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CASE STUDY

Assessment of distance-based multi-attribute group decision-making methods from a maintenance strategy perspective

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Abstract Maintenance has been acknowledged by industrial management as a significant influencing factor of plant performance. Effective plant maintenance can be realized by developing a proper maintenance strategy. However, selecting an appropriate maintenance strategy is difficult because maintenance is a non-repetitive task such as production activity. Maintenance also does not leave a consistent traceable record that can be referred to during the decision-making process. The involvement of tangible and intangible factors in the assessment process further increases the complexity of the decision-making process. The technique of preference order by similarity to ideal solution (TOPSIS) is one of the most well-known decision-making methods and has been widely used by organizations to conduct effective decisions regarding maintenance issues. TOPSIS has also evolved by integrating different approaches such as the fuzzy concept. Although numerous TOPSIS applications for maintenance decision making have been published, the effectiveness of crisp TOPSIS and fuzzy TOPSIS needs to be investigated further. This paper attempts to present a comparison between conventional crisp TOPSIS and fuzzy TOPSIS from a group maintenance decision-making perspective by an empirical illustration. Sensitivity analysis is conducted to demonstrate further the resilience of crisp TOPSIS and fuzzy TOPSIS.

Keywords Group decision making · Crisp TOPSIS · Fuzzy TOPSIS maintenance strategy · Sensitivity analysis

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Introduction

Effective and efficient maintenance greatly depends on the type of maintenance strategy applied. Maintenance strategy assessment involves the identification of the most suitable strategy for machine maintenance to maximize benefits within a given set of resource constraints. A proper maintenance strategy will not only improve the competitiveness of the organization, but also lead to maximizing the profits (Faghihinia and Mollaverdi 2012). This assessment is important because maintenance costs can reach 15–70 %of the total production cost depending on the industry type. One-third of the maintenance cost is wasted because of improper decision-making strategies (Bashiri et al. 2011). However, the advantages of an effective maintenance strategy are well beyond the value of money. Employee safety, environmental effects and production performance are significantly influenced by maintenance.

Organizations have acknowledged the importance of maintenance strategies. Nevertheless, determining the most suitable maintenance strategy is difficult because of the large amount of tangible and intangible factors, such as maintenance skills, employee safety, possible production loss and investment cost. Intangible factors mainly denote on-monetary aspects and require proper justification from decision makers. In many cases, the decision maker has difficulty reaching a decision because of inaccurate information on alternatives and their different factors. Moreover, the existence of different maintenance strategies and the involvement of a large number of decision-making factors have made the decision-making process a complex and challenging task.

Regardless of the subject in decision making, the decision-making process usually involves the process of evaluating a finite set of alternatives to rank them from the best to the worst (Zavadskas and Turkis 2011). Therefore, multi-attribute decision-making (MADM) methods have provided an ideal structure to determine the most suitable maintenance strategy on the basis of multiple factors. Among the MADM methods developed, the technique for order preference by similarity to ideal solution (TOPSIS) is proposed to evaluate the maintenance strategy corresponding to both qualitative and quantitative evaluation factors. TOPSIS has received global interest from researchers and practitioners and has exponentially grown in the last three decades (Behzadian et al. 2012; Zavadskas et al. 2014). The core idea of TOPSIS is based on the distance concept, where the chosen alternative should have the shortest and farthest distance from the positive ideal solution (PIS) and negative ideal solution (NIS), respectively (Hong et al. 2012). PIS is composed of all the best benefit values from indicators, whereas NIS is composed of the worst values from indicators.

The straightforward geometric system computation of TOPSIS increases the popularity of this technique. This type of computation allows for the search of the most preferable alternatives for each indicator in a simple mathematical form, thus making the results understandable and usable by the general public. Moreover, TOPSIS does not require indicator preferences to be constructed based on pairwise comparisons. Computational time increases along with increasing indicators in pairwise comparisons. The maximum number of elements that can be handled by humans in a pairwise comparison is under seven (Mousavi et al. 2009). A high number of elements hinder data analysis. Thus, the computational complexity of TOPSIS can be dramatically reduced by avoiding pairwise comparisons between indicators (Wang and Chang 2007; Dagdeviren et al. 2009; Bao et al. 2012).The input involved is in the form of exact quantitative values. This conventional TOPSIS form is described as crisp TOPSIS.

According to Kahraman et al. (2013), humans are more capable of making qualitative judgment instead of quantitative judgment. Thus, it has led to the development and integration of fuzzy concept into decision-making analyses. The fuzzy concept is one of the most feasible and effective approximating approaches in translating vague, ambiguous, qualitative, and imprecise information into quantitative terms (Nasrabadi et al. 2013). The integration of the fuzzy concept allows TOPSIS to cope with imprecise or uncertain information in a consistent and logical manner with regard to the estimates provided by experts. This approach is helpful during evaluations that involve intangible factors because the fuzzy concept allows for the use of linguistic descriptions rather than exact quantitative values.

TOPSIS is frequently applied in decision making for maintenance strategies, because maintenance is one of the most significant factors that contribute to the success of the manufacturing industry. For instance, Shyjith et al. (2008) used crisp TOPSIS to rank maintenance strategies that can improve the availability of ring-spinning components in the textile industry by considering machine indicators and environmental and economic effects. Ilangkumaran and Kumanan (2009) also conducted a similar approach with the integration of the fuzzy concept to increase input data accuracy. The application of crisp TOPSIS can also be found in Thor et al. (2013), who presented a study on the identification of the optimal maintenance strategy for plating machines in electronic circuit production. In this study, the evaluation was performed from different aspects including the safety, reliability, and feasibility of the maintenance policy from an organizational perspective. The TOPSIS had also been applied by Pourjavad et al. (2013) to rank the maintenance strategy in the mining industry. Ding et al. (2014a) had applied TOPSIS to determine the maintenance strategy that could reduce the failure risk for stripping system in the palm oil industry. While the application of TOPSIS has also been found in Ding et al. (2014b) where a TOPSIS-based decision-making approach has been presented to determine the optimal maintenance strategy for a press system.

Momeni et al. (2011) also used fuzzy TOPSIS to determine the most efficient strategy for Electrofan Company. Moreover, Chan and Prakash (2012) conducted research on the application of fuzzy TOPSIS to determine the optimal maintenance strategy at the firm level instead of machine level by incorporating the economic merit figures with strategic performance variables. Ding and Kamaruddin (2012) demonstrated the practicality of fuzzy TOPSIS in determining the optimal maintenance strategy for a screw press system in the palm oil extraction industry. TOPSIS has also been adopted to evaluate the potential of suppliers to provide different goods in an aircraft manufacturing company (Mohammad et al. 2013).

