MULTI-ATTRIBUTE DECISION-MAKING FOR CNC MACHINE TOOL SELECTION IN FMC BASED ON THE INTEGRATION OF THE IMPROVED CONSISTENT FUZZY AHP AND TOPSIS

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Abstract

Globalization of business and the competitiveness of manufacturing have motivated companies to improve the facilities to respond to the market requirements. Machine tool selection plays a major role in the improvement of productivity, flexibility in uncertain manufacturing. The objective of this study is to present the simple approach for machine tool selection based on the integration of consistent fuzzy AHP and TOPSIS. In particular, the fuzzy linguistic reference relation is integrated into AHP to solve the imprecise and vague information, and simplify the data collection in the pair-wise comparison matrix, which determines the weight of attributes. The output of fuzzy AHP is imported into the TOPSIS method for ranking alternatives through the closeness coefficient. The numerical example is implemented based on the data collecting by questionnaire and literature to validate the model. The results show that the proposed approach is a simple tool and reaches an effective multi-attribute decision in machine tool selection.

Keywords: Decision-making, FMC, Machine tool selection

Introduction

Globalization of business, the competitiveness of manufacturing force companies must invest and improve production facilities, especially is the introduction of new equipment in the market. Therefore, the machine tool selection to invest and improve the facilities, is an important decision, and plays the survival to the development of the manufacturing facilities. Improperly selected machines can have the negative impact on the overall performance of the system such as the productivity, precision, flexibility, adaption and responsiveness. So, this is a time-consuming and intractable problem, and the largest drawback for engineers and managers due to the lack of the deeply knowledge and experience and the technology understanding [1,2].

The development of the production economy always requires the companies to find a replacement manufacturing solution to respond and satisfy the demand of customers. One of the important strategies to meet the optimal operational performance is applying the production automation through the implementation of the flexible manufacturing system (FMS) [3]. FMS achieves the efficiency of an automatic batch manufacturing system, while using the flexibility of a manual job shop to simultaneously machine several part types. The structure of FMS comprises of many CNC machine tools, workstation and material handling system linking mechanically together and electrically controlled by the computer-centered system [4]. However, the investment cost for FMS is very expensive. Thus, the small and medium enterprises (SME) in the developing countries usually choose the flexible manufacturing cells (FMC) like a competitive strategy for improving the technology as well as the productivity. Machine tools are particularly the system centered-equipment and the critical linkage which are responsible for transforming the raw materials into the finished discrete parts and components which can be assembled into the end products. Machine tool selection problem plays a crucial role to improve the performance of FMC [5].

Researchers have had the different contributions of solutions for decision-making in selecting the most suitable candidate machines. For example, Ayağ and Özdemir [6] use the fuzzy AHP to select the best machine tool from the alternatives in the market. The multi-criteria decision-making (MCDM) model is constructed based on the quantitative and qualitative factors. The fuzzy logic is utilized to solving the vague and imprecise information of the uncertain judgments from experts. The fuzzy AHP method is used to evaluate the weights of criteria and the ranking of alternatives. Finally, the Benefit/Cost (B/C) ratio analysis is implemented for each alternative, and the ultimate candidate for machine tools responding to the highest B/C ratio. The decision support system (DSS) for selecting the machine tool in the implementation of FMC using the fuzzy AHP and artificial neural network (ANN) also is proposed by Taha and Rostam [3]. The ANN with the feedback propagation is utilized to learn and verify the results of the fuzzy AHP for predicting the candidate ranking. Önüt et al [7] describes the hybrid fuzzy MCDM approach for the machine tool selection based on the integration of the fuzzy AHP and the fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) in order to evaluate the vertical CNC machining centers. The priorities of criteria are obtained by fuzzy AHP to handle the qualitative criteria, and the result from the alternative's ranking is quantified by fuzzy TOPSIS. Besides, Ayağ [8] presented the integration of the AHP and simulation technique for the machine tool selection. Taha and Rostam [9] presented the DSS using fuzzy AHP and PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluation) for evaluating the best computer numerical controlled (CNC) turning machines in FMC and Dağdeviren [10] also proposed the integration of the AHP and PROMETHEE. Durán and Aguilo [11] used fuzzy AHP for the machine-tool selection, and fuzzy AHP is also used to evaluate the equipment of the reconfigurable machining system by Abdi [12]. Ic et al., [13] developed a component-based machining center selection model using AHP for MCDM process in machine tool alternatives.

