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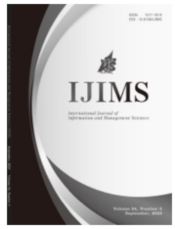

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Fuzzy Quality Evaluation of Recyclable Products in Circular Economy Manufacturing

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Keywords

Circular Economy (CE); Recyclable Products; Remanufacturing; Interval-Valued Hesitant Fuzzy Set (IVHFS); Fuzzy Process Capability Index (FPCI); Socket Storage Tray

Abstract

In the context of globalized manufacturing, the circular economy (CE) has become a crucial driver of industrial competitiveness. Due to the reusability and variability of recyclable products, manufacturers often rely on manual inspection to ensure the quality of reclaimed materials. However, the accuracy of such inspections is frequently influenced by differences in quality manager' experience, subjective bias, and environmental fluctuations, resulting in instability in quality assessments. Furthermore, measurement errors and process variability introduce additional uncertainty into remanufactured products, making traditional quality evaluation methods inadequate for complex and ambiguous production environments. To address these challenges, this study proposes an integrated quality evaluation approach that combines the interval-valued hesitant fuzzy entropy function (IVHFEF) with fuzzy process capability index (FPCI). The proposed approach integrates subjective assessments with objective production data to effectively capture hesitation and ambiguity in manual inspection, offering a more comprehensive and quantitative depiction of process capability while enhancing the interpretability of quality evaluation under uncertainty. An empirical case study on socket storage trays is conducted to verify the feasibility and effectiveness of the proposed approach. The results demonstrate that the proposed approach can accurately identify weak points in remanufacturing quality, improve decision-making in quality control, and support sustainable production practices within the CE framework.

1. Introduction

In recent years, the intensifying global consumption of resources and the worsening problem

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of environmental pollution have made the circular economy (CE) a crucial pathway toward sustainable development (Afshari et al., 2024). The traditional linear economic model, characterized by the sequential stages of production, consumption, and disposal, has resulted in low resource efficiency and severe ecological degradation. In contrast, the CE emphasizes efficient resource utilization, waste minimization, and material recirculation, and is widely regarded as an effective approach to reconciling economic growth with environmental protection (Aslam et al., 2025). From a practical perspective, CE principles have been increasingly adopted across various sectors such as manufacturing, agriculture, construction, and services (Felice et al., 2025). In the manufacturing sector in particular, companies are implementing modular design, disassemblable structures, and recyclable materials to extend product lifecycles and reduce resource consumption. By reintegrating materials from end-of-life products into new production processes, the CE reduces dependence on virgin resources, decreases waste emissions, and promotes closed-loop material utilization, thereby playing an essential role in advancing industrial sustainability and resource efficiency (Munoz-Briones et al., 2025). However, the implementation of CE practices has also raised higher demands for product quality control and recyclability. Recycling is a critical component of the CE system, and products of higher quality are easier to disassemble, classify, and remanufacture. This improves recycling efficiency and increases the value of regenerated materials, forming a positive cycle that contributes to both corporate competitiveness and environmental sustainability. Therefore, balancing product quality and recyclability during the production process has become a key issue. It is essential to ensure that products meet performance and durability requirements while remaining suitable for subsequent reuse and remanufacturing, which is vital for achieving the goals of the CE and promoting green and sustainable development.

In the context of the CE, quality control during the production and recycling processes often relies primarily on manual inspection to assess the condition of components or products before they enter the remanufacturing stage. Manual inspection offers certain advantages such as operational flexibility and relatively low cost, but it also exhibits significant limitations (Chu et al., 2024). One major issue is the variation in the experience and judgment of inspectors. Even within the same batch of components or products, different inspectors may produce noticeably inconsistent assessments (Swann et al., 2024). In addition, inspection outcomes are easily affected by subjective preferences, fatigue, and environmental conditions during production and recycling, including lighting, noise, and workspace constraints. These factors often lead to inconsistent and unstable inspection results (Yang et al., 2024). When manual inspection outcomes display a high degree of ambiguity and uncertainty, defective products may enter the reuse or remanufacturing stages. This not only increases production risks but can also undermine the efficiency and cost advantages that the CE aims to achieve (Shih et al., 2024). On the other hand, during the remanufacturing process, process capability indices are commonly employed to evaluate product quality (Yang et al., 2019). However, traditional process capability indices generally assume that production data follow a specific and precise statistical distribution. Such assumptions are difficult to satisfy in complex and dynamic manufacturing environments, limiting the applicability of these indices in real-world industrial settings (Yang and Chen, 2021). Consequently, achieving reliable quality evaluation under conditions of uncertainty and vagueness has become a critical challenge in the transformation and upgrading of traditional manufacturing industries. Developing evaluation approaches that can accommodate imprecise information is therefore essential for improving product quality management, enhancing resource efficiency, and supporting the sustainable advancement of the CE.

