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ForestSoft Set for Mechanical Automation Production Control Systems Analysis Based on an Intelligent Manufacturing Environment

Li Song, Jianyong Liu, Han Ding, Wenhui Zhang*

Jiangxi Vocational College of Industry and Engineering, Pingxiang, Jiangxi, 337000, China

*Corresponding author, E-mail: aloxi@163.com; zhangwh@jxvcie.edu.cn

Abstract: Intelligent manufacturing has become a disruptive force in the global industrial landscape in the age of Industry 4.0. In mechanical automation, responsive and flexible control systems are essential as manufacturing lines become increasingly intricate. The purpose of this research is to assess production control systems for mechanical automation in the context of intelligent manufacturing settings. The evaluation of system effectiveness, flexibility, data integration, and real-time responsiveness is prioritized. The study investigates how intelligent settings affect system performance and decision-making quality by examining important operational and technological factors. We use the ForestSoft set to split each main criterion into a TreeSoft set and in each TreeSoft we compute the criteria weights and rank the alternatives. We use the WPM method as an MCDM to rank alternatives. The results highlight how crucial it is to include smart infrastructure and advanced analytics into production systems to improve flexibility and competitiveness in contemporary manufacturing.

Keywords: ForestSoft Set; Mechanical Automation Production; Control Systems; Intelligent Manufacturing Environment.

1. Introduction

Technological developments and growing demands for sustainability, quality, and personalization are causing a major upheaval in the manufacturing sector. Among these advancements, the emergence of intelligent manufacturing environments, made possible by AI, IoT, and cyber-physical systems, has completely changed conventional production paradigms[1], [2]. These settings enable autonomous decision-making, smooth machine-to-machine connection, and real-time data transmission.

Production control systems for mechanical automation are essential for organizing manufacturing procedures. They manage production schedules, streamline operational operations, and guarantee synchronization between different hardware components[3], [4]. However, when faced with the changing demands of contemporary manufacturing environments, classic control systems are limited in their capacity to adapt and respond.

Control systems that are not just automated but also intelligent—able to learn, adapt, and optimize operations through data-driven insights—are essential in intelligent industrial environments[4], [5]. These systems need to be strong enough to manage intricate decision-making situations and adaptable enough to consider regular modifications to delivery dates, batch sizes, and product designs.

Aligning performance measurements with smart factory aspirations is a major difficulty in assessing mechanical automation control systems. Newer metrics like system interoperability, data integration, predictive maintenance, and scalability must now be used in addition to more traditional ones like speed, accuracy, and uptime.

The emphasis has switched from solely mechanical performance to a more comprehensive view of system intelligence due to the integration of smart sensors, edge computing, and real-time analytics[6], [7]. These days, evaluating control systems includes determining how well they use data to detect errors, improving operational efficiency, and predictably adjusting to shifting production floor conditions.

Control systems that are in line with intelligent manufacturing principles offer competitive advantages from a strategic and managerial standpoint. These include improved product quality, lower operating expenses, and a quicker time to market[8]. Therefore, for manufacturers looking for long-term resilience, assessing and enhancing these systems is not only a technical issue but also a strategic requirement.

By creating a multifaceted assessment methodology specifically suited for intelligent manufacturing scenarios, our study tackles these problems. Technical, operational, and intelligent performance metrics are all included in the framework[9], [10]. The study assesses several automation control systems to determine their advantages, disadvantages, and areas for development using a mix of qualitative and quantitative data.

Finally, by highlighting the significance of intelligent system integration, this article adds to the larger conversation on digital transformation in manufacturing. For engineers, researchers, and decision-makers working on automated production control design or management in the context of Industry 4.0, it also offers practical insights.

Six additional categories of soft sets were added by Smarandache between 2018 and 2024: HyperSoft Set, IndetermSoft Set, IndetermHyperSoft Set, SuperHyperSoft Set, TreeSoft Set, and ForestSoft Set[11], [12], [13]. These sets can deal with the criteria values to show the relations between them. The ForestSoft set is used to divide each main criterion into a TreeSoft set and each TreeSoft set we can compute the criteria weights and ranking the alternatives.

1.1 Motivation Behind the Study

In recent years, manufacturing has been changing rapidly. The rise of smart technologies like artificial intelligence and the Internet of Things has transformed how production lines operate. Traditional systems often struggle to keep up with this fast pace. This study was motivated by the need to explore better ways to manage and control manufacturing processes in this new environment.

1.2 Problem Statement

Most existing mechanical control systems were not built with flexibility or intelligence in mind. They work well in stable settings but cannot quickly adapt when production conditions change. The main problem this research addresses is how to evaluate and improve these systems to meet the demands of modern smart factories.

1.3 Objectives of the Research

This study aims to provide a way to measure how well control systems perform in intelligent manufacturing environments. It focuses on key areas like how responsive the system is, how it integrates with data, and how flexible it can be. The goal is to help engineers choose or design systems that truly match today's manufacturing needs.

1.4 Literature Review

When it comes to handling attributes, Plithogenic-based decision-making techniques are more flexible and accommodating. Sathya et al. [14] created a Plithogenic-centered decision-making model using PFHS representations and presents the ideas of the Plithogenic Forest hypersoft set (PFHS).
The recently presented PFHS representations are combined with the Plithogenic method of making decisions based on contradictions to create a strong decision-making process that can handle attributes and sub-attributive values on a bigger scale. The decision-making dilemma of choosing a location for manufacturing plant establishment is addressed by the integrated approach put forward in this work. The key characteristics are determined, and using the potential sub-attributes, the corresponding Plithogenic forest hypersoft sets are created.

In this instance, the alternatives are exposed to each criterion to ascertain the best ranking according to the criteria, and each of the core characteristics itself creates a Plithogenic tree hypersoft set representations with many sub-attribute values. To provide a more thorough ranking, aggregate score values are also calculated. To develop new approaches to decision-making, the PFHS concept will be combined with other approaches.

It is well known that the Plithogenic Set generalizes ideas like Neutrosophic Sets and Fuzzy Sets. By providing a framework for approximating subsets using lower and upper boundaries determined by equivalence relations, rough sets help to capture uncertainty in data analysis and classification. Concepts like Hyper Plithogenic Sets, Super hyper Plithogenic Sets, Hyperrough Sets, and Superhyperrough Sets are extensions of these fundamental ideas. By presenting the Forest HyperPlithogenic Set, the Forest SuperHyperPlithogenic Set, the Forest HyperRough Set, and the Forest SuperHyperRough Set, Fujita [15] expanded upon these ideas. These frameworks are broad extensions of established paradigms in set theory.

1.4.1 Evolution of Intelligent Manufacturing Systems

Manufacturing has evolved from simple automation to highly intelligent systems. These smart systems use data, sensors, and learning algorithms to make decisions on their own. Over time, researchers have developed many models to describe and improve this process.

1.4.2 Comparative Analysis of Existing Control Frameworks

Various approaches like fuzzy sets, neutrosophic sets, and plithogenic models have been proposed to improve decision-making in manufacturing. Each has its strengths and weaknesses. This research builds on these ideas and suggests that ForestSoft Sets may offer a more detailed and organized way to evaluate system performance.

1.4.3 Gaps in Current Research

Despite many advancements, most existing studies do not fully consider the complex structure of smart factories. They often miss how different performance factors interact with each other. There’s a clear need for a more complete method that can handle detailed sub-criteria and link them together meaningfully.

2. ForestSoft Set

To create a single function whose domain is the union of all tree-nodes' power sets and whose values in P(H) combine the data provided by the separate TreeSoft Sets, a ForestSoft Set is created by "gluing" (uniting) a collection of TreeSoft Sets together[16].

Let U be a universal of discourse and $H \subseteq U$ be a non-empty subset, and P(H) is the power set of H. We have a set of TreeSoft sets such as:

$$\left\{F_t\colon P\left(Tree\left(A^{(t)}\right) \to P(H)\right)\right\}_{t\in T} \quad (1)$$

We can define the forest by union of all trees

$$Forest\ \left(\left\{A^{(t)}\right\}_{t\in T}\right) = \bigcup_{t\in T} A^{(t)} \quad (2)$$

$$F: P\left(Forest\left(A^{(t)}\right)\right) \to P(H) \tag{3}$$

The evaluation process followed the WPM method to rank the alternatives based on expert input. First, a decision matrix was developed by comparing each alternative against a set of defined criteria. Experts provided their assessments using a normalized scale from 0 to 1, reflecting the relative performance of each alternative under each criterion.

Once all expert inputs were collected, the individual matrices were merged into a single, unified decision matrix. From this, the relative importance of each criterion was calculated using a simple averaging method. These weights were then applied to create a weighted decision matrix, which enabled a more balanced and meaningful comparison across the alternatives.

$$F_{ij} = \left(H_{ij}\right)^{w_j} \tag{4}$$

Where H_{ij} refers to the decision matrix.

Find the final score

$$k_i = \prod_{i=1}^{n} F_{ij} \tag{5}$$

Rank the alternatives.

2.1 Structure and Composition of the ForestSoft Framework

ForestSoft Sets are made by combining several TreeSoft Sets. Each TreeSoft Set represents a group of related performance factors. When these are connected, they form a larger structure, the ForestSoft Set which gives a clearer picture of the overall system performance.

2.2 Justification for Using the WPM Method

The Weighted Product Method (WPM) was chosen because it is simple yet powerful. It allows us to compare alternatives by multiplying weighted scores, which makes it easier to see which system performs better overall. It also handles different types of values smoothly.