Lin and Yang [14] also used the AHP for evaluation of machine selection. Ic and Yurdakul [15] developed the DSS to choose the most appropriate machining center, involving the integration of the fuzzy AHP and fuzzy TOPSIS. In particular, the priorities of criteria are determined by fuzzy AHP and fuzzy TOPSIS is employed for calculating the ranking of alternatives. Qi [16] proposed a fuzzy MCDM model based on the modified fuzzy AHP and grey theory to determine the weights of criteria and the performance of each alternative through the Sugeno fuzzy integral.

The literature survey has revealed that the application of fuzzy AHP algorithm in the decision-making process is very fascinating. Fuzzy AHP archived the acceptable results in evaluating the alternatives and is widely used in manufacturing environment. One of the important benefits of fuzzy AHP is to generate the weights of criteria and the priorities of alternatives from the pair-wise comparison matrices of expert's judgments. However, the fuzzy AHP in many previous research works has shown the existing disadvantages in collecting the judgments for decision matrices because the process for collecting data is very long and time-consuming.

To overcome the drawback of the existing fuzzy AHP method, the integration of the consistent fuzzy AHP and TOPSIS is introduced in this paper for machine tool selection. The Consistency Ratio (CR) is skipped when the fuzzy linguistic preference relation is employed to integrate into the AHP. This proposed method of machine tool selection is very simple and easy implemented without any constraints.

The rest of the paper is organized as follows: next section describes the methodology which contains the proposed model and approach for decision-making in machine tool selection; then, the numerical example is implemented, and the final section contains discussion and conclusions.

Methodology

The Consistent Fuzzy AHP

The AHP presented by Saaty in 1980 and has become the most popular in the multi-criteria decision making (MCDM) method [17]. In manufacturing environment, many problems can be not solved with the vague and imprecise information. Thus, fuzzy logic is integrated within the model to solve the uncertain problem, and fuzzy AHP combines the pair-wise comparison matrix of expert judgments and theory of fuzzy sets to handle the uncertain problems in manufacturing environment. Especially, this method becomes very famous for multi-attribute decision-making (MADM) process.

The existing fuzzy AHP uses the pair-wise comparison matrices with the collection of n(n-1)/2 comparisons. Thus, the table of questionnaire design is implemented to get feedback from expert's judgments. Larger number of attributes, the more pair-wise comparison questions and the questionnaire design table is more complicated. Therefore, the experts will be easy in the careless situation when to answer too many questions. That leads to the inconsistent result through the consistent ratio is not less than 0.1, and finally, the experts will be required to check and re-answer again the questions. Thus, it leads to wastage of time and inefficiency [17].

To overcome this problem, Wang and Chen [18] proposed the integration of consistent fuzzy preference relations (CFPR) in the AHP approach to improve the consistency of fuzzy AHP. When to use CFPR, the number of pair-wise comparisons is dramatically reduced from n(n-1) to (n-1) comparisons and the rest of other comparisons can be computed through the fuzzy preference relations. Thus, expert or decision-makers will spend less power and focus more effort to make the pair-wise comparisons of attributes [17]. For example, if we have ten attributes and five alternatives, the number of the pair-wise comparison matrices will be eleven matrices. In particular, one 10x10 pair-wise comparison matrix for attributes contains 10(10-1)/2=45 judgments and ten 5x5 pairwise comparison matrices contain 10*5(5-1)/2=100 judgments. Thus, the minimum number of judgments collected from experts must be 145 judgments. Besides, one more thing needs to remember for evaluating alternative is the consistent ratio (CR) must be less than 0.1. If the CR is not less than 0.1, we must ask the expert to re-evaluate the judgments among the criteria and alternatives. However, the number of pair-wise comparisons is only (10-1) = 9 if the integration of the improved consistent fuzzy AHP and TOPSIS is used for decision-making.

The TOPSIS

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is employed to rank the alternative through the priorities. To calculate the ranking of alternatives, the closeness coefficient is introduced and determined by the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) [2].

The Proposed Model

The structure of the proposed model is depicted in Figure 1. The required date is initially prepared for decision-making process. The database is collected from some sources such as literature, expert’s judgments and the catalogues of many manufacturers by questionnaire design. The meeting is frequently organized to get the feedback from the expert for the alternatives and attributes, and determination of data inputs for the fuzzy AHP. The priorities or weights of attributes are calculated by the fuzzy AHP with the pair-wise comparison matrix. Then, the outputs of fuzzy AHP are imported into TOPSIS for determination of ranking of alternatives. The decision-makers use this result for decision-making process. If the result is not satisfied, the data justification is implemented for inputs of fuzzy AHP and otherwise, the final decision is carried out by decision-makers.

