American Journal of Industrial Engineering, 2016, Vol. 4, No. 1, 7-13
Available online at http://pubs.sciepub.com/ajie/4/1/2

DOI:10.12691/ajie-4-1-2

Machine Selection by AHP and TOPSIS Methods

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Abstract Selection of the most suitable machine is very crucial in the modern economy to prompt production level as well as revenue generation. In order to endure in the global business scenario, companies must find out the proper way that leads to the successful production environment. Machine selection has become challenging as the number of alternatives and conflicting criteria increase. A decision support system has been developed in this research in machine evaluation process. This framework will act as a guide for decision makers to select the suitable machine via an integrated approach of AHP & TOPSIS. The anticipated methods in this research consist of two steps at its core. In the first step, the criteria of the existing problem are inspected and identified and then the weights of the sector and sub-sector are determined that have come to light by using AHP. In the second step, eligible alternatives are ranked by using TOPSIS. A demonstration of the application of these methodologies in a real life problem is presented.

Keywords: *multi criteria decision making, machine selection, decision support system, AHP, TOPSIS*

Cite This Article: Rubayet Karim, and C. L Karmaker, “Machine Selection by AHP and TOPSIS Methods.” *American Journal of Industrial Engineering*, vol. 4, no. 1 (2016): 7-13. doi: 10.12691/ajie-4-1-2.

1. Introduction

Recently, to acquire the competitive advantages in order to survive in the global business scenario, the selection of the most appropriate machine has become a remarkable concern for many manufacturing companies. It is very crucial in industries where machines are intensively used to prompt production level as well as revenue generation. To survive in the modern economy, companies must be careful in making decisions. Improper decisions, increase companies’ costs in terms of resource wastage as well as affect customer satisfaction. Modern manufacturing companies are now facing some problems like the selection of machines because of time consumption & lack of advanced knowledge as well as experience. The difficulty of the machine evaluation and selection problem has driven the researchers to develop models for helping decision-makers.

The aim of machine selection decision by a manufacturing company often persuades the owner, investors, partners, employees, and other stakeholders to maintain a certain point of view about it, its productivity, efficiency, revenue generation or of its total costing**.**

The strategic decision, backed by the company, is to be implemented effectively to increase productivity & safety. As it requires a large investment and since it is irrecoverable in most of the instances, the choice of a machine selection among eligible alternatives is a very powerful decision. Some researchers have pointed out the dramatic results in quality, flexibility, productivity, etc. for taking poor decisions of machine selection [1]. As decisions regarding machines are a crucial element in a company’s quality success or failure, companies must analyze in order to keep the production line smoothly as well as provide high -quality parts that best matches the needs of its target customer. The manufacturers need to pay attention to deal with this challenge of selecting the most suitable machine in order to ensure full workability as well as the complete safety of their unit.

To select the desired machine, a company must undertake some pragmatic steps that comply with its mission and strategy. The general steps for making machine selection decisions usually consist of the following steps: Decide on the criteria that will be used to evaluate machine; select the criteria that are important; developing alternatives and select the alternatives evaluated [12].

In order to select the most suitable machine among various alternatives, the decision maker must consider meaningful criteria & possess special knowledge of the machine properties. But those criteria should be considered that maximize the benefit of the manufacturing company. Gerrard [7] conducted a survey to determine the percentage contribution of various levels of management. The result indicated that the role of engineering staff in the selection process was only 6 percent; the remaining (94 percent) belongs to top & middle management. It also gave a signal of the abridged approach for the machine evaluation process. In this study, the evaluation criteria for the selection decision were selected from the studies in the literature and the discussions with the company’s managers in different areas.