2.3 Mapping of Criteria to TreeSoft Nodes

Each major performance area is broken into smaller parts and mapped into TreeSoft nodes. For example, "System Intelligence" includes things like real-time decision-making and fault diagnosis. This detailed breakdown helps experts focus on specific system features during evaluation.

3. Detailed Analysis and Ranking of System Alternatives

This section presents the outcomes of the proposed evaluation approach applied to seven alternative control systems using a structured, multi-level decision framework. The analysis was organized around four main performance criteria, each designed to reflect a key aspect of intelligent manufacturing systems. Each criterion was modeled as a TreeSoft set to allow a hierarchical breakdown into detailed sub-criteria, capturing both technical and operational characteristics.

The first criterion, System Intelligence and Adaptability, focused on a system's ability to respond to changes, process data in real-time, and improve over time through self-learning. This included evaluating decision-making speed, accuracy of learning models, and how quickly and effectively the system can detect and recover from faults.

The second criterion, System Integration and Compatibility, assessed how well the system connects and communicates with other hardware and software components within the manufacturing environment. Sub-criteria included sensor network quality, compatibility with existing software interfaces, and the ability to support legacy systems.

The third criterion, Production Performance and Efficiency, measured the system's contribution to optimizing manufacturing processes. This included task execution times, reduction of idle periods, throughput rates, and energy consumption efficiency—factors directly linked to cost savings and operational effectiveness.

The fourth criterion, Maintainability and Scalability, examined how easily the system can be updated, expanded, and maintained. It covered aspects such as modular system design, cost of maintenance, firmware flexibility, and diagnostic capabilities.

For each of these criteria, a separate TreeSoft set was created. Expert evaluations were collected for all sub-criteria across the seven alternatives. Three domain experts provided structured assessments, which were consolidated into a single decision matrix for each criterion.

First TreeSoft Set (System Intelligence and Adaptability)

The first decision matrix was constructed based on expert input, as shown in Figure 1. From this, the relative importance of each sub-criterion was calculated, with the resulting weights shown in Figure 2. These weights were applied to generate a weighted decision matrix (Figure 3), and the overall performance scores for each alternative were then computed (Figure 4). Based on these scores, the alternatives were ranked in order of performance (Figure 5).

Second TreeSoft Set (System Integration and Compatibility)

In the second TreeSoft set, the process was repeated following the same methodology. Expert evaluations were merged (Figure 6), and the weights of the sub-criteria were calculated accordingly (Figure 7). The weighted decision matrix was then generated (Figure 8), and final scores for each system were derived (Figure 9). The ranking based on these scores is shown in Figure 10.

Third TreeSoft Set (Production Performance and Efficiency)

For the third set, expert judgments were gathered and compiled into a single matrix (Figure 11). After determining the sub-criteria weights (Figure 12), the weighted matrix was built (Figure 13), and the overall performance scores were calculated (Figure 14). These scores were used to determine the final rankings (Figure 15).

Fourth TreeSoft Set (Maintainability and Scalability)

Finally, the fourth TreeSoft set was developed using the same structured process. Experts completed the evaluation matrix (Figure 16), and the importance of each sub-criterion was calculated (Figure 17). A weighted matrix followed (Figure 18), leading to the final performance scores (Figure 19), and the ranking of alternatives (Figure 20).

Each TreeSoft set offered insights into how well the alternatives performed in specific functional areas. The results showed a noticeable variation in performance across the alternatives. Some systems performed well in adaptability but fell short in maintainability, while others demonstrated strong energy efficiency but lacked integration flexibility.

By using this multi-layered approach, the evaluation captured both the strengths and weaknesses of each alternative in a structured and transparent way. The detailed breakdown helped reveal not just which system was best overall, but why it achieved that ranking—providing a valuable decision-making tool for selecting or improving intelligent control systems in smart manufacturing environments.

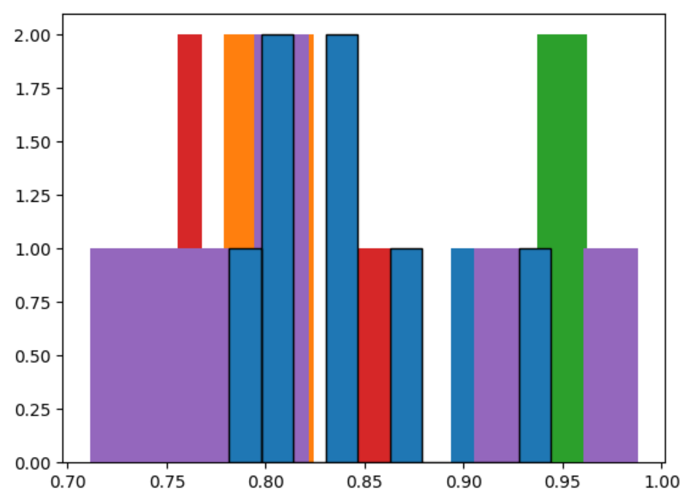

Fig 1. Combined decision matrix.

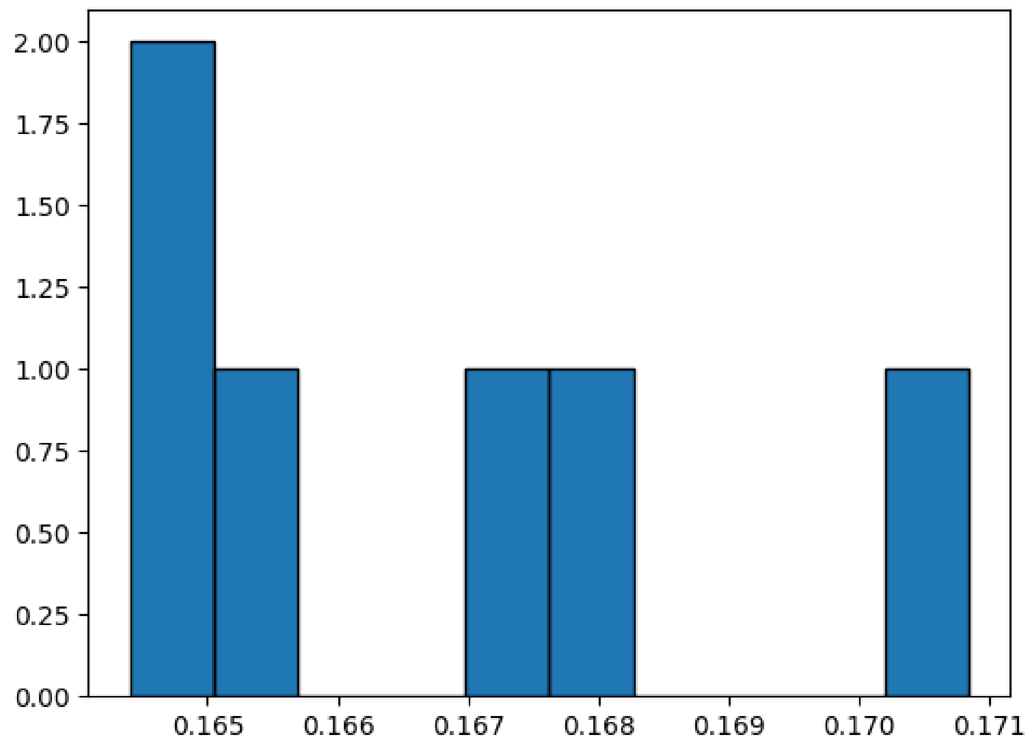

Fig 2. The criteria weights.

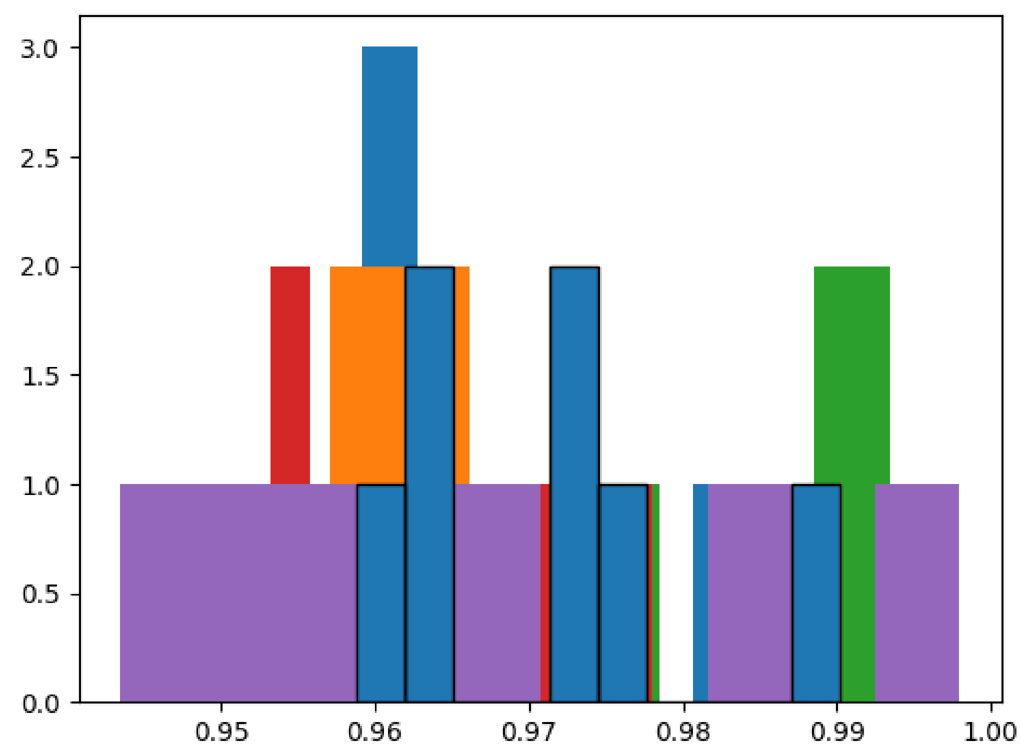

Fig 3. The weighted decision matrix.

