	μ	I	ν
C1	0.4042	0.1931	0.1400
C2	0.1852	0.3656	0.3986
C3	0.4694	0.1254	0.0715
C4	0.1676	0.3831	0.4157
C5	0.4662	0.1321	0.0804
C6	0.3343	0.2916	0.2655
C7	0.3861	0.2193	0.1741
C8	0.4509	0.1451	0.0918
C9	0.2895	0.2936	0.2802
C10	0.1003	0.3986	0.4488

To represent the picture fuzzy evaluations obtained from the experts under a single collective value, a PFWA aggregation operator was employed. At this stage, the PFNs obtained from each expert for every criterion were aggregated by considering the predefined expert weights. As a result of this aggregation process, aggregated PFNs were obtained for each criterion. The obtained aggregated PFN values constitute the main input for the subsequent analysis used to determine the relative importance levels of the criteria. The aggregated PFN values are presented in Table 5.

For C1 criteria the aggregated values of μ, I, and ν was calculated as:

$$\mu = 1 - [(1-0.5)^{0.314} \times (1-0.4)^{0.36} \times (1-0.3)^{0.326}]$$

$$\mu = 0.4042$$

$$I = [(0.10)^{0.314} \times (0.20)^{0.36} \times (0.35)^{0.326}]$$

$$I = 0.1931$$

$$\nu = [(0.05)^{0.314} \times (0.15)^{0.36} \times (0.35)^{0.326}]$$

$$\nu = 0.1400$$

To convert the aggregated PFNs obtained from picture fuzzy evaluations into a single comparable measure, a score function was applied in the analysis. Through this function, a scalar score value was calculated for each criterion using Eq. (14), enabling the comparison of their relative importance levels. For instance, the score value for criterion C1 is calculated as follows:

Score(C1) = (0.4042 + 0.1931 − 0.1400 + 1) / 2 = 0.7286

Criteria with higher score values were considered more important. Accordingly, the criteria were ranked based on their score values and rearranged according to their relative importance levels prior to the application of the SWARA method. The ranking results along with the corresponding score values are presented in Table 6.

Table 6. Importance ranking of criteria based on score values.

Rank	Criteria	Score Value
1	Lead Time (C3)	0.7616
2	Failure Frequency (C5)	0.7589
3	Production Loss Cost (C8)	0.7521
4	Price (C1)	0.7286
5	Critical Equipment Impact (C7)	0.7156
6	Maintenance Plan (C6)	0.6802
7	Supplier Distance (C9)	0.6515
8	Demand Quantity (C2)	0.5761
9	Number of Suppliers (C4)	0.5675
10	Repair Time (C10)	0.5250

After determining the importance ranking of the criteria, the SWARA method was applied to calculate the final weights of the criteria. In this stage, the criteria were arranged according to their importance levels. Subsequently, the comparative importance coefficient (s_j), the recalculated coefficient (k_j), the recalculated weight (q_j), and the final weight of each criterion (w_j) were determined following the SWARA procedure. The comparative coefficients were calculated according to Eq. (15), after which the recalculated weights were obtained using Eq. (16). Finally, the normalized weights of the criteria were computed based on Eq. (17). The resulting criterion weights are presented in Table 7.

Table 7. Final criteria weights obtained using the SWARA method.

Criteria	s_j	k_j	q_j	w_j
C3	0.0000	1.0000	1.0000	0.1089
C5	0.0027	1.0027	0.9973	0.1086
C8	0.0069	1.0069	0.9905	0.1078
C1	0.0234	1.0234	0.9678	0.1054
C7	0.0130	1.0130	0.9555	0.1040
C6	0.0354	1.0354	0.9227	0.1005
C9	0.0287	1.0287	0.8970	0.0977
C2	0.0754	1.0754	0.8341	0.0908
C4	0.0086	1.0086	0.8270	0.0900
C10	0.0425	1.0425	0.7933	0.0864

To enhance the transparency of the SWARA procedure, a sample calculation is presented for the second-ranked criterion (C5). Based on the ranking obtained from the score values, the comparative importance coefficient is calculated as:

$s_2 = (0.7616 - 0.7589) = 0.0027$

Then, the recalculated coefficient is determined as:

