International Journal of Global Optimization and Its Application
Vol. 3, No. 2, June 2024, pp.62-74
e-ISSN: 2948-4030
DOI: 10.56225/ijgoia.v3i2.272


*Original Article*

# Unprejudiced Strategic Suppliers Selection and Inspection: An Automated Industrial Approach

**Prithwiraj Jana** [1,*]

[1] Haldia Institute of Technology, 721657 Haldia, West Bengal, India.
[2] NDT Engineer of Inspection Survey & Surveillance Privet Limited, 700016 Kolkata, West Bengal, India.
* Correspondence: prithwiraj.janahit@gmail.com (P.J.)

**Citations:** Jana, P. (2024). Unprejudiced Strategic Suppliers Selection and Inspection: An Automated Industrial Approach. *International Journal of Global Optimization and Its Application, 3*(2), 62-74.

Received: 7 February 2024 Revised: 24 May 2024 Accepted: 3 June 2024 Published: 30 June 2024

**Abstract:** The world is changing rapidly to global automated marketplaces. As a result, the environment forces companies to make accurate decisions and considerations simultaneously. The relationship between the supplier and the company has been developed for a long time, so selecting the supplier is a significant task. This study highlighted one of the major concerns in the field of industrial engineering and quality management in the automated selection and inspection domain. This study also determines the unprejudiced selection accuracy and defect rate for present & future inspection, respectively, in supplier evaluation of the industry. Analyze the decision about future inspection 100% or not, on the basis of inspection cost during the examination and decision-making activity. After the supplier selection process, the next step is to check the supplier's efficiency, so inspection is implemented. Two models are dealt with in this paper: automated selection and the implementation of inspection.

**Keywords:** Quality control; Inspection accuracy; Entropy method; Cross check; Decision; MCDM.



## 1. Introduction

The entropy method is used to determine an accurate, unbiased weighted factor. The final suppliers' selection goes through three types of MCDM methods to decide the true value of ranking. Sensitivity analysis appears to measure the impact of input variables' uncertainties on a model's output variables. This paper also deals with creating an inspection model to minimize risk. Inspection accuracy refers to the capability of the inspection process to avoid these types of errors. As Drury (1992) suggested, inspection accuracy measures for the case in which an inspector classifies parts. Inspected items of good quality are incorrectly classified as not conforming to accepted specifications, and non-conforming items are mistakenly classified as conforming. These errors are called "False alarm" and "Miss" respectively. Also, inspection or No inspection: A model for deciding to inspect at a certain point in the production sequence is proposed (see Juran et al., 1979; Juran & Godfrey, 1999). The model uses the fraction defect rate in the inspection batch, the inspection cost per unit inspected, and the cost of damage that one defective unit would cause if it were not inspected.

For a particular type of Supplier/vendor selection in the industry, assume that six different types of Supplier/vendors are provided (A,B,C,D,E,F). Four different machines are to be ranked or selected considering nine conflicting criteria: Ordered number of items (C1), Number of On-time delivered items (C2), number of delayed items (C3), Number of conforming items (C4), Number of non-conforming items (C5), Machine velocity (m/sec) (C6), Load Capacity (kg) (C7), Repeatability in mm (C8), Cost in dollars (C9). C3, C5, and C9 are non-beneficiary criteria, while the rest of the criteria are beneficiary.

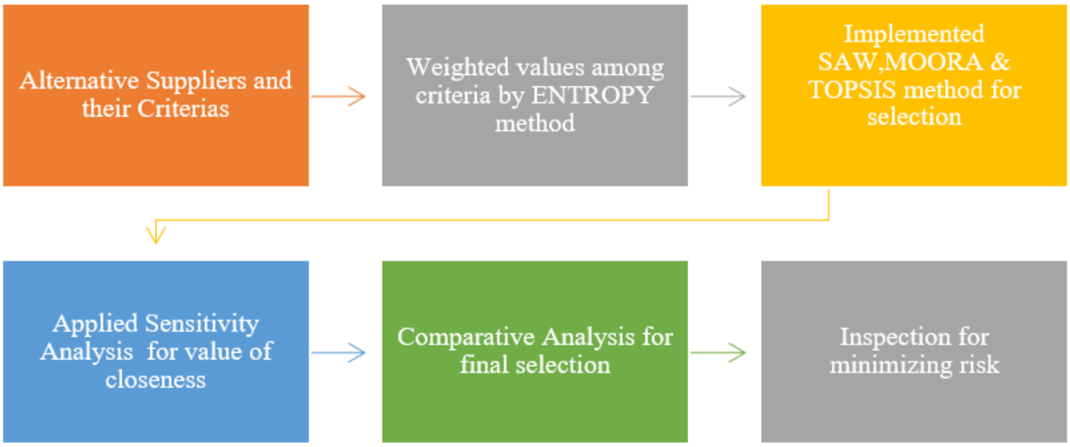


Table 1 shows the performance matrix of the alternative supplier with the importance weight of criteria. The present problem of supplier selection with six alternatives and nine conflicting criteria satisfies the condition of MCDM. The proposed approach has been applied to find the best robot as well as their ranking. During raw material supply time, the efficiency checking of this supplier is an important part of supply chain management inspection (Telsang, 1998). Sometimes, errors occur in the inspection procedure, such as items of good quality being incorrectly classified and vice versa. In manual inspection, these errors result from factors such as (i) Inherent variations in the inspection procedure, (ii) Complexity, hazard, and other various difficulties of the inspection task, (iii) Inaccuracy in measuring instruments, and (iv) Mental fatigue, etc.