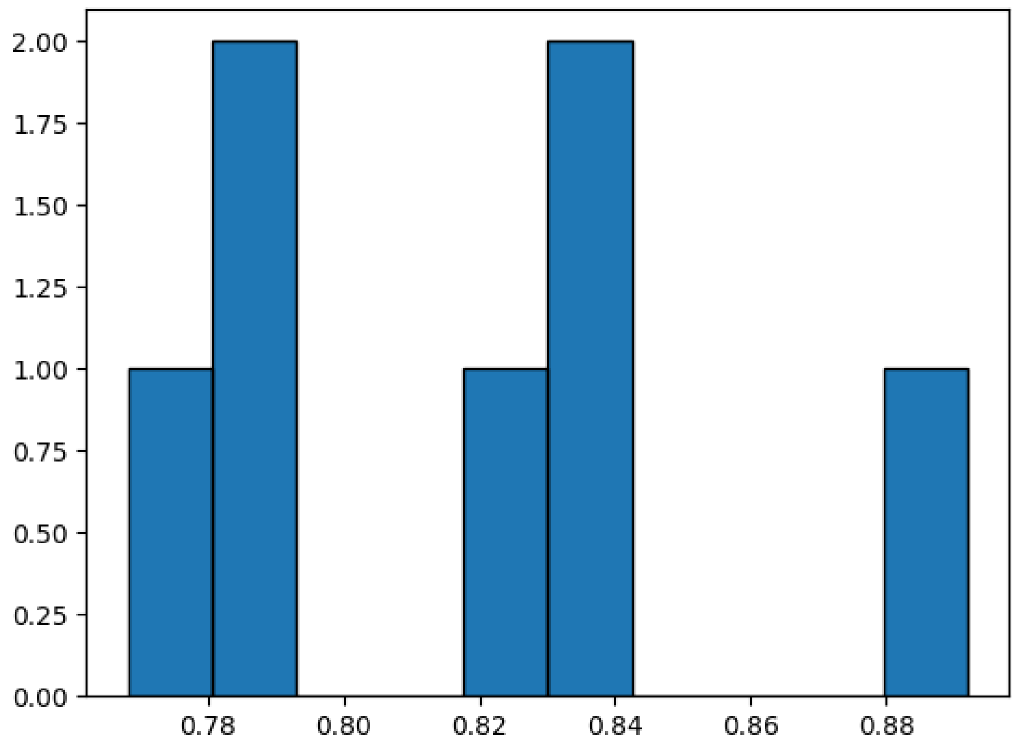

Fig 4. The final score of each alternative.

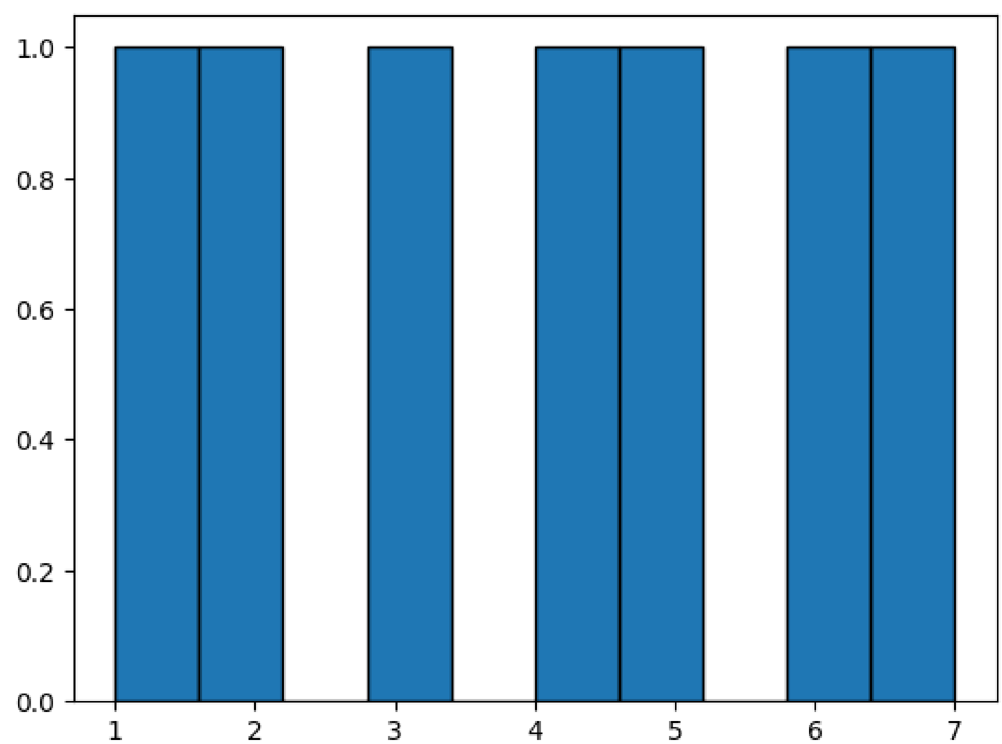

Fig 5. The rank of alternatives.

In the second TreeSoft set, the evaluation process followed a similar structured approach. Three experts assessed how each alternative performed in relation to the defined criteria. Their evaluations were combined with forming a single decision matrix that reflected a shared perspective, as illustrated in Figure 6. After collecting the data, the next step was to determine the weight of each criterion. These weights represent how important each factor is in the decision-making process and were calculated by averaging the experts' inputs. The resulting values are shown in Figure 7. Using these weights, a weighted decision matrix was developed. This helped to adjust the influence of each criterion based on its importance, providing a more accurate comparison between the alternatives. The weighted values are displayed in Figure 8. From this matrix, a final score for each alternative was calculated using the given formula. These scores, shown in Figure 9, offer a clear view of how each system performed overall. Finally, based on these results, the alternatives were ranked from highest to lowest performance in Figure 10.

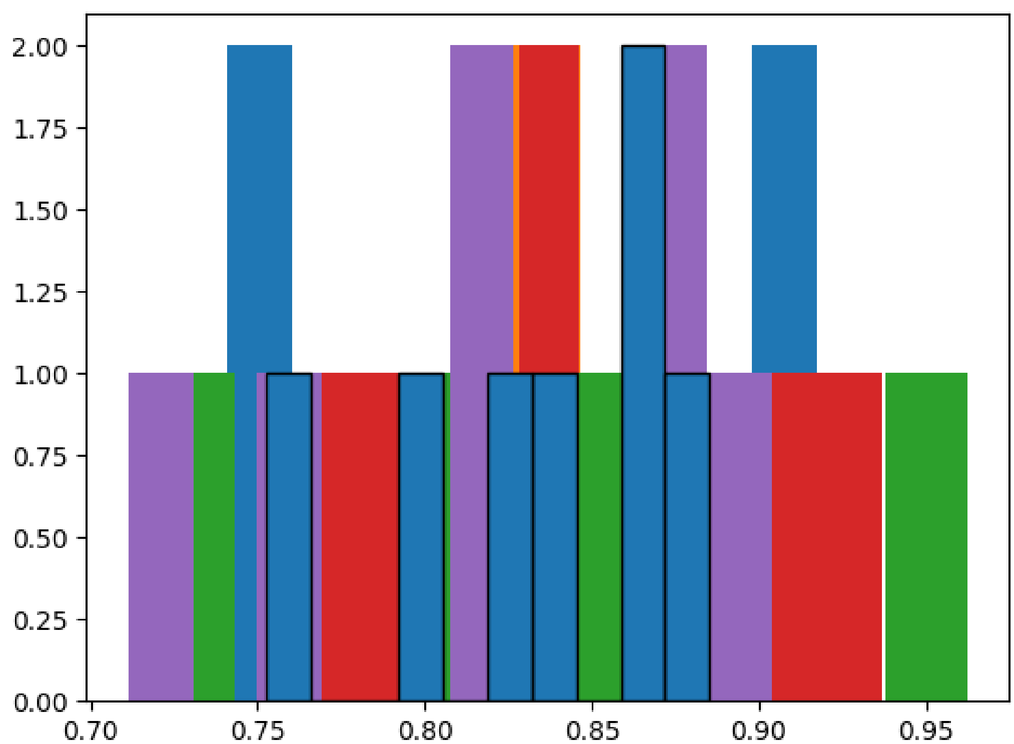

Fig 6. Combined decision matrix.