A number of alternatives and conflicting criteria are increasing very rapidly. So, robust evaluation models are crucial in order to incorporate several conflicting criteria meritoriously. With its need to trade-off multiple criteria, the selection problem like machine selection is a multi-criteria decision-making (MCDM) problem. To evaluate the machine selection process, different methods have been widely applied in the literature: analytic hierarchy process (AHP), fuzzy multiple attribute decision- making model, linear 0-1 integer programming, weighted average method, genetic algorithms etc. are some of these methods. In this research, a prototype framework using AHP & TOPSIS methods has been employed to evaluate the selection of the suitable machine to prompt the production level.

The machine selection problem has been studied mostly for specific type of environment, such as flexible manufacturing systems [1]. Somashekhar [10] presented a structure that included a tailor-made package in order to design & evaluate flexible manufacturing systems for small prismatic components. Dong-Shang Chang [6] used stochastic linear programming model for the evaluation of the opportunity cost of flexible manufacturing systems (FMS). In addition, Tabucanon et al. [13] proposed a decision support system to select the appropriate machine of flexible manufacturing systems (FMS). Arslan [1] developed a decision support system that included qualitative and quantitative criteria to assist the decision maker in solving, selection problem using multi-criteria weighted average method. The objective of the study was to select the most suitable machine from available machines aiming the reduction of difficulties arising from the selection process. Besides the assessable aspects of the machine selection decision, soft criteria having subjective factors that are difficult to enumerate, are needed to be measured.

In real world applications, assessment of eligible alternatives for subjective criteria is expressed in linguistic terms. For this, several researchers have incorporated fuzzy set theory to efficiently resolve the ambiguity obtained from the available information [9]. The fuzzy set theory seems as an operative tool in dealing with the imprecise or uncertainty intrinsic in the location selection process. In the literature, there are a number of studies that apply different fuzzy based decision making techniques in order to classify locations.

A number of studies have focused on the use of fuzzy multi-criteria decision making (MCDM) techniques for machine selection process. Wang et al. [15] offered a structured framework based on the fuzzy multiple attribute decision making approach for machine selection in a flexible manufacturing cell. The objective of the model was to help decision maker in dealing difficulty arising from machine selection problem.

In this paper, an integrated approach of AHP & TOPSIS methods has been utilized. The aim of this study is to propose a model to evaluate the best machine by using the comparison of three existing machines. During the assessment procedure, AHP method has been applied to determine the weights of the criteria and to rank the machines, TOPSIS method has been used.

The rest of this study is arranged as follows: Section 2 frameworks the methodology and provides a stepwise depiction of the anticipated multi-criteria decision making approach. In Section 3, the application of the proposed framework for the selection of machine has been given. And finally, in section four, the result of the application has been presented and insights for the future studies are clarified. This section wraps up this study.

2. MCDM Methods

Multiple-criteria decision analysis (MCDA) or Multiple-criteria decision making (MCDM) is a sub-discipline and full-grown branch of operations research that is concerned with designing mathematical and computational tools to support the subjective evaluation of a finite number of decision alternatives under a finite number of performance criteria by a single decision maker or by a group [10]. MCDM refers to screening, prioritizing, ranking, or selecting a set of alternatives under usually independent, incommensurate or conflicting attributes [8]. Determining the attributes is very crucial to MCDM as they play a very substantial role in the decision making process. Several methods have been proposed for solving related problems, but a major problem of MCDM is that different techniques may yield different results for the same problem.

Therefore, how making a trade-off between these conflicting attributes and then make a decision could pose a difficult problem [5]. The evaluation procedure in this paper consists of three main steps as summarized in Figure 1.