**Table 1.** Two types of errors in cross-check inspection

| | Conforming Item | Non-Conforming Item |
|---|---|---|
| Accepted Item | Right decision | Miss |
| Rejected Item | False alarm | Right decision |

For these irresolute inspection errors, it's possible to reduce the company's risk before the next inspection results, which are production loss, drain of money, idle times increase, etc. (Groover, 1990). Inspection accuracy is very important in these critical inspection cases (Mahajan, 1986). However, the exact accuracy and defect rate remain undetermined in these situations. Whenever the risk of inspection failure is found, it is impossible to assess the accuracy of past inspections on the basis of inspected data (Jana and Dan, 2017; Jana, 2020)—modeling a system to make automated inspection accuracy for minimizing the decision criticality (Tannock et al., 1990). Implemented alternative/cross-check inspections are frequently used to minimize this error.

## 2. Materials and Methods

In this study, the objectives are divided into two parts. First, several MCDM methods and sensitivity analyses were used to determine suppliers' ranking accuracy, and second, an inspection model was used to determine the efficiency of selected suppliers in the long term (Latorella & Prabhu, 2017). Considering multiple conflicting criteria, selecting the best path from a set of feasible alternatives is called Multiple criteria decision-making (MCDM). This process always goes through at least two alternatives and two conflicting criteria. MCDM are divided into two broad categories: Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM). Several useful tools for solving MCDM problems are Simple Additive Weighting method (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multi-Objective Optimization Ratio Analysis (MOORA), Analytical Hierarchy Method (AHP) and Analytical Network Method ANP, etc.

In practical approaches, errors frequently come out of hazardous conditions during the first inspection. To avoid this kind of situation, a different approach has been implemented i.e., sample inspection, spot sampling, etc. As a result, the processing time of the inspection is maximized, risk factor is unpredictable, no future inspection can be done because of increasing the inspection cost, etc. In this study, the author addresses the analysis of the inspection accuracy by (i) Automated computational methodology to determine the accuracy in cross-check approaches. (ii) Finding the errors for future inspection and (iii) Simplifying whether the plates will be replaced.

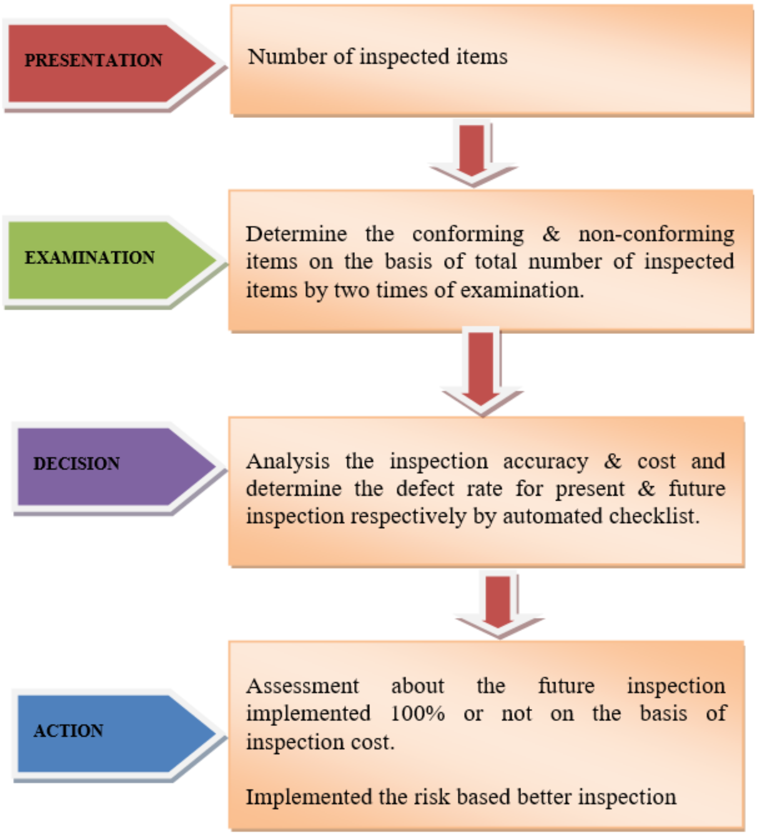


**Figure 1.** Modeling Inspection System Flow Diagram.

## 3. Results

### 3.1. Supplier selection and sensitivity analysis

**Table 2.** Result of Supplier Selection Criteria

| Criteria / Suppliers | Ordered number of items (C1) | Number of on-time delivered items (C2) | Number of delayed items (C3) | Number of conforming items (C4) |
|---|---|---|---|---|
| A | 16 | 15 | 1 | 12 |
| B | 14 | 14 | 1 | 14 |
| C | 04 | 03 | 1 | 03 |
| D | 27 | 20 | 7 | 18 |
| E | 155 | 155 | 3 | 146 |
| F | 81 | 68 | 13 | 68 |

**Table 2.** Result of Supplier Selection Criteria (Cont'd)

| Criteria / Suppliers | Number of non-conforming items (C5) | Machine velocity (m/sec) (C6) | Load Capacity (kg) (C7) | Repeatability (mm) (C8) | Cost ($) (C9) |
|---|---|---|---|---|---|
| A | 3 | 1.8 | 90 | 0.45 | 9500 |
| B | 1 | 1.4 | 80 | 0.35 | 5500 |
| C | 1 | 0.8 | 70 | 0.20 | 4500 |
| D | 2 | 0.8 | 60 | 0.15 | 4000 |
| E | 9 | 0.9 | 50 | 0.25 | 7000 |
| F | 1 | 1.5 | 50 | 0.30 | 6500 |

The weighted values in Table 3 (Columns 1 through 9) are calculated using entropy.