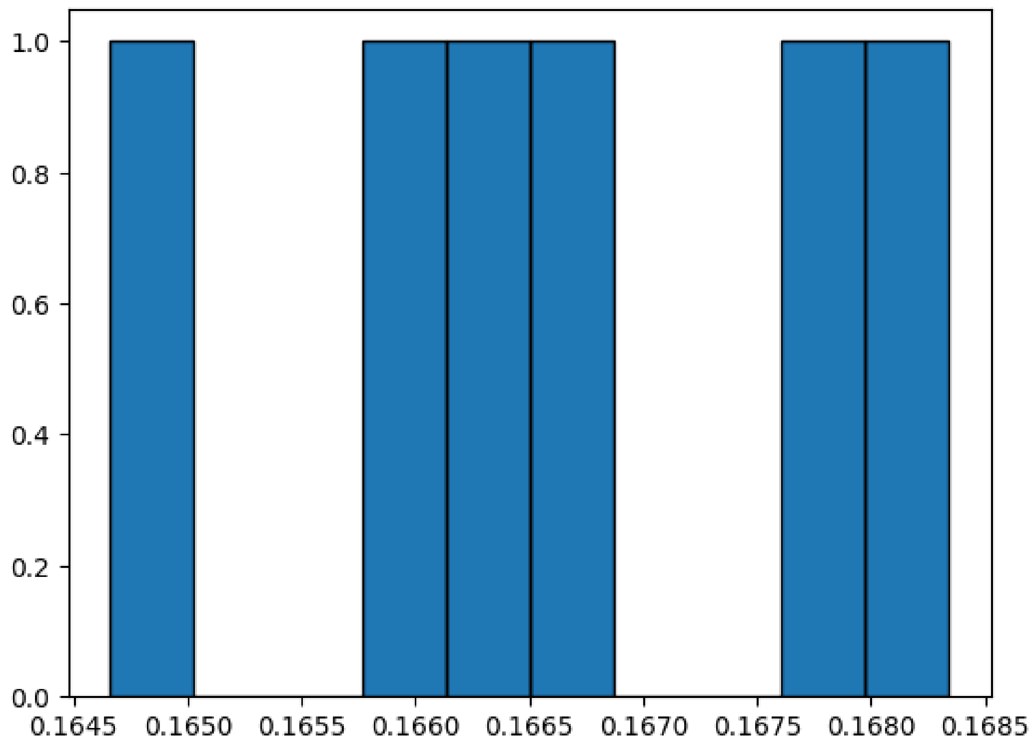

Fig 7. The criteria weights.

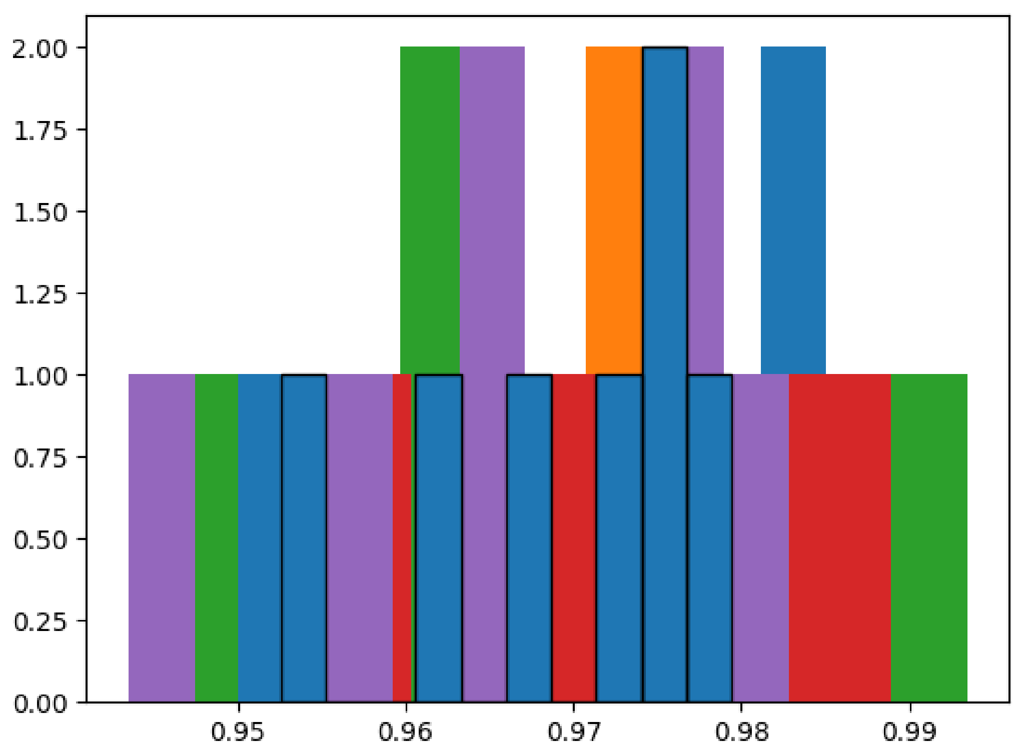

Fig 8. The weighted decision matrix.

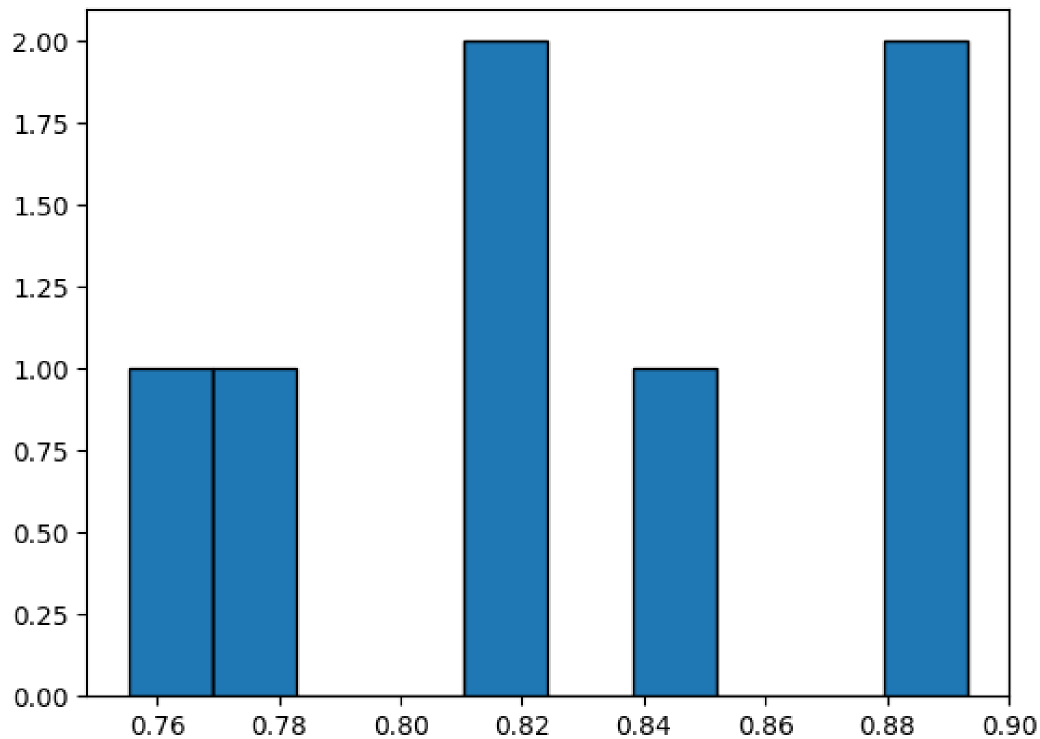

Fig 9. The final score of each alternative.

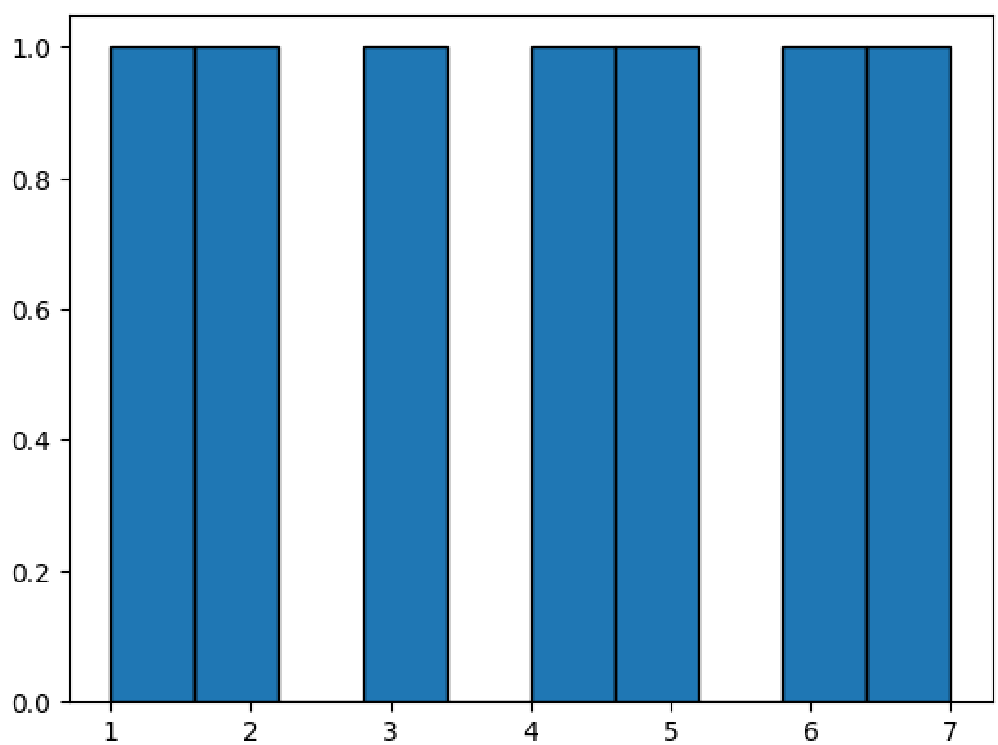

Fig 10. The rank of alternatives.