The attributes in the model are adapted from the literature, catalogues and interviews from the expert of manufacturing. The hierarchical structure of the model is described in Figure 2. It contains three top-down levels: At the top level (level 1), the manufacturing goal is determined for machine tool selection; the middle level (level 2) consists of attributes for decision-making process such as turning diameter (Dia), top RPM (rpm), number of tools (No.T), number of axes (No.Axes), machine weight (MW), floor layout (FL) and horse power (HP) [9]; and the machine tool's candidate is listed in the bottom level (level 3) for ranking process [3].

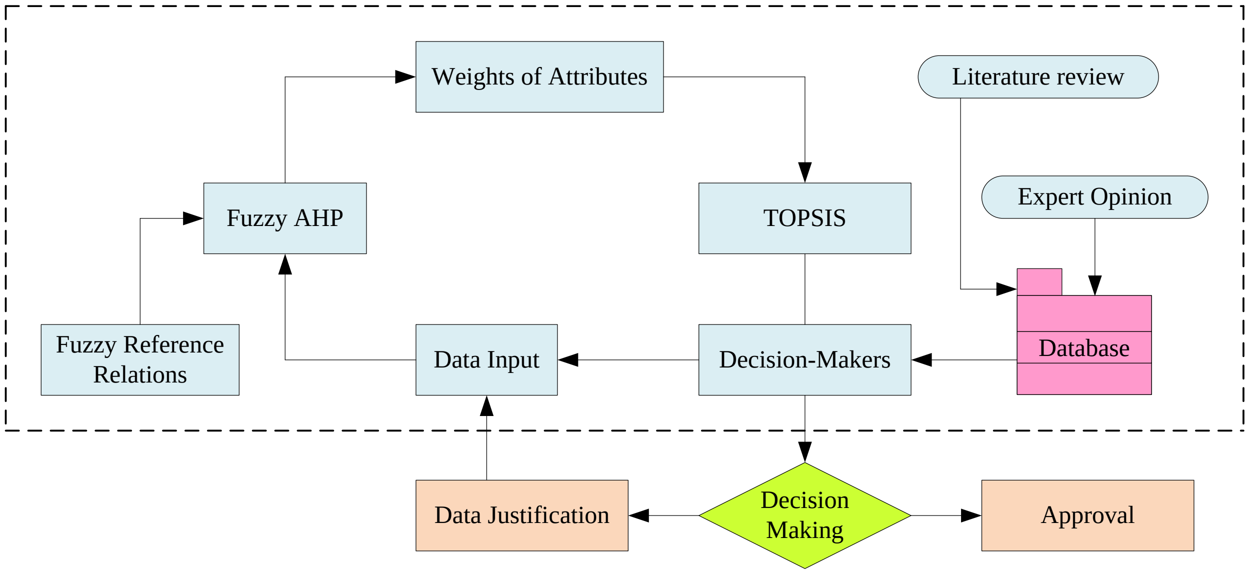

Figure 1. Scheme of the proposed model [9]

The Integration of Improved Fuzzy AHP and TOPSIS

This method based on the integration of fuzzy AHP and TOPSIS is developed for decision-making process in machine tool selection. It makes use of the advantages of fuzzy AHP in determination of weights of attributes and the simplicity of TOPSIS for ranking alternatives. The flowchart of method is shown in Figure 3 and comprises 16 steps as follows.

