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Neutrosophic Hammer Operator for Assessment of Product Processing Quality Monitoring System in a Machining Line

Shuai Yuan*

Institute of Mechanical Technology, Anhui Vocational College of Defense Technology, Luan, 237000, Anhui, China

*Corresponding author, E-mail: a1020674476@163.com

Abstract: In modern manufacturing, especially within machining lines, product quality monitoring has evolved from manual inspections to intelligent, real-time automated systems. Ensuring consistent product quality while minimizing downtime and defects has become a critical aspect of competitive production environments. The innovation of digital technologies, including advanced sensors, artificial intelligence (AI), and Internet of Things (IoT) frameworks, has significantly improved the ability to track, evaluate, and control processing quality throughout the production lifecycle. This study presents a multi-criteria decision making (MCDM) comprehensive evaluation of product processing quality monitoring systems in machining lines by considering multiple performance and integration criteria. By applying a MCDM evaluation framework, the research aims to determine the most efficient and scalable solutions adaptable to various production settings. We use the average method to obtain the criteria weights and the ARLON method to rank alternatives. An application with eight criteria and ten alternatives is constructed to show the validation of the proposed approach. The neutrosophic set is used to deal with vague information. Hammer Operator is used to combine the decision matrices.

Keywords: Hammer Operator; Product Processing Quality Monitoring System; Machining Line; Neutrosophic Sets.

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1. Introduction

In today's high-demand manufacturing industries, particularly those involving precision machining, quality monitoring is no longer a post-process activity, it is an integral, real-time function. The shift from reactive to proactive quality control systems has fundamentally transformed the landscape of production management. This transformation is driven by the increased necessity for zero-defect manufacturing, where even slight variations in product parameters can result in significant operational or financial loss[1], [2]. Machining lines, which involve processes like turning, milling, drilling, and grinding, are inherently prone to deviations due to tool wear, material inconsistencies, and equipment anomalies. As a result, relying solely on manual inspections or traditional quality control approaches is no longer viable. There is a growing demand for intelligent monitoring systems that not only detect but also predict deviations before they affect final product quality. These systems, supported by real-time data collection and analytics, contribute to improved decision-making on the shop floor[3], [4].

The innovation of smart sensors and industrial IoT has enabled manufacturers to collect vast amounts of real-time process data. This includes vibration signals, acoustic emissions, thermal readings, and dimensional measurements. With proper interpretation using machine learning or statistical models, these data streams can reveal complex patterns indicating quality degradation. Therefore, the choice of a monitoring system must consider not only its technological capability but also its adaptability to diverse machining environments[5], [6]. The usability and interface of these systems play a crucial role in operator acceptance. A highly capable system with poor visualization tools can still underperform if users struggle to interpret or act on the data. User-centric design, interactive dashboards, and customizable alerts have emerged as vital features for practical implementations. Systems that allow operators to quickly isolate root causes and implement corrective actions reduce downtime and increase process stability[7], [8].

Integration with broader production management systems is another significant consideration. Quality monitoring tools that connect seamlessly with Manufacturing Execution Systems (MES) or Enterprise Resource Planning (ERP) platforms allow for closed-loop control and automated quality traceability. This ensures consistency across multiple production lines and enhances compliance with regulatory standards and customer specifications[9], [10].

Another evolving aspect is predictive analytics and the incorporation of digital twins. By building virtual models of machining processes and comparing them in real-time to actual performance, manufacturers can foresee quality issues and adapt proactively. This predictive capacity is invaluable for industries such as aerospace or medical device manufacturing, where quality failures carry significant consequences.

Implementing these advanced systems is not without challenges. Factors such as the initial cost, system complexity, training requirements, and compatibility with existing infrastructure must be carefully evaluated[11]. An effective quality monitoring system must not only excel in detection accuracy but must also be sustainable and scalable across different production scales and contexts.

This paper presents a structured evaluation approach to compare various product processing quality monitoring systems in machining lines. It incorporates a comprehensive set of technical, operational, and human-centered criteria to assess the effectiveness and suitability of different alternatives. By providing clear insight into each system's strengths and trade-offs, the study contributes to more informed decision-making in manufacturing environments aiming for operational excellence

As a novel theory of uncertainty, the neutrosophic theory has gained acceptance recently and been quickly implemented in a variety of domains, including roughness assessment, electrical engineering, and medical diagnostics[12], [13]. Classical philosophy gave rise to the neutrosophic number (NN), a subfield of neutrosophy. The neutrosophic number, which includes both determinate and indeterminate information for an uncertainty issue, was first developed by Smarandache[14], [15]. To address decision-making issues, Ye created three vector similarity metrics—the Jaccard, Dice, and cosine similarity metrics—and integrated them into the neutrosophic number.

To address decision-making issues, Ye [16] later merged the possibility degree ranking approach with ordered weighted aggregation operators of interval neutrosophic numbers. Numerous expansions of neutrosophic theory have been proposed in recent years to address various issues. Roy and Das [17] used linear programming techniques to tackle the multicriteria production planning issue. The neutrosophic mining algorithm, which Abdel-Baseet et al. suggested as a novel method of massive data analysis, produced more association rules. A straightforward and trustworthy method for evaluating uncertainty in the actual world, such as probability analysis of different failure occurrences, is the neutrosophic number[18], [19].