Maintenance performance assessment is also an important task after the implementation process to evaluate the efficiency of the implemented maintenance activity. Zhong and Sun (2007) presented a fuzzy TOPSIS application in the assessment of the sustainability of a maintenance task on a landing gear system. Chen and Chen (2010) presented a TOPSIS application with gray relational analysis to access the maintenance performance of semiconductor factories. Soltan Panah et al. (2011) applied fuzzy TOPSIS to rank the maintenance projects of large bridges based on the different risks that can influence the bridge structure. The fuzzy TOPSIS had also been adopted by Mahdevari et al. (2014) to evaluate the maintenance risk assessment in underground coal mines. Fuat et al. (2014) had also proposed the fuzzy TOPSIS to determine the system most affected by failures of marine diesel engine and auxiliary systems.

Certain TOPSIS applications have gained popularity in the maintenance field. Despite the popularity and concept simplicity of TOPSIS, this technique is often criticized on its capability to manage uncertainty and imprecision when using crisp value measurements (Dagdeviren et al. 2009).This issue has led to the implementation of fuzzy TOPSIS to solve maintenance decision-making problems in indefinite or fuzzy environments. However, the index ranking results should be compared to discover the significance of the fuzzification effect on fuzzy TOPSIS. A clear insight into the dependent relationships involved in the preference ranking order of fuzzy and crisp TOPSIS with regard to certain attributes is provided by using sensitivity analysis. This paper is organized as follows. Section 2 presents the algorithm of crisp and fuzzy TOPSIS. Section 3 describes an empirical illustration of both TOPSIS methods with regard to a coating machine and the discussion and sensitivity analysis results. Section 4 concludes with the findings of the comparison study.

Crisp TOPSIS and fuzzy TOPSIS algorithms

This section presents the crisp and fuzzy TOPSIS algorithms that are used to decide the maintenance strategy in Sect. 3. To prepare the application for group decisions, all the ratings obtained from decision makers will be aggregated based on the mean aggregation concept. The normalization process of the decision matrix is performed according to the linear normalization algorithm. In the distance computation algorithm, the Euclidean and Vertex methods are applied to crisp and fuzzy TOPSIS, respectively.

Regardless of the different distance computation algorithms, the initial step of both TOPSIS algorithms is to form a committee with K numbers of decision makers to conduct the assessment process. Decision makers need to rate two different issues, namely the factor weight carried during the assessment process and the score of the alternative against factors. Factor weight is the level of importance of related factors with respect to the overall goal. After assessing the former, decision makers are required to provide suitable values that describe the score of the alternative against corresponding factors individually. Mean aggregation is then adopted to aggregate all rating scores from decision makers for further analysis.

Crisp TOPSIS algorithm

In the crisp TOPSIS algorithm, the rating is provided in the form of a quantitative value by using a five-point Likert scale. The Likert scale is a rating scale wherein respondents select the most relevant answer to the question (Dawes 2008). The Likert scale is relatively popular because of its ease of completion and consistency in data encoding. The Likert scale can also prevent the occurrence of central tendency errors. Table 1 illustrates the rating scale and the corresponding descriptions.

Table 1 Evaluation of factor weights

Rating scale	Description
1	Equally important
2	Moderately important
3	Important
4	Very important
5	Extremely important

Table 2 Maintenance strategy assessment ratings

Rating scale	Description
1	Very low
2	Low
3	Medium
4	High
5	Very high

Rating 1 is the lowest score and describes the factor as "equally important" with regard to the overall goal (Table 1), followed by moderately important by Rating 2 and important by Rating 3. Very important and extremely importance are represented by Ratings 4 and 5, respectively. The maintenance strategy assessment ratings are described in Table 2.

Similar to the factor weights rating scale, the same rating value is adopted but with different descriptions for the maintenance strategy assessment ratings. The descriptions are modified to "very low", "low", "medium", "high", and "very high" with corresponding values from one to five. Further analysis by using crisp TOPSIS is conducted after decision makers answer the questionnaire based on the described rating scale. The obtained results are aggregated by using the mean aggregation before proceeding to further analysis.

Mean aggregation

The initial step of TOPSIS algorithm is to aggregate the rating of the factor weights and maintenance strategy assessment obtained from decision makers. The formula used for aggregation of the rating is determined by Eqs. (1) and (2):

$$\bar{x}_{ij} = \sum_{k=1}^{K} x_{ijk}/K \tag{1}$$

in which x_{ijk} represents the rating value of the ith maintenance strategy with the respective jth factor given by decision maker k where $i = 1, 2, 3,\ldots, m, j = 1, 2, 3, \ldots, n$, and $k = 1, 2, 3, \ldots,K$;

$$\bar{w}_i = \sum_{k=1}^{K} w_{ik}/K \tag{2}$$

where $\bar{w}_i$ represents the average value of the weight rating corresponding to the ith factor from K decision makers.

Decision matrix formulation

Then the mean ratings regarding the m maintenance strategy under n factors obtained from Eqs. (1) and (2) are organized into the decision matrix D, as shown in Eq. (3)

$$D = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_j \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_i \end{array} & \begin{bmatrix} \bar{x}_{11} & \bar{x}_{12} & \cdots & \bar{x}_{1n} \\ \bar{x}_{21} & \bar{x}_{22} & \cdots & \bar{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \bar{x}_{m2} & \cdots & \bar{x}_{mn} \end{bmatrix} \end{array} \text{ where} \quad i = 1,2,3,\ldots,m; \quad j = 1,2,3,\ldots,n \tag{3}$$

where D represents the decision matrix with maintenance strategy, A_i $(i = 1,2,\ldots,m)$ and factor C_j $(j = 1,2,\ldots,n)$. $\bar{x}_{ij}$ is the average rating gains from Eq. (1).

Decision matrix normalization

The process of normalization will be conducted to transform the rating value from decision matrix D to the range 0–1. The normalized value is formed into decision matrix R as given by Eq. (4):

$$R = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_j \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_i \end{array} & \begin{bmatrix} \bar{r}_{11} & \bar{r}_{12} & \cdots & \bar{r}_{1n} \\ \bar{r}_{21} & \bar{r}_{22} & \cdots & \bar{r}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{r}_{m1} & \bar{r}_{m2} & \cdots & \bar{r}_{mn} \end{bmatrix} \end{array} \text{ where} \quad i = 1,2,\ldots,m; \quad j = 1,2,\ldots,n, \tag{4}$$

where

$$\bar{r}_{ij} = \begin{cases} \bar{x}_{ij}/\bar{x}_j^+, \forall_j, \bar{x}_j \text{ is a benefit factor} \\ \bar{x}_j^-/\bar{x}_{ij}, \forall_j, \bar{x}_j \text{ is a cost factor} \end{cases}$$

$\bar{x}_j^+$ and $\bar{x}_j^-$ represent the highest and lowest values for each factor, respectively.