When quality managers encounter ambiguous situations in product evaluation, they often exhibit hesitant judgments. Such subjective hesitation cannot be fully captured by traditional data models. The interval-valued hesitant fuzzy set (IVHFS), as an advanced extension of fuzzy set theory, has been widely applied in multi-criteria decision-making (MCDM) due to its strong ability to represent uncertainty and hesitation in human decision processes (Xie et al., 2023). According to Liu et al. (2020), IVHFS can flexibly describe hesitant situations in decision-making and enhance the scientific validity and rationality of decisions by introducing measures of hesitation degree and the least common multiple principle. Similarly, Mishra et al. (2022) emphasized that IVHFS effectively captures the hesitation of decision-makers facing uncertain or incomplete information, thereby improving the accuracy and reliability of decisions. At the same time, the fuzzy process capability index (FPCI) serves as a crucial indicator for evaluating process stability and conformity under uncertain conditions. Yalçın and Kaya (2022) highlighted that process capability analysis is an important statistical quality control method used to measure and analyze the ability of a process to meet specified standards. Traditional process capability indices are usually derived from precise data; however, in real-world manufacturing, data uncertainty is unavoidable due to variations in raw materials, equipment conditions, and operator performance (Chen et al., 2019b). Integrating fuzzy theory into process capability analysis helps to overcome the limitations of conventional indices when dealing with imprecise or vague data, allowing for a more realistic representation of the actual performance of manufacturing processes (Abdolshah et al., 2011).

In summary, under the dual emphasis on CE implementation and production efficiency improvement, this study proposes a quality evaluation approach that integrates the concepts of IVHFS and FPCI. The proposed approach can effectively handle the hesitation and fuzziness that arise in manual inspection processes, provide a more complete representation of process capability characteristics, and demonstrate strong adaptability and interpretability when addressing complex and uncertain quality data. This contributes to achieving efficient quality control and resource utilization in manufacturing systems. The structure of this paper is organized as follows. Section 2 reviews the related literature on the CE, IVHFS, and FPCI. Section 3 outlines the research methodology. Section 4 presents an empirical case study based on the production process of a socket storage tray. Section 5 concludes the paper by summarizing the key findings and providing directions for future research.

2. Literature Review

2.1 Circular Economy (CE)

CE has emerged as a sustainable economic model that has gained considerable global attention and extensive academic discussion in recent years (Aslan et al., 2025). The CE represents an economic development paradigm centered on efficient resource utilization and material regeneration. Its fundamental objective is to achieve sustainable economic and environmental development by reducing resource consumption, minimizing waste generation, and promoting the reuse and recycling of materials and energy. The CE framework is primarily built upon five key principles: reduction, reuse, recycling, recovery, and reclamation. These five dimensions collectively form the foundation of the circular economy and have been widely implemented across various industries and sectors.

- Reduction: this principle emphasizes minimizing the use of raw materials and energy consumption during production. Felice et al. (2024) indicated that by optimizing production processes and reducing raw material input, companies can decrease unit energy consumption by more than 30 percent.
- Reuse: reuse refers to extending the lifecycle of products or components through secondary use, refurbishment, or functional transformation, thereby avoiding unnecessary resource waste. Afshari et al. (2024) emphasized that the implementation of effective reuse-oriented systems and incentive policies can enable over 50 percent of reusable materials in urban waste streams to be reintegrated into productive use.
- Recycling: recycling involves transforming waste materials into new raw materials or products that can re-enter production or consumption systems. Aslam et al. (2025) noted that by dismantling and extracting materials from end-of-life electronic products, metals, plastics, and other resources can be efficiently recovered, reducing dependence on virgin resource extraction.
- Recovery: recovery focuses on converting waste into energy or valuable materials, such as biomass energy, waste-to-energy incineration, or metal extraction. This model has become increasingly important under the growing pressures of energy shortages and environmental pollution (Felice et al., 2025).
- Reclamation: Reclamation emphasizes restoring the functionality or creating new value from waste or retired products through technological processes. Examples include wastewater reclamation, soil remediation, and redevelopment of abandoned land. This process not only enables the reintegration of resources into productive use but also contributes positively to ecological restoration and environmental improvement (Aslan et al., 2025).

Collectively, these five CE models are interrelated and mutually reinforcing, driving the efficient use of resources and supporting sustainable environmental development. In practical applications, different industries and companies can adopt suitable combinations of these models according to their operational characteristics. Such strategic integration can enhance environmental performance, strengthen corporate social responsibility, and achieve a synergistic balance between economic profitability and ecological sustainability (Munoz-Briones, 2025).

2.2 Interval-Valued Hesitant Fuzzy Sets (IVHFS)

The theory of fuzzy sets, first proposed by Zadeh in 1965, has become a fundamental tool for handling uncertainty and vagueness in real-world problems. Its core concept allows elements to have degrees of membership ranging from 0 to 1, rather than the binary membership (0 or 1) defined in classical set theory (Liang et al., 2023). With the advancement of research, the traditional single-valued membership function has been found insufficient for addressing complex decision-making problems. Consequently, several extensions of fuzzy sets have been developed, including intuitionistic fuzzy sets, interval-valued fuzzy sets, and hesitant fuzzy sets (Quirós et al., 2015). Among these extensions, the hesitant fuzzy set (HFS) represents a significant advancement as it captures the hesitation and uncertainty that decision-makers experience when evaluating multiple possible alternatives (Hu et al., 2019). The concept of HFS was first introduced by Torra and Narukawa in 2010, allowing an element to possess several possible membership degrees with respect to a set. This feature enables HFS to describe uncertainty more accurately than conventional fuzzy models (Quirós et al., 2017). IVHFS is an enhanced version of HFS, providing greater flexibility and expressive power in representing uncertain information. Unlike traditional fuzzy or HFS, IVHFS allows decision-makers to assign multiple interval values as the membership degrees of an element, thereby capturing both hesitation and uncertainty in a more comprehensive manner (Hu et al., 2019).