2. Decision Making Problem

Since abrasive machining is among the priciest procedures used in the wood processing industry, it deserves consideration and research. The random nature and distribution of the grains on the abrasive belts make it challenging to describe and evaluate abrasive machining operations. The procedure becomes more difficult, and several factors need to be considered when abrasive machining a highly variable, non-homogeneous material like wood. Because abrasive machining belts are expensive per unit and have a short lifespan, they represent a significant investment in the machining process[20].

The depth of cut and feed rate of the wood being sanded, as well as the material removal rate, were all positively connected with the power used by a belt sander. When using an aluminum oxide abrasive belt, the material removal rate was always higher—in fact, it was occasionally almost twice as high as that of other abrasive materials. The three primary outputs of abrasive machining—material removal rate, surface quality, and power consumption—were also shown to be correlated with the most important controllable variables: interface pressure, wood species, rotational speed, grit size, and abrasive mineral[21].

The overall procedure and the impact of the factors on the results were explained by multiple linear regressions; nonetheless, significant variation in surface quality and material removal rates was noted, illustrating the characterization's complexity[22], [23].

3. Hammer Operator

This section shows the Hammer Operator with single valued neutrosophic numbers (SVNNs) such as[24]:

$$HO(x_1, \dots x_n) = \left(\begin{array}{c} \frac{\prod_{j-1}^{n}\left(1+(\varphi-1)T_j\right)^{w_j} - \prod_{j-1}^{n}\left(1-T_j\right)^{w_j}}{\prod_{j-1}^{n}\left(1+(\varphi-1)T_j\right)^{w_j} + (\varphi-1)\prod_{j-1}^{n}\left(1-T_j\right)^{w_j}}, \\ \frac{\varphi\prod_{j-1}^{n}\left(I_j\right)^{w_j}}{\prod_{j-1}^{n}\left(1+(\varphi-1)I_j\right)^{w_j} + (\varphi-1)\prod_{j-1}^{n}\left(1-I_j\right)^{w_j}}, \\ \frac{\varphi\prod_{j-1}^{n}\left(F_j\right)^{w_j}}{\prod_{j-1}^{n}\left(1+(\varphi-1)F_j\right)^{w_j} + (\varphi-1)\prod_{j-1}^{n}\left(1-F_j\right)^{w_j}} \end{array} \right) \tag{1}$$

$$HO(x_1, \dots x_n) = \left(\begin{array}{l} h\left(\sum_{j=1}^{n} w_j h^{-1}\left(T_j\right)\right), \\ g\left(\sum_{j=1}^{n} w_j g^{-1}\left(I_j\right)\right), \\ g\left(\sum_{j=1}^{n} w_j g^{-1}\left(F_j\right)\right) \end{array} \right) \tag{2}$$

$$= \left(\begin{array}{l} h\left(\sum_{j=1}^{n} w_j h^{-1}(T)\right), \\ g\left(\sum_{j=1}^{n} w_j g^{-1}(I)\right), \\ g\left(\sum_{j=1}^{n} w_j g^{-1}(F)\right) \end{array} \right) \tag{3}$$

$$= \left(h\left(h^{-1}(T)\right), g\left(g^{-1}(I)\right), g\left(g^{-1}(F)\right)\right) = (T, I, F) = x \tag{4}$$

$$kx_j = \left(\begin{array}{l} h\left(\sum_{j=1}^{n} w_j h^{-1}\left(h\left(kh^{-1}\left(T_j\right)\right)\right)\right), \\ g\left(\sum_{j=1}^{n} w_j h^{-1}\left(g\left(kg^{-1}\left(I_j\right)\right)\right)\right), \\ g\left(\sum_{j=1}^{n} w_j h^{-1}\left(g\left(kg^{-1}\left(F_j\right)\right)\right)\right) \end{array} \right) \tag{5}$$

$$= \begin{pmatrix} h\left(\sum_{j=1}^{n} w_j h^{-1}\left(\left(k h^{-1}(T_j)\right)\right)\right), \\ g\left(\sum_{j=1}^{n} w_j h^{-1}\left(\left(k g^{-1}(I_j)\right)\right)\right), \\ g\left(\sum_{j=1}^{n} w_j h^{-1}\left(\left(k g^{-1}(F_j)\right)\right)\right) \end{pmatrix} \tag{6}$$

$$= \begin{pmatrix} h\left(\sum_{j=1}^{n} w_j h^{-1}(T_j)\right), \\ g\left(\sum_{j=1}^{n} w_j h^{-1}(I_j)\right), \\ g\left(\sum_{j=1}^{n} w_j h^{-1}(F_j)\right) \end{pmatrix} \tag{7}$$

$$= \begin{pmatrix} h\left(k\sum_{j=1}^{n} w_j h^{-1}(T_j)\right), \\ g\left(k\sum_{j=1}^{n} w_j h^{-1}(I_j)\right), \\ g\left(k\sum_{j=1}^{n} w_j h^{-1}(F_j)\right) \end{pmatrix} \tag{8}$$

We show the steps of the ARLON method such as:

SVNNs are used to create the decision matrix. Hammer Operator is used to combine the decision matrix. After, we use the score function to obtain crisp values. Then we obtain the criteria weights by the average method.