$k_2 = 0.0027 + 1 = 1.0027$

Next, the recalculated weight is obtained using:

$q_2 = q_1 / k_2 = 1 / 1.0027 = 0.9973$

Finally, the normalized weight is computed as:

$w_2 = q_2 / \sum_{k=1}^{n} q_k = 0.9973 / 9.1852 = 0.1086$

When the criterion weights obtained through the SWARA method are examined, it can be observed that the factors directly affecting operational continuity in spare parts criticality analysis have higher importance levels. In particular, the fact that the criteria of lead time, failure frequency, and production loss cost have the highest weights indicates that the rapid resolution of equipment failures and the timely supply of critical spare parts are of vital importance for maintaining production continuity in energy generation facilities.

In contrast, criteria such as repair time, number of suppliers, and demand quantity were found to have relatively lower importance levels. This situation can be attributed to the availability of alternative supply options for certain spare parts in the energy sector or by the possibility of managing failures within scheduled maintenance plans.

The criterion weights obtained were used as key inputs in the subsequent Taguchi loss function analysis to evaluate spare part criticality levels and stock decision processes.

4.2. Taguchi loss function-based evaluation

Following the determination of the criteria weights, the proposed framework is applied to a real-world case study. The case study is based on real operational data obtained from a grid-connected renewable energy production facility. The facility has an approximate annual electricity generation capacity of 35,000 MWh. In this system, maintenance-related expenditures account for approximately 4% of the total investment budget, highlighting the economic importance of effective spare parts management and maintenance planning.

Table 8. Raw operational data of spare parts used in the case study.

Part Code	Spare Part	Price (₺)	Demand Quantity (units/year)	Lead Time (days)	Number of Suppliers (count)	Failure Frequency (units/year)	Maintenance Plan (score)	Critical Equipment Impact (score)	Production Loss Cost (₺/day)	Supplier Distance (km)	Repair Time (days)
P01	Inverter Fan	18000	6	14	3	0.40	4	4	65000	420	1
P02	DC String Fuse	3500	25	7	5	0.60	5	3	15000	300	1
P03	AC Breaker	22000	4	21	2	0.20	4	4	70000	550	2
P04	Inverter Control Card	95000	2	45	1	0.15	3	5	180000	900	4
P05	Tracker Motor	38000	3	30	2	0.25	3	4	90000	600	3
P06	Tracker Gearbox	120000	1	60	1	0.10	2	5	220000	1100	5
P07	Pitch Motor	145000	1	75	1	0.08	2	5	260000	1300	6
P08	Yaw Motor	160000	1	80	1	0.07	2	5	280000	1350	6
P09	Pitch Encoder	28000	4	25	2	0.30	3	4	85000	650	2
P10	Yaw Encoder	30000	3	28	2	0.28	3	4	88000	670	2
P11	Hydraulic Valve	42000	2	35	2	0.18	3	4	95000	720	3
P12	Hydraulic Pump	180000	1	90	1	0.06	2	5	300000	1500	7
P13	PLC Module	65000	2	40	2	0.12	4	4	140000	800	3
P14	SCADA Communication Card	55000	2	32	3	0.15	4	4	120000	750	2
P15	Temperature Sensor	6000	12	10	4	0.50	5	3	30000	280	1
P16	Vibration Sensor	120000	6	18	3	0.35	4	4	60000	400	1
P17	Anemometer	20000	3	22	3	0.22	4	4	75000	500	2
P18	Wind Vane	15000	4	20	3	0.26	4	3	55000	480	1
P19	Generator Bearing	85000	1	55	1	0.09	2	5	200000	1000	5
P20	Brake System Valve	48000	2	33	2	0.17	3	4	100000	700	3
P21	Power Supply Unit	26000	3	16	3	0.32	4	3	45000	350	1
P22	Data Logger	34000	2	24	3	0.20	4	3	65000	520	2
P23	Inverter Filter	9000	8	12	4	0.45	5	3	35000	300	1
P24	DC Switch	14000	5	15	4	0.38	5	3	40000	320	1
P25	Surge Protection Device	11000	6	14	4	0.42	5	3	38000	310	1

The operational data of the spare parts analyzed in this study were obtained from the maintenance and inventory management unit of the energy production facility. The dataset includes information for 25 spare parts, covering criteria such as price, demand quantity, lead time, number of suppliers, failure frequency, maintenance plan implementation status, critical equipment impact, production loss cost, supplier distance, and repair time. The detailed dataset used in the analysis is presented in Table 8.