**Table 3.** Result of Supplier Selection Using Entropy Method

| Criteria | (C1) | (C2) | (C3) | (C4) | (C5) | (C6) | (C7) | (C8) | (C9) |
|---|---|---|---|---|---|---|---|---|---|
| Weighted values | 0.1151 | 0.1458 | 0.0722 | 0.1505 | 0.1349 | 0.0929 | 0.1073 | 0.1126 | 0.0687 |

### 3.1.1. Simple Additive Weighting Method

Simple Additive Weighting (SAW) is a widely used multi-criteria decision-making method that aggregates the performance of different alternatives across various criteria to determine the best option (Ho et al., 2010). Integrating the entropy method into SAW helps objectively determine the weights of the criteria. The weighted values are obtained from the entropy method.

STEP1: Determination of normalized decision matrix - Normalization transforms the decision matrix into a dimensionless scale, making it easier to compare different criteria.

**Table 4.** Result of Normalized Decision Matrix using SAW

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|
| A | 0.1032 | 0.0968 | 0.0769 | 0.0822 | 0.3333 | 1.0000 | 0.5556 | 0.3333 | 0.4211 |
| B | 0.0903 | 0.0903 | 0.0769 | 0.0959 | 0.1111 | 0.7778 | 0.6250 | 0.4286 | 0.7273 |
| C | 0.0258 | 0.0194 | 0.0769 | 0.0205 | 0.1111 | 0.4444 | 0.7143 | 0.7500 | 0.8889 |
| D | 0.1742 | 0.1290 | 0.5385 | 0.1233 | 0.2222 | 0.4444 | 0.8333 | 1.0000 | 1.0000 |
| E | 1.0000 | 1.0000 | 0.2308 | 1.0000 | 1.0000 | 0.5000 | 1.0000 | 0.6000 | 0.5714 |
| F | 0.5226 | 0.4387 | 1.0000 | 0.4658 | 0.1111 | 0.8333 | 1.0000 | 0.5000 | 0.6154 |

STEP 2: Determination of weighted normalized decision matrix

**Table 5.** Result of Weighted Normalized Decision using SAW

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|
| A | 0.0119 | 0.0141 | 0.0056 | 0.0124 | 0.0450 | 0.0929 | 0.0596 | 0.0375 | 0.0289 |
| B | 0.0104 | 0.0132 | 0.0056 | 0.0144 | 0.0150 | 0.0722 | 0.0671 | 0.0483 | 0.0500 |
| C | 0.0030 | 0.0028 | 0.0056 | 0.0031 | 0.0150 | 0.0413 | 0.0767 | 0.0844 | 0.0611 |
| D | 0.0201 | 0.0188 | 0.0389 | 0.0186 | 0.0300 | 0.0413 | 0.0894 | 0.1126 | 0.0687 |
| E | 0.1151 | 0.1458 | 0.0167 | 0.1505 | 0.1349 | 0.0464 | 0.1073 | 0.0676 | 0.0393 |
| F | 0.0602 | 0.0640 | 0.0722 | 0.0701 | 0.0150 | 0.0774 | 0.1073 | 0.0563 | 0.0423 |

STEP 3: Computation of composite score s (…) by sum of all weighted normalized rows. The values of (s) are:

**Table 6.** Value of (s) by sum of all weighted normalized using SAW

| A | B | C | D | E | F |
|---|---|---|---|---|---|
| 0.3078 | 0.2961 | 0.2929 | 0.4383 | 0.8235 | 0.5647 |

STEP 4: Arranging the final value (s) in descending Order: E > F >D >A > B > C in SAW method (see Figure 2)

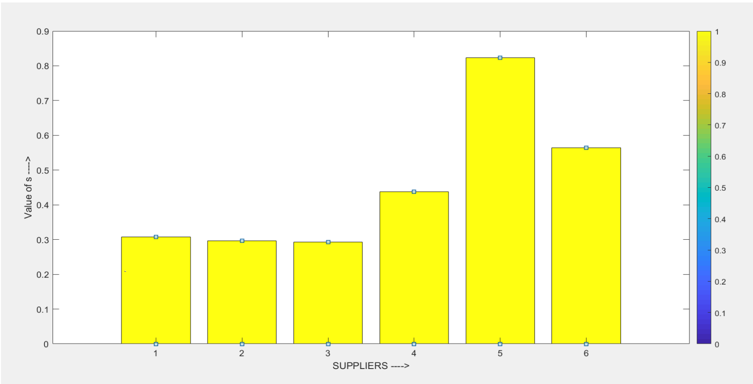


**Figure 2.** Final value (s) in Descending Order using Simple Additive Weighting

In the realm of multi-criteria decision-making, the Simple Additive Weighting (SAW) method is widely employed for its straightforward approach to aggregating various performance criteria into a single score (Madoranova & Horvath, 2013). However, one critical aspect that often requires further examination is the sensitivity of the decision outcomes to changes in the criteria weights. Sensitivity analysis allows decision-makers to understand how weight variations can influence the ranking of alternatives, thus providing insights into the robustness of their decisions. This analysis is particularly valuable in complex decision scenarios where uncertainties and subjective judgments may affect weight assignments. By employing SAW in conjunction with sensitivity analysis, we can create visual representations highlighting alternative rankings' stability, guiding stakeholders in making informed and resilient choices (Taylor et al., 2004). SAW to determine the sensitivity analysis graph. The value of closeness co-efficient in the SAW method (see Figure 2) when alpha=0 and alpha=1. The result is seen in Table 7 below:

**Table 7.** Result of closeness co-efficient in SAW method using alpha=0 and alpha=1

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| Alpha=0 | 0.1261 | 0.1653 | 0.2222 | 0.2707 | 0.2141 | 0.2059 |
| Alpha=1 | 0.1817 | 0.1308 | 0.0707 | 0.1676 | 0.6094 | 0.3588 |