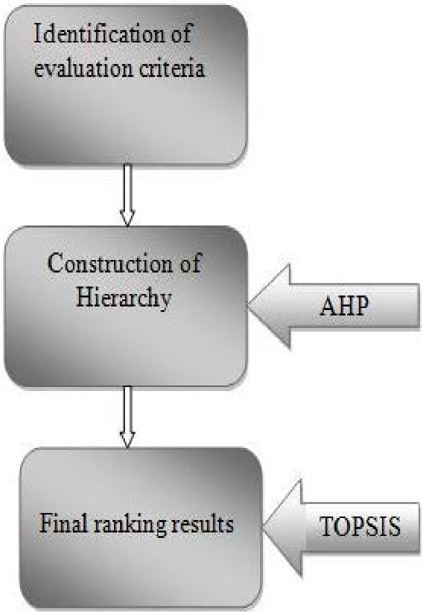

Figure 1. Steps of evaluation procedure

Step 1: Identify the evaluation criteria considered as the most important performance measures for the machine selection problem.
Step 2: Construct the hierarchy of the evaluation criteria and calculate the weights of these criteria using the AHP method.
Step 3: Conduct the TOPSIS method to achieve the final ranking results.

The detailed descriptions of each step are illustrated in the following sections.

2.1. Determining the Criteria Weights by AHP

The analytic hierarchy process (AHP) is a multiple criteria decision making tool for organizing and analyzing complex decisions and firstly developed by Thomas L. Saaty [11]. This method is used to solve a complex decision making problem having several attributes by modeling unstructured problem under study into hierarchical forms of elements. The essential components of a hierarchical system are the main goal, criteria that affect the overall goal, sub-criteria that influence the main-criteria and finally the alternatives available to the problem. To obtain the degree of relative importance of elements at each level, a pairwise comparison matrix is developed using Saaty 1-9 preference scale as shown in Table 1. Then the eigenvector and the maximum eigenvalue (λ_{max}) are derived from pairwise comparison matrices. The significance of the eigenvalue is to assess the strength of the consistency ratio CR (Saaty, 2000) of the comparative matrix in order to validate whether the pairwise comparison matrix provides a completely consistent evaluation. The final step is to derive the consistency index and consistency ratio.

Table 1. Saaty's pairwise comparison scale

Scale	Compare factor of I & j
1	Equally Important
3	Weakly Important
5	Strongly Important
7	Very strongly Important
9	Extremely Important
2,4,6,8	Intermediate value between adjacent scales

The stepwise procedure of AHP is presented as follows:

Step 1: Construct the structural hierarchy.

Step 2: Construct the pairwise comparison matrix.

Assuming n attributes, the pairwise comparison of attribute i with attribute j yields a square matrix $A_{n\times n}$ where a_{ij} denotes the comparative importance of attribute i with respect to attribute j. In the matrix, a_{ij} = 1 when i = j and $a_{ji} = 1/a_{ij}$.

$$A_{n\times n} = \begin{array}{c} Attribute \\ 1 \\ 2 \\ 3 \\ .... \\ .... \\ n \end{array} \begin{bmatrix} a_{11} & a_{12} & a_{13} & .... & .... & a_{1n} \\ a_{21} & a_{22} & a_{23} & .... & .... & a_{2n} \\ a_{31} & a_{32} & a_{33} & .... & .... & a_{3n} \\ .... & .... & .... & .... & .... & .... \\ .... & .... & .... & .... & .... & .... \\ a_{n1} & a_{n2} & r_{n3} & .... & .... & a_{nn} \end{bmatrix}$$

Step 3: Construct normalized decision matrix

$$c_{ij} = a_{ij} \Big/ \sum_{J=1}^{n} a_{ij} \quad (1)$$

$$i = 1,2,3,......., n,\ j = 1,2,3,......., n$$

Step 4: Construct the weighted, normalized decision matrix

$$w_i = \sum_{J=1}^{n} c_{ij} / n, i = 1,2,3,......., n \quad (2)$$

$$W = \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ w_n \end{bmatrix} \quad (3)$$

Step 5: Calculate Eigenvector & Row matrix

$$E = N^{th} rootvalue / \sum N^{th} rootvalue \quad (4)$$

$$Rowmatrix = \sum_{j=1}^{n} a_{ij} * e_{j1} \quad (5)$$

Step 6: Calculate the maximum Eigenvalue, $\lambda_{\max}$.

$$\lambda_{\max} = Rowmatrix / E \quad (6)$$

Step 7: Calculate the consistency index & consistency ratio.

$$CI = (\lambda_{\max} - n) / (n-1) \quad (7)$$

$$CR = CI / RI \quad (8)$$

Where n & RI denote the order of matrix & Randomly Generated Consistency Index respectively.