Due to these properties, IVHFS has demonstrated strong advantages in multi-dimensional and group-based decision-making problems. Shen et al. (2024) pointed out that IVHFS can effectively describe complex fuzzy information and is well-suited for information aggregation and weight determination in multi-attribute decision-making. Lu et al. (2025) emphasized that inclusion relations within the framework of HFS form one of their fundamental definitions, which plays a crucial role in constructing robust decision models. In recent years, IVHFS has been widely applied in various fields, such as MCDM, group decision-making, and complex system analysis. Liu et al. (2020) proposed an MCDM method based on IVHFS and applied it to quality evaluation in industrial production. Mishra et al. (2022) developed a decision-making model using interval-valued hesitant Fermatean fuzzy sets (IVHFFS), enabling decision-makers to express their subjective judgments more comprehensively when dealing with uncertain information, and successfully applied the model to the selection of seawater desalination technologies. To further enhance the practicality of IVHFS, several weighted aggregation methods have been proposed. Asan et al. (2018) constructed an improved decision making and trial evaluation laboratory (DEMATEL) model based on IVHFS by introducing weighting coefficients to compute the weighted average of intervals, thus improving the model's stability and accuracy. Ali et al. (2021) explored a technique for order preference by similarity to ideal solution (TOPSIS) model under probabilistic interval-valued hesitant fuzzy environments, integrating probability distributions with IVHFS to achieve more precise decision analysis in complex settings.

2.3 Fuzzy Process Capability Index (FPCI)

Process capability index is a useful tool to assess whether a manufacturing process can consistently meet product specification requirements. Its core concept lies in comparing the distribution of product quality characteristics in actual production with the design specification limits, thereby providing a scientific basis for improving product quality and optimizing process performance (Chen et al., 2019a). The PCI is generally expressed as a numerical value, where a higher index indicates a more stable process and a greater ability to produce items that conform to specifications (Yang and Chen, 2019). Traditional indices such as C_p and C_{pk} are typically based on the assumption of normal distribution. The C_p measures the potential capability of a process, reflecting the ratio between the process spread and the tolerance range, while C_{pk} takes into account the deviation of the process mean from the target value, representing the actual capability of the process (Ouyang et al., 2024).

With the advancement of modern manufacturing technologies, the limitations of traditional process capability indices have become increasingly evident, as they assume all data are precise and deterministic. In practice, uncertainties arising from measurement errors, environmental fluctuations, and differences in quality managers' experience or subjective judgment often led to instability and inconsistency in quality assessments (Yalçın and Kaya, 2022). To address these challenges, researchers have incorporated fuzzy set theory into process capability indices, leading to the development of the FPCI as an extension of the classical process capability index for uncertain environments. The fundamental idea of FPCI is to fuzzify both process parameters and specification limits by using membership functions to represent the degree to which each data point satisfies the specification boundaries (Abdolshah et al., 2011). This approach enables a more comprehensive representation of process performance under uncertainty (Yalçın and Kaya, 2022). Various forms of FPCIs have been proposed in the literature, including fuzzy C_p, fuzzy C_{pk}, fuzzy C_{pm}, fuzzy C_{pmk}, and other extensions based on fuzzy sets. Khan et al. (2023) developed a method for measuring process capability when both upper and lower specification limits are fuzzy parameters. Their approach converts the specification limits into fuzzy intervals and employs membership functions to calculate the capability index. Yalçın and Kaya (2022) proposed an approach by incorporating neutrosophic sets into process capability analysis to manage uncertainty, inconsistency, and indeterminacy in manufacturing data. Abdolshah et al. (2011) compared several types of FPCIs, including C_{pmk}, C_p, and C_{pk}, and concluded that C_{pmk}, which is based on a loss function, more effectively reflects the deviation between the process mean and target value, particularly in fuzzy manufacturing environments. In addition, Hadian and Rahimifard (2019) proposed a cost-based FPCI model that incorporates confidence intervals to enhance the robustness of the evaluation results.

3. Proposed Approach

This study proposes an integrated approach combining the interval-valued hesitant fuzzy entropy function (IVHFEF) with FPCI to reduce human misjudgment and enhance the quality of remanufactured products. The approach effectively captures ambiguity and hesitation in human judgment, thereby improving the robustness and reliability of quality evaluation under uncertainty.