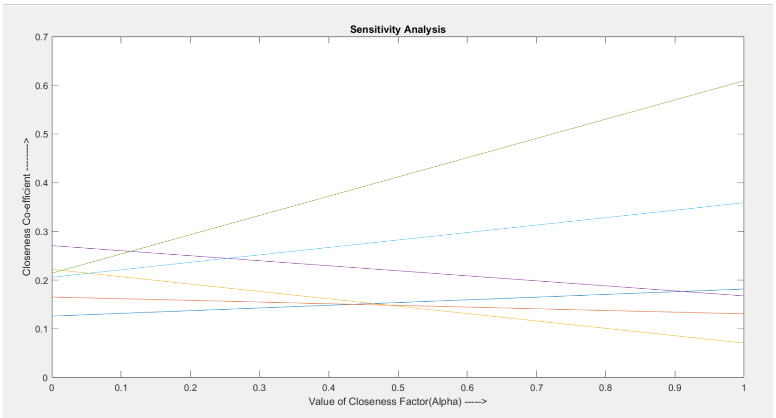


**Figure 3.** Closeness Co-efficient in SAW method

### 3.1.2. Multi Objective Optimization Ratio Analysis (MOORA)

Multi-Objective Optimization Ratio Analysis (MOORA) is a robust decision-making method designed to evaluate and select alternatives based on multiple, often conflicting criteria. The essence of MOORA lies in its ability to simplify complex comparisons through a ratio-based approach, allowing decision-makers to assess how well each alternative performs relative to the others. The process begins with constructing a decision matrix that captures the performance of various alternatives across different criteria. This matrix is then normalized to ensure that all measurements are comparable, regardless of their units. Following normalization, MOORA calculates performance ratios for each alternative, representing their effectiveness in achieving the specified objectives. These ratios facilitate the aggregation of scores, enabling a clear ranking of other options. This methodology is particularly valuable in scenarios where trade-offs must be made, such as balancing cost against quality in manufacturing or evaluating sustainability alongside profitability in energy management. MOORA's versatility allows it to be applied across diverse fields, including engineering, healthcare, and logistics, making it an essential tool for informed decision-making in complex environments. By using MOORA, organizations can achieve a more nuanced understanding of their options, ultimately leading to better strategic outcomes. In the MOORA method

STEP 1: Determination of normalized decision matrix

Determining a weighted normalized decision matrix using the Multi-Objective Optimization Ratio Analysis (MOORA) method is critical in the multi-criteria decision-making process. This matrix is constructed to provide a clear and systematic representation of the performance of various alternatives across multiple criteria. Initially, a raw decision matrix is established, where each element corresponds to the performance of an alternative under specific criteria. The first step involves normalizing these values to eliminate any discrepancies arising from differing units of measurement. This normalization ensures that each criterion contributes equally to the analysis. Once the values are normalized, the next step is to assign weights to each criterion based on their relative importance, which reflects the decision-maker's priorities. The author creates a weighted normalized decision matrix by multiplying the normalized values by their corresponding weights. This matrix effectively highlights the significance of each alternative about the prioritized criteria. Ultimately, this structured approach allows for a more nuanced comparison of alternatives, facilitating informed decision-making by clearly indicating which options align best with the desired objectives in a multi-faceted decision environment.

**Table 8.** Result of Normalized Decision Matrix using MOORA

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|
| A | 0.0897 | 0.0874 | 0.0659 | 0.0736 | 0.3046 | 0.5828 | 0.5379 | 0.6124 | 0.6033 |
| B | 0.0785 | 0.0815 | 0.0659 | 0.0858 | 0.1015 | 0.4533 | 0.4781 | 0.4763 | 0.3493 |
| C | 0.0224 | 0.0175 | 0.0659 | 0.0184 | 0.1015 | 0.2590 | 0.4183 | 0.2722 | 0.2858 |
| D | 0.1514 | 0.1165 | 0.4616 | 0.1103 | 0.2031 | 0.2590 | 0.3586 | 0.2041 | 0.2540 |
| E | 0.8694 | 0.9028 | 0.1978 | 0.8950 | 0.9138 | 0.2914 | 0.2988 | 0.3402 | 0.4445 |
| F | 0.4543 | 0.3961 | 0.8572 | 0.4168 | 0.1015 | 0.4856 | 0.2988 | 0.4082 | 0.4128 |

STEP 2: Determination of weighted normalized decision matrix

Determining a weighted normalized decision matrix is a fundamental process in multi-criteria decision-making that helps evaluate alternatives based on various criteria with differing units and scales. This matrix begins with constructing a raw decision matrix, where each entry represents the performance of an alternative against specific criteria. The first step is normalization, which adjusts these raw values to a standard scale, ensuring that each criterion can be compared fairly. Various normalization techniques can be employed, such as linear normalization, which rescales values between 0 and 1, or vector normalization, which adjusts values based on their overall distribution. After normalization, the next critical step is to assign weights to each criterion, reflecting their relative importance to the decision-making context. These weights can be derived from expert judgment, stakeholder input, or statistical methods. Once the weights are assigned, they are applied to the normalized values through multiplication, resulting in a weighted normalized decision matrix. This matrix enhances the comparability of the alternatives and emphasizes the criteria that matter most to the decision-maker, ultimately facilitating a more informed and balanced selection process. By providing a structured framework for analysis, the weighted normalized decision matrix plays a crucial role in identifying the most suitable alternatives in complex decision scenarios.