In this stage, the Taguchi loss function approach is applied to evaluate the economic impact of deviations in the performance levels of spare parts. The evaluation criteria are first classified according to their performance characteristics. Accordingly, most criteria are treated as lower-is-better (LB), whereas the number of suppliers and maintenance plan are considered as higher-is-better (HB) criteria.

Following the classification of the criteria, specification limits representing the acceptable performance boundaries were determined for each criterion. These limits were used as reference values in the calculation of the Taguchi loss coefficients. After determining the specification limits, the Taguchi loss coefficients (k) for each criterion were calculated using Eq. (18) given in the methodology section. In this calculation, the parameter A represents the economic loss occurring when the performance reaches the specification limit.

For LB-type criteria, the loss value at the specification limit was assumed as A = 100 in accordance with the commonly accepted practice in the literature [28]. For example, for the price criterion with a 20% specification limit, the tolerance interval is $\Delta = 0.20$, and the loss coefficient is calculated as:

$$k = \frac{A}{\Delta^2} = \frac{100}{(0.20)^2} = 2500$$

For HB-type criteria, since system performance improves as the criterion value increases, the tolerance interval was determined using the formulation $\Delta = 1 - SL$ (see Eq. (19)). For instance, with a specification limit of 80%, $\Delta=0.20$. The acceptable loss at the specification limit is set to A=2.56 to ensure scale consistency and avoid excessive penalization. Accordingly, the loss coefficient is calculated as:

$$k = \frac{A}{\Delta^2} = \frac{2.56}{(0.20)^2} = 64$$

The specification limits and the calculated loss coefficients for all criteria are summarized in Table 9.

Table 9. Specification limits and Taguchi loss coefficients for the criteria.

Criteria	Type	Specification Limit	Loss Coefficient (k)
Price (C1)	LB	20%	2500
Demand Quantity (C2)	LB	25%	1600
Lead Time (C3)	LB	15%	4444.44
Failure Frequency (C5)	LB	20%	2500
Critical Equipment Impact (C7)	LB	20%	2500
Production Loss Cost (C8)	LB	20%	2500
Supplier Distance (C9)	LB	15%	4444.44
Repair Time (C10)	LB	20%	2500
Number of Suppliers (C4)	HB	80%	64
Maintenance Plan (C6)	HB	80%	64

After determining the specification limit values, the raw data of the criteria were transformed into RV values using the RV formulation. This transformation was applied to ensure comparability among criteria measured in different units by converting them into a common evaluation scale.

For LB type criteria, the RV values were calculated using Eq. (20) provided in the methodology section, while for HB type criteria the RV values were obtained using Eq. (21).

To illustrate the calculation of RV, a sample computation is presented for criterion C1 (Price), which is classified as a LB criterion. For spare part P01, the observed value is x_{11}= 18000 (see Table 8), and the minimum value among all alternatives for this criterion is x_1^{min}= 3500. The relative value is calculated as:

RV_{11}= ((18000 − 3500) / 3500) × 100 = 414.29

For a higher-is-better (HB) criterion, a sample calculation is provided for criterion C4 (Number of Suppliers). For spare part P01, the observed value is x_{14}= 3 (see Table 8), and the maximum value among all alternatives is x_4^{max} = 5. The relative value is calculated as:

RV_{14} = (3 / 5) × 100 = 60.00

Similar calculations were performed for all criteria and spare parts. The calculated RV values for the 25 spare parts are presented in Table 10.

After obtaining the RV values, the Taguchi loss function approach was applied to determine the quality loss associated with each criterion. The Taguchi loss function is a quality engineering method developed to quantify the economic loss resulting from deviations of performance values from the target value. In this study, the criteria were evaluated under two categories according to their performance characteristics: LB and HB. For LB-type criteria, the Taguchi loss values were calculated using Eq. (22) presented in the methodology section, while for HB-type criteria the loss values were obtained using Eq. (23).