In the third TreeSoft set, the evaluation began with three experts providing their judgments on how each alternative performed according to the selected criteria. Their individual assessments were carefully reviewed and then merged into one unified decision matrix, as presented in Figure 11. Once the combined matrix was ready, the importance of each criterion was calculated based on the experts' input. These weights reflect which criteria had the most influence on the final decision and are shown in Figure 12.

With the criteria weights in place, a weighted decision matrix was created. This matrix allowed the influence of each criterion to be factored into how each alternative was scored, making the comparison more balanced and realistic. The weighted values are displayed in Figure 13.

The next step was to calculate a final score for each alternative, summarizing their performance across all weighted criteria. These scores, shown in Figure 14, helped identify which systems performed best overall. Based on these results, the alternatives were ranked accordingly, as shown in Figure 15.

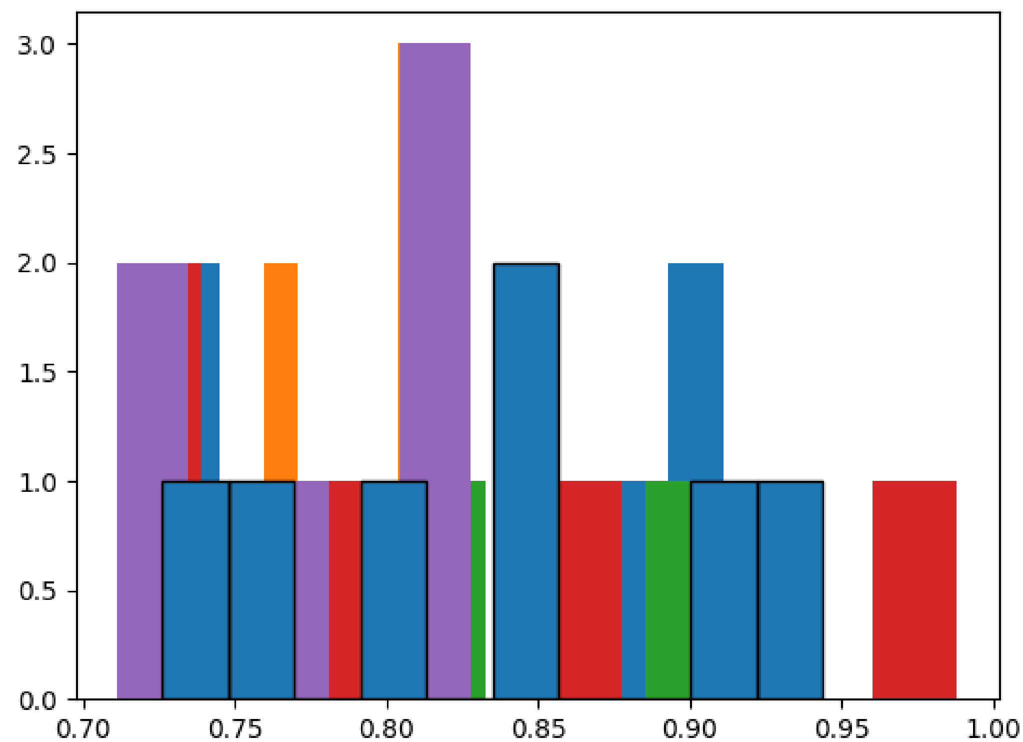

Fig 11. Combined decision matrix.

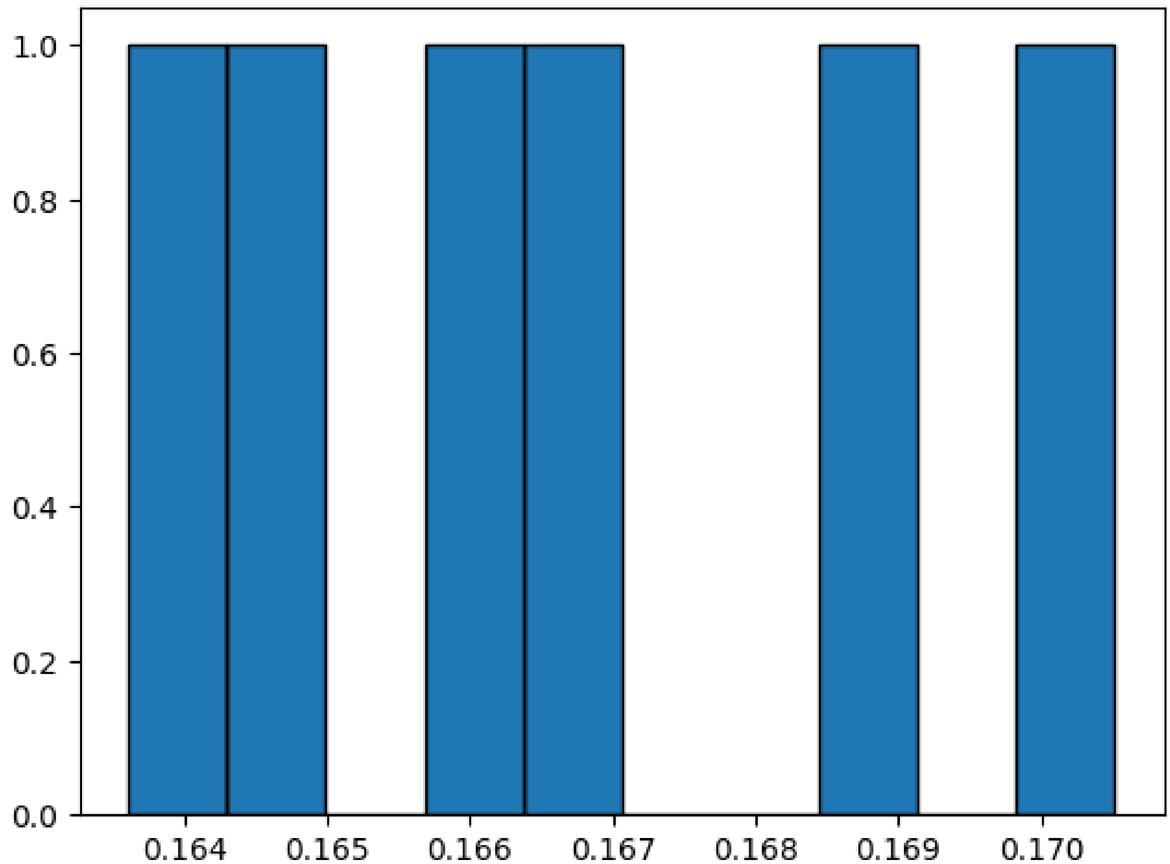

Fig 12. The criteria weights.

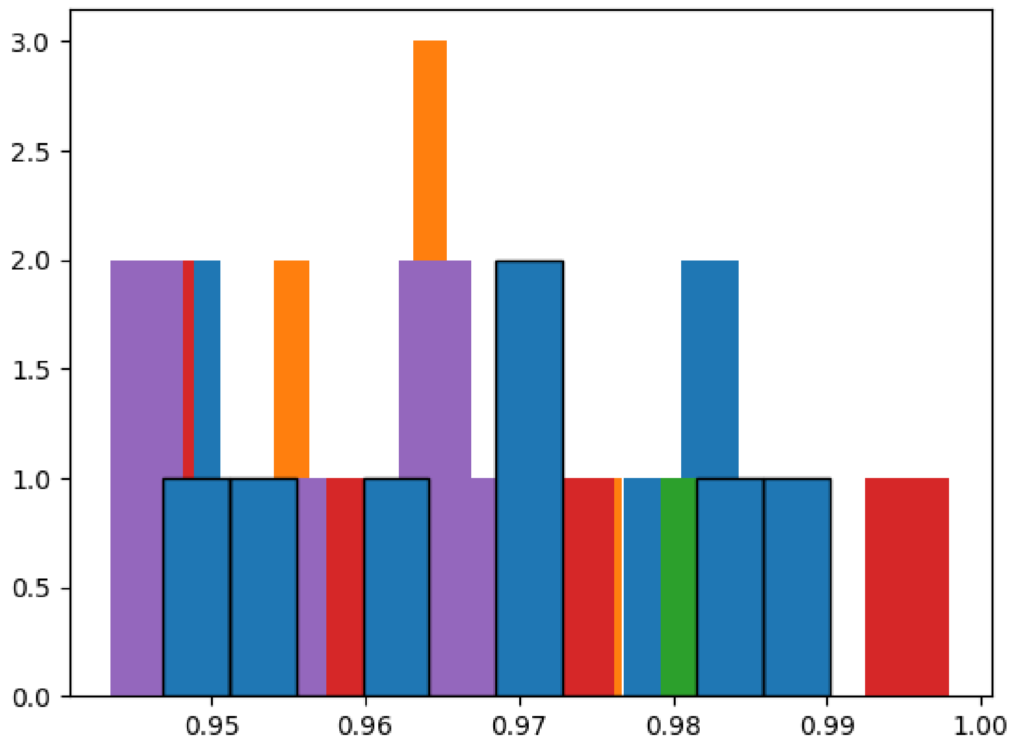

Fig 13. The weighted decision matrix.