3.1 Interval-Valued Hesitant Fuzzy Entropy Function (IVHFEF)

Chen et al. (2013) introduced the concept of IVHFS as an extension of the traditional fuzzy set theory. Its main advantage lies in allowing multiple possible interval-valued memberships for a single element, which effectively represents uncertainty and hesitation in human judgment. IVHFS is defined as follows:

Definition 1: Let X be a non-empty set, and an IVHFS on X be denoted as $\tilde{Q}=\left\{\left\langle x_i,\tilde{h}_{\tilde{E}}(x_i)\right\rangle \mid x_i\in X, i=1,2,\ldots,n\right\}$, where $\tilde{h}_{\tilde{E}}(x_i)=\bigcup_{\tilde{\gamma}\in\tilde{h}_{\tilde{E}}(x_i)}\tilde{\gamma}$ is the basic unit of IVHFS, called an interval-valued hesitant fuzzy element (IVHFE). Here, $\tilde{\gamma}=\left[\tilde{\gamma}^L,\tilde{\gamma}^U\right]$ is an interval number, where $\tilde{\gamma}^L=\inf\tilde{\gamma}$ and $\tilde{\gamma}^U=\sup\tilde{\gamma}$ represent the lower and upper bounds of the interval $\tilde{\gamma}$, respectively.

(a) $\tilde{h}^c=\bigcup_{\left[1-\tilde{\gamma}^L,1-\tilde{\gamma}^U\right]\in\tilde{h}}\left\{\left[1-\tilde{\gamma}^L,1-\tilde{\gamma}^U\right]\right\}$;

(b) $\beta\tilde{h}=\bigcup_{\left[\tilde{\gamma}^L,\tilde{\gamma}^U\right]\in\tilde{h}}\left\{\left[1-\left(1-\tilde{\gamma}^L\right)^\beta,1-\left(1-\tilde{\gamma}^U\right)^\beta\right]\right\},\beta>0$;

(c) $\tilde{h}_1 \cup \tilde{h}_2 = \bigcup_{\left[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U\right] \in \tilde{h}_1, \left[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U\right] \in \tilde{h}_1} \left\{\left[\max\left(\tilde{\gamma}_1^L, \tilde{\gamma}_2^L\right), \max\left(\tilde{\gamma}_1^U, \tilde{\gamma}_2^U\right)\right]\right\}$;

(d) $\tilde{h}_1 \oplus \tilde{h}_2 = \bigcup_{\left[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U\right] \in \tilde{h}_1, \left[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U\right] \in \tilde{h}_1} \left\{\left[\tilde{\gamma}_1^L + \tilde{\gamma}_2^L - \tilde{\gamma}_1^L \cdot \tilde{\gamma}_2^L, \tilde{\gamma}_1^U + \tilde{\gamma}_2^U - \tilde{\gamma}_1^U \cdot \tilde{\gamma}_2^U\right]\right\}$.

Definition 2: Let $\tilde{h}_1 = \bigcup_{\left[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U\right] \in \tilde{h}_1} \left[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U\right]$ and $\tilde{h}_2 = \bigcup_{\left[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U\right] \in \tilde{h}_2} \left[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U\right]$, then the basic arithmetic operations between them are defined as follows:

(a) $\tilde{h}^c = \bigcup_{\left[\tilde{\gamma}^L, \tilde{\gamma}^U\right] \in \tilde{h}} \left\{\left[1 - \tilde{\gamma}^U, 1 - \tilde{\gamma}^L\right]\right\}$;

(b) $\beta \tilde{h} = \bigcup_{\left[\tilde{\gamma}^L, \tilde{\gamma}^U\right] \in \tilde{h}} \left\{\left[1 - \left(1 - \tilde{\gamma}^L\right)^\beta, 1 - \left(1 - \tilde{\gamma}^U\right)^\beta\right]\right\}, \beta > 0$, where β is a constant;

(c) $\tilde{h}_1 \cup \tilde{h}_2 = \bigcup_{\left[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U\right] \in \tilde{h}_1, \left[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U\right] \in \tilde{h}_2} \left\{\left[\max\left(\tilde{\gamma}_1^L, \tilde{\gamma}_2^L\right), \max\left(\tilde{\gamma}_1^U, \tilde{\gamma}_2^U\right)\right]\right\}$;

(d) $\tilde{h}_1 \cap \tilde{h}_2 = \bigcup_{\left[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U\right] \in \tilde{h}_1, \left[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U\right] \in \tilde{h}_2} \left\{\left[\min\left(\tilde{\gamma}_1^L, \tilde{\gamma}_2^L\right), \min\left(\tilde{\gamma}_1^U, \tilde{\gamma}_2^U\right)\right]\right\}$;

(e) $\tilde{h}_1 \oplus \tilde{h}_2 = \bigcup_{\left[\tilde{\gamma}_1^L, \tilde{\gamma}_1^U\right] \in \tilde{h}_1, \left[\tilde{\gamma}_2^L, \tilde{\gamma}_2^U\right] \in \tilde{h}_2} \left\{\left[\tilde{\gamma}_1^L + \tilde{\gamma}_2^L - \tilde{\gamma}_1^L \cdot \tilde{\gamma}_2^L, \tilde{\gamma}_1^U + \tilde{\gamma}_2^U - \tilde{\gamma}_1^U \cdot \tilde{\gamma}_2^U\right]\right\}$.