The first and second logarithmic normalization methods are obtained such as

$$Z_{ij}^{1st} = \begin{cases} Z_{ij}^{1st(+)} = \frac{\ln(y_{ij})}{\ln(\prod_{i=1}^{m} y_{ij})} \; positive\ criteria \\ Z_{ij}^{1st(-)} = \left(\frac{1-\frac{\ln(y_{ij})}{\ln(\prod_{i=1}^{m} y_{ij})}}{m-1}\right) cost\ criteria \end{cases} \tag{9}$$

$$Z_{ij}^{2st} = \begin{cases} Z_{ij}^{2st(+)} = \frac{\log_2(y_{ij})}{\sum_{i=1}^{m}(\log_2(y_{ij}))} \ positive\ criteria \\ Z_{ij}^{2st(-)} = \left(1 - \frac{\log_2(y_{ij})}{\sum_{i=1}^{m}(\log_2(y_{ij}))}\right) \ cost\ criteria \end{cases} \tag{10}$$

Obtain the combined normalized matrix

$$Z_{ij}^{com} = \left((1-k)\sqrt{\left(Z_{ij}^{1st} + Z_{ij}^{2st}\right)} + (k)\left(\frac{Z_{ij}^{1st}+Z_{ij}^{2st}}{2}\right)\right) \tag{11}$$

The weighted normalized decision is obtained such as:

$$U_{ij} = w_j Z_{ij}^{com} \tag{12}$$

The total weighted normalized decision matrix is obtained for positive and cost criteria

$$E_i^- = sum\left(U_{ij}\right) for\ positive\ criteria \tag{13}$$

$$E_i^+ = sum\left(U_{ij}\right) for\ cost\ criteria \tag{14}$$

Rank the alternatives

$$E_i = (E_i^+)^{\beta} + (E_i^-)^{(1-\beta)} \tag{15}$$

4. Application

This section shows the application of the proposed approach. We use eight criteria and ten alternatives as shown in Fig 1.

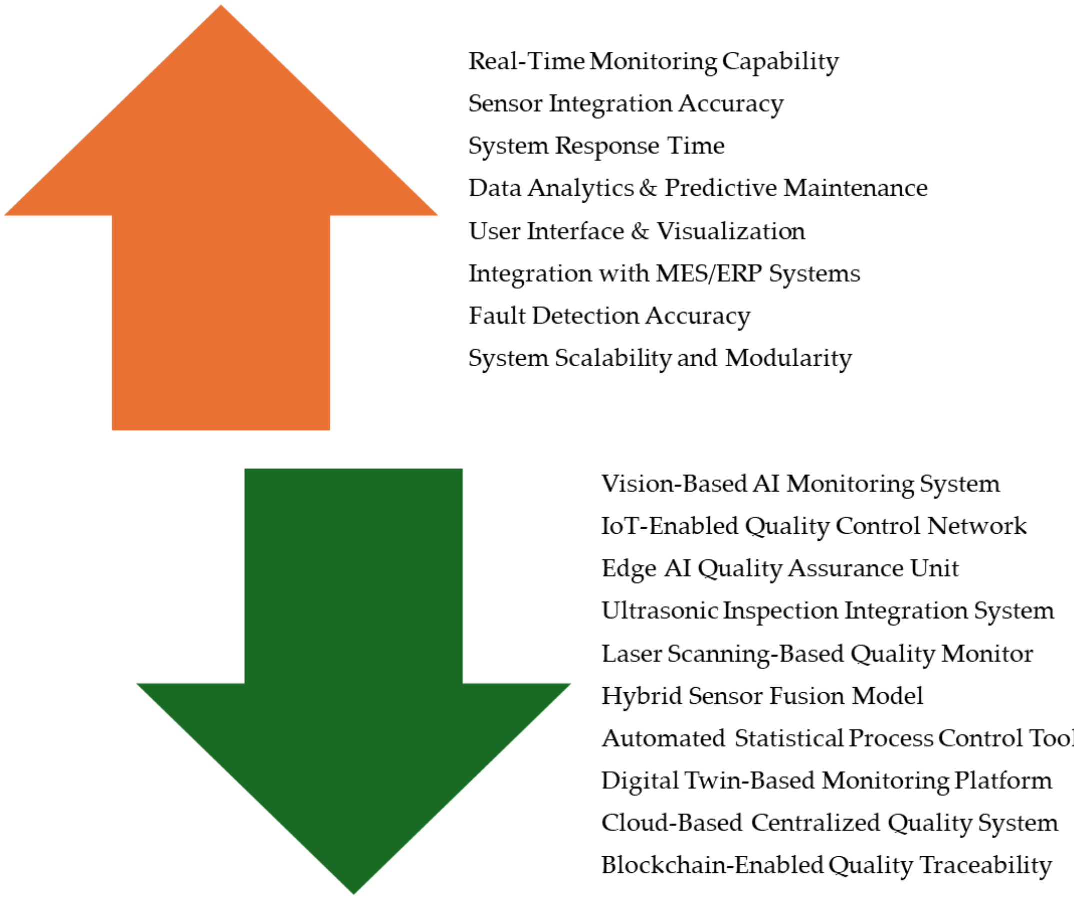

Fig 1. The criteria for this study.