Weighted normalized decision matrix

Considering the different degrees of importance of each factor, the aggregated weighted value obtained from Eq. (2) is multiplied into the normalized decision matrix to form the weighted normalized decision matrix:

$$V = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_j \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_i \end{array} & \begin{bmatrix} \bar{v}_{11} & \bar{v}_{12} & \cdots & \bar{v}_{1n} \\ \bar{v}_{21} & \bar{v}_{22} & \cdots & \bar{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{v}_{m1} & \bar{v}_{m2} & \cdots & v_{mn} \end{bmatrix} \end{array} \text{ where} \quad i = 1,2,\ldots,m; \quad j = 1,2,\ldots,n \tag{5}$$

where

$\bar{v}_{ij} = \bar{r}_{ij}(.)\bar{w}_j.$

Determining the PIS and NIS

According to the TOPSIS algorithm, PIS, A^+ and NIS, A^- are identified from the weighted normalized decision matrix according to Eqs. (6) and (7):

$$A^+ = \{\bar{v}_1^+, \bar{v}_2^+, \ldots, \bar{v}_n^+\} \text{ where } \bar{v}_j^+ = \max_i\{\bar{v}_{ij}\}, \quad i = 1,2,\ldots,m; \quad j = 1,2,\ldots,n, \tag{6}$$

$$A^- = \{\bar{v}_1^-, \bar{v}_2^-, \ldots, \bar{v}_n^-\}, \text{ where } \bar{v}_j^- = \min_i\{\bar{v}_{ij}\}, \quad i = 1,2,\ldots m, \quad j = 1,2,..,n. \tag{7}$$

Separation distance computation

The separation distance of each maintenance strategy from the PIS and NIS is calculated by using the Euclidean distance as presented in Eqs. (8) and (9):

$$d_i^+ = \sum_{j=1}^{n} \sqrt{(\bar{v}_{ij} - \bar{v}_j^+)^2}, \quad j = 1,2,\ldots,n, \tag{8}$$

$$d_i^- = \sum_{j=1}^{n} \sqrt{(\bar{v}_{ij} - \bar{v}_j^-)^2}, \quad j = 1,2,\ldots,n, \tag{9}$$

where d_i^+ represents the separation distance of maintenance strategy A_i from the PIS and d_i^-represents the separation distance from the NIS.

Closeness coefficient calculation

The relative closeness of the ith maintenance strategy to the ideal solution is denoted as C_i^*. The measurement of the closeness coefficient is conducted by referring to Eq. (10):

$$C_i^* = \frac{d_i^-}{d_i^* + d}, 0 < C_i^* < 1, \quad i = 1,2,\ldots,n. \tag{10}$$

The maintenance strategies are then ranked from the highest to the lowest according to the closeness coefficient value. The maintenance strategy with the highest closeness value will be considered the most preferable strategy for implementation.

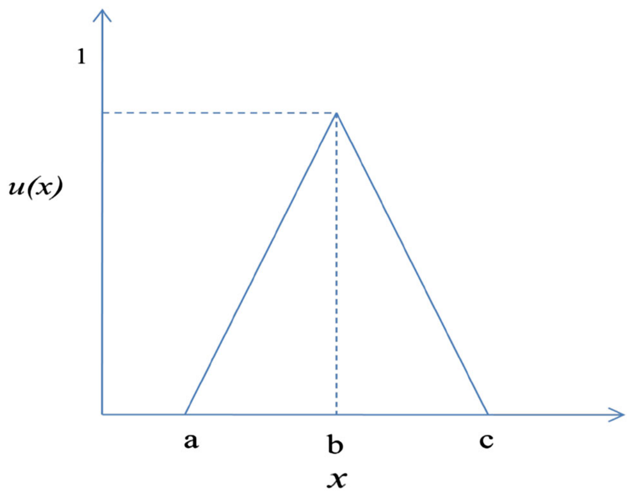

Fig. 1 Triangular membership function

Fuzzy TOPSIS algorithm

The assessment rating in fuzzy TOPSIS is conducted by using linguistic variables instead of crisp values. A linguistic variable applies words or sentences in a natural or artificial language to describe the degree of value. Two different linguistic variables for factors weights fuzzy rating and maintenance strategy assessment rating are proposed. The factors weights is described as 'important' while 'low/high' is adopted to illustrate the performance of maintenance policy. Each linguistic variable is divided into five different scales. For criteria, significant fuzzy rating scale is described by using 'equally important' (EI), 'moderately important' (MI), 'strongly important' (SI), 'very strongly important' (VI) and 'extremely important' (XI). The linguistic variable for maintenance policy performance fuzzy rating is illustrated through 'very low' (VL), 'low' (L), 'fair' (F), 'high' (H) and 'very high' (VH).The membership function of these linguistics variables is represented by a triangular fuzzy number as displayed in Fig. 1.

x represents the specified rating, and $u(x)$ represents the value of the membership function (Fig. 1). The value of the membership function is zero (i.e., $u(a) = 0$) when the rating does not belong to the linguistic term, whereas the value of the membership function is one (i.e., $u(b) = 1$) when the rating completely belongs to the linguistic term. The triangular fuzzy number is commonly used in various decision-making processes in engineering including supplier selection and maintenance decision making. The triangular fuzzy number can be modeled and interpreted easily while adequately capturing the vagueness of linguistic assessments.

However, the linguistic descriptions of decision makers vary depending on personal experience. For example, the value of the linguistic term "equally important" by one decision maker may range from one to three, whereas that of another decision maker may range from zero to four. Thus, a fuzzy membership function that suits all decision makers should be developed to improve the assessment results. Decision makers are asked to provide a value of $b_i = X$ to represent the value that belongs to the linguistics term and a pair of values (a_i, c_i) to represent the interval of the linguistic terms. Then, the values of a, b, and c for the triangular fuzzy numbers obtained from decision makers will be aggregated by using Eq. (11) to form the fuzzy set number for linguistic variables that is used for maintenance strategy assessment rating and factor weight rating:

$$a = \frac{1}{K}\sum_{k=1}^{K} a_k, \quad b = \frac{1}{K}\sum_{k=1}^{K} b_k, \quad c = \frac{1}{K}\sum_{k=1}^{K} c_k, \tag{11}$$

Decision makers then perform assessments according to the intervals of the linguistic terms developed from Eq. (11), and the results are analyzed in the fuzzy TOPSIS algorithm.