**Table 9.** Result of Weighted Normalized Decision Matrix using MOORA

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|
| A | 0.0103 | 0.0127 | 0.0048 | 0.0111 | 0.0411 | 0.0541 | 0.0577 | 0.0689 | 0.0414 |
| B | 0.0090 | 0.0119 | 0.0048 | 0.0129 | 0.0137 | 0.0421 | 0.0513 | 0.0536 | 0.0240 |
| C | 0.0026 | 0.0025 | 0.0048 | 0.0028 | 0.0137 | 0.0241 | 0.0449 | 0.0306 | 0.0196 |
| D | 0.0174 | 0.0170 | 0.0333 | 0.0166 | 0.0274 | 0.0241 | 0.0385 | 0.0230 | 0.0174 |
| E | 0.1001 | 0.1316 | 0.0143 | 0.1347 | 0.1232 | 0.0271 | 0.0321 | 0.0383 | 0.0305 |
| F | 0.0523 | 0.0577 | 0.0619 | 0.0627 | 0.0137 | 0.0451 | 0.0321 | 0.0460 | 0.0284 |

STEP 3: Determination of weighted multi-objective optimization

Determining weighted multi-objective optimization involves calculating the sum of all weighted normalized values for beneficial criteria, which is a crucial step in effectively evaluating alternatives. In this process, each criterion is assigned a weight that reflects its relative importance to the decision-making context. Normalization transforms the raw data into a standard scale, allowing fair comparisons across different criteria with varying units. Once the values are normalized, they are multiplied by their respective weights to account for their significance. The sum of these weighted normalized values provides a comprehensive score for each alternative, highlighting its overall performance relative to the beneficial criteria. This aggregated score serves as a key indicator for decision-makers, facilitating the identification of the most favorable options. Emphasizing beneficial criteria—such as cost efficiency, quality, and sustainability—ensures that the selected alternatives align with the organization's or project's overarching goals. Thus, determining the sum of all weighted normalized values is fundamental to achieving an informed and balanced decision in multi-objective optimization scenarios—the value of (a) the sum of all weighted normalized values for all beneficial columns.

**Table 10.** Result of the value of (a) from the sum of all weighted normalized values using MOORA

| A | B | C | D | E | F |
|---|---|---|---|---|---|
| 0.1341 | 0.0944 | 0.0504 | 0.1358 | 0.5310 | 0.2935 |

The value of (b) is the sum of all weighted normalized values for all non-beneficial columns, as seen in Table 11 below:

**Table 11.** Result of value of (b) sum of all weighted normalized values for all non-beneficial using MOORA

| A | B | C | D | E | F |
|---|---|---|---|---|---|
| 0.1681 | 0.1289 | 0.0952 | 0.0789 | 0.1009 | 0.1064 |

STEP 4: Calculating the value of a-b

**Table 12.** Results the value of (a-b)

| A | B | C | D | E | F |
|---|---|---|---|---|---|
| -0.0340 | -0.0345 | -0.0448 | 0.0569 | 0.4301 | 0.1871 |

STEP 5: Arranging the final value (a-b) in descending Order: E > F > D > A > B >C

In the context of multi-criteria decision-making, arranging the final values derived from the evaluation process is a crucial step for effective decision analysis. The final values, often calculated as the difference between aggregated scores for beneficial and non-beneficial criteria (denoted as \(a - b\)), clearly indicate each alternative's overall performance. By arranging these values in descending order, decision-makers can easily identify which alternatives are the most favourable choices. This systematic ranking not only simplifies the comparison of options but also aids in visualizing the trade-offs involved, ultimately leading to more informed and strategic decisions. In this way, the descending order arrangement serves as a pivotal tool in synthesizing complex information into actionable insights.

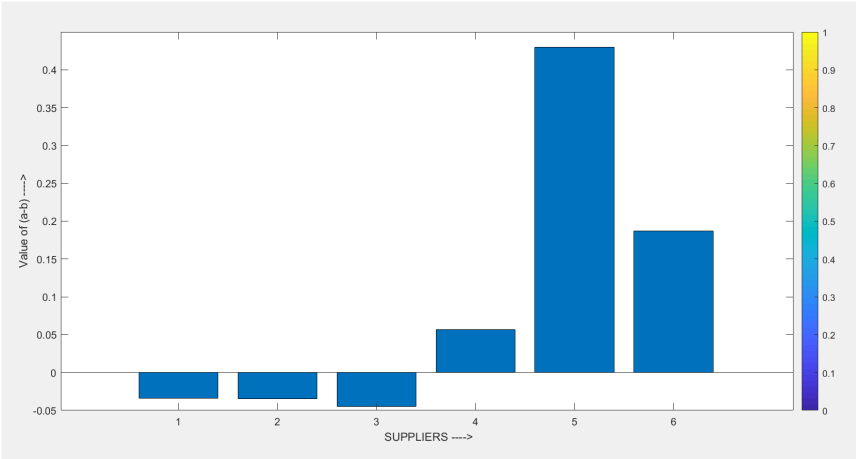


**Figure 4.** Final value (a-b) in Descending Order: E > F > D > A > B > C

Using the Multi-Objective Optimization Ratio Analysis (MOORA) method to determine the sensitivity analysis graph involves assessing how changes in the criteria weights influence the ranking of alternatives. Sensitivity analysis is essential in multi-criteria decision-making, as it allows decision-makers to understand the robustness of their choices considering potential fluctuations in criteria importance. In the context of MOORA, the initial step entails calculating the weighted normalized scores for each alternative based on a set of predefined weights. Analysts can observe the resulting changes in the alternatives' overall scores by systematically varying these weights—either by increasing or decreasing them. The outcomes are then plotted on a sensitivity analysis graph, which visually represents the relationship between the criterion weights and the rankings of the alternatives. This graphical representation helps to highlight which criteria are most influential in determining the preferred options and reveals the degree of stability or volatility in the decision outcomes. Ultimately, employing MOORA for sensitivity analysis enhances the decision-making process by providing insights into how sensitive the rankings are to changes in criteria weights, thereby guiding stakeholders in making more resilient and informed decisions. The value of closeness co-efficient in the MOORA method [Fig: 4] when alpha=0 and alpha=1