2.2. Ranking Alternatives by TOPSIS

For the assessment of machine selection, one of the MCDM methods named TOPSIS has been applied in this research. In this section, TOPSIS method is explained.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), developed by Hwang and Yoon [19], is one of the MCDA/MCDM methods for resolving real-world decision problems satisfactorily. TOPSIS attempts to indicate the best alternative that simultaneously has the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution [2]. The positive ideal solution is a solution that tries to maximize the profit criteria and minimize the cost criteria, whereas the negative ideal solution is just opposite to previous one [4,14,16,17]. According to Wang 2007, the positive ideal solution is composed of all the good values attainable of criteria, whereas the negative ideal solution consists of all worst values attainable of criteria. In the TOPSIS method, precise scores that each alternative receives from all the criteria are used in the formation of a decision matrix and normalized decision matrix. By taking into consideration the rates of all attributes, positive and negative ideal solutions are found. By comparing the distance coefficient of each alternative, the preference order of the alternatives is determined.

The stepwise procedure of Hwang and Yoon [8] for implementing TOPSIS is presented as follows:

Step 1: Construct normalized decision matrix of beneficial and non-beneficial criteria.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{J} x_{ij}^2}}, j = 1,2,3,..........., J; i = 1,2,3,.........., n \quad (9)$$

Where x_{ij} and r_{ij} are original and the normalized score of decision matrix respectively.

Step 2: Construct the weighted normalized decision matrix by multiplying the weights w_i of evaluation criteria with the normalized decision matrix r_{ij}.

$$v_{ij} = w_i * r_{ij}, j = 1,2,3,......., J, i = 1,2,3,......., n \quad (10)$$

Step 3: Determined the positive ideal solution (PIS) and negative ideal solution (NIS)

$$A^* = \{v_1^*, v_2^*, ..., v_n^*\} \max imum\ values \quad (11)$$

Where $v_i^* = \{\max(v_{ij}) \text{ if } j \in J; \min(v_{ij}) \text{ if } j \in J^-\}$

$$A^- = \left\{v_1^-, v_2^-, \ldots\ldots\ldots, v_n^-\right\} \textit{ minimum values} \tag{12}$$

Where $v^- = \{\min(v_{ij}) \textit{ if } j \in J; \max(v_{ij}) \textit{ if } j \in J^-\}$.

Step 4: Calculate the separation measures of each alternative from PIS and NIS

$$d_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2}, \ j = 1, 2, \ldots\ldots., J \tag{13}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}, \ i = 1, 2, \ldots\ldots., J \tag{14}$$

Step 5: Calculate the relative closeness coefficient to the ideal solution of each alternative

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}, \ i = 1, 2, \ldots\ldots., J. \tag{15}$$

Step 6: Based on the decreasing values of closeness coefficient, alternatives are ranked from most valuable to worst. The alternative having highest closeness coefficient (CC_i) is selected.

3. Proposed Framework with Example

A comparison of three existing machines of the renowned company in Bangladesh serves to validate the model by testing the propositions that were developed. To preserve confidentiality, the name of the company has been keeping undisclosed and the three machines are referenced as A_1, A_2 *and* A_3. The Company desires to decide which machine among the three alternatives a machine should be selected based on its vision and strategy. First of all, the evaluation criteria for the selection decision were taken from the studies in the literature and the discussions with the company's managers in different areas. The hierarchical structure which contains 7 main criteria and 26 sub-criteria for the selection of the best alternative among three machines is constructed in Table 2.