Definition 3: Let an IVHFE be $\tilde{h} = \bigcup_{j \in J_{\tilde{h}}} \left[\tilde{\gamma}_j^L, \tilde{\gamma}_j^U\right]$, then the mean function $M\left(\tilde{h}\right)$ and the precision function $H\left(\tilde{h}\right)$ are defined as follows (Quirós et al., 2017):

$$M\left(\tilde{h}\right) = \frac{1}{\#\tilde{h}} \sum_{\tilde{\gamma} \in \tilde{h}} \left[\frac{\tilde{\gamma}^L + \tilde{\gamma}^U}{2}\right] \tag{1}$$

$$H\left(\tilde{h}\right) = \frac{1}{\#\tilde{h}} \sum_{\tilde{\gamma} \in \tilde{h}} \left(\tilde{\gamma}^U - \tilde{\gamma}^L\right) \tag{2}$$

where $\#\tilde{h}$ represents the number of interval values in $\tilde{h}$.

If two IVFHEs $\tilde{h}_1$ and $\tilde{h}_2$ contain $\#\tilde{h}_1$ and $\#\tilde{h}_2$ interval numbers, respectively, then:

(a)If $M\left(\tilde{h}_1\right) < M\left(\tilde{h}_2\right)$, then $\tilde{h}_1 \leq \tilde{h}_2$;

(b)If $M\left(\tilde{h}_1\right) = M\left(\tilde{h}_2\right)$ and $H\left(\tilde{h}_1\right) < H\left(\tilde{h}_2\right)$, then $\tilde{h}_1 \geq \tilde{h}_2$;

(c)If $M\left(\tilde{h}_1\right) = M\left(\tilde{h}_2\right)$, $H\left(\tilde{h}_1\right) = H\left(\tilde{h}_2\right)$ and $\#\tilde{h}_1 < \#\tilde{h}_2$, then $\tilde{h}_1 \leq \tilde{h}_2$.

Recent studies have further explored the structural properties of IVHFEs, often assuming that the number of interval elements within each IVHFE is equal. In practice, however, the number of intervals within an IVHFE may vary, and additional or missing elements can affect the accuracy of aggregation results, increasing computational complexity. To address this, this study adopts the entropy function proposed by Chen et al. (2022) to measure the degree of fuzziness and hesitation in IVHFEs.

Definition 4: Suppose k quality managers provide evaluation results represented by IVHFEs as $\tilde{H}=\bigcup_{k=1}^{m}\tilde{h}_k=\left\{\left[\tilde{\gamma}_i^L,\tilde{\gamma}_i^U\right]\middle|\left[\tilde{\gamma}_i^L,\tilde{\gamma}_i^U\right]\in\tilde{h}_k, k=1,2,...,o\right\}$, then the entropy function E for an IVHFE $\tilde{H}$ is defined as

$$E: IVHF \to [0,1] \tag{3}$$

Thus, IVHFEF θ can be expressed as:

$$\theta=E(A,B)=A^2+B^2 \tag{4}$$

where

$$A=\frac{1}{2\#\tilde{h}}\sum_{i=1}^{\#\tilde{h}}\left(1-2\left|\gamma_i^L-0.5\right|+1-2\left|\gamma_i^U-0.5\right|\right) \tag{5}$$

$$B=\begin{cases}\dfrac{1}{\#\tilde{h}\left(\#\tilde{h}\text{-}1\right)}\displaystyle\sum_{i,j=1,i<j}^{\#\tilde{h}}\left(\left|\gamma_i^L-\gamma_j^L\right|+\left|\gamma_i^U-\gamma_j^U\right|\right), \#\tilde{h}>1\\ 0, \#\tilde{h}=1\end{cases} \tag{6}$$

3.2 Fuzzy Process Capability Index (FPCI) for Recyclable Products

IVHFEF can only assess whether recyclable products meet recovery requirements, but it cannot directly reflect the remanufacturing quality of the recycled products. Therefore, this study adopts FPCI to evaluate their remanufacturing quality of recyclable products. First, process capability index for recyclable products R_{cp} is defined as follows (Chen et al., 2019b; Yang and Deng, 2023):

$$R_{cp}=\frac{1-|\eta|}{\omega}+1.5 \tag{7}$$

where $\eta=(\mu-T)/d$, $\omega=\sigma/d$, the target value T = $(USL+LSL)/2$, the tolerance d = $(USL\text{-}LSL)/2$, μ is the mean, σ is the standard deviation, USL is the upper specification limit, and LSL is the lower specification limit of recyclable products.

Assume that a recyclable product x follows a normal distribution $N(\eta,\omega^2)$. Let $x_1,\ldots,x_i,\ldots,x_m$ be a random sample, and $\hat{\eta}$ and $\hat{\omega}$ denote the sample mean and sample standard deviation, respectively, defined as:

$$\hat{\eta}=\frac{\sum_{i=1}^{m}x_i}{n} \quad \text{and} \quad \hat{\omega}=\sqrt{\frac{\sum_{i=1}^{m}(x_i-\hat{\eta})^2}{n-1}} \tag{8}$$

where n is the sample size.