Mean aggregation

The fuzzy ratings of all decision makers, k ($k = 1, 2, 3, \ldots,$ K), are aggregated by using mean aggregation. The fuzzy rating value in this case is described based on triangular fuzzy numbers, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$. The aggregated fuzzy ratings of maintenance strategy with respect to each factor are determined as follows:

$$a_{ij} = \min_k\{a_{ijk}\}, \quad b_{ij} = \frac{1}{K}\sum_{k=1}^{K} b_{ijk}, \quad c_{ij} = \max_k\{c_{ijk}\}. \tag{12}$$

The mean aggregated fuzzy weights $\widetilde{w_j} = (w_{j1}, w_{j2}, w_{j3})$ of k decision makers are calculated as follows:

$$w_{ij1} = \min_k\{w_{jk1}\}, \quad w_{j2} = \frac{1}{K}\sum_{k=1}^{K} w_{jk2}, \quad w_{j3} = \max_k\{w_{jk3}\}. \tag{13}$$

Fuzzy decision matrix formulation

The mean linguistic ratings regarding the assessment of maintenance strategy A_i with factors C_j obtained from Eq. (12) are expressed in the fuzzy decision matrix:

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_j \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \quad \text{where} \quad i = 1, 2, \ldots, m$$
$$\text{and} \quad j = 1, 2, \ldots, n \tag{14}$$

where $\tilde{D}$ represents the fuzzy decision matrix with maintenance strategy A_i and factors C_j. $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ denotes the aggregated fuzzy linguistic rating linguistic variables obtained from Eq. (12).

Fuzzy decision matrix normalization

Similar to crisp TOPSIS algorithm, the normalization of the fuzzy decision matrix $\tilde{R}$ is given by the following:

$$\tilde{R} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_j \end{array} \\ \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \cdots & \tilde{r}_{1n} \\ \tilde{r}_{21} & \tilde{r}_{22} & \cdots & \tilde{r}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{m1} & \tilde{r}_{m2} & \cdots & \tilde{r}_{mn} \end{bmatrix} \end{array} \text{ where } \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{15}$$

$$\tilde{r}_{ij} = \begin{cases} \tilde{x}_{ij}(:)x_j^{+} = \left(\dfrac{a_{ij}}{c_j^{+}}, \dfrac{b_{ij}}{b_j^{+}}, \dfrac{c_{ij}}{a_j^{+}}\right), \forall_j, \tilde{x}_j \text{ is a benefit criterion}, & i = 1, 2, .., m; \quad j = 1, 2, \ldots, m \\ \tilde{x}_j^{-}(:)\tilde{x}_{ij} = \left(\dfrac{a_j^{-}}{c_{ij}}, \dfrac{b_j^{-}}{b_{ij}}, \dfrac{c_j^{-}}{a_{ij}}\right), \forall_j, \tilde{x}_j \text{ is a cost criterion}, & i{=}1, 2, .., m; \quad j = 1, 2, \ldots, m \end{cases}$$

where $\tilde{x}_j^{+} = (a_j^{+}, b_j^{+}, c_j^{+})$ and $\tilde{x}_j^{-} = (a_j^{-}, b_j^{-}, c_j^{-})$ represent the highest and lowest fuzzy value for each factor, respectively. As indicated in Eq. (15), the normalization process is different between the benefit criterion and cost criterion. The benefit criterion and cost criterion are justified based on the trend of values. If the value of the criterion is preferred when increasing, it is a benefit criterion. In contrast, if the value of criterion is preferred when lower, it will be the cost criterion.

Weighted normalized fuzzy decision matrix

Considering the different degrees of importance of each factor, the aggregated weighted value obtained from Eq. (13) is multiplied into the normalized decision matrix to form the weighted normalized decision matrix (16):

$$\tilde{V} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_j \end{array} \\ \begin{bmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1n} \\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{m1} & \tilde{v}_{m2} & \cdots & \tilde{v}_{mn} \end{bmatrix} \end{array} \tag{16}$$

where

$$\tilde{v}_{ij} = \tilde{r}_{ij}(.)\tilde{w}_j = \begin{cases} \left(\dfrac{a_{ij}}{c_j^{+}}\tilde{w}_j, \dfrac{b_{ij}}{b_j^{+}}\tilde{w}_j, \dfrac{c_{ij}}{a_j^{+}}\tilde{w}_j\right), \forall_j, \tilde{x}_j \text{ is a benefit criterion}, & i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \\ \left(\dfrac{a_j^{-}}{c_{ij}}\tilde{w}_j, \dfrac{b_j^{-}}{b_{ij}}\tilde{w}_j, \dfrac{c_{ij}^{-}}{a_{ij}}\tilde{w}_j\right), \forall_j, \tilde{x}_j \text{ is a cost criterion}, & i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \end{cases}.$$

Fuzzy PIS and fuzzy NIS

The fuzzy PIS and fuzzy NIS will be identified from Eq. (16) according to Eqs. (17) and (18) presented as follows:

$$A^+ = \{\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\}, \quad (17)$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\}, \quad (18)$$

where

$$\tilde{v}_j^* = \max_i\{v_{ij3}\}, \tilde{v}_j^- = \min_i\{v_{ij1}\} \quad i = 1, 2, \ldots, m; \quad j = 1, 2, .., n.$$

Separation distance computation

The separation distance of each maintenance strategy from the fuzzy PIS and fuzzy NIS is calculated via the vertex method:

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \quad (19)$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \quad (20)$$

where

$$d(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]}.$$

Closeness coefficient calculation

The relative closeness of the *i*th maintenance strategy with respect to the ideal solution is denoted as C_i^*. The measurement of the closeness coefficient is conducted by referring to Eq. (21).

$$C_i^* = \frac{d_i^-}{d_i^* + d_i^*}, \quad 0 < C_i^* < 1, \quad i = 1, 2, \ldots, n. \quad (21)$$

A larger index value leads to a better maintenance strategy performance. By using the ranking process, decision makers are able to obtain an overview of the preference order of all the maintenance strategies and make informed final decisions accordingly.

Case study

The maintenance strategy for coating machines used for the production of electronic circuit panels is adopted to examine both crisp and fuzzy TOPSIS. Considering the significant role and frequent failure of the coating machine, maintenance management aims to investigate the most suitable maintenance strategy that can improve the performance of the coating machine with existing resources. After a discussion, five maintenance strategies with respect to six evaluation factors are determined as potential candidates in the assessment process. Autonomous maintenance (AM), corrective maintenance (CM), design out maintenance (DOM), predictive maintenance (PdM), and preventive maintenance (PM) are the five potential maintenance strategies considered during the assessment process.