The weights of the main criteria and the sub-criteria considering the decision makers' subjective judgments are estimated by using AHP. A pairwise comparison matrix of the main criteria (Table 3) and the calculation of the weights are given as follows. A normalized matrix, C has been calculated by using Eq. (1):

$$C = \begin{bmatrix} 0.13 & 0.22 & 0.10 & 0.10 & 0.34 & 0.23 & 0.28 \\ 0.03 & 0.04 & 0.07 & 0.02 & 0.02 & 0.10 & 0.02 \\ 0.65 & 0.31 & 0.50 & 0.70 & 0.34 & 0.23 & 0.28 \\ 0.13 & 0.13 & 0.07 & 0.10 & 0.20 & 0.16 & 0.17 \\ 0.03 & 0.13 & 0.10 & 0.03 & 0.07 & 0.16 & 0.17 \\ 0.02 & 0.01 & 0.07 & 0.02 & 0.01 & 0.03 & 0.02 \\ 0.03 & 0.13 & 0.10 & 0.03 & 0.02 & 0.10 & 0.06 \end{bmatrix}.$$

Then the priority weights are calculated by using Eq.(2):

$$w_1 = 1.40 \times 1/7 = 0.20 \quad w_5 = 0.69 \times 1/7 = 0.10$$

$$w_2 = 0.30 \times 1/7 = 0.04 \quad w_6 = 0.19 \times 1/7 = 0.03$$

$$w_3 = 3.00 \times 1/7 = 0.43 \quad w_7 = 0.47 \times 1/7 = 0.07$$

$$w_4 = 0.97 \times 1/7 = 0.14$$

Table 2. Hierarchical Representation of Criteria

Criteria			Symbol
Main Criteria		Productivity	C_1
		Flexibility	C_2
		Cost	C_3
		Quality	C_4
		Reliability	C_5
		Service facility	C_6
		Safety	C_7
Sub Criteria	Productivity	M/C Speed	C_{11}
		Parts Change time	C_{12}
		Setup time	C_{13}
	Flexibility	Use of diff. dimension Of needle	C_{21}
		Easy to operate	C_{22}
		Easy to move	C_{23}
		Diff. types of stitch operation	C_{24}
		M/C can handle multiple operation	C_{25}
	Cost	M/C Cost	C_{31}
		Maintenance cost	C_{32}
		Energy cost	C_{33}
		Parts cost	C_{34}
	Quality	Quality of operation	C_{41}
		Number of m/c (Needle) breakdown	C_{42}
		Running thread cut-off	C_{43}
	Reliability	Life time of the m/c	C_{51}
		Oil leakage rate	C_{52}
		Professional skill	C_{53}
	Service facility	Communication Capability	C_{61}
		Service Warranty	C_{62}
		Parts Warranty	C_{63}
		On time delivery	C_{64}
		Lead time of m/c delivery	C_{65}
	Safety	Safe guards	C_{71}
		Safety Device	C_{72}
		Ergonomically	C_{73}

Table 3. Aggregated pair-wise comparison matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
C_1	1	5	0.2	1	5	7	5
C_2	0.2	1	0.14	0.2	0.33	3	0.33
C_3	5	7	1	7	5	7	5
C_4	1	3	0.14	1	3	5	3
C_5	0.2	3	0.2	0.33	1	5	3
C_6	0.14	0.33	0.14	0.2	0.2	1	0.33
C_7	0.2	3	0.2	0.33	0.33	3	1

Table 4. Weights of sub-criteria

Sub-criteria	Weight	Sub-criteria	Weight
C_{11}	0.11	C_{42}	0.14
C_{12}	0.26	C_{43}	0.18
C_{13}	0.63	C_{51}	0.72
C_{21}	0.10	C_{52}	0.08
C_{22}	0.46	C_{53}	0.19
C_{23}	0.07	C_{61}	0.06
C_{24}	0.17	C_{62}	0.35
C_{25}	0.21	C_{63}	0.31
C_{31}	0.52	C_{64}	0.18
C_{32}	0.06	C_{65}	0.11
C_{33}	0.28	C_{71}	0.26
C_{34}	0.15	C_{72}	0.11
C_{41}	0.69	C_{73}	0.63