Thus, the estimated PCI for recyclable products $\hat{R}_{cp}$ can be expressed as:

$$\hat{R}_{cp} = \frac{1-|\hat{\eta}|}{\hat{\omega}} + 1.5 \tag{9}$$

Let

$$Z = \sqrt{n} \times \left[(\hat{R}_{cp} - 1.5) \times (\hat{\omega}/\omega) - (M_{ts} - 1.5) \right] \text{ and } \chi = (n-1)(\hat{\omega}/\omega)^2 \tag{10}$$

Assuming normality, Z follows the standard normal distribution $Z \sim N(0,1)$, while χ follows a chi-square distribution with n–1 degree of freedom (i.e., χ^2_{n-1}).

$$\sqrt{1-\alpha} = \Pr\left\{ -Z_{\alpha'/2} \le Z \le Z_{\alpha'/2} \right\} \tag{11}$$

$$\sqrt{1-\alpha} = \Pr\left\{ \chi^2_{\alpha'/2,n-1} \le \chi \le \chi^2_{1-(\alpha'/2),n-1} \right\} \tag{12}$$

where $Z_{\alpha'/2}$ is the upper $\alpha'/2$ quantile of $N(0,1)$, $\chi^2_{\alpha'/2,n-1}$ and $\chi^2_{1-(\alpha'/2),n-1}$ are the lower and upper $\alpha'/2$ quantiles of the chi-square distribution χ^2_{n-1}, respectively, $\alpha' = 1-\sqrt{1-\alpha}$, and α is the significance level.

Since Z and χ are independent, it follows that:

$$1-\alpha = \Pr\left\{ -Z_{\alpha'/2} \le Z \le Z_{\alpha'/2}, \chi^2_{\alpha'/2,n-1} \le \chi \le \chi^2_{1-(\alpha'/2),n-1} \right\} \tag{13}$$

Consequently, we obtain:

$$1-\alpha \le \Pr\left\{ (\hat{R}_{cp} - 1.5)\sqrt{\frac{\chi^2_{1-(\alpha'/2),n-1}}{n-1}} - \frac{Z_{\alpha'/2}}{\sqrt{n}} + 1.5 \le R_{cp} \right.$$

$$\left. \le (\hat{R}_{cp} - 1.5)\sqrt{\frac{\chi^2_{\alpha'/2,n-1}}{n-1}} + \frac{Z_{\alpha'/2}}{\sqrt{n}} + 1.5 \right\} \tag{14}$$

According to Buckley (2005) and Chen et al. (2019b), the triangular fuzzy number of FPCI for recyclable products $\tilde{R}_{cp}$ can be obtained through α-cuts as follows:

$$\tilde{R}_{cp}[\alpha] = \begin{cases} \left[(\hat{R}_{cp} - 1.5)e_U - q \times s_Z + 1.5(\alpha), (\hat{R}_{cp} - 1.5)e_L + q \times s_Z + 1.5(\alpha) \right], 0.01 \le \alpha \le 1 \\ \left[(\hat{R}_{cp} - 1.5)e_U - q \times s_Z + 1.5(0.01), (\hat{R}_{cp} - 1.5)e_L + q \times s_Z + 1.5(0.01) \right], 0 \le \alpha \le 0.01 \end{cases} \tag{15}$$

where $e_L = \sqrt{\frac{\chi^2_{1-(\alpha'/2),n-1}}{\chi^2_{0.5,n-1}}}$, $e_U = \sqrt{\frac{\chi^2_{\alpha'/2,n-1}}{\chi^2_{0.5,n-1}}}$, $s_Z = \frac{Z_{\alpha'/2}}{\sqrt{\chi^2_{0.5,n-1}}}$, and $q = \sqrt{\frac{n-1}{n}}$.

When α=1, by combining Equations (14) and (15), we obtain:

$$(\hat{R}_{cp}-1.5)e_U-q\times s_Z+1.5(1)=(\hat{R}_{cp}-1.5)\sqrt{\frac{\chi^2_{0.5,n-1}}{n-1}}+1.5=(\hat{R}_{cp}-1.5)e_L+q\times s_Z+1.5(1) \quad (16)$$

Therefore, the FPCI of recyclable products $\tilde{R}_{cp}$ can be represented as a triangular fuzzy number as follows:

$$\tilde{R}_{cp}=(\tilde{R}^L_{cp},\tilde{R}^M_{cp},\tilde{R}^R_{cp}) \quad (17)$$

where

$$\tilde{R}^L_{cp}(\alpha)=(\tilde{R}_{cp}-1.5)e_U-q\times s_Z+1.5(0.01)$$
$$\tilde{R}^M_{cp}(\alpha)=\tilde{R}^L_{cp}(1)=\tilde{R}^R_{cp}(1)$$
$$\tilde{R}^R_{cp}(\alpha)=(\tilde{R}_{cp}-1.5)e_L+q\times s_Z+1.5(0.01)$$

The membership function of $\tilde{R}_{cp}$ is defined as follows:

$$\tilde{R}^{\psi}_{cp}(x)=\begin{cases}0, & if\ x<\tilde{R}^L_{cp}\\ I, & if\ \tilde{R}^L_{cp}\le x<\tilde{R}^M_{cp}\\ 1, & if\ x=\tilde{R}^M_{cp}\\ Q, & if\ \tilde{R}^M_{cp}<x\le\tilde{R}^R_{cp}\\ 0, & if\ \tilde{R}^R_{cp}<x\end{cases} \quad (18)$$