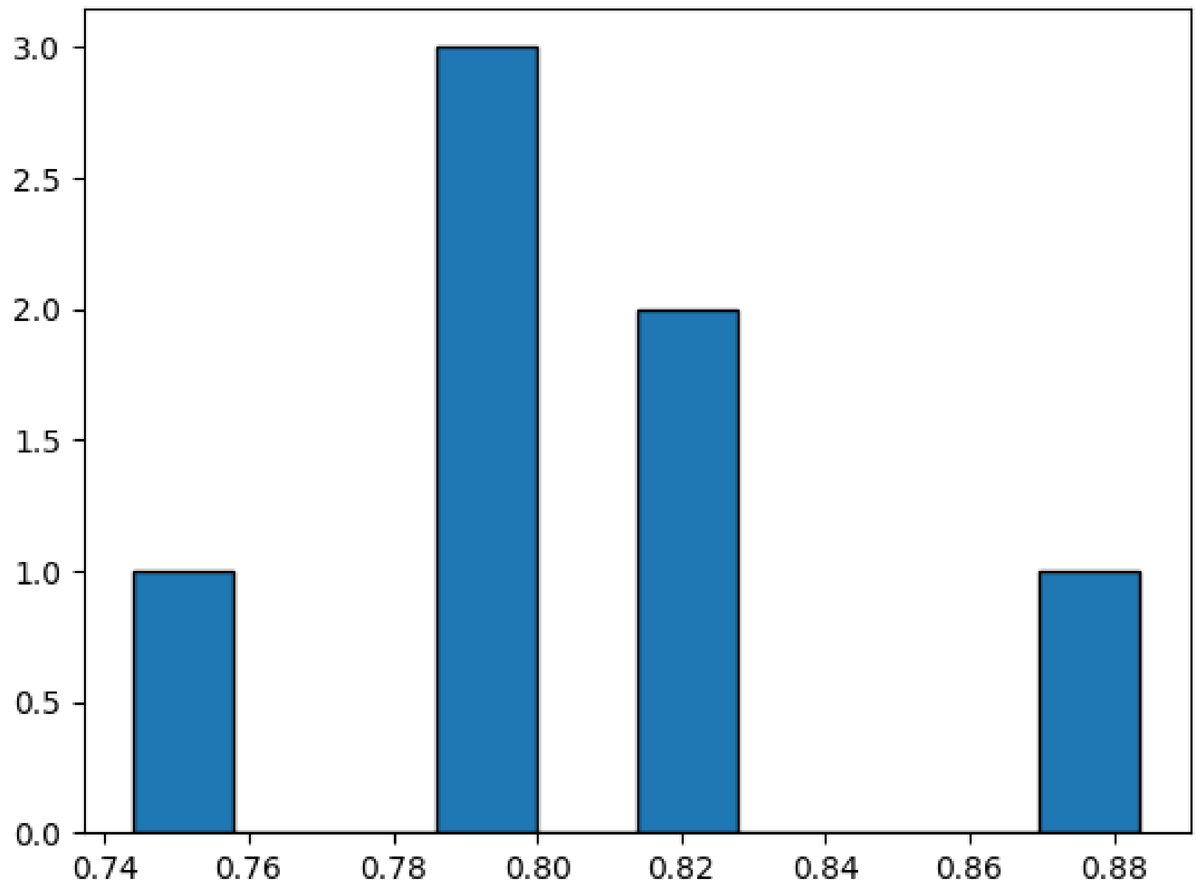

Fig 14. The final score of each alternative.

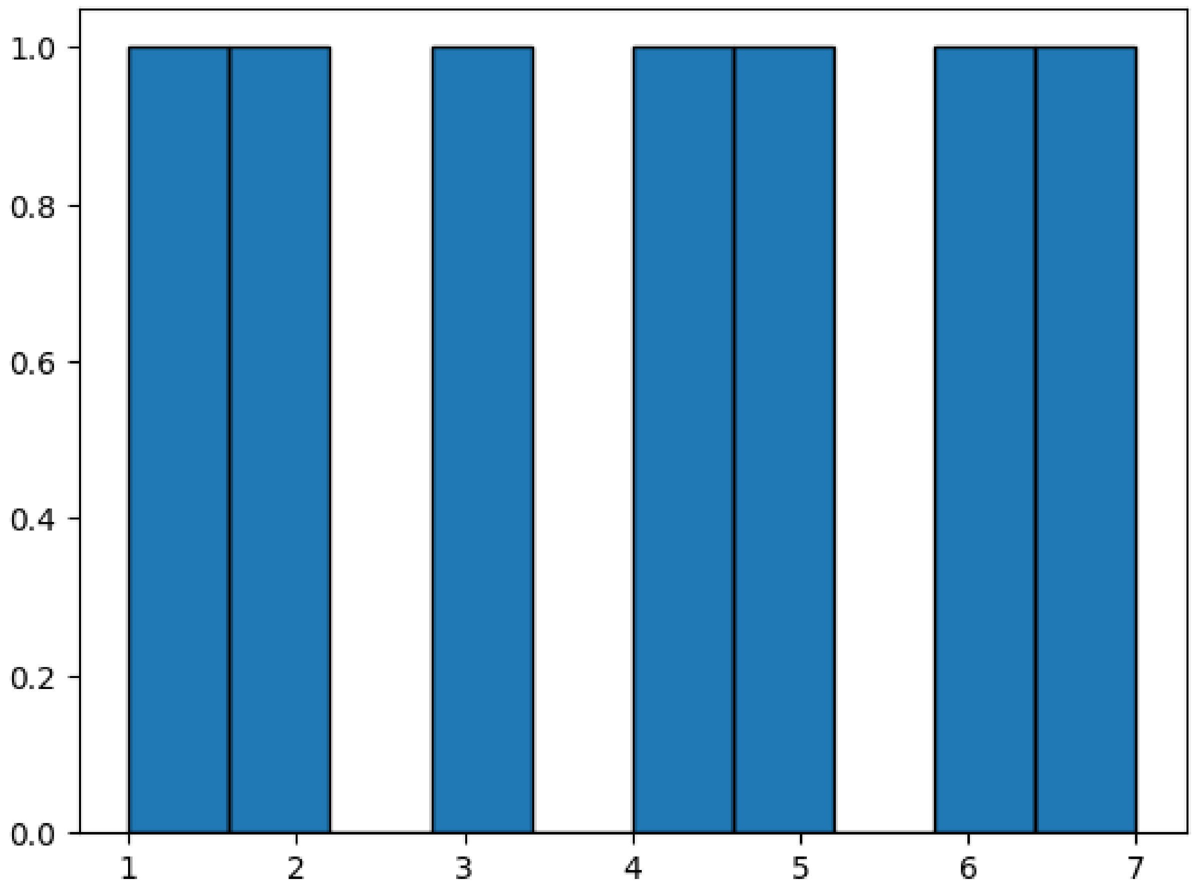

Fig 15. The rank of alternatives.

In the fourth TreeSoft set, three experts were involved in evaluating the alternatives against the set of defined criteria. Each expert provided their assessments separately, and their inputs were then merged into a single, combined matrix to represent a shared view, as illustrated in Figure 16. Once the matrix was prepared, the next step was to calculate the weights for each criterion, reflecting their importance in the decision process. These weights were derived from the average of expert opinions and are shown in Figure 17.

Using the assigned weights, a weighted decision matrix was constructed. This matrix helped to highlight how each alternative performed after considering the importance of each criterion. The weighted matrix is presented in Figure 18.

Afterward, the overall score for each alternative was calculated using the formula provided earlier. These final scores, shown in Figure 19, represent the combined performance of each system across all the criteria. Based on these scores, the alternatives were ranked from best to worst in Figure 20, completing the evaluation for this TreeSoft set.

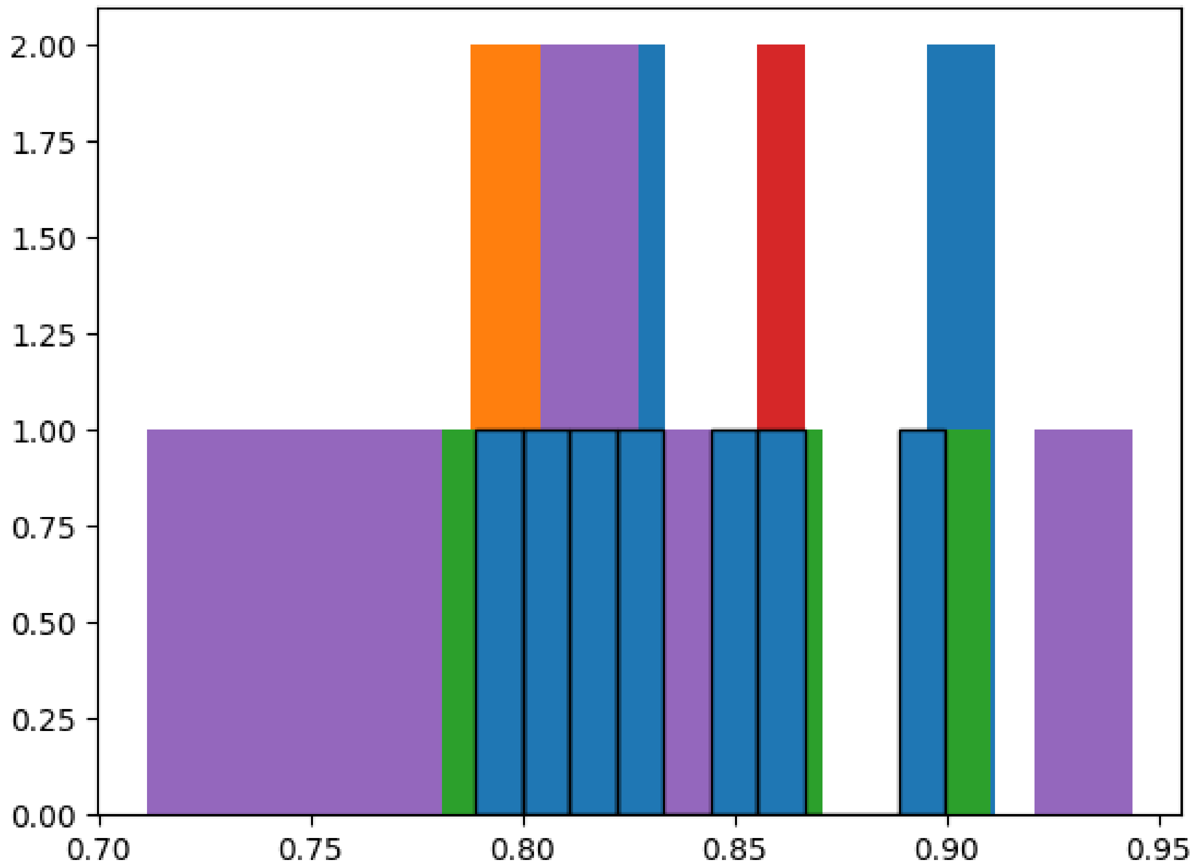

Fig 16. Combined decision matrix.