**Table 13.** Results of the value of closeness co-efficient in MOORA when alpha=0 and alpha=1

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| Alpha=0 | -0.1681 | -0.1289 | -0.0952 | -0.0789 | -0.1009 | -0.1064 |
| Alpha=1 | 0.1341 | 0.0944 | 0.0504 | 0.1358 | 0.5310 | 0.2935 |

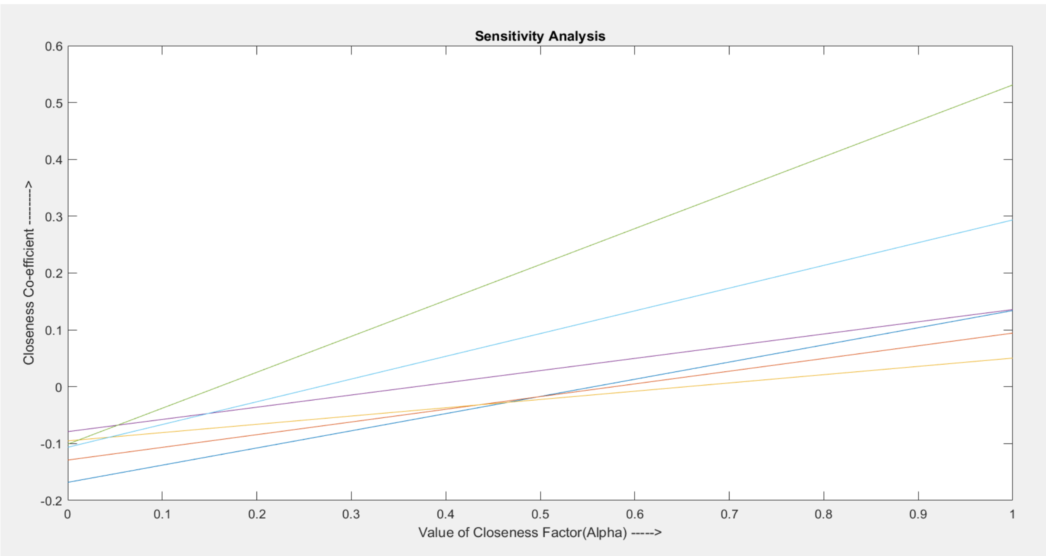


**Figure 5.** Closeness Co-Efficient in MOORA when alpha=0 and alpha=1

### 3.1.3. Technique for Order Preference by Similarity to Ideal Solution

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a popular and effective method used in multi-criteria decision-making (MCDM) to identify the best alternative from a set of options by measuring their similarity to an ideal solution. The core principle of TOPSIS is based on the idea that the best alternative is the one that has the shortest distance to the ideal solution and the farthest distance from the negative ideal solution. The ideal solution represents the best possible performance across all criteria, while the negative ideal solution corresponds to the worst possible performance. To apply TOPSIS, the decision matrix is first normalized to eliminate the effect of different units of measurement. Next, a weighted normalized decision matrix is computed, where each criterion is assigned a weight based on importance. The weighted normalized values are then used to determine each alternative's distance from the ideal and negative ideal solutions. These distances are typically calculated using Euclidean distance formulas. The optimal choice is the alternative with the highest relative closeness to the ideal solution (i.e., the smallest distance to the ideal and largest distance from the negative ideal). TOPSIS is particularly valuable when decision-makers deal with conflicting criteria and need a clear and rational way to rank alternatives. Its simplicity, logical consistency, and intuitive appeal make it a widely adopted method in fields like engineering, business, healthcare, and environmental management. By focusing on the proximity to an ideal solution, TOPSIS provides decision-makers with a clear, actionable way to evaluate alternatives and make informed choices. The weighted values obtained from the entropy method

STEP1: Determination of normalized decision matrix

**Table 14.** normalized decision matrix (TOPSIS)

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|
| A | 0.1032 | 0.0968 | 0.0769 | 0.0822 | 0.3333 | 1.0000 | 0.5556 | 0.3333 | 0.4211 |
| B | 0.0903 | 0.0903 | 0.0769 | 0.0959 | 0.1111 | 0.7778 | 0.6250 | 0.4286 | 0.7273 |
| C | 0.0258 | 0.0194 | 0.0769 | 0.0205 | 0.1111 | 0.4444 | 0.7143 | 0.7500 | 0.8889 |
| D | 0.1742 | 0.1290 | 0.5385 | 0.1233 | 0.2222 | 0.4444 | 0.8333 | 1.0000 | 1.0000 |
| E | 1.0000 | 1.0000 | 0.2308 | 1.0000 | 1.0000 | 0.5000 | 1.0000 | 0.6000 | 0.5714 |
| F | 0.5226 | 0.4387 | 1.0000 | 0.4658 | 0.1111 | 0.8333 | 1.0000 | 0.5000 | 0.6154 |

STEP 2: Determination of positive ideal solution: taking the maximum values of each column from the normalized decision matrix

**Table 15.** Result of positive ideal solution (TOPSIS) with a normalized decision matrix

| C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

Determination of negative ideal solution: taking the minimum values of each column from the normalized decision matrix

**Table 16.** Result of negative ideal solution (TOPSIS) with a normalized decision matrix

| C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|
| 0.0258 | 0.0194 | 0.0769 | 0.0205 | 0.1111 | 0.4444 | 0.5556 | 0.3333 | 0.4211 |

STEP 3: Calculation of the separation measure from the positive ideal solution (di_Plus)