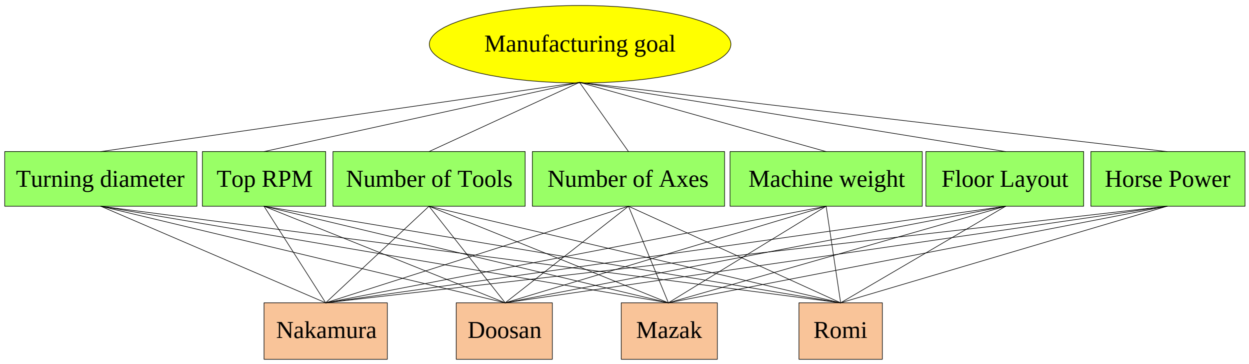

Figure 2. The hierarchical structure for machine tool selection [9]

Fuzzy Number [18,19]

Let $\tilde{A}$ be a fuzzy triangular number on $\mathbb{R}$, $\tilde{A}$ is defined as follows: $\tilde{A} = (l, m, u)$ if the membership function $\mu_{\tilde{A}}(x)$ satisfies the following rules:

$\mu_{\tilde{A}}(x) : \mathbb{R} \rightarrow [0,1]$ and expressed as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-l}{m-l}, l \le x \le m \\ \dfrac{u-x}{u-m}, m \le x \le u \\ 0, \qquad \text{otherwise} \end{cases} \tag{1}$$

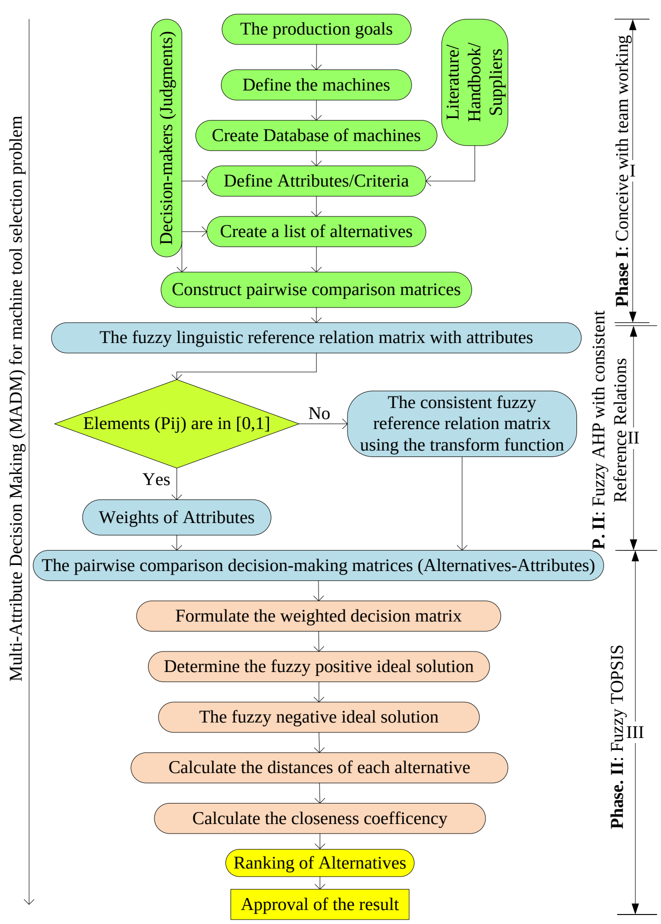

Figure 3. Flowchart of the proposed model

Table 1. Fuzzy Linguistic Assessment Variable [18,2]

Linguistic Variables	Triangular Fuzzy Numbers
Very poor (VP)	(0,0,0.1)
Poor (P)	(0,0.1,0.3)
Medium poor (MP)	(0.1,0.3,0.5)
Medium (M)	(0.3,0.5,0.7)
Medium good (MG)	(0.5,0.7,0.9)
Good (G)	(0.7,0.9,1)
Very Good (VG)	(0.9,1,1)

The AHP with consistent fuzzy reference relation [17]:
Step 1: Define the manufacturing goal.
Step 2: Define the machine tool for manufacturing system.
Step 3: Create the database of the machine tool from manufacturing supplier.
Step 4: Choose the desirable criteria/attributes implemented by decision-makers (DMs).
Step 5: Choose the machine tool alternatives.
Step 6: Build the hierarchical structure for decision-making process in machine tool selection.
Step 7: Questionnaire design for data collection from expert's judgments.
Step 8: Establish decision matrix A from each judgment of expert. Let A_i (i = 1,2,…,n) be a set of attributes (a_{ij}), and the relative importance between two attributes is evaluated using the scale numbers in Table 2:

Step 9: Determine the pair-wise comparison matrix between the attributes

Table 2. Pair-Wise Comparison Matrix for Each Attribute

Goal	A_1	A_2	A_3	…	A_n
A_1	1	$\tilde{a}_{12}$	$\tilde{a}_{13}$	…	$\tilde{a}_{1n}$
A_2	$\tilde{a}_{12}^{-1}$	1	$\tilde{a}_{23}$	…	$\tilde{a}_{2n}$
…	…	…	…	…	…
A_n	$\tilde{a}_{1n}^{-1}$	$\tilde{a}_{2n}^{-1}$	$\tilde{a}_{3n}^{-1}$	…	1

Step 10: Determine the fuzzy linguistic reference relation matrix for the attributes

Table 3. The Fuzzy Linguistic Reference Relation Matrix

Goal	A_1	A_2	A_3	…	A_n
A_1	1	$\tilde{p}_{12}$	$\tilde{p}_{13}$	…	$\tilde{p}_{1n}$
A_2	$\tilde{p}_{12}^{-1}$	1	$\tilde{p}_{23}$	…	$\tilde{p}_{2n}$
…	…	…	…	…	…
A_n	$\tilde{p}_{1n}^{-1}$	$\tilde{p}_{2n}^{-1}$	$\tilde{p}_{3n}^{-1}$	…	1

Step 11: Using the transform function to obtain/preserve the consistent fuzzy reference relation matrix from the fuzzy linguistic reference relation matrix with attributes [18].

Table 4. The Fuzzy Linguistic Reference Relation Matrix with the Transformation

Goal	A1	A2	A3	…	An	Average	Weights
A1	1	$\tilde{p}_{12}$	$\tilde{p}_{13}$	…	$\tilde{p}_{1n}$	$\bar{A}_1$	w_{a_1}
A2	$\tilde{p}_{12}^{-1}$	1	$\tilde{p}_{23}$	…	$\tilde{p}_{2n}$	$\bar{A}_2$	w_{a_2}
…	…	…	…	…	…	$\bar{A}_i$	w_{a_i}
An	$\tilde{p}_{1n}^{-1}$	$\tilde{p}_{2n}^{-1}$	$\tilde{p}_{3n}^{-1}$	…	1	$\bar{A}_n$	w_{a_n}

Where,

$$\bar{A}_i = \frac{1}{n}\sum_{j=1}^{n} p_{ij} = \left(\frac{1}{n}\sum_{j=1}^{n} p_{ij}^{L}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{M}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{R}\right) \tag{2}$$

$$w_{a_i} = \frac{\bar{A}_i}{\sum_{i=1}^{m}\bar{A}_i} = \frac{\left(\frac{1}{n}\sum_{j=1}^{n} p_{ij}^{L}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{M}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{R}\right)}{\bar{A}_1 + \bar{A}_2 + \bar{A}_3 + \cdots + \bar{A}_m} \tag{3}$$

Step 12: Determine the pair-wise comparison decision-making matrices of alternatives for attributes $(w_{p_{ij}})$.

Step 13: Formulate the weighted decision matrix based on the fuzzy linguistic reference relation as follows [18].

$\tilde{D} = (\tilde{u}_{ij}), i = \{1, 2, ..., m\},\ j = \{1, 2, ..., n\}$

Where $\tilde{u}_{ij} = w_{a_i} \cdot w_{p_{ij}}, i = \{1, 2, ..., m\},\ j = \{1, 2, ..., n\}$.