Here, I and Q are defined as follows:

$$\begin{cases}(\hat{R}_{cp}-1.5)\times e^*_U-q\times s^*_Z+1.5=x, \text{ for } \tilde{R}^L_{cp}\le x<\tilde{R}^M_{cp}\\ (\hat{R}_{cp}-1.5)\times e^*_L+q\times s^*_Z+1.5=x, \text{ for } \tilde{R}^M_{cp}<x\le\tilde{R}^R_{cp}\end{cases} \quad (19)$$

where $e^*_L=\sqrt{\frac{\chi^2_{1-(Q/2),n-1}}{\chi^2_{0.5,n-1}}}$, $e^*_U=\sqrt{\frac{\chi^2_{I/2,n-1}}{\chi^2_{0.5,n-1}}}$, and $d^*_Z=\frac{Z_{I/2}}{\sqrt{\chi^2_{0.5,n-1}}}$.

Based on Equation (18), the defuzzified FPCI for recyclable products $\tilde{R}'_{cp}$ is calculated as follows:

$$\tilde{R}'_{cp}=\frac{\tilde{R}^L_{cp}+\tilde{R}^M_{cp}+\tilde{R}^R_{cp}}{3} \quad (20)$$

When the FPCI of recyclable products $\tilde{R}'_{cp}\ge 3$, it indicates that the production quality is acceptable (Yang and Chen, 2019), and consequently, the quality of recycled products is also more reliable. Conversely, a lower index value $\tilde{R}'_{cp}<3$ implies poor quality. In such cases, companies should immediately implement quality improvement activities and provide training and education for production line personnel.

3.3 Procedural Steps of the Proposed Approach

The procedural steps of the proposed approach are delineated below.

Step 1: Use the interval value [0,1] to evaluate the key inspection items of recyclable products.

Step 2: Calculate the IVHFEF ϑ for the quality assessment of recyclable products using Equations (4)-(6). Recyclable products with $\vartheta \geq 0.5$ are considered qualified and proceed to the next step; otherwise, they are reclassified for resale or scrapping. This threshold of $\vartheta \geq 0.5$ was determined through consensus among domain experts, indicating that quality characteristics with an importance value of 0.5 or above are critically significant to the overall assessment.

Step 3: Use Equations (15)-(20) to calculate the FPCI of the recyclable product $\tilde{R}'_{cp}$ after remanufacturing.

Step 4: When $\tilde{R}'_{cp} \geq 3$, the remanufactured recyclable product is deemed to meet the quality requirements. Otherwise, the company should strengthen the inspection methods or adjust the production model, and provide improvement recommendations.

4. Case Study

The socket storage tray is a practical accessory made of plastic, specifically designed for socket tools. It is widely used for organizing and storing sockets of various sizes. With the growing emphasis on CE principles, an increasing number of manufacturers have begun to focus on the recycling and reuse of socket storage trays to achieve more efficient resource utilization and environmental protection. During the production process of these trays, a considerable amount of plastic waste is generated. Such waste can be crushed into recycled plastic granules using a crushing machine, which are then reintroduced into the production line. This approach not only helps maintain environmental sustainability but also reduces production costs. Therefore, this study applies the approach proposed in Section 3 to analyze the quality of the recycling and remanufacturing process of socket storage trays, aiming to promote their sustainable development within the CE context.

First, five quality managers (k=5) conducted subjective evaluations of 300 socket storage trays using visual and tactile inspection methods. The selection of five managers (k=5) aimed to incorporate the collective expertise of key decision-makers responsible for production quality, ensuring a comprehensive and authoritative assessment. The sample size of 300 trays (n=300) was chosen to provide a statistically stable and representative basis for estimating process capability under typical operating conditions. The assessments were performed for three key inspection items as: contamination (G1), staining (G2), and oxidation (G3). All rating intervals were defined within [0,1], where larger values indicate closer proximity to ideal recycling quality. Specifically,

- [0.8,1.0] represents excellent recycling quality,
- [0.6,0.8] represents good recycling quality,
- [0.4,0.6] represents acceptable recycling quality,
- [0.2,0.4] represents nonconforming recycling quality, and
- [0.0, 0.2] represents defective recycling quality.

Table 1 presents the IVHFE evaluations of the socket storage trays by the five quality managers for the three key inspection items. Table 2 displays the results of the IVHFEF θ for the three key inspection items. As shown in Table 2, all assessed trays achieved $\theta \geq 0.5$, indicating that this batch of socket storage trays meets the acceptable recycling quality threshold and can proceed to the next stage of remanufacturing.

Table 3 summarizes the specifications, tolerances, means, and standard deviations of five critical quality characteristics of the socket storage tray as: 4mm (C1), 5.5mm (C2), 9mm (C3), 13mm (C4), and 15mm (C5). According to Table 4, the FPCI $\tilde{R}'_{cp}$ values for these five critical characteristics range between 2.5 and 6.2, reflecting varying manufacturing capability levels. Among them, the quality characteristics 4mm (C1), 9mm (C3), and 13mm (C4) exhibit $\tilde{R}'_{cp} > 4.3$, indicating stable processes and good product quality. However, 5.5mm (C2) and 15mm (C5) show $\tilde{R}'_{cp}$ values of 2.5 and 2.69, respectively, both below the standard threshold of 3, suggesting insufficient manufacturing capability and the need for quality improvement.