Three experts created the decision matrix as shown in Table 1. Hammer Operator is used to combine the decision matrix as shown in Fig 2. Then we obtain crisp values. Then we obtain the criteria weights by the average method as shown in Fig 3.

Table 1. The decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.3,0.6,0.7)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.8,0.2,0.3)	(0.4,0.5,0.6)	(0.4,0.5,0.6)
A_2	(0.3,0.6,0.7)	(0.5,0.5,0.5)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.8,0.2,0.3)
A_3	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.5,0.6)
A_4	(0.5,0.5,0.5)	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.5,0.5,0.5)
A_5	(0.6,0.4,0.5)	(0.3,0.6,0.7)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.6,0.4,0.5)
A_6	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.4,0.5,0.6)	(0.7,0.3,0.4)
A_7	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.8,0.2,0.3)

A_8	(0.4,0.5,0.6)	(0.7,0.3,0.4)	(0.4,0.5,0.6)	(0.3,0.6,0.7)	(0.3,0.6,0.7)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.4,0.5,0.6)
A_9	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.5,0.5,0.5)	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.8,0.2,0.3)
A_{10}	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.4,0.5,0.6)	(0.5,0.5,0.5)	(0.4,0.5,0.6)
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.4,0.5,0.6)	(0.8,0.2,0.3)	(0.4,0.5,0.6)	(0.9,0.1,0.2)
A_2	(0.8,0.2,0.3)	(0.4,0.5,0.6)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.9,0.1,0.2)
A_3	(0.7,0.3,0.4)	(0.4,0.5,0.6)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.4,0.5,0.6)	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)
A_4	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.3,0.6,0.7)	(0.9,0.1,0.2)	(0.3,0.6,0.7)	(0.7,0.3,0.4)	(0.6,0.4,0.5)
A_5	(0.5,0.5,0.5)	(0.4,0.5,0.6)	(0.5,0.5,0.5)	(0.9,0.1,0.2)	(0.8,0.2.0.3)	(0.7,0.3,0.4)	(0.3,0.6,0.7)	(0.7,0.3,0.4)
A_6	(0.7,0.3,0.4)	(0.3,0.6,0.7)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.4,0.5,0.6)	(0.8,0.2,0.3)
A_7	(0.3,0.6,0.7)	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.7,0.3,0.4)	(0.9,0.1,0.2)
A_8	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.8,0.2,0.3)
A_9	(0.8,0.2,0.3)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.4,0.5,0.6)
A_{10}	(0.4,0.5,0.6)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.4,0.5,0.6)	(0.4,0.5,0.6)	(0.5,0.5,0.5)
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.4,0.5,0.6)	(0.3,0.6,0.7)	(0.4,0.5,0.6)	(0.4,0.5,0.6)
A_2	(0.3,0.6,0.7)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.8,0.2,0.3)
A_3	(0.4,0.5,0.6)	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.4,0.5,0.6)	(0.4,0.5,0.6)	(0.6,0.4,0.5)	(0.9,0.1,0.2)
A_4	(0.5,0.5,0.5)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.5,0.5,0.5)
A_5	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.4,0.5,0.6)	(0.3,0.6,0.7)	(0.4,0.5,0.6)	(0.3,0.6,0.7)	(0.6,0.4,0.5)
A_6	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.3,0.6,0.7)	(0.8,0.2,0.3)	(0.4,0.5,0.6)	(0.7,0.3,0.4)
A_7	(0.3,0.6,0.7)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.3,0.6,0.7)	(0.3,0.6,0.7)
A_8	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.9,0.1,0.2)
A_9	(0.8,0.2,0.3)	(0.3,0.6,0.7)	(0.3,0.6,0.7)	(0.3,0.6,0.7)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.8,0.2,0.3)
A_{10}	(0.4,0.5,0.6)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.3,0.6,0.7)	(0.4,0.5,0.6)	(0.5,0.5,0.5)	(0.4,0.5,0.6)