Table 5. Weighted Decision Matrix

Alternatives	A1	A2	A3	…	An
P1	$w_{a_1} \cdot w_{p_{11}}$	$w_{a_2} \cdot w_{p_{12}}$	$w_{a_3} \cdot w_{p_{13}}$	…	$w_{a_n} \cdot w_{p_{1n}}$
P2	$w_{a_1} \cdot w_{p_{21}}$	$w_{a_2} \cdot w_{p_{22}}$	$w_{a_3} \cdot w_{p_{23}}$	…	$w_{a_n} \cdot w_{p_{2n}}$
…	…	…	…	…	…
Pm	$w_{a_1} \cdot w_{p_{m1}}$	$w_{a_2} \cdot w_{p_{m2}}$	$w_{a_3} \cdot w_{p_{m3}}$	…	$w_{a_n} \cdot w_{p_{mn}}$

Step 14: Determine the Positive Ideal Solution (PIS, Q^+) and the Negative Ideal Solution (NIS, Q^-) as follows [2,7,20,15]:

$$Q^{+} = \left(\tilde{u}_1^{+}, \tilde{u}_2^{+}, \tilde{u}_3^{+}, ..., \tilde{u}_n^{+}\right) \quad (4)$$

$$Q^{-} = \left(\tilde{u}_1^{-}, \tilde{u}_2^{-}, \tilde{u}_3^{-}, ..., \tilde{u}_n^{-}\right) \quad (5)$$

Where, $\tilde{u}_j^{+} = {}_{i=1}^{m} \max_{j=1}^{n} \{\tilde{u}_{ij}\}$ and $\tilde{u}_j^{-} = {}_{i=1}^{m} \min_{j=1}^{n} \{\tilde{u}_{ij}\}$.

Step 15: Calculate the distances of each alternative from (PIS, Q^+) and (NIS, Q^-) [2,7,20,15]:

$$q_i^{+} = \sqrt{\frac{\sum_{j=1}^{n} (\tilde{u}_j - \tilde{u}_j^{+})^2}{n}} \quad (6)$$

$$q_i^{-} = \sqrt{\frac{\sum_{j=1}^{n} (\tilde{u}_j - \tilde{u}_j^{-})^2}{n}} \quad (7)$$

Step 16: Calculate the closeness coefficient (CC_i) and the sequence for alternatives can be determined according to the decreasing order of CC_i (i = 1,2,…,m) [2,7,20,15].

$$CC_i = \frac{q_i^{-}}{q_i^{+} + q_i^{-}} \quad (8)$$

Numerical Example

The survey for formulating the comparison decision matrix is conducted by the expert or decision-makers with seven attributes, which are extracted from literature and catalogue of CNC machines. They are shown on the decision hierarchical structure as in Fig. 2, and the Nakamura, Doosan, Mazak and Romi are chosen as alternatives for decision-making process. The procedure to select the best machine is described in Fig.3 and the proposed model in Fig. 1. The pair-wise comparison matrix of the attributes is collected with fuzzy linguistic assessment variables as follows.

Table 6. Pair-wise Comparison Matrix among Attributes of CNC Machines

	Dia	**rpm**	**No.T**	**No.Axes**	**MW**	**FL**	**HP**
Dia	*	MP	M	M	MG	M	P
rpm		*					
No.T			*				
No.Axes				*			
MW					*		
FL						*	
HP							*

After the pair-wise comparison matrix among the attributes of machines is formulated with six elements corresponding to six judgments from the expert, the rest of the elements within the matrix are calculated by applying “(9)” – “(17)” in APPENDIX. The result of elements is shown in Table 7.

Table 7. The Fuzzy Linguistic Reference Relation Matrix with Attributes

	Dia	rpm	No.T	No.Axes	MW	FL	HP
Dia	(0.5,0.5,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0,0,0.1)
rpm	(0.3,0.5,0.7)	(0.5,0.5,0.5)	(0.7,0.7,0.7)	(0.7,0.7,0.7)	(0.9,0.9,0.9)	(0.7,0.7,0.7)	(0.4,0.2,0.1)
No.T	(0.3,0.5,0.7)	(0.3,0.3,0.3)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.7,0.7,0.7)	(0.5,0.5,0.5)	(0.2,0,-0.1)
No.Axes	(0.3,0.5,0.7)	(0.3,0.3,0.3)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.7,0.7,0.7)	(0.5,0.5,0.5)	(0.2,0,-0.1)
MW	(0.1,0.3,0.5)	(0.1,0.1,0.1)	(0.3,0.3,0.3)	(0.3,0.3,0.3)	(0.5,0.5,0.5)	(0.3,0.3,0.3)	(0,-0.2,-0.3)
FL	(0.3,0.5,0.7)	(0.3,0.3,0.3)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.7,0.7,0.7)	(0.5,0.5,0.5)	(0.2,0,-0.1)
HP	(0.9,1,1)	(0.9,0.8,0.6)	(1.1,1,0.8)	(1.1,1,1.2)	(1.3,1.2,1)	(1.1,1,0.8)	(0.5,0.5,0.5)

Because there are some elements of Table 7 fall out of the interval [0, 1]. Thus, the transforming function f(x) = (x+3)/(1+0.6) is used to preserve the consistency of matrix, and the result is shown in Table 8.