Table 1. *IVHFEs Provided by Five Quality Managers for the Socket Storage Tray*

Item	k_1	k_2	k_3	k_4	k_5
G1	{[0.7,0.8],[0.8,0.9]}	{[0.6,0.8],[0.7,0.9]}	{[0.7,0.9]}	{[0.6,0.7],[0.8,0.9]}	{[0.7,0.8],[0.8,0.9]}
G2	{[0.5,0.7],[0.6,0.8]}	{[0.6,0.7],[0.7,0.8]}	{[0.5,0.6],[0.7,0.8]}	{[0.6,0.8]}	{[0.5,0.6],[0.6,0.8]}
G1	{[0.7,0.8],[0.8,0.9]}	{[0.6,0.8],[0.7,0.9]}	{[0.7,0.9]}	{[0.6,0.7],[0.8,0.9]}	{[0.7,0.8],[0.8,0.9]}

Table 2. *Values of Fuzziness (A), Hesitation (B), and IVHFEF θ for the Socket Storage Tray*

Item	A	B	θ
G1	0.8333	0.0667	0.6989
G2	0.7667	0.1333	0.6090
G3	0.7000	0.1500	0.5225

Table 3. *Specifications, Mean, and Standard Deviations of the Socket Storage Tray*

(unit: mm)

Characteristic	LSL	USL	d	T	μ	σ
C1	3.9	4.1	±0.1	4	4.015	0.03
C2	5.4	5.6	±0.1	5.5	5.560	0.04
C3	8.8	9.2	±0.2	9	8.985	0.05
C4	12.7	13.3	±0.3	13	13.02	0.06
C5	14.5	15.5	±0.5	15	15.00	0.42

Table 4. *Values of $\tilde{R}'_{cp}$ for the Socket Storage Tray*

Characteristic	$\tilde{R}^L_{cp}$	$\tilde{R}^M_{cp}$	$\tilde{R}^R_{cp}$	$\tilde{R}'_{cp}$	Status ($\tilde{R}'_{cp} \geq 3$)
C1	3.949	4.333	4.467	4.333	Qualified
C2	2.281	2.500	2.464	2.500	Unqualified
C3	4.737	5.200	5.414	5.200	Qualified
C4	5.617	6.167	6.471	6.167	Qualified
C5	2.454	2.690	2.672	2.690	Unqualified

5. Conclusions

Against the backdrop of sustainable development and circular manufacturing, companies are increasingly required to ensure both production efficiency and product recyclability under uncertain quality conditions. To meet this dual demand, this study developed an integrated quality evaluation approach that combines the IVHFEF with the FPCI. This approach captures the inherent hesitation and ambiguity in human judgment while quantitatively reflecting process variability, thereby bridging the gap between qualitative inspection and quantitative control. Through an empirical case involving socket storage trays, the study validates the feasibility and diagnostic capability of the proposed approach, demonstrating its effectiveness in evaluating the quality of recyclable products and enhancing decision support for sustainable manufacturing.

The analysis of the empirical case reveals that among the three key inspection items, contamination (C1) exhibits the highest IVHFEF value (θ=0.6989). This result indicates that inspectors regarded this quality attribute as closest to the ideal standard and demonstrated a relatively high level of consensus. In contrast, oxidation (C3) has the lowest IVHFEF value (θ=0.5225), reflecting greater divergence in the quality managers' judgments. This suggests that oxidation issues require further monitoring and control in future quality assessments. According to the analysis of the FPCI, among the five critical quality characteristics of the socket storage tray, 5.5mm (C2) and 15mm (C5) fail to meet the required process capability threshold. Further diagnostic insight, based on the data in Table 3, clarifies the distinct nature of their deficiencies and points to potential root causes. For characteristic C2 (5.5mm), the primary issue is a significant deviation of the process mean from the target nominal value. This systematic shift suggests potential causes such as incorrect machine calibration, progressive tool wear, or a suboptimal setting of the forming/molding parameters. Corrective action should therefore first focus on re-centering the process through equipment recalibration or tool adjustment. For characteristic C5 (15mm), the problem is excessive process variability, indicated by its substantially larger standard deviation compared to other characteristics. This high scatter could stem from several sources, including: (1) inconsistency in raw material properties, or (2) instability in the clamping or positioning mechanism during machining/assembly. To improve C5, efforts must prioritize reducing variation by investigating and controlling these potential sources of instability, possibly through supplier quality management, preventive maintenance, or process control enhancements.

Consequently, the proposed approach not only identifies underperforming characteristics but, through this diagnostic breakdown, guides distinct and targeted improvement strategies. Future research can further expand the applicability of the proposed approach to multi-stage production processes or complex assembly systems to validate its robustness under different manufacturing conditions. Moreover, incorporating dynamic fuzzy parameters or alternative types of fuzzy numbers could enhance the approach's applicability in real-time quality monitoring. Finally, from the perspectives of CE and sustainable manufacturing, future studies may explore the potential of this approach in resource recycling, green manufacturing, and product lifecycle quality management.

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