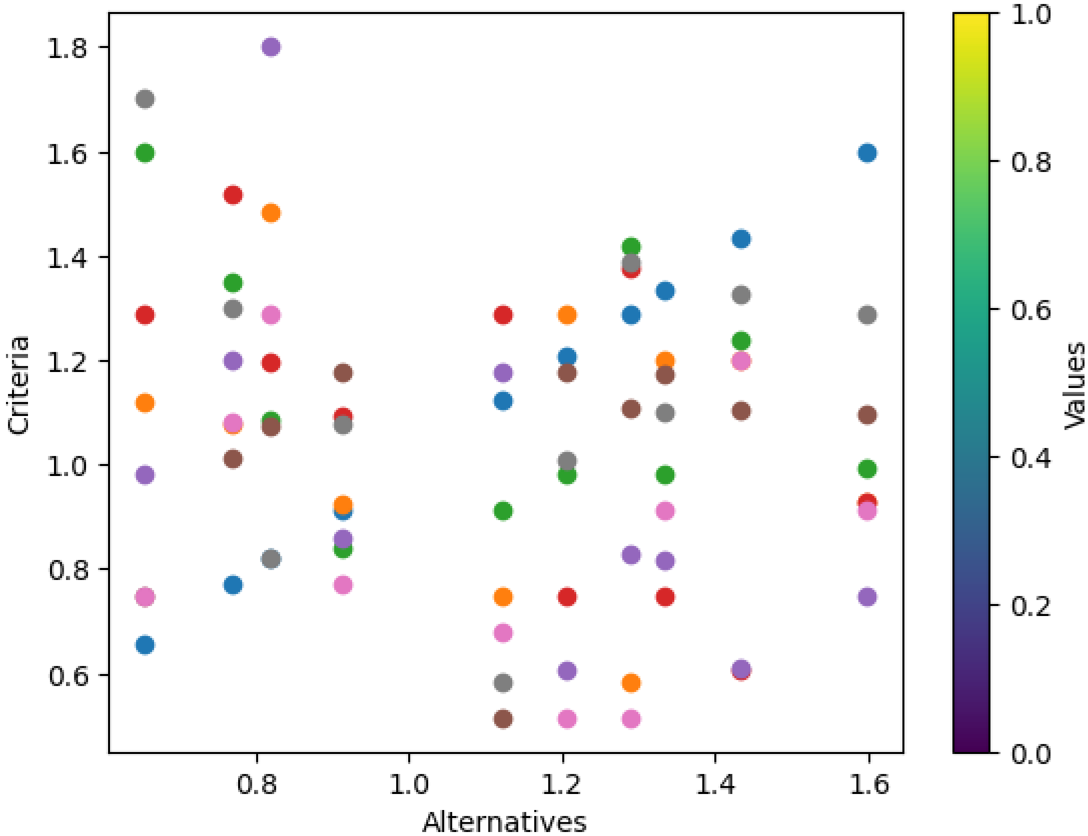

Fig 2. The combined decision matrix.

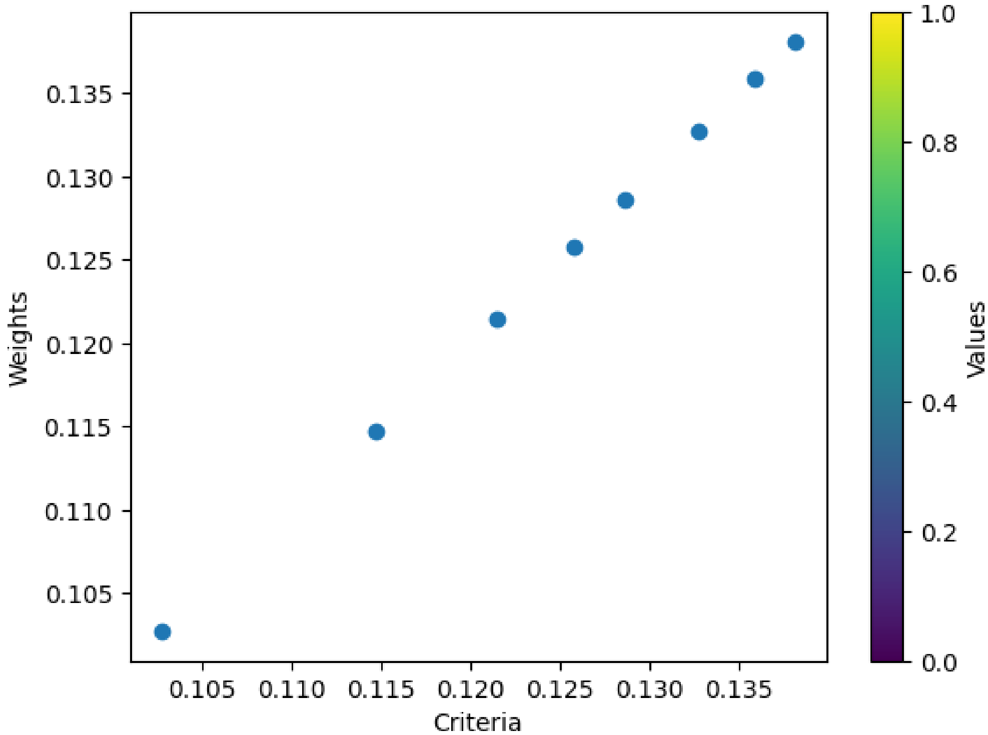

Fig 3. The criteria weights.

We obtained the two logarithmic normalization values using eqs. (9 and 10) as shown in Figs 4 and 5.

We obtain the combined normalized matrix using eq. (11) as shown in Fig 6.

The weighted normalized decision is obtained using eq. (12) as shown in Fig 7.

The total weighted normalized decision matrix is obtained for positive and cost criteria using eqs. (13 and 14).

Rank the alternatives using eq. (15). Fig 8 shows the values of E_i. Fig 9 shows the rank of the alternatives.