The normalized weight vector respect to the main criteria is $W = (0.20, 0.04, 0.43, 0.14, 0.10, 0.03, 0.07)$. The normalized weight vector respect to the main goal is portrayed in Figure 2. According to Figure 2, the most valuable criteria having priority of 0.43 is "Cost" in the decision makers' subjective judgments which are followed by the others. The same computational ways are anticipated to determine the weights of the sub-criteria (w_i) which are presented in Table 4.

Table 5. Decision matrix for TOPSIS method

	A_1			A_2			A_3		
	D_1	D_2	D_3	D_1	D_2	D_3	D_1	D_2	D_3
C_{11}	9	9	7	7	8	8	8	6	8
C_{12}	7	7	8	6	8	7	8	6	7
C_{13}	8	7	7	8	8	8	8	6	8
C_{21}	7	9	9	8	8	8	6	6	8
C_{22}	8	7	8	6	6	8	6	6	6
C_{23}	7	9	8	6	6	5	5	5	6
C_{24}	7	8	8	8	6	7	6	6	6
C_{25}	7	8	7	7	6	8	6	6	8
C_{31}	6	7	6	3	4	6	7	8	6
C_{32}	8	6	7	6	5	6	7	8	7
C_{33}	6	5	7	6	6	6	6	8	8
C_{34}	5	5	6	5	5	7	6	6	8
C_{41}	8	6	7	9	9	7	6	6	8
C_{42}	7	9	7	8	8	8	8	6	8
C_{43}	7	7	9	8	8	6	8	6	6
C_{51}	8	7	6	8	9	7	6	6	5
C_{52}	6	6	8	9	9	9	6	6	5
C_{53}	7	7	9	8	9	8	5	5	5
C_{61}	5	5	5	8	7	9	6	6	7
C_{62}	5	6	5	7	7	7	7	7	6
C_{63}	5	3	5	8	8	9	5	6	7
C_{64}	5	6	5	9	9	9	8	7	6
C_{65}	6	6	5	8	7	9	7	6	7
C_{71}	9	9	7	6	6	6	5	5	6
C_{72}	7	7	8	6	6	7	5	5	5
C_{73}	9	9	9	8	7	8	6	6	5

Table 6. Aggregated decision matrix of TOPSIS method

	A_1	A_2	A_3
C_{11}	8.333333	7.666666667	7.333333
C_{12}	7.333333	7	7
C_{13}	7.333333	8	7.333333
C_{21}	8.333333	8	6.666667
C_{22}	7.666667	6.666666667	6
C_{23}	8	5.666666667	5.333333
C_{24}	7.666667	7	6
C_{25}	7.333333	7	6.666667
C_{31}	6.333333	4.333333333	7
C_{32}	7	5.666666667	7.333333
C_{33}	6	6	7.333333
C_{34}	5.333333	5.666666667	6.666667
C_{41}	7	8.333333333	6.666667
C_{42}	7.666667	8	7.333333
C_{43}	7.666667	7.333333333	6.666667
C_{51}	7	8	5.666667
C_{52}	6.666667	9	5.666667
C_{53}	7.666667	8.333333333	5
C_{61}	5	8	6.333333
C_{62}	5.333333	7	6.666667
C_{63}	4.333333	8.333333333	6
C_{64}	5.333333	9	7
C_{65}	5.666667	8	6.666667
C_{71}	8.333333	6	5.333333
C_{72}	5.333333	7.666666667	7
C_{73}	5.333333	7	6.666667

Table 7. Calculation steps of the TOPSIS method for the machine selection process.