**Table 17.** Result of positive ideal solution (di_Plus) - TOPSIS

| A | B | C | D | E | F |
|---|---|---|---|---|---|
| 0.7444 | 0.7541 | 0.7793 | 0.6583 | 0.3108 | 0.5124 |

Calculation of the separation measure from the negative ideal solution (di_Minus)

**Table 18.** Result of positive ideal solution (di_Plus) - TOPSIS

| **A** | **B** | **C** | **D** | **E** | **F** |
|---|---|---|---|---|---|
| 0.1935 | 0.1427 | 0.1931 | 0.3229 | 0.7302 | 0.4317 |

STEP 3: Calculation of R_i

**Table 19.** Result of R_i

| **A** | **B** | **C** | **D** | **E** | **F** |
|---|---|---|---|---|---|
| 0.2063 | 0.1591 | 0.1986 | 0.3291 | 0.7014 | 0.4573 |

STEP 4: Arranging the final value in descending order: E > F > D > A > C > B

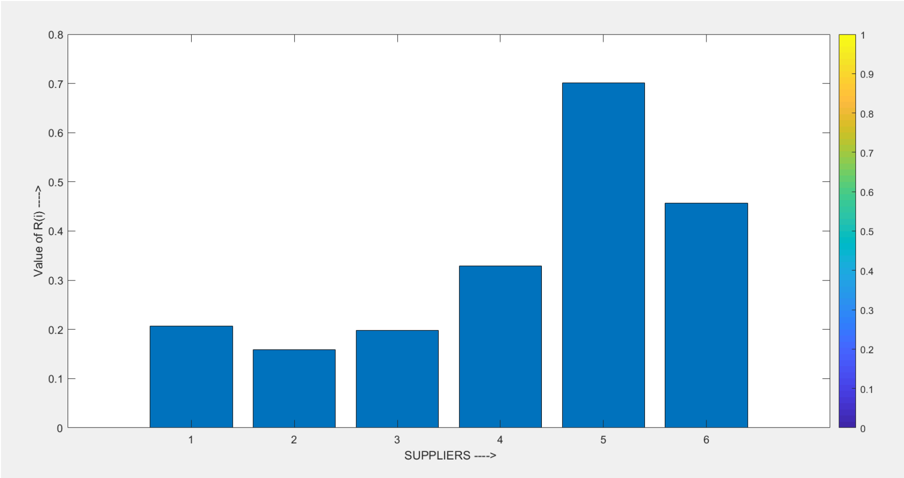


**Figure 6.** Result of final value in descending order: E > F > D > A > C > B

### 3.1.4. Comparative Analysis of Supplier Selection Ranking

A comparative analysis of supplier selection ranking among SAW (Simple Additive Weighting), MOORA (Multi-Objective Optimization Ratio Analysis), and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) involves evaluating the strengths, weaknesses, and applicability of each method in the context of selecting the best supplier from a set of alternatives based on multiple, often conflicting criteria. All three techniques are widely used in multi-criteria decision-making (MCDM) for supplier evaluation but differ in their approach to ranking alternatives. In summary, the comparative analysis of SAW, MOORA, and TOPSIS reveals that while SAW is simple and effective for less complex problems, MOORA and TOPSIS offer more sophisticated ways to handle trade-offs and varying levels of importance between criteria. TOPSIS is preferred when a clear ideal solution can be defined, while MOORA is advantageous for scenarios where relative performance is more critical. The choice of method depends on the specific needs of the supplier selection process, such as the complexity of criteria, the availability of data, and the desired level of analytical rigor.

**Table 20.** Result of Comparative analysis of supplier selection ranking

| | SAW | MOORA | TOPSIS |
|---|---|---|---|
| A | 4 | 4 | 4 |
| B | 5 | 5 | 6 |
| C | 6 | 6 | 5 |
| D | 3 | 3 | 3 |
| E | 1 | 1 | 1 |
| F | 2 | 2 | 2 |

## 3.2. Supplier Inspection

Basically, in an industry looking over an inspection problem during supply lead time, as the result of manual inspection, various types of errors occur and the inspection report becomes incorrect due to human error. The cross-check policy should be implemented and executed to make the inspection accurate. Total number of inspected items of delivery = J. (i) Each item inspection cost = $C_S$. (ii) Each item damage cost = $C_d$

### 3.2.1. Inspection and Data Analysis

- In the First Inspection Report, the number of defective items is detected = X
- The second inspection is implemented to minimize the risk. In this Inspection Report, it was found that Y of these reported defects were good pieces. A total of Z defective plates in a tank were undetected during the inspection. So, the total "FALSE ALARME" = Y
  The total "MISSES" = Z

### 3.2.2. Constructing computing logic on the inspection data by Microsoft Excel as following

Microsoft Excel has the basic features of all spreadsheets, using a grid of cells arranged in numbered rows and letter-named columns to organize data manipulations like arithmetic operations. It has several supply functions for statistical, engineering, and financial needs. Developed a check sheet by Microsoft Excel [Figure: 11]:

- Actual Acceptance (A) = Good (G) in the 1st inspection + False Alarm (F) during cross-check – Miss (M) during cross-check.
- Actual Reject (R) = Bad (B) in the 1st inspection + Miss (M) during cross-check – False Alarm (F) during cross-check
- Probability of conforming item (P1) = [Total Item (Q) in batch – {Bad (B) in the 1st inspection + Miss (M) during cross check}] / Actual Acceptance (A)
- Probability of non-conforming item (P2) = [Total Item (Q) in batch – {Good (G) in the 1st inspection + False Alarm (F) during cross check}] / Actual Reject (R)
- Accuracy = {Probability of conforming item (P1) + Probability of Non-conforming item (P2)} / 2
- Defect Rate (q) = (1 - overall inspection accuracy)
- Batch cost for 100% inspection (Cb) = Q.CS (Q= total parts in a batch) &
- Cs = inspection cost
- Batch cost for NO inspection (Cn) = Q.q. Cd (Cd = inspection damage cost)
- The critical defect value (QC) = CS / Cd [critical value represents the break-even point between inspection or no inspection]