AM is a strategy that involves the cooperation between the production department and maintenance department. Operators will provide their capabilities and assistance on maintenance issues, such as cleaning and lubricating the

Table 3 Outcome of maintenance strategy assessment

Factor, C_j	Maintenance strategy, A_i	Maintenance strategy assessment from decision maker, k		
		K1	K2	K3
C1	CM	3	5	5
	PM	2	3	3
	PdM	4	3	3
	AM	4	3	3
	DOM	3	2	2
C2	CM	3	4	3
	PM	3	3	2
	PdM	4	4	3
	AM	4	4	4
	DOM	3	3	3
C3	CM	2	4	3
	PM	2	3	3
	PdM	3	4	5
	AM	1	1	1
	DOM	3	4	3
C4	CM	1	1	1
	PM	1	4	1
	PdM	3	4	3
	AM	4	4	4
	DOM	4	5	3
C5	CM	3	4	3
	PM	3	4	4
	PdM	4	4	4
	AM	4	4	3
	DOM	3	4	3
C6	CM	4	4	5
	PM	4	3	5
	PdM	5	4	5
	AM	4	4	5
	DOM	4	4	5

Table 4 Factor's weight assessment results

C_j	K1	K2	K3
C1	3	5	5
C2	3	5	4
C3	5	4	5
C4	4	5	5
C5	4	5	4
C6	5	5	3

Table 5 Mean aggregated decision matrix

Maintenance strategy	C1	C2	C3	C4	C5	C6
CM	4.00	3.33	3.00	1.00	3.33	4.33
PM	2.67	2.67	2.67	2.00	3.67	4.00
PdM	3.67	3.67	4.00	3.33	4.00	4.67
AM	3.67	4.00	1.00	4.00	3.67	4.33
DOM	2.33	3.00	3.33	4.00	3.33	4.33
$\tilde{W}$	4.33	4.00	4.67	4.67	4.33	4.33

Table 6 Weighted and normalized decision matrix

Maintenance strategy	C1	C2	C3	C4	C5	C6
CM	4.33	3.33	1.56	1.67	3.61	4.02
PM	2.89	2.67	1.75	2.33	3.97	3.71
PdM	4.00	3.67	1.17	3.89	4.33	4.33
AM	4.00	4.00	4.67	4.67	3.97	4.02
DOM	2.53	3.00	1.40	4.67	3.61	4.02

Table 7 Separation distances and closeness coefficients

Maintenance strategy	d^+	d^-	C_i^*
CM	3.6706	3.6104	0.4945
PM	3.2225	3.2517	0.5022
PdM	0.9350	4.7710	0.8361
AM	3.7150	3.8739	0.5105
DOM	2.244	4.8092	0.6818

Table 8 Linguistic variables with the respective interval values

Linguistic variable	K1			K2			K3		
	a_i	b_i	c_i	a_i	b_i	c_i	a_i	b_i	c_i
Linguistic variables for factors weights rating									
EI	0	0.2	0.3	0	0.2	0.4	0	0.1	0.3
MI	0.2	0.3	0.4	0.3	0.4	0.6	0.2	0.3	0.5
SI	0.2	0.4	0.7	0.5	0.6	0.8	0.4	0.5	0.7
VI	0.5	0.6	0.9	0.6	0.7	0.9	0.5	0.6	0.9
XI	0.9	1.0	1.0	0.8	0.9	1.0	1.0	1.0	1.0
Linguistic variables for maintenance strategy assessment									
VL	0.0	1.0	3.0	0.0	2.0	4.0	0.0	1.0	3.0
L	2.0	3.0	5.0	3.0	5.0	6.0	2.0	3.0	5.0
M	4.0	5.0	6.0	5.0	6.0	7.0	4.0	5.0	7.0
H	5.0	7.0	8.0	7.0	8.0	9.0	5.0	6.0	9.0
VH	8.0	9.0	10.0	8.0	9.0	10.0	10.0	10.0	10.0

machine components. Operators will inform the maintenance department when abnormal machine conditions are detected to prevent failures. CM is a passive strategy where maintenance action was only taken after failure occurred. DOM provided the option to either improve or redesign the machine to solve the failure permanently. PdM is a strategy that tries to monitor the machine condition, and maintenance is performed only at the critical point right before failure occurs. PM is a strategy wherein the maintenance interval is scheduled according to certain attributes such as machine operation duration.

These maintenance strategies will be assessed according to the six factors listed below:

a. Maintainability (C1): measure of the time required to restore the machine from the time taken to diagnose the problem until the start of operations after repair.
b. Feasibility (C2): the possibility of performing the maintenance strategy in actual circumstances.
c. Implementation cost (C3): the investment required to start the maintenance strategy (e.g., the cost required to install hardware, software, and training cost).
d. Environment condition (C4): the capability of the maintenance strategy to improve the working environment factors such as humidity and temperature to prolong the service life of machines.
e. Fault detection (C5): capability of related maintenance strategies to detect weakness before total breakdown of the machine.
f. Safety (C5): the possibility of the maintenance strategy to improve the safety level of machine practitioners and the environment.

The potential of the maintenance strategy will be evaluated according to these six factors on the basis of the experience and knowledge of decision makers. In this study, three decision makers labeled as K1, K2, and K3 are involved in the evaluation process. The results of the assessment are then analyzed by using crisp and fuzzy TOPSIS.

Crisp TOPSIS analysis

The maintenance strategy rating corresponding with six factors given by decision makers K1, K2, and K3 are tabulated in Table 3.

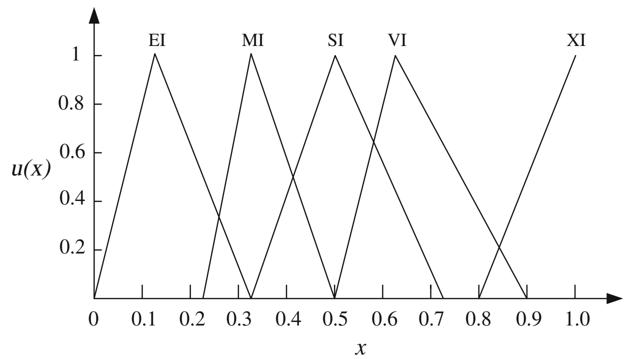

Fig. 2 Linguistic variable of factor weight rating

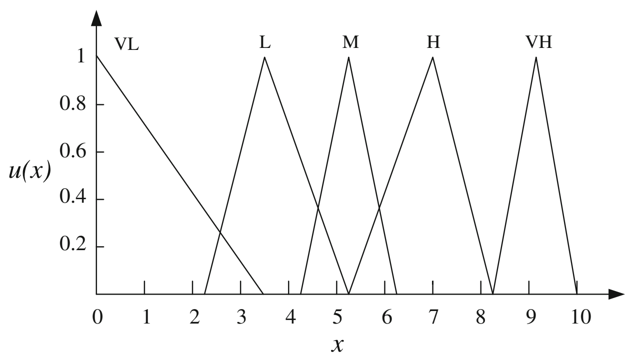

Fig. 3 Linguistic variables for maintenance strategy assessment

Table 9 Fuzzy decision matrix

Maintenance strategy	Decision maker	C1	C2	C3	C4	C5	C6
CM	K1	M	M	L	VL	M	H
	K2	VH	H	H	VL	H	H
	K3	H	M	M	VL	M	VH
PM	K1	L	M	L	VL	M	M
	K2	M	M	M	H	H	H
	K3	M	L	M	VL	H	M
PdM	K1	H	H	M	M	H	VH
	K2	M	H	H	H	H	H
	K3	H	M	VH	M	H	VH
AM	K1	H	H	VL	H	H	H
	K2	M	H	VL	H	H	H
	K3	H	H	VL	H	M	VH
DOM	K1	M	M	M	H	M	H
	K2	L	M	H	VH	H	H
	K3	L	M	M	M	M	VH
w	K1	I	I	AI	VI	VI	AI
	K2	AI	AI	VI	AI	AI	AI
	K3	AI	VI	AI	AI	VI	I

The factor weight assessment results obtained from the same group of decision makers are summarized in Table 4.