	Weighted normalized values			PIS (A^*)	NIS (A^-)
	A_1	A_2	A_3		
C_{11}	0.0656	0.0603	0.0577	0.0656	0.0577
C_{12}	0.1551	0.1480	0.1480	0.1480	0.1551
C_{13}	0.3546	0.3868	0.3546	0.3546	0.3868
C_{21}	0.0602	0.0578	0.0481	0.0602	0.0481
C_{22}	0.2968	0.2581	0.2322	0.2968	0.2322
C_{23}	0.0480	0.0340	0.0320	0.0480	0.0320
C_{24}	0.1088	0.0994	0.0852	0.1088	0.0852
C_{25}	0.1268	0.1210	0.1153	0.1268	0.1153
C_{31}	0.3142	0.2150	0.3472	0.2150	0.3472
C_{32}	0.0348	0.0282	0.0365	0.0282	0.0365
C_{33}	0.1507	0.1507	0.1841	0.1507	0.1841
C_{34}	0.0757	0.0804	0.0946	0.0757	0.0946
C_{41}	0.3758	0.4473	0.3579	0.4473	0.3579
C_{42}	0.0785	0.0819	0.0750	0.0750	0.0819
C_{43}	0.1095	0.1047	0.0952	0.0952	0.1095
C_{51}	0.4204	0.4805	0.3403	0.4805	0.3403
C_{52}	0.0442	0.0597	0.0376	0.0376	0.0597
C_{53}	0.1197	0.1301	0.0780	0.1301	0.0780
C_{61}	0.0255	0.0409	0.0324	0.0409	0.0255
C_{62}	0.1680	0.2206	0.2101	0.2206	0.1680
C_{63}	0.1189	0.2286	0.1646	0.2286	0.1189
C_{64}	0.0774	0.1307	0.1016	0.1307	0.0774
C_{65}	0.0259	0.0366	0.0305	0.0259	0.0366
C_{71}	0.1876	0.1351	0.1201	0.1876	0.1201
C_{72}	0.0485	0.0697	0.0637	0.0697	0.0485
C_{73}	0.3060	0.4016	0.3824	0.4016	0.3060
d^*	0.215625	0.080073	0.254601		
d^-	0.149411	0.279287	0.111506		
CC_i	0.409305	0.777178	0.304573		

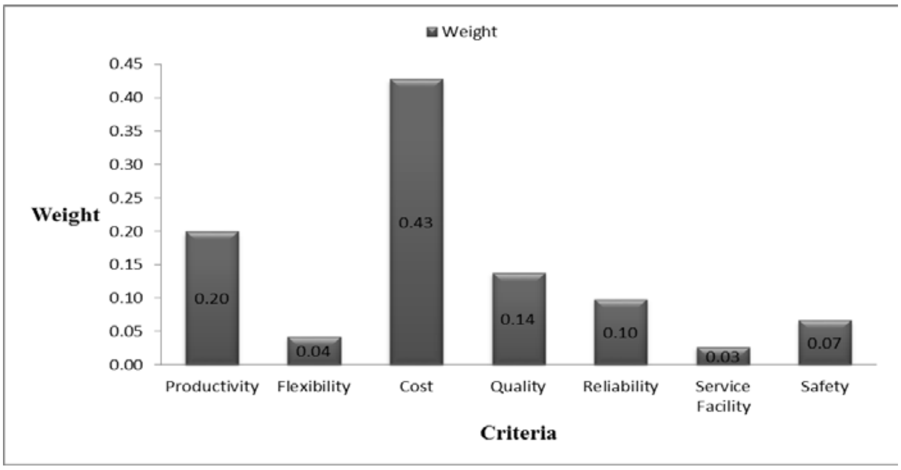

Figure 2. Normalized weights of main criteria

Table 8. Ranking of the machine selection

Order	Alternatives	Closeness coefficients
1	A_2	0.777178
2	A_1	0.409305
3	A_3	0.304573

$$w_1 = 2.09 \otimes (1/10.43) = 0.20 \quad w_5 = 0.93 \otimes (1/10.43) = 0.09$$
$$w_2 = 0.41 \otimes (1/10.43) = 0.04 \quad w_6 = 0.26 \otimes (1/10.43) = 0.03$$
$$w_3 = 4.59 \otimes (1/10.43) = 0.44 \quad w_7 = 0.63 \otimes (1/10.43) = 0.06$$
$$w_4 = 1.52 \otimes (1/10.43) = 0.15$$

The elements of eigenvector are calculated by using Eq. (4).