### 3.2.3. Empirical Testing

- The proportion of good parts reported as conforming is =$P_1$
- The proportion of defective parts reported as non-conforming is = $P_2$
- The overall inspection accuracy = A
- Defect Rate = q
- In quality assurance approaches, if we consider the overall inspection accuracy average, then the inspection status is shown as a graph in Poisson distribution by MINITAB. (i) Batch cost for 100% inspection = $C_u$, (ii) Batch cost for NO inspection = $C_n$ and (iii) The critical defect value = $Q_C$

On the basis of history with the inspected items, the batch fraction defect rate q is less than this critical level, so no inspection is indicated. On the other hand, if the fraction defect rate is expected to be greater than $Q_C$, then further inspection is necessary.

| | |
|---|---|
| If, $Q_C < q$ | Inspection is indicated |
| If, $Q_C > q$ | NO inspection is indicated |

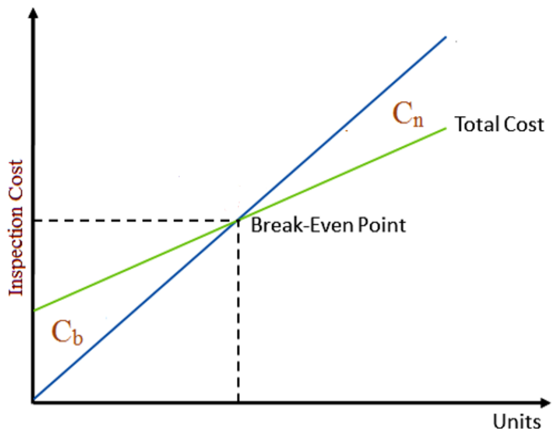


**Figure 7.** Result of Break-Even Analysis

### 3.2.4. Advantages of Methodology

- Determine the inspection accuracy easily in excel sheet.
- Assessment of the inspector's responsibility on the job
- Analysis the risk-based inspection report
- Inspections are less time consuming
- Determine the decision about future inspection under cost-based inspection.
- Minimize the human error

## 4. Conclusions

This study indicates that ranking a proper vendor for a supplier application involves many considerations. SAW, TOPSIS, and MOORA methods are quite capable and computationally easy to evaluate and select the proper supplier from a given set of alternatives. These methods use the measures of the considered criteria with their relative importance to arrive at the final ranking of the alternative. This paper shows that the result is almost the same for the three MCDM methods. A sample inspection model is deployed. Decisions such as length of contracts, vendor of vendors employed, and vendor location should be analyzed considering their strategic implications. Given the inherent multi-objective nature of vendor selection decisions and the financial importance of such decisions in highly competitive environments, multi-objective programming techniques could prove extremely useful in such strategic planning.

**Author Contributions:** Conceptualization, P.J.; methodology, P.J.; software, P.J.; validation, P.J.; formal analysis, P.J.; investigation, P.J.; resources, P.J.; data curation, P.J.; writing—original draft preparation, P.J.; writing—review and editing, P.J.; visualization, P.J.; project administration, P.J.; funding acquisition, P.J. Author has read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** The author would like to thank Haldia Institute of Technology and NDT Engineer of Inspection Survey & Surveillance Privet Limited, India, for supporting this research and publication. The author would also like to thank the reviewers for all their constructive comments.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

Drury, CG. (1992). Inspection performance. *Handbook of Industrial Engineering*. New York: John Wiley & Sons,Inc.,

Groover, M. P. (2016). *Automation, production systems, and computer-integrated manufacturing*. Pearson Education India.

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision-making approaches for supplier evaluation and selection: A literature review. *European Journal of operational research*, *202*(1), 16-24. http://dx.doi.org/10.1016/j.ejor.2009.05.009.

Jana, P. (2020). Supplier selection under strategic decision environment. *Independent Journal of Management & Production*, *11*(1), 065-080.

Jana, P., & Dan, P. K. (2017). Optimization Treatment of Material Selection in Machine Design-Considering Technical, Economic and Supply Aspect. *ISJ Theoretical & Applied Science*, *3*(47), 128-138.

Juran, J. M., & Godfrey, A. B. (1999). *The quality control process*. McGraw-Hill.

Juran, J. M., Gryna, F. M., & Bingham, R. S. (1979). *Quality Control Handbook* (3rd Ed). New York: McGraw-Hill.

Latorella, K. A., & Prabhu, P. V. (2017). A review of human error in aviation maintenance and inspection. *Human Error in Aviation*, 521-549.

Madoranova, M., & Horvath, M. (2013). Multi-Criteria Decision Matrix Approach for Suppliers Evaluation in Micro and Small Organisations. *Quality Innovation Prosperity*, *17*(1), 120-126. https://doi.org/10.12776/qip.v17i1.185.

Mahajan, M. (1986). *Statistical quality control*. Edition-1998, Dhanpat Rai & Sons, India.

Tannock, J. D. T., Wort, R. G., & Savage, B. M. (1990). Automating quality systems. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *204*(4), 231-236.

Taylor, W., Melloy, B., Dharwada, P., Gramopadhye, A., & Toler, J. (2004). The effects of static multiple sources of noise on the visual search component of human inspection. *International journal of industrial ergonomics*, *34*(3), 195-207.

Telsang, M. T. (1998). Industrial Engineering *and Production Management*. S. Chand Publishing.