Then, the rating assessment of maintenance strategy performance assessment as well as factors weighting obtained from the three decision makers (as tabulated in Tables 3, 4) are aggregated using Eqs. (1) and (2). The aggregation results are tabulated in Table 5.

Subsequently, the decision matrix is weighted and normalized according to Eqs. (3) and (4). Table 6 shows the results of the weighted and normalized decision matrix.

The PIS (A^+) and NIS (A^-) are then identified based on Table 6. The PIS refers to the maximum value of each factor, whereas the NIS refers to the minimum value of each factor:

$$A^+ = \{4.33, 4.00, 1.00, 4.67, 4.33, 4.33\},$$
$$A^- = \{2.53, 3.33, 4.67, 1.67, 3.61, 3.71\}.$$

Finally, the separation distance between potential maintenance strategies from the PIS and NIS are measured according to Eq. (9). The closeness coefficient value is then computed from Eq. (10). The results of the computation are shown in Table 7.

Table 7 shows that the PdM maintenance strategy has the highest value and is the most preferable maintenance strategy for plating machines, followed by DOM, AM, PM, and CM.

Fuzzy TOPSIS analysis

With the same group of decision makers, the maintenance strategy is evaluated against the six factors according to the linguistic variables tabulated in Tables 1 and 2. As stated in the fuzzy TOPSIS algorithm section, the fuzzy number set which suits the linguistic variables will be formed at the initial stage of the evaluation process. Decision makers were required to give a value that indicates the exact value (b_i) for factors weights rating linguistic variable and a pair of values that represents the interval (a_i and c_i) within the range of 0–1. A similar process is performed for the maintenance strategy assessment linguistic variables within the range of 0–10. Table 8 tabulates the linguistic variables as well as the value that belongs to the linguistic variable (b_i) and a pair of values that represent the interval of the linguistic variables (a_i, c_i).

The preferences of the decision makers for both membership functions of the linguistic variables are then collected and aggregated by Eq. (11). Linguistic variables with related fuzzy set number for the factor weight rating and maintenance strategy assessment are displayed in Figs. 2 and 3, respectively.

Three decision makers who used to provide assessments for crisp TOPSIS are employed to perform a similar evaluation, but with the linguistic rating (Figs. 2, 3). The collected information is presented in Table 9.

Table 10 Mean aggregated fuzzy decision matrix

Maintenance strategy	C1	C2	C3	C4	C5	C6
CM	4.3, 7.2, 10	4.3, 5.9, 8.7	2.3, 5.3, 8.7	1.0, 1.3, 3.3	4.3, 5.9, 8.7	5.7, 7.8, 8.7
PM	2.3, 4.8, 6.7	2.3, 4.8, 6.7	2.3, 4.8, 6.7	1.0, 3.2, 8.7	4.3, 6.4, 8.7	4.3, 5.9, 8.7
PdM	4.3, 6.4, 8.7	4.3, 6.4, 8.7	4.3, 7.2, 8.7	4.3, 5.9, 4.3	5.7, 7.0, 8.7	5.7, 8.8, 10
AM	4.3, 6.4, 8.7	5.7, 7.0, 8.7	1.0, 1.3, 3.3	5.7, 7.0, 8.7	4.3, 6.4, 8.7	5.7, 7.8, 8.7
DOM	2.3, 4.2, 6.7	4.3, 5.3, 6.7	4.3, 5.9, 8.7	4.3, 7.2, 10	4.3, 5.9, 8.7	5.7, 7.8, 8.7
$\tilde{W}$	0.4, 0.8, 1.0	0.4, 0.7, 1.0	0.5, 0.9, 1.0	0.5, 0.9, 1.0	0.5, 0.7, 0.9	0.4, 0.8, 1.0

Table 11 Weighted normalized decision matrix

Factor	CM	PM	PdM	AM	DOM
C1	0.16, 0.81, 2.31	0.09, 0.54, 1.54	0.16, 0.73, 2.00	0.16, 0.73, 2.00	0.09, 0.48, 1.54
C2	0.18, 0.59, 1.53	0.10, 0.48, 1.18	0.19, 0.64, 1.53	0.24, 0.70, 1.53	0.19, 0.53, 1.18
C3	0.06, 0.21, 1.45	0.08, 0.24, 1.43	0.06, 0.16, 0.77	0.16, 0.86, 3.33	0.06, 0.19, 0.77
C4	0.05, 0.16, 1.45	0.05, 0.16, 1.53	0.23, 0.70, 0.76	0.30, 0.83, 1.53	0.23, 0.86, 1.76
C5	0.26, 0.63, 1.38	0.26, 0.68, 1.38	0.35, 0.74, 1.38	0.26, 0.68, 1.38	0.26, 0.63, 1.38
C6	0.21, 0.72, 1.53	0.16, 0.55, 1.53	0.21, 8.10, 1.76	0.21, 0.72, 1.53	0.21, 0.72, 1.53

The linguistic ratings from the decision makers are combined by using the mean aggregation displayed in Eqs. (12) and (13). The mean aggregation results are organized according to the fuzzy decision matrix defined in Eq. (14) and presented in Table 10.

The second step in the analysis is to perform the weighting and normalization process on the fuzzy decision matrix by using Eqs. (15) and (16). Table 11 displays the computation results of the weighted normalized matrix.

The fuzzy PIS, A^+, and fuzzy NIS, A^-, are identified in Table 10 by referring to Eqs. (17) and (18):

$$A^+ = \{(0.16, 0.81, 2.31), (0.24, 0.7, 1.53), (0.06, 0.16, 0.77), (0.30, 0.86), (0.35, 0.74, 1.38), (0.21, 0.81, 1.76)\}$$

$$A^- = \{(0.09, 0.48, 1.54), (0.1, 0.48, 1.18), (0.16, 0.86, 3.33), (0.05, 0.16, 0.59), (0.26, 0.625, 1.38), (0.16, 0.55, 1.53)\}$$

Finally, the separation distance of each maintenance strategy from the fuzzy PIS and fuzzy NIS are computed by using Eqs. (19) and (20), respectively. The values of separation distance from the PIS, d^+ and NIS, d^-, as well as the closeness coefficient C_i^* of each maintenance strategy are presented in Table 12.

PdM obtains the highest order preference followed by DOM, AM, CM, and PM. To observe the effectiveness of the fuzzy TOPSIS in decision-making maintenance strategies, a comparison with the conventional crisp TOPSIS is conducted. The results of both conventional crisp TOPSIS and fuzzy TOPSIS are shown in Table 13.