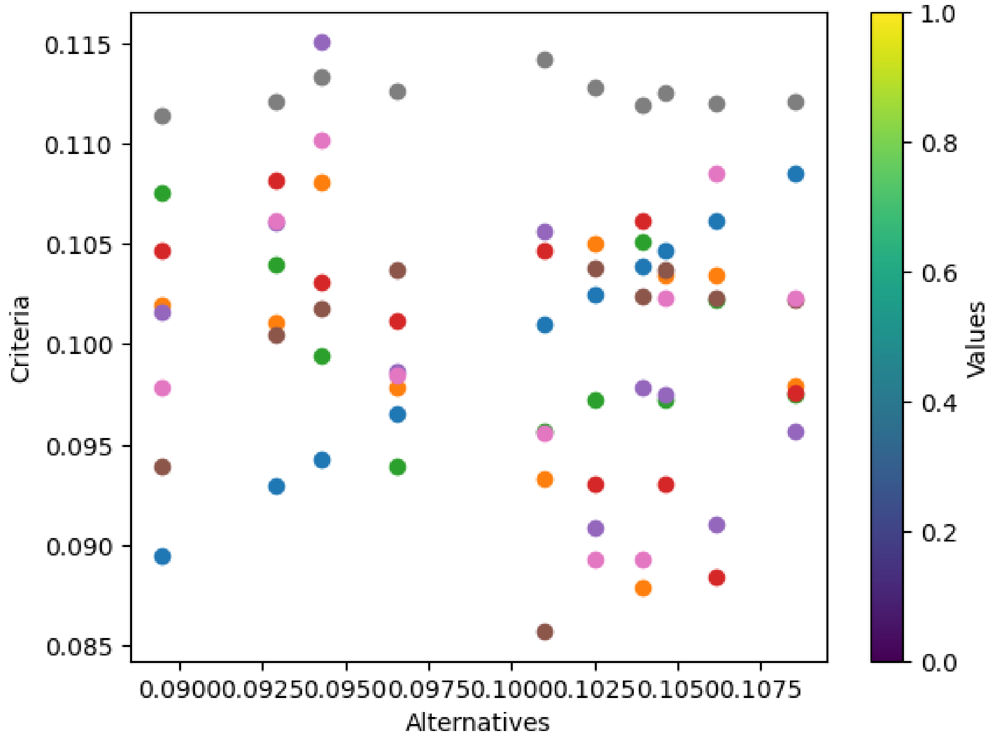

Fig 4. The First logarithmic normalization values.

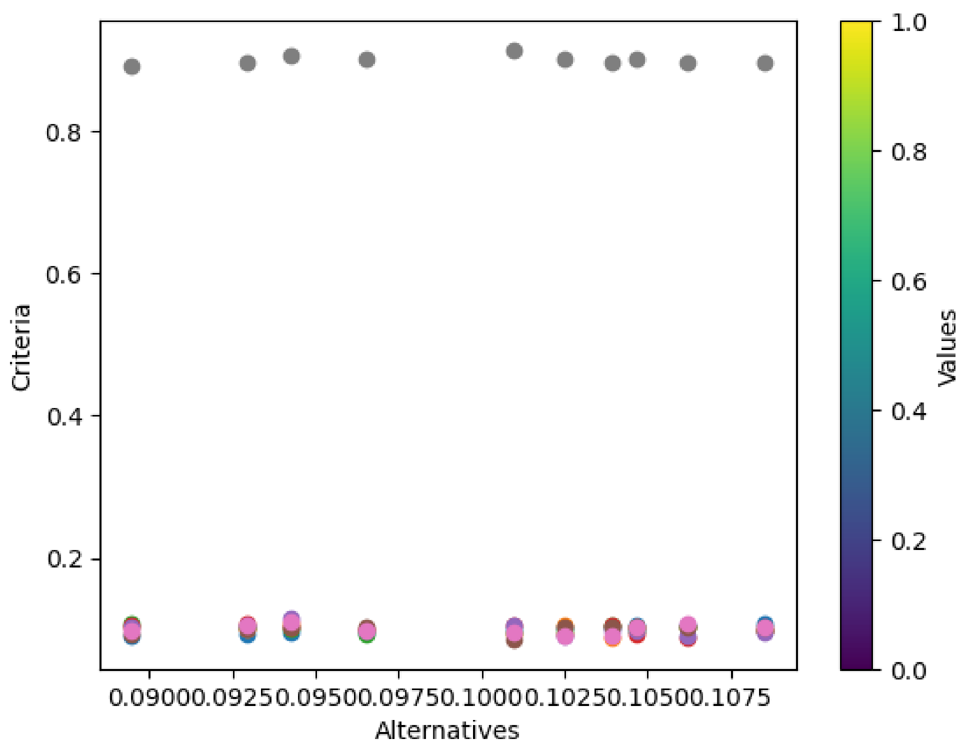

Fig 5. The second logarithmic normalization values.