Table 10. RV scores of the spare parts with respect to the evaluation criteria.

Part Code	Spare Part	C1 (RV)	C2 (RV)	C3 (RV)	C4 (RV)	C5 (RV)	C6 (RV)	C7 (RV)	C8 (RV)	C9 (RV)	C10 (RV)
P01	Inverter Fan	414.29	500.00	100.00	60.00	566.67	80.00	33.33	333.33	50.00	100.00
P02	DC String Fuse	0.00	2400.00	0.00	100.00	900.00	100.00	0.00	0.00	7.14	0.00
P03	AC Breaker	528.57	300.00	200.00	40.00	233.33	80.00	33.33	366.67	96.43	300.00
P04	Inverter Control Card	2614.29	100.00	542.86	20.00	150.00	60.00	66.67	1100.00	221.43	700.00
P05	Tracker Motor	985.71	200.00	328.57	40.00	316.67	60.00	33.33	500.00	114.29	500.00
P06	Tracker Gearbox	3328.57	0.00	757.14	20.00	66.67	40.00	66.67	1366.67	292.86	900.00
P07	Pitch Motor	4042.86	0.00	971.43	20.00	33.33	40.00	66.67	1633.33	364.29	1100.00
P08	Yaw Motor	4471.43	0.00	1042.86	20.00	16.67	40.00	66.67	1766.67	382.14	1100.00
P09	Pitch Encoder	700.00	300.00	257.14	40.00	400.00	60.00	33.33	466.67	132.14	300.00
P10	Yaw Encoder	757.14	200.00	300.00	40.00	366.67	60.00	33.33	486.67	139.29	300.00
P11	Hydraulic Valve	1100.00	100.00	400.00	40.00	200.00	60.00	33.33	533.33	157.14	500.00
P12	Hydraulic Pump	5042.86	0.00	1185.71	20.00	0.00	40.00	66.67	1900.00	435.71	1300.00
P13	PLC Module	1757.14	100.00	471.43	40.00	100.00	80.00	33.33	833.33	185.71	500.00
P14	SCADA Communication Card	1471.43	100.00	357.14	60.00	150.00	80.00	33.33	700.00	167.86	300.00
P15	Temperature Sensor	71.43	1100.00	42.86	80.00	733.33	100.00	0.00	100.00	0.00	100.00
P16	Vibration Sensor	3328.57	500.00	157.14	60.00	483.33	80.00	33.33	300.00	42.86	100.00
P17	Anemometer	471.43	200.00	214.29	60.00	266.67	80.00	33.33	400.00	78.57	300.00
P18	Wind Vane	328.57	300.00	185.71	60.00	333.33	80.00	0.00	266.67	71.43	100.00
P19	Generator Bearing	2328.57	0.00	685.71	20.00	50.00	40.00	66.67	1233.33	257.14	900.00
P20	Brake System Valve	1271.43	100.00	371.43	40.00	183.33	60.00	33.33	566.67	150.00	500.00
P21	Power Supply Unit	642.86	200.00	128.57	60.00	433.33	80.00	0.00	200.00	25.00	100.00
P22	Data Logger	871.43	100.00	242.86	60.00	233.33	80.00	0.00	333.33	85.71	300.00
P23	Inverter Filter	157.14	700.00	71.43	80.00	650.00	100.00	0.00	133.33	7.14	100.00
P24	DC Switch	300.00	400.00	114.29	80.00	533.33	100.00	0.00	166.67	14.29	100.00
P25	Surge Protection Device	214.29	500.00	100.00	80.00	600.00	100.00	0.00	153.33	10.71	100.00

Table 11. Weighted Taguchi loss values for the spare parts.