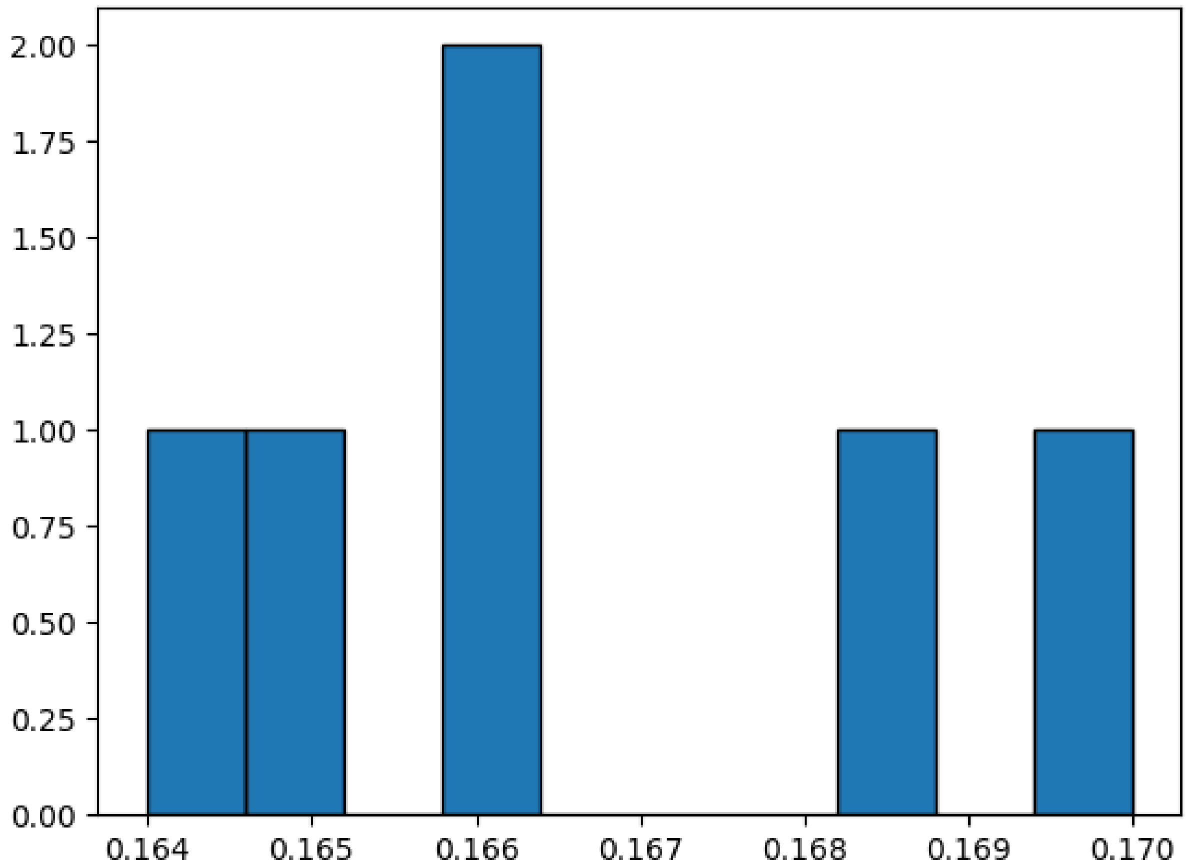

Fig 17. The criteria weights.

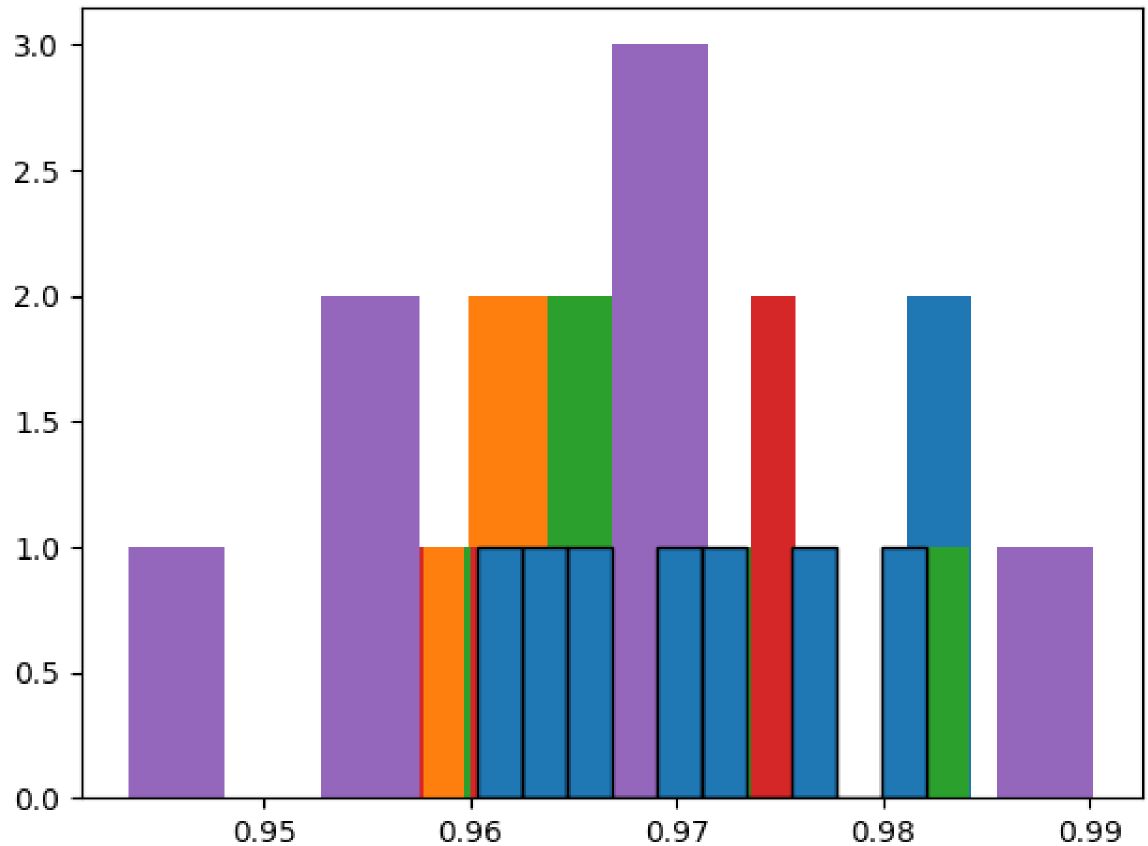

Fig 18. The weighted decision matrix.

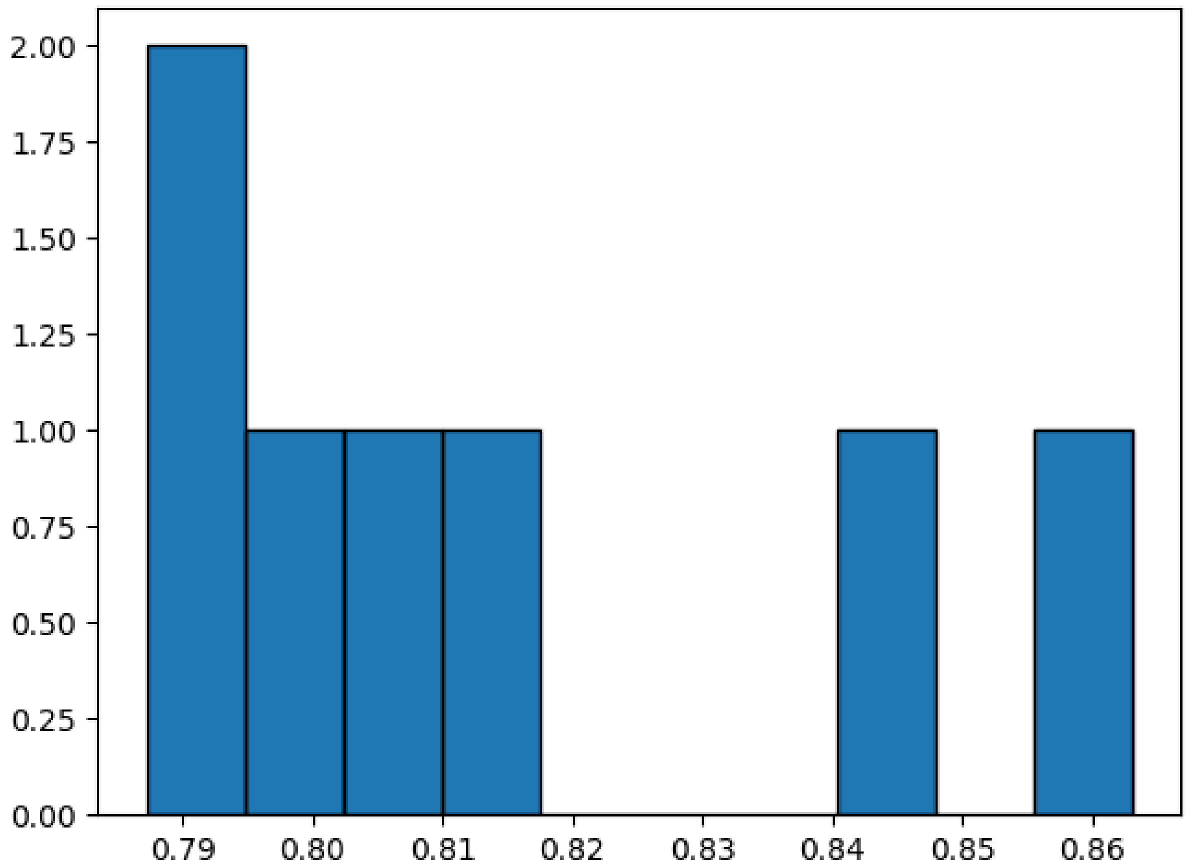

Fig 19. The final score of each alternative.