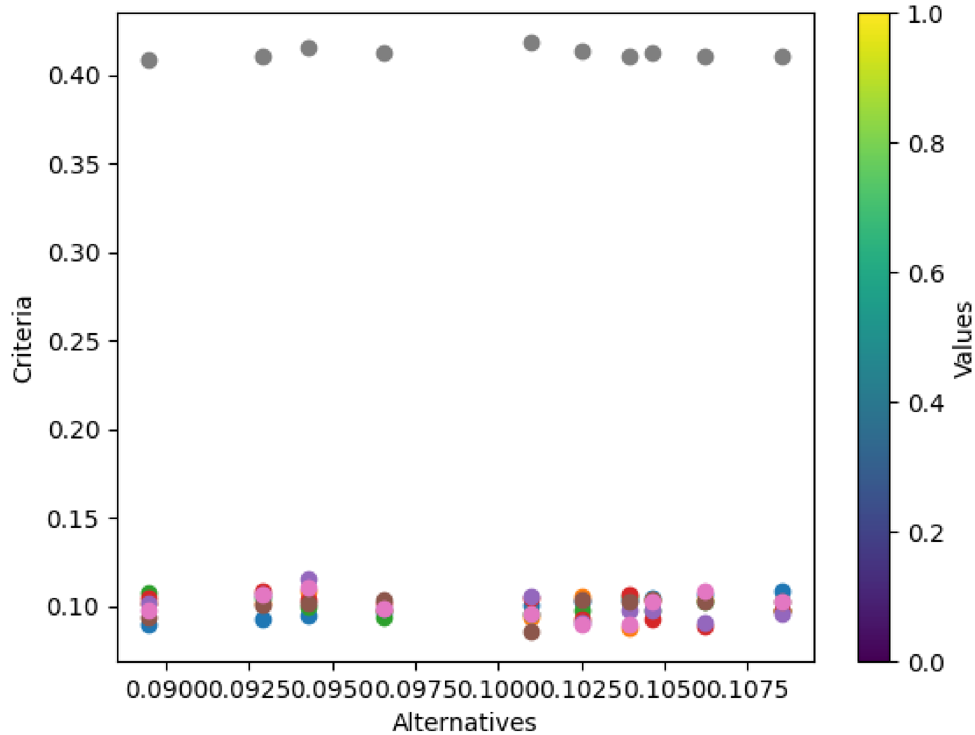

Fig 6. The combined normalized matrix.

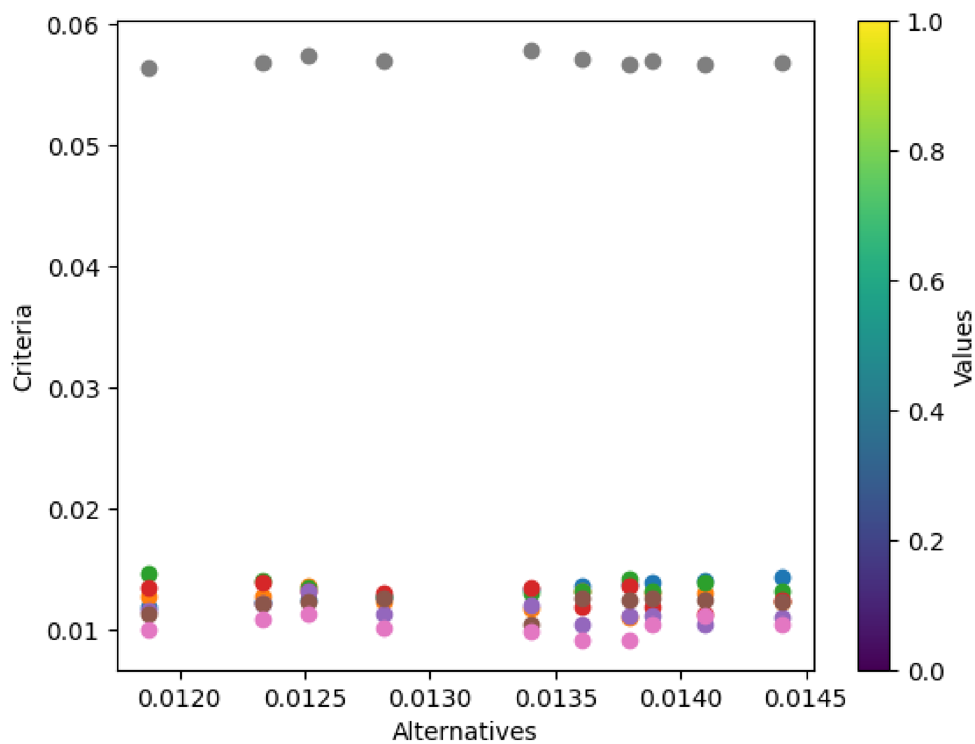

Fig 7. The weighted normalized decision matrix.