Part Code	Spare Part	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Total Loss
P01	Inverter Fan	45.21	36.32	4.84	1.60	87.16	1.00	0.29	29.95	1.09	0.00	204.87
P02	DC String Fuse	0.00	836.90	0.00	0.58	219.87	0.64	0.00	0.00	0.02	0.00	1056.79
P03	AC Breaker	73.60	13.08	19.35	3.60	14.78	1.00	0.29	36.25	4.04	2.16	163.54
P04	Inverter Control Card	1800.35	1.45	142.59	14.41	6.11	1.79	1.16	326.21	21.28	19.43	2318.58
P05	Tracker Motor	255.95	5.81	52.24	3.60	27.22	1.79	0.29	67.40	5.67	8.64	423.21
P06	Tracker Gearbox	2918.54	0.00	277.38	14.41	1.21	4.02	1.16	503.54	37.22	34.55	3773.60
P07	Pitch Motor	4305.53	0.00	456.61	14.41	0.30	4.02	1.16	719.22	57.59	53.98	5594.39
P08	Yaw Motor	5266.75	0.00	526.23	14.41	0.08	4.02	1.16	841.44	63.38	53.98	6753.01
P09	Pitch Encoder	129.08	13.08	31.99	3.60	43.43	1.79	0.29	58.71	7.58	2.16	286.32
P10	Yaw Encoder	151.01	5.81	43.55	3.60	36.49	1.79	0.29	63.85	8.42	2.16	311.58
P11	Hydraulic Valve	318.74	1.45	77.42	3.60	10.86	1.79	0.29	76.68	10.72	8.64	504.79
P12	Hydraulic Pump	6698.90	0.00	680.27	14.41	0.00	4.02	1.16	973.24	82.40	77.73	8513.69
P13	PLC Module	813.33	1.45	107.54	3.60	2.71	1.00	0.29	187.22	14.97	8.64	1136.14
P14	SCADA Communication Card	570.33	1.45	61.72	1.60	6.11	1.00	0.29	132.10	12.23	2.16	786.39
P15	Temperature Sensor	1.34	175.81	0.89	0.90	145.98	0.64	0.00	2.70	0.00	0.00	326.71
P16	Vibration Sensor	2918.54	36.32	11.95	1.60	63.41	1.00	0.29	24.26	0.80	0.00	3055.58
P17	Anemometer	58.54	5.81	22.22	1.60	19.30	1.00	0.29	43.14	2.68	2.16	154.14
P18	Wind Vane	28.44	13.08	16.69	1.60	30.16	1.00	0.00	19.17	2.21	0.00	109.75
P19	Generator Bearing	1428.33	0.00	227.52	14.41	0.68	4.02	1.16	410.08	28.70	34.55	2131.01
P20	Brake System Valve	425.83	1.45	66.75	3.60	9.12	1.79	0.29	86.57	9.77	8.64	608.42
P21	Power Supply Unit	108.86	5.81	8.00	1.60	50.97	1.00	0.00	10.78	0.27	0.00	184.70
P22	Data Logger	200.04	1.45	28.54	1.60	14.78	1.00	0.00	29.95	3.19	2.16	280.11
P23	Inverter Filter	6.50	71.19	2.47	0.90	114.69	0.64	0.00	4.79	0.02	0.00	199.67
P24	DC Switch	23.71	23.25	6.32	0.90	77.21	0.64	0.00	7.49	0.09	0.00	138.06
P25	Surge Protection Device	12.10	36.32	4.84	0.90	97.72	0.64	0.00	6.34	0.05	0.00	157.37

Note: C4 and C6 are scaled by10^3, while all other criteria are scaled by 10^6.

In these calculations, the previously determined loss coefficients together with the calculated RV values were used for each criterion. In this way, the economic impact of deviations in criterion performance levels from their target values was quantitatively represented. After calculating the Taguchi loss values for each criterion, these values were weighted using the criterion weights obtained from the SWARA method in order to incorporate the relative importance of the criteria into the decision-making process. Accordingly, the Taguchi loss value calculated for each criterion was multiplied by its corresponding criterion weight to obtain the weighted Taguchi loss values, which were calculated using Eq. (24).

In the final stage, the total Taguchi loss value for each alternative was calculated using Eq. (25) by summing the weighted loss values across all criteria. The weighted loss values for each spare part with respect to all evaluation criteria, together with the corresponding total loss values, are presented in Table 11.

Based on the total loss values obtained, the spare parts were ranked according to their relative economic impact on the system. The resulting criticality ranking of the spare parts is presented in Table 12.

Table 12. Criticality ranking of spare parts based on total Taguchi loss values.