Table 8. Transformation Result of the Fuzzy Linguistic Reference Relation Matrix

	Dia	rpm	No.T	No.Axes	MW	FL	HP
Dia	(0.5,0.5,0.5)	(0.38,0.5,0.63)	(0.38,0.5,0.63)	(0.38,0.5,0.63)	(0.5,0.63,0.75)	(0.38,0.5,0.63)	(0.19,0.19,0.25)
rpm	(0.38,0.5,0.63)	(0.5,0.5,0.5)	(0.63,0.63,0.63)	(0.63,0.63,0.63)	(0.75,0.75,0.75)	(0.63,0.63,0.63)	(0.44,0.31,0.25)
No.T	(0.38,0.5,0.63)	(0.38,0.38,0.38)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.63,0.63,0.63)	(0.5,0.5,0.5)	(0.31,0.19,0.13)
No. Axes	(0.38,0.5,0.63)	(0.38,0.38,0.38)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.63,0.63,0.63)	(0.5,0.5,0.5)	(0.31,0.19,0.13)
MW	(0.25,0.38,0.5)	(0.25,0.25,0.25)	(0.38,0.38,0.38)	(0.38,0.38,0.38)	(0.5,0.5,0.5)	(0.38,0.38,0.38)	(0.19,0.06,0)
FL	(0.38,0.5,0.63)	(0.38,0.38,0.38)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.63,0.63,0.63)	(0.5,0.5,0.5)	(0.31,0.19,0.13)
HP	(0.75,0.81,0.81)	(0.75,0.69,0.56)	(0.875,0.81,0.69)	(0.875,0.81,0.94)	(1,0.94,0.81)	(0.875,0.81,0.69)	(0.5,0.5,0.5)

The average value and weights of attributes are determined with “(2)” and “(3)”. Then, defuzzication of the attributed fuzzy weights is shown in Table 9 and Figure 4.

Table 9. Weights of Attributes

	Average	Weights	Defuzzied weights
Dia	(0.387,0.474,0.574)	(0.11,0.14,0.17)	0.14
rpm	(0.5657,0.5643,0.5743)	(0.157,0.161,0.166)	0.16
No.T	(0.457,0.457,0.467)	(0.1268,0.1302,0.135)	0.131
No.Axes	(0.457,0.457,0.467)	(0.1268,0.1302,0.135)	0.131
MW	(0.333,0.333,0.341)	(0.092,0.095,0.0985)	0.095
FL	(0.457,0.457,0.467)	(0.1268,0.1302,0.135)	0.131
HP	(0.804,0.767,0.714)	(0.223,0.219,0.206)	0.216
Total	(3.461,3.51,3.604)		

Table 10 contains the value of each attribute to machine tools, extracted from catalog, literature, handbooks.

Table 10. Database of Machines and Attributes [9]

	Dia$_{(in)}$	rpm	No.T	No.Axes	MW$_{(lbs)}$	FL	HP
Nakamura	7.48	5000	24	9	26400	1074.52	15
Dossan	9.5	6000	12	8	16534	921.188	20
Romi	11.02	6000	12	4	19000	2620.8	25
Mazak	16.93	4000	12	6	24250	1881.49	30

Table 11. Normalized Data of Machines and Attributes

The data value is normalized in [0,1] for decision-making process.

	Dia	rpm	No.T	No.Axes	MW	FL	HP
Nakamura	0.32	0.47	0.76	0.64	0.60	0.30	0.32
Dossan	0.40	0.56	0.38	0.57	0.38	0.26	0.43
Romi	0.47	0.56	0.38	0.28	0.43	0.74	0.54
Mazak	0.72	0.38	0.38	0.43	0.55	0.53	0.65

Table 12. Weighted Normalized Decision Matrix

The weighted normalized decision matrix is formulated by Table 5. The PIS and NIS is determined by "(4)" and "(5)".