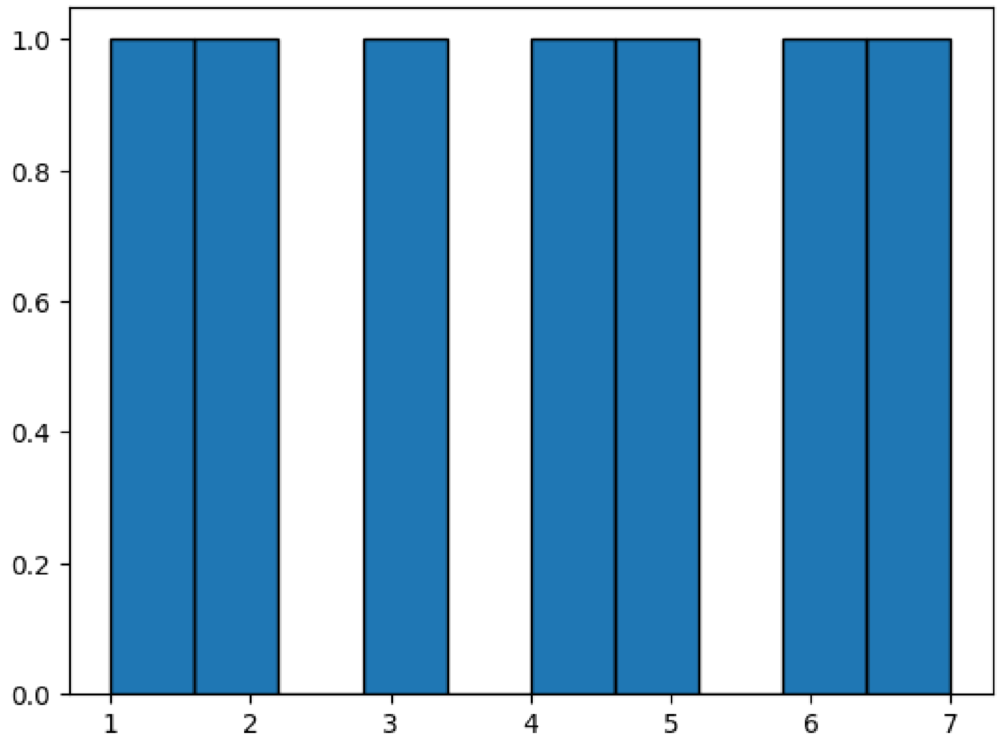

Fig 20. The rank of alternatives.

After evaluating all four TreeSoft sets, the performance of each alternative revealed interesting patterns. Alternative A1 showed a steady performance overall. While it didn't reach the top in any category, it performed consistently, especially in the third tree where it came in second place. This suggests that A1 is a balanced option, offering reliability without sharp ups or downs.

A2, on the other hand, performed slightly below average across the board. It struggled more in the first and second trees but held a consistent fourth-place rank in the last two. This reflects a level of stability, though it doesn't stand out as a strong performer.

A3 kept a middle-ground position throughout the evaluation. It ranked third in the first two trees and dropped a bit in the last two. Its results didn't shift dramatically, which makes it appear dependable, though it didn't show any signs of exceptional strength.

Alternative A4 started off strong with the best and second-best rankings in the first two trees. However, its performance dropped sharply in the later evaluations, ending up at the bottom. This sharp decline may mean that while A4 handles certain criteria very well, it struggles when the focus shifts to other areas.

A5 had a more mixed journey. It came in second and first in the early trees but fell to sixth in the third. Interestingly, it bounced back again in the fourth tree, showing that it has strong potential but lacks consistent performance across all areas.

A6 had one of the most notable shifts. It started low, ranking sixth and fourth in the first two trees, but then rose to first place in both the third and fourth trees. This major improvement highlights its strength in areas related to later evaluation criteria, possibly adaptability or maintainability.

Finally, A7 ranked the lowest or nearly the lowest among most trees. It only saw a slight improvement in the third tree, which wasn't enough to change the overall picture. Its performance suggests it may not be suitable in its current form for environments with diverse and dynamic requirements.

4.1 Summary of Individual TreeSoft Set Evaluations

Each of the four main criteria was analyzed separately using its own TreeSoft Set. The results showed how each alternative system performed in each specific area. Some systems did well in intelligence but not in maintainability, for instance.

4.2 Cross-Comparison Among Alternatives

By comparing the rankings across all criteria, we can see which systems are strong all around and which ones have more specialized strengths. For example, one system may be excellent in integration but only average in energy efficiency.

4.3 Discussion of Ranking Trends

The ranking results revealed some interesting trends. Some alternatives started strong but dropped in later evaluations. Others, like A6, started with low scores but improved over time. These patterns give clues about the systems' consistency and long-term potential.

6. Validation of the Evaluation Method

The method used in this study depends on expert ratings and a ranking process that combines many factors using the ForestSoft and WPM approaches. To make sure the results are trustworthy, it's important to check if the method gives similar outcomes when tested under different conditions.

One way to test this is by changing the weights of the criteria just a little and seeing if the rankings change a lot. If the rankings stay mostly the same, the method is considered stable. Another check is comparing how different experts rated the systems. If their answers are very close, this supports the accuracy of the method.

Even though the evaluation process in this study was based on expert input, these checks help confirm that the results are not random or biased. They also show that the method can be used again in other cases and give useful results.

7. Practical Implications and Use in Real Factories

This study gives a structured way to evaluate control systems in smart manufacturing, but it's also important to think about how this can be used in real factories. Managers and engineers can apply this model when they are choosing or upgrading systems.

For example, before buying a new control system, a team can use the same steps—defining criteria, collecting expert ratings, and calculating rankings—to compare options. This saves time and reduces the risk of choosing a system that doesn't fit the factory's needs.

Also, factories can use this model to review their current systems. If a system scores low in flexibility or energy use, that tells the team where improvements are needed. Over time, this can help improve efficiency, reduce downtime, and make smarter decisions about upgrades.

The evaluation process doesn't need special tools. With a basic setup and expert input, factories can apply the same method to their own environment. This makes the model practical and useful—not just a research idea, but a tool that can be used on the ground.

8. Involving Stakeholders in System Evaluation

Control systems are used by many people in a factory, not just designers or analysts. The people who operate, maintain, or manage these systems see things from different angles. What works well for a developer might not be easy for a technician on the factory floor.

To make the evaluation better, future models should include opinions from different users. For example, criteria like user-friendliness, support tools, or how quickly errors can be fixed could be added. This makes the ranking of systems more realistic.

When people feel involved in the choice of new systems, they are more likely to use them effectively. This improves the chance of success after implementation. So, the evaluation process should not just be about numbers—it should also include the experience of the people who use the system every day.

9. Conclusions

A notable change in assessment paradigms is revealed by the examination of production control systems for mechanical automation in intelligent manufacturing settings. Mechanical efficiency alone is no longer sufficient to gauge system performance; instead, systems must exhibit intelligence, adaptability, and data reactivity. The need for sophisticated frameworks that represent the intricacy and interdependencies of smart production environments is highlighted by this study. It also emphasizes how technological innovation, human skills, and strategic vision must all come together for implementation to be successful. Integrating intelligent control systems will be crucial to maintaining operational excellence and maintaining global competitiveness as manufacturing continues to change. We used the MCDM methodology for computing the criteria weights and ranking the alternatives. We used the WPM methodology to rank the alternatives. We use the ForestSoft set to dela with different criteria values. This study used four main criteria, six sub criteria and seven alternatives.

9.1 Key Takeaways for Manufacturing Practitioners

For people working in smart manufacturing, this research provides clear guidelines on what to look for when choosing or improving a control system. It shows the importance of adaptability, data usage, and system flexibility.

9.2 Implications for Future Research

This study opens the door for more advanced research. Future studies might combine ForestSoft Sets with machine learning techniques or apply this method in specific industries like automotive or electronics for deeper insights.

9.3 Limitations of the Current Study

Like any research, this one has its limits. It relied on a small number of expert evaluations and used a fixed number of alternatives. More diverse expert input or applying the method in real-world factory settings could make the results even stronger.

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