Rank	Part Code	Spare Part
1	P12	Hydraulic Pump
2	P08	Yaw Motor
3	P07	Pitch Motor
4	P06	Tracker Gearbox
5	P16	Vibration Sensor
6	P04	Inverter Control Card
7	P19	Generator Bearing
8	P13	PLC Module
9	P02	DC String Fuse
10	P14	SCADA Communication Card
11	P20	Brake System Valve
12	P11	Hydraulic Valve
13	P05	Tracker Motor
14	P15	Temperature Sensor
15	P10	Yaw Encoder
16	P09	Pitch Encoder
17	P22	Data Logger
18	P01	Inverter Fan
19	P23	Inverter Filter
20	P21	Power Supply Unit
21	P03	AC Breaker
22	P25	Surge Protection Device
23	P17	Anemometer
24	P24	DC Switch
25	P18	Wind Vane

According to the results, Hydraulic Pump (P12) was identified as the most critical spare part in the system. This component has the highest total loss value, indicating that deviations in its performance parameters lead to significant economic losses and operational disruptions. It is followed by Yaw Motor (P08) and Pitch Motor (P07), which also exhibit relatively high loss values and therefore play a crucial role in maintaining the operational continuity of the energy production system. Similarly, Tracker Gearbox (P06) and Vibration Sensor (P16) were identified as highly critical components. Failures or performance deviations in these parts significantly affect system monitoring, mechanical stability, and overall operational reliability. Due to their high economic impact on system performance, these components should receive priority in maintenance planning and spare parts inventory management.

In contrast, components such as Anemometer (P17), DC Switch (P24), and Wind Vane (P18) were identified as the least critical spare parts due to their comparatively lower total loss values. The relatively low economic impact associated with these components suggests that performance deviations in these parts are less likely to cause significant operational or economic consequences for the system.

Overall, the obtained ranking provides a quantitative representation of the relative economic impact of each spare part on system performance. Spare parts with higher total loss values represent components whose performance deviations are associated with greater operational risks and economic losses. Therefore, these components should be prioritized in maintenance planning, spare parts inventory management, and reliability improvement strategies within renewable energy production systems.

4.3. Criticality-based inventory policy implications

This section discusses the practical implications of the obtained criticality levels from an inventory management perspective. The proposed framework does not aim to directly optimize inventory parameters such as order quantities or reorder points. Instead, it provides a structured decision-support mechanism that translates criticality assessment results into differentiated inventory control strategies.

ABC analysis is a widely used inventory classification technique based on the Pareto principle [29]. In this study, a criticality-based ABC classification is developed using total Taguchi loss values rather than traditional consumption-based measures. Unlike conventional ABC approaches, which are typically based on annual demand or monetary usage [30], the proposed classification reflects the overall economic impact of spare parts on system performance.

Based on the total Taguchi loss values, spare parts are categorized into three classes (A, B, and C) as presented in Table 13. The results are consistent with the Pareto principle, indicating that a limited number of components account for a substantial proportion of the total economic loss. In particular, Hydraulic Pump (P12), Yaw Motor (P08), and Pitch Motor (P07) are identified as highly critical components due to their significant contribution to system-level economic impact.

Table 13. Criticality-based ABC classification results.

Class	Spare Parts	Description
A	P12, P08, P07, P06, P16, P04	High criticality
B	P19, P13, P02, P14, P20, P11, P05, P15	Medium criticality
C	P10, P09, P22, P01, P23, P21, P03, P25, P17, P24, P18	Low criticality

From an inventory control perspective, it is well established that spare parts with higher criticality levels require stricter control policies, higher service level targets, and increased safety stock levels [2,7]. Accordingly, Class A components should be managed with high service level targets (e.g., 95–99%), tighter control policies, and more frequent monitoring. Class B components follow moderate control strategies with balanced service levels. In contrast, Class C components can be managed using more relaxed inventory policies, including lower safety stock levels and less frequent review mechanisms.

In this respect, the proposed framework operationalizes criticality assessment by explicitly linking classification results to key inventory control parameters, including service level targets, safety stock policies, and monitoring frequency. Therefore, the approach extends beyond a simple ranking exercise by establishing a structured linkage between analytical results and practical inventory control decisions.