The eigenvector of the relative importance of the main-criteria is (0.20, 0.04, 0.44, 0.15, 0.09, 0.03, 0.06). To calculate λ_{max},, elements of the row matrix are estimated by using Eq. (5) and forms as (1.55, 0.29, 3.66, 1.10, 0.69, 0.19, 0.46). Eq. (6) gives the four estimates of λ_{max} & the mean of these values (7.75) is the estimated λ_{max}. Consistency Index (CI) & Consistency Ratio (CR) are calculated through Eqs. (7) & (8) respectively (for RI=1.32). As the value of CR (0.09) is less than 0.10, it is accepted.

As indicated before, one of well-known MCDM methods named TOPSIS method is used to rank the potential alternatives considering the weights of all criteria which are obtained by AHP. In the first step of the algorithm, a decision matrix using three decision makers' opinion (D_1, D_2, D_3) is developed using numerical values. The decision matrix of TOPSIS method is shown in Table 5. Then, the aggregated values of each sub-criterion are calculated by using the average technique in TOPSIS method as shown in Table 6. After calculating the aggregated values of the sub-criteria, eligible locations are ranked by using TOPSIS method. These aggregated values are the main input. Normalization of these values is made through Eq. (9). The positive and negative ideal solution is determined by taking the maximum and minimum values for each criterion in the TOPSIS method. Then the distance of each alternative from PIS (A^*) and NIS (A^-) with respect to each criterion are calculated like in Eqs. (13) & (14). Afterwards, the closeness coefficients (CC_i) of three alternatives are calculated with Eq. (15) and the ranking is done in a decreasing order. Calculation steps of the TOPSIS method are given in Table 7. In Table 8, selections of the machine are ranked with respect to TOPSIS method.

4. Results and Discussions

Depending on the values of closeness coefficients of three suitable machines, machine A_2 becomes the most dominating alternative having highest CC_i of 0.777178 which is followed by the others. So, A_2 should be selected as best machine among three alternatives.

5. Conclusions and Future Work

To keep pace with competitors in the modern economy, the company must make a decision that leads to the way of selecting the appropriate machine from available machines. The proper decision paves the way for inclusive growth and ultimate profit of a company. Machine properties influence the ultimate output, manufacturing capabilities, revenue generation of a company. Several factors are crucial for machine selection. But, the consideration of this several criteria and sub-criteria makes the process of selection more difficult. For that reason, this paper has presented a prototype framework using the analytic hierarchy process (AHP) with TOPSIS algorithm as an effective tool for supporting machine selection decision. In this research, the weights of the different criteria are calculated using the AHP method and for selecting the most desirable machine one of well-known MCDM methods namely TOPSIS method has been used. For both methods, some results are obtained by hand computation and some are calculated by Microsoft Office Excel. In the future, it is not an option but essential to implement this method for dealing a variety of multi-criteria decision making problems due to its flexibility. The proposed method is also effective in a group decision environment where it is found to be difficult to come to a moot point individually. Thus, it will also help in future researches as well. In addition to the proposed methods in this study, some other MCDM methods such as ELECTRE; PROMETHEE; MOORA and ORESTE can be used comparatively in a fuzzy environment and the results can be compared.

Acknowledgements

The authors wish to acknowledge the support and assistance provided by the Department of Industrial and Production Engineering, Jessore University Science and Technology, Bangladesh. The efforts of the chairman of the department, teachers and students who collaborated in this study are also appreciated.

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