Both conventional crisp and fuzzy TOPSIS from Table 13 have the same preference orders except for the fourth and fifth rank. The ranking trend is similar to Yang and Hung (2007), who conducted a comparison of crisp and fuzzy TOPSIS in the selection of the most suitable plant layout design for an IC packaging company. Another study of the comparison between TOPSIS and fuzzy TOPSIS chose the best facility layout among 18 possible designs (Maniya and Bhatt 2011); the results showed that both methods are ranked first in the alternative ranking.

Table 12 Separation distance and closeness correlation

Maintenance strategy	d^+	d^-	C_i^*
CM	1.4989	1.9599	0.5666
PM	1.8266	1.7689	0.4920
PdM	0.9617	2.7050	0.7377
AM	2.0580	1.3834	0.4020
DOM	1.0045	2.4887	0.7124

A series of sensitivity analyses are conducted to further examine the stability and resiliency of fuzzy and crisp TOPSIS. Sensitivity analysis is useful in providing an overall view of the complex relationships between the evaluating attributes inherent in the decision-making process. This type of analysis also helps decision makers make sound judgments. The examination is conducted under extreme states where only one attribute has the maximum possible weight and the other attributes have the minimum possible weights (as proposed by Kahraman et al. 2007).Thereafter, the normalized relative closeness coefficient is computed for each state according to Eq. (21):

$$\text{Normalized } C_i^* = \frac{C_i^*}{\sum_{i=1}^{m} C_i^*}. \tag{22}$$

Table 13 Comparison of TOPSIS ranking

Maintenance strategy	Crisp TOPSIS	Fuzzy TOPSIS
CM	0.4945	0.5666
PM	0.5022	0.4920
PdM	0.8361	0.7377
AM	0.5105	0.4020
DOM	0.6818	0.7124
Order preference	PdM > DOM > AM > PM > CM	PdM > DOM > CM > PM > AM

Six different examination states are shown for fuzzy and crisp TOPSIS. The analysis results are presented in Table 14.

Figure 4 displays the results of the sensitivity analysis graphically to provide an illustration of the changes in preference order.

In fuzzy TOPSIS, the maintenance strategy rankings change significantly during States 3 and 4. The cost factor has the maximum weight under State 3, the order preference of AM drastically drops to last place, and OM obtains a comparable status with PdM. The preference order changes to OM > PdM > PM > CM > AM. During State 4 in the examination process, the weight carried by the environment condition also shows a noteworthy impact on the order preference. The ranking order is altered to OM > AM > PdM > PM > CM when the important weight carried by the environmental attribute increases. OM replaces PdM as the most preferred maintenance strategy.

The sensitivity analysis shows that the weight is very influential in maintenance strategy decision making. The results indicate that both the cost attribute and environmental attribute are relatively sensitive during the evaluation process. Thus, decision makers should be careful when making judgments regarding these attributes. Deviations exist in the other alternatives, but PdM is still the highest-ranking strategy. The stability and resilience of fuzzy TOPSIS in maintenance decision making has been proven in this sensitivity analysis

By contrast, the sensitivity result of crisp TOPSIS has shown fluctuating changes in the maintenance strategy rankings. The AM strategy obtains the highest ranking for all states except during State 3 when the cost factor has the maximum weight. During the sensitivity analysis, AM overtakes PdM as the most preferable maintenance strategy when compared with the original crisp TOPSIS. Thus, all six factor weights of crisp TOPSIS are highly sensitive and can eventually affect the final preference ranking of the maintenance strategies.

Table 14 Evaluation states and normalized closeness coefficient

Type of TOPSIS	State	CM	PM	PdM	AM	OM
Fuzzy TOPSIS	1 (Max C1)	0.2451	0.1484	0.2529	0.1602	0.1932
	2 (Max C2)	0.2043	0.1470	0.2496	0.1734	0.2254
	3 (Max C3)	0.2075	0.2001	0.2678	0.0579	0.2664
	4 (Max C4)	0.1289	0.1751	0.2185	0.1972	0.2802
	5 (Max C5)	0.1873	0.1802	0.2666	0.1308	0.2349
	6 (Max C6)	0.2020	0.1597	0.2504	0.1425	0.2451
Crisp TOPSIS	1 (Max C1)	0.2429	0.1077	0.2459	0.2897	0.1135
	2 (Max C2)	0.1432	0.1389	0.2135	0.3420	0.1622
	3 (Max C3)	0.0565	0.11547	0.2407	0.3184	0.2687
	4 (Max C4)	0.1444	0.1702	0.2424	0.2641	0.1786
	5 (Max C5)	0.1649	0.1398	0.2301	0.2645	0.2005
	6 (Max C6)	0.2429	0.1077	0.2459	0.2897	0.1135

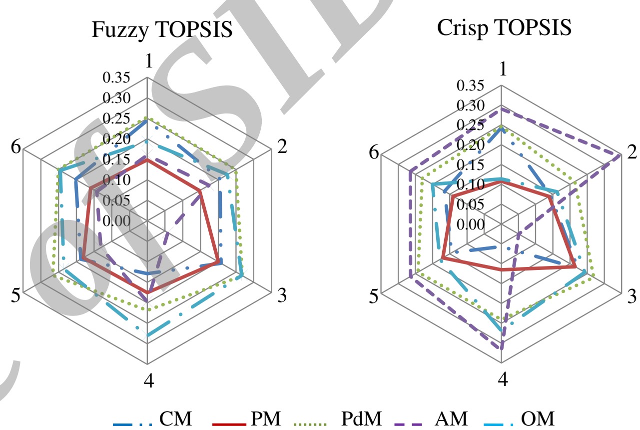

Fig. 4 Sensitivity analysis results

Compared with fuzzy TOPSIS, the resilience and stability of crisp TOPSIS are relatively low because the preference ranking changes significantly in all six states of the sensitivity analysis. The high level of the factor weights sensitivity requires intensive concentrations for all factor weight-rating processes. However, the requirement to conduct precise ratings by using the crisp rating scale ultimately limits the capability of decision maker to create suitable expressions. A certain degree of information is lost when precise ratings are required.

Although fuzzy and crisp TOPSIS produce similar results, decision makers believe that the judgments made under linguistic variables are relatively easy because many of the practical constraints are unquantifiable. Decision makers should be given flexibility in expressing their judgments, because they are familiar with the linguistic variables applied to words and sentences in the description of the degree of value. The vagueness, ambiguities, and uncertainties faced by decision makers from their subjective perceptions and experiences in conducting judgments based on unquantifiable constraints can be solved effectively by using linguistic variables. Thus, fuzzy TOPSIS is a viable, feasible, and flexible approach for solving maintenance group decision-making problems. Fuzzy TOPSIS provides a systematic approach to facilitate the decision-making process and provide reasonable evidence to support decisions.