It should be emphasized that the proposed framework does not replace classical inventory models such as EOQ or ROP. Instead, it complements these models by providing criticality-based inputs for parameter tuning and policy selection. In this way, the framework contributes to bridging the gap between spare parts criticality analysis and practical inventory decision-making.

4.4. Sensitivity analysis

4.4.1. Sensitivity analysis under weight variations

In order to examine the robustness of the proposed PF-SWARA-Taguchi integrated decision framework, a sensitivity analysis was conducted by analyzing how variations in criteria weights affect the final ranking of spare parts. Since the criteria weights were initially obtained using the SWARA method, alternative weight configurations were generated through pairwise exchanges of criteria weights. In this context, a total of 45 ranking scenarios with varying weights were generated, in addition to the base scenario.

Figure 2 illustrates the ranking variations of spare parts across different ranking scenarios obtained under varying weight configurations. The horizontal axis represents the analyzed scenarios, while the vertical axis indicates the ranking positions of the spare parts. Each line corresponds to a specific spare part and shows how its ranking position changes as the criteria weights vary.

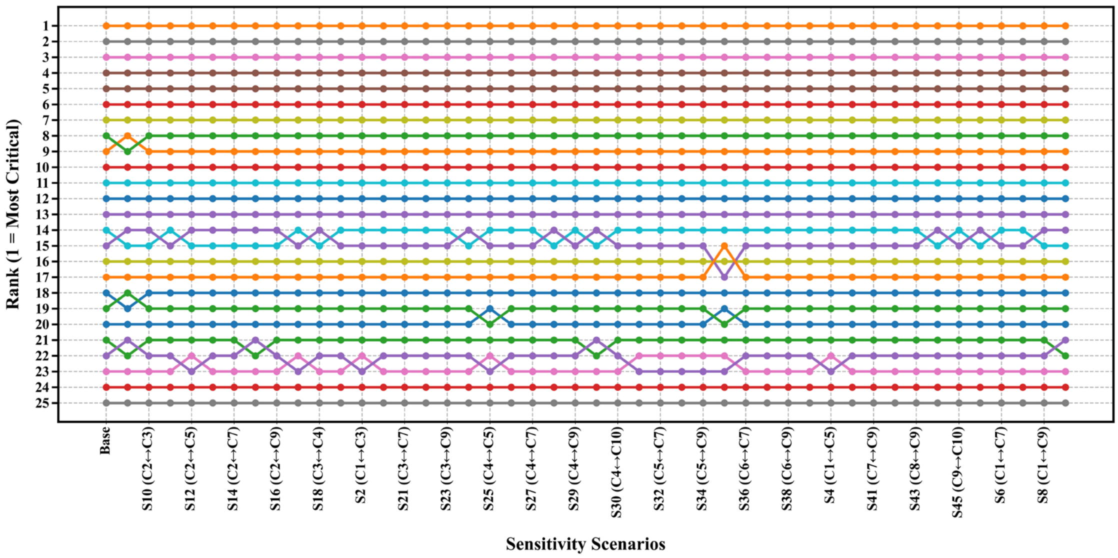

Figure 2. Sensitivity analysis of spare part rankings under weight variations.

Based on the total loss values obtained under different weight configurations, the spare parts were re-ranked in each case. The sensitivity analysis demonstrates that the overall ranking structure remains largely stable across different ranking scenarios, confirming the robustness of the proposed decision framework.

In particular, Hydraulic Pump (P12), Yaw Motor (P08), and Pitch Motor (P07) consistently remain in the top three positions across all sensitivity scenarios, indicating their dominant contribution to the total economic loss. This confirms that their criticality levels are highly robust against variations in criteria weights. Tracker Gearbox (P06), Vibration Sensor (P16), and Inverter Control Card (P04) also maintain relatively high-ranking positions, although with slightly greater variability compared to the top three components. This suggests that they represent secondary critical components with significant but less dominant impact.

For several mid-ranked spare parts, minor fluctuations are observed under different weight configurations. However, these variations remain limited and do not alter the overall ranking hierarchy.

In contrast, components such as Anemometer (P17), DC Switch (P24) and Wind Vane (P18) consistently rank lowest, indicating low criticality and minimal influence on the total economic loss.