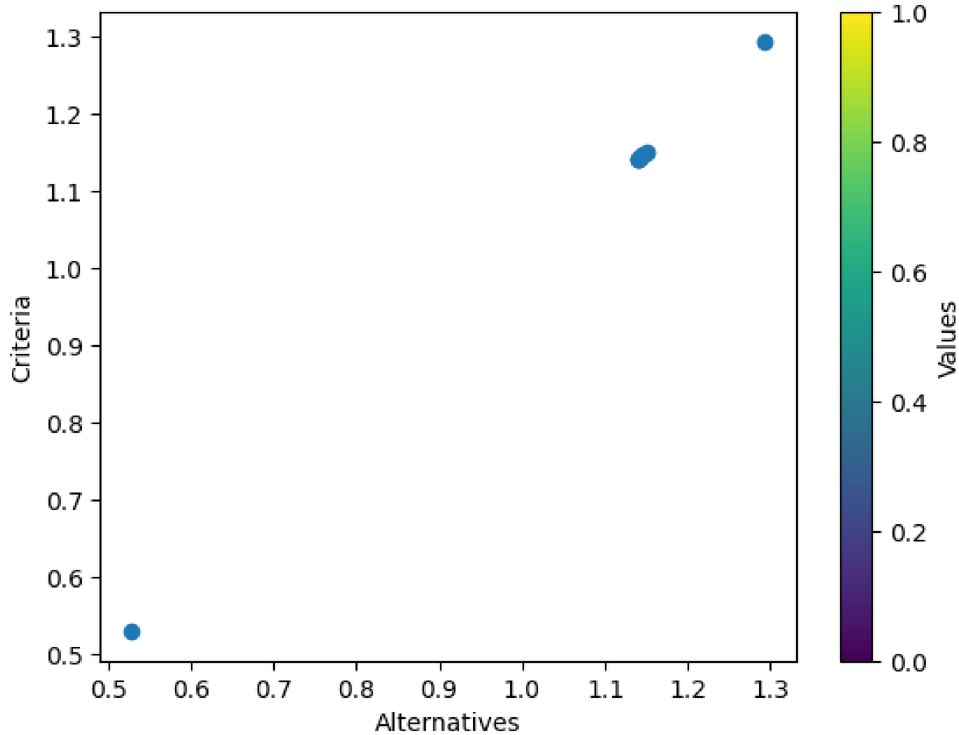

Fig 8. The values of E_i.

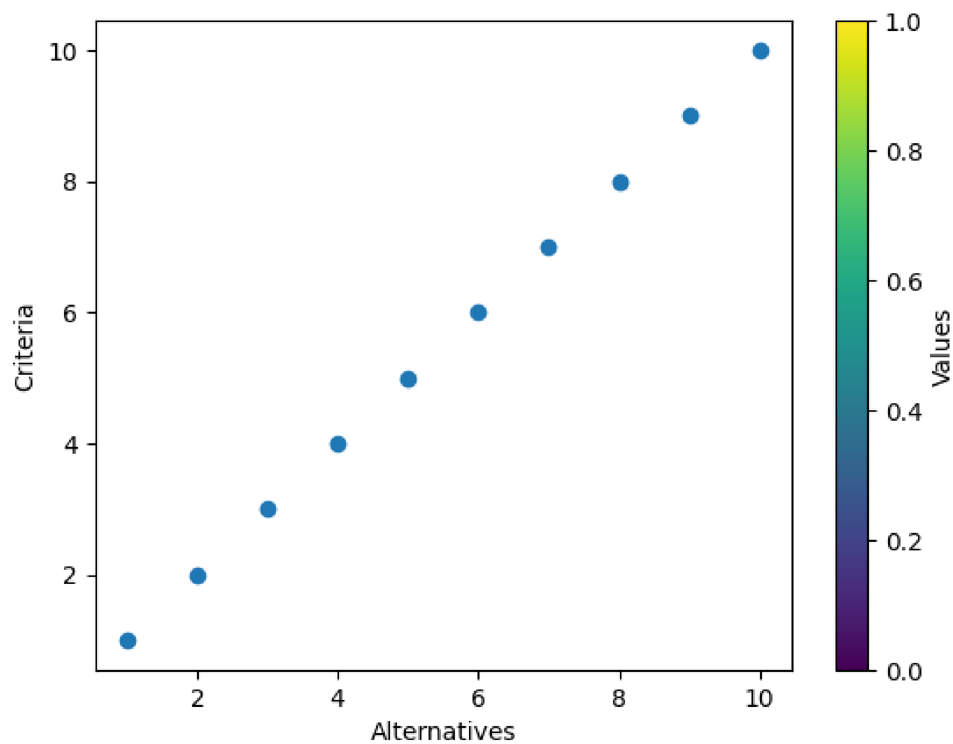

Fig 9. The rank of alternatives.

5. Conclusions

The evaluation of product processing quality monitoring systems in machining lines is a multifaceted task that requires consideration of both technological and operational dimensions. As machining operations become more complex and tolerance thresholds become stricter, the role of intelligent, real-time monitoring systems is more crucial than ever. This study has provided a framework to assess various solutions based on key performance indicators such as accuracy, integration, predictive capability, and user experience. The analysis emphasizes the need for systems that not only detect quality deviations but also support adaptive and predictive responses. Moving forward, the successful implementation of such systems will depend on balancing innovation with practical usability, ensuring both efficiency and reliability in future manufacturing operations. We used the MCDM methodology to deal with decision making process. The average method is used to compute the criteria weights, and the ARLON method is used to rank alternatives. We used SVNNs to deal with vague information. The Hammer Operator is used to combine the decision matrix. We provided an application with eight criteria and ten alternatives to show the validation of the proposed approach.

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