Conclusions

Maintenance is considered one of the most important issues in the manufacturing industry in terms of generating effective plant performance. This paper has explored the use of crisp and fuzzy TOPSIS in solving the problems that surround maintenance strategy decision making. In the case study, both methods rank PdM as the most suitable maintenance strategy for the coating machine. However, sensitivity analysis shows that the fluctuating preference ranking of crisp TOPSIS is relatively low in terms of resilience and stability.

By contrast, fuzzy TOPSIS provides a consistent maintenance group decision-making method based on an empirical study, because the maintenance strategy preference ranking only changes under two factors, namely, cost and environment. Fuzzy TOPSIS is relatively effective in capturing information to justify the advantages and disadvantages of maintenance strategies that correspond to different aspects. For the extension of this work, comparisons with other multi-attribute decision-making methods from a maintenance group decision-making perspective will be conducted.

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Author contributions Siew-Hong Ding participated in the design of the study, acquisition of data and performed the analysis. Besides, author also involves in sequence alignment and drafted the manuscript. Shahrul Kamaruddin has participated in revising it critically for important intellectual content and given final approval of the version to be published. Both authors read and approved the final manuscript.

References

Bao Q, Ruan D, Shen Y, Hermans E, Janssens D (2012) Improved hierarchy fuzzy TOPSIS for road safety performance evaluation. Knowl-Based Syst 32:84–90

Bashiri M, Badri H, Hejazi TH (2011) Selecting optimum maintenance strategy by fuzzy interactive linear assignment method. Appl Math Model 35(1):152–164

Behzadian M, Otaghsara SK, Yazdani M, Ignatius J (2012) A state-of the-art survey of TOPSIS applications. Expert Syst Appl 39:13051–13069

Chan FTS, Prakash A (2012) Maintenance policy selection in manufacturing firms using the fuzzy MCDM approach. Int J Prod Res 50(23):7044–7056

Chen FL, Chen YC (2010) Evaluating the maintenance performance of the semiconductor factories based on the analytical hierarchy process and grey relational analysis. Am J Appl Sci 7(4):567–574

Dagdeviren M, Yavuz S, Kilinc N (2009) Weapon selection using the AHP and TOPSIS methods under fuzzy environment. Exp Syst Appl 36:8143–8151

Dawes J (2008) Do data characteristics change according to the number of scale points used? An experiment using 5-point, 7-point and 10-point scales. Int J Market Res 50(1):61–77

Ding SH, Kamaruddin S (2012) Selection of optimal maintenance policy by using fuzzy multi criteria decision making method. In: Proceedings of international conference on industrial engineering and operations management, Istanbul, Turkey, 3–6 July

Ding SH, Kamaruddin S, Azid IA (2014a) Development of a model for optimal maintenance policy selection. Eur J Ind Eng 8(1):50–68

Ding SH, Kamaruddin S, Azid IA (2014b) Maintenance policy selection model—a case study in the palm oil industry. J Manuf Technol Manag 25(3):415–435

Faghihinia E, Mollaverdi N (2012) Building a maintenance policy through a multi-criterion decision-making model. J Ind Eng Int 8:14

Fuat A, Abit B, Hakan D (2014) fuzzy AHP and Fuzzy TOPSIS integrated hybrid method for auxiliary systems of ship main engines. J Mar Eng Technol 13(1):3–11

Hong DS, Kamaruddin S, Azid IA (2012) Maintenance policy selection: a review towards building proper selection model. Int J Ind Syst Eng 10(3):355–375

Ilangkumaran M, Kumanan S (2009) Selection of maintenance policy for textile industry using hybrid multi-criteria decision making approach. J Manuf Technol Manag 20(7):1009–1022

Kahraman C, Ates NY, Cevik S, Gulbay M, Erdogan SA (2007) Hierarchy fuzzy TOPSIS model for selection among logistics information technologies. J Enterp Inf Manag 20(2):143–168

Kahraman C, Suder A, Cebi S (2013) Fuzzy multi-criteria and multi-experts evaluation of government investment in higher education: the case of Turkey. Technol Econ Dev Econ 19(4):549–569

Mahdevari S, Shahriar K, Esfahanipour A (2014) Human health and safety risks management in underground coal mines using fuzzy TOPSIS. Sci Total Environ 488–489:85–99

Maniya KD, Bhatt MG (2011) An alternative multiple attribute decision making methodology for solving optimal facility layout design selections problems. Comput Ind Eng 61(3):542–549

Mohammad AS, Kamali A, Naji B, Ghorbani M (2013) DEA and TOPSIS techniques for purchasing management: the case of aircraft manufacturing industry. Int J Logist Syst Manag 14(2):242–260

Momeni M, Fathi MR, Zarchi MK, Azizollahi S (2011) A fuzzy TOPSIS-based approach to maintenance strategy selection: a case study. Middle-East J Sci Res 8(3):699–706

Mousavi SS, Nezami FG, Heydar M, Aryanejad MB (2009) A hybrid group decision making and factor analysis for selecting maintenance strategy. In: Proceedings of international conference of computers and industrial engineering, 1204–1209, Troyes, 6–9 July

Nasrabadi AM, Hosseinpour MH, Ebrahimnejad (2013) Strategy-aligned fuzzy approach for market segment evaluation and selection: a modular decision support system by dynamic network process 9:11

Pourjavad E, Shirouyehzad H, Shanin A (2013) Selecting maintenance strategy in mining industry by analytic network process and TOPSIS. Int J Ind Syst Eng 15(2):171–192

Shyjith K, Ilangkumaran M, Kumanan S (2008) Multi-criteria decision-making approach to evaluate optimum maintenance strategy in textile industry. J Qual Maint Eng 14(4):375–386

SoltanPanah H, Farugi H, Heshami S (2011) Ranking repair and maintenance projects of large bridges in Kurdestan province using fuzzy TOPSIS method. J Am Sci 7(6):227–233

Thor J, Ding SH, Kamaruddin S (2013) Development of maintenance policy evaluation model: a case study of the semiconductor industry for achieving production demand. Int J Logist Syst Manag 15(4):405–423

Wang TC, Chang TH (2007) Application of TOPSIS in evaluating initial training aircraft under a fuzzy environment. Exp Syst Appl 33:870–880

Yang T, Hung CC (2007) Multiple-attribute decision making methods for plant layout design problem. Robot Comput-Integr Manuf 23:126–137

Zavadskas EK, Turkis Z (2011) Multiple criteria decision making (MCDM) methods in economics: an overview. Technol Econ Dev Econ 17(2):397–427

Zavadskas EK, Turkis Z, Kildiene S (2014) State of art surveys of overviews on MCDM/MADM methods. Technol Econ Dev Econ 20(1):165–179

Zhong L, Sun Y (2007) Research on maintainability evaluation model based on fuzzy theory. Chin J Aeronaut 20:402–407