Overall, the sensitivity analysis confirms the robustness and reliability of the proposed PF-SWARA-Taguchi integrated framework. The most and least critical spare parts remain largely unchanged across different ranking scenarios derived from weight variations, indicating that the ranking structure is highly stable and not significantly sensitive to moderate changes in criteria weights.

4.4.2. Robustness analysis under different fuzzy environments

To evaluate the robustness of the proposed framework, an additional analysis was conducted under the intuitionistic fuzzy environment. The aggregated picture fuzzy evaluations were transformed into an intuitionistic fuzzy environment by retaining the membership and non-membership degrees, and, based on these values, an alternative set of criterion weights was obtained using the intuitionistic fuzzy SWARA (IF-SWARA) method.

Accordingly, the obtained criteria weights were integrated with the Taguchi loss function described in the previous section to determine the alternative rankings. The resulting rankings under the IF-SWARA–Taguchi and PF-SWARA–Taguchi approaches are presented in Table 14.

Table 14. Comparative ranking results of spare parts.

	Ranking
IF-SWARA and Taguchi Loss Function	P12 > P08 > P07 > P06 > P16 > P04 > P19 > P13 > P14 > P20 > P11 > P05 > P10 > P09 > P02 > P22 > P01 > P15 > P21 > P23 > P17 > P03 > P25 > P24 > P18
PF-SWARA and Taguchi Loss Function	P12 > P08 > P07 > P06 > P16 > P04 > P19 > P13 > P02 > P14 > P20 > P11 > P05 > P15 > P10 > P09 > P22 > P01 > P23 > P21 > P03 > P25 > P17 > P24 > P18

When the obtained results are compared, it is observed that the rankings derived under both fuzzy environments are largely consistent. In particular, the most critical spare parts, namely P12, P08, P07, P06, P16, and P04, maintain their positions in both fuzzy environments, indicating strong agreement in identifying high-impact components.

Although minor positional changes are observed among mid- and lower-ranked alternatives (e.g., P14–P02 and P20–P11), these variations are limited and do not significantly affect the overall ranking structure, confirming the robustness of the proposed framework.

These findings demonstrate that the proposed framework produces stable, reliable results across different uncertainty modeling approaches. The observed minor differences can be attributed to the explicit modeling of hesitation in the picture fuzzy environment. Unlike intuitionistic fuzzy sets, the picture fuzzy approach allows hesitation to be directly represented, thereby enabling a more comprehensive representation of expert evaluations [9,12].

5. Conclusion

This study proposes an integrated decision-support framework that combines the PF-SWARA method and the Taguchi loss function to evaluate the criticality levels of spare parts used in renewable energy systems. The proposed approach captures uncertainty and hesitation in expert evaluations through the picture fuzzy environment. It integrates the derived criteria weights with the Taguchi loss function to quantify the economic impact of spare part failures and to support the interpretation of criticality results in terms of their economic implications.

The empirical results indicate that Hydraulic Pump (P12), Yaw Motor (P08), and Pitch Motor (P07) are the most critical spare parts within the analyzed system. Failures in these components can lead to significant economic losses and disruptions in production continuity. In contrast, components such as Anemometer (P17), DC Switch (P24) and Wind Vane (P18) exhibit relatively lower loss values, indicating a comparatively limited impact on system performance.

The sensitivity analysis further demonstrates that the overall ranking structure remains largely stable under different weight scenarios. The consistency of the most and least critical spare parts across scenarios confirms the robustness and reliability of the proposed framework, suggesting that moderate variations in criterion importance do not significantly alter the ranking results.

From a practical perspective, the proposed PF-SWARA-Taguchi integrated framework provides decision-support implications for maintenance managers and decision-makers in spare-part prioritization, maintenance planning, and inventory management within renewable energy facilities. By identifying the most critical components, the approach facilitates system reliability improvement and supports efforts to reduce potential operational losses.

This study contributes to the literature by integrating picture-fuzzy-based weighting into economic loss evaluation for spare-part criticality analysis in renewable energy systems and by linking criticality assessment results with inventory-related decision considerations. Future research could extend the proposed framework to different industrial contexts, compare it with alternative multi-criteria decision-making approaches, and incorporate real-time maintenance or operational data to enhance decision-making accuracy further.

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