	Dia	rpm	No.T	No.Axes	MW	FL	HP
Weights	0.14	0.16	0.131	0.131	0.095	0.131	0.216
Optimization	Max	Max	Max	Max	Min	Min	Max
Nakamura	0.045	0.0752	0.10	0.084	0.057	0.039	0.069
Dossan	0.056	0.0896	0.05	0.747	0.036	0.034	0.093
Romi	0.0658	0.0896	0.05	0.037	0.041	0.097	0.117
Mazak	0.101	0.061	0.05	0.056	0.052	0.069	0.140
PIS	0.101	0.0896	0.10	0.747	0.036	0.034	0.140
NIS	0.045	0.061	0.05	0.037	0.057	0.097	0.069

The distances and closeness coefficient is calculated with "(6)", "(7)" and "(8)". The ranking of alternatives is determined with the highest closeness coefficient. The result of alternatives is shown in Fig. 5.

Table 13. The Closeness Coefficient

Ranking of Machines	q^+	q^-	CC_i	Ranking
Nakamura	0.253	0.0104	0.0395	4
Dossan	0.031	0.270	0.897	1
Romi	0.271	0.023	0.0782	3
Mazak	0.262	0.037	0.124	2

The results in table 13 and Figure 5 show that the closeness coefficient is highest for Dossan (0.897>0.124>0.0395>0.0782). Thus, the ranking of alternatives is determined according to the order of descending in the closeness coefficient (Dossan > Mazak > Romi > Nakamura). Finally, we release that Dossan is the best alternative from a set of the potential machine tools based on the data collected from expert's judgments.

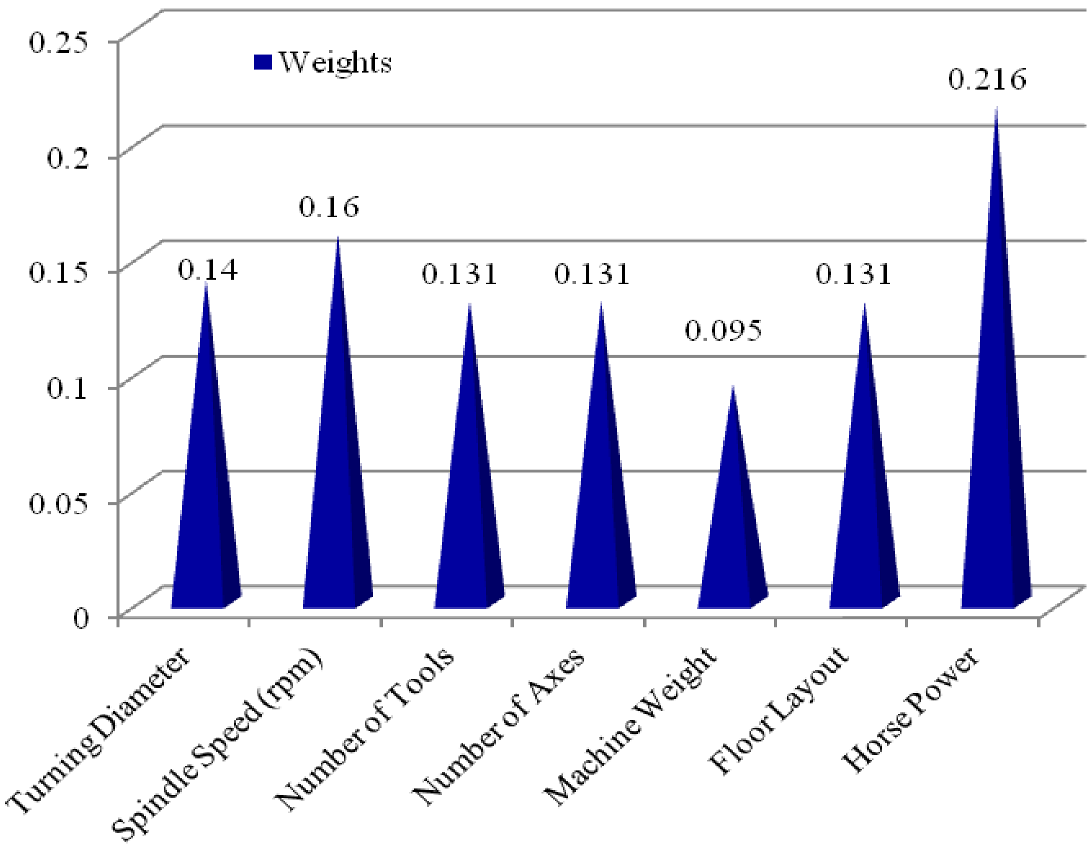

Figure 4. The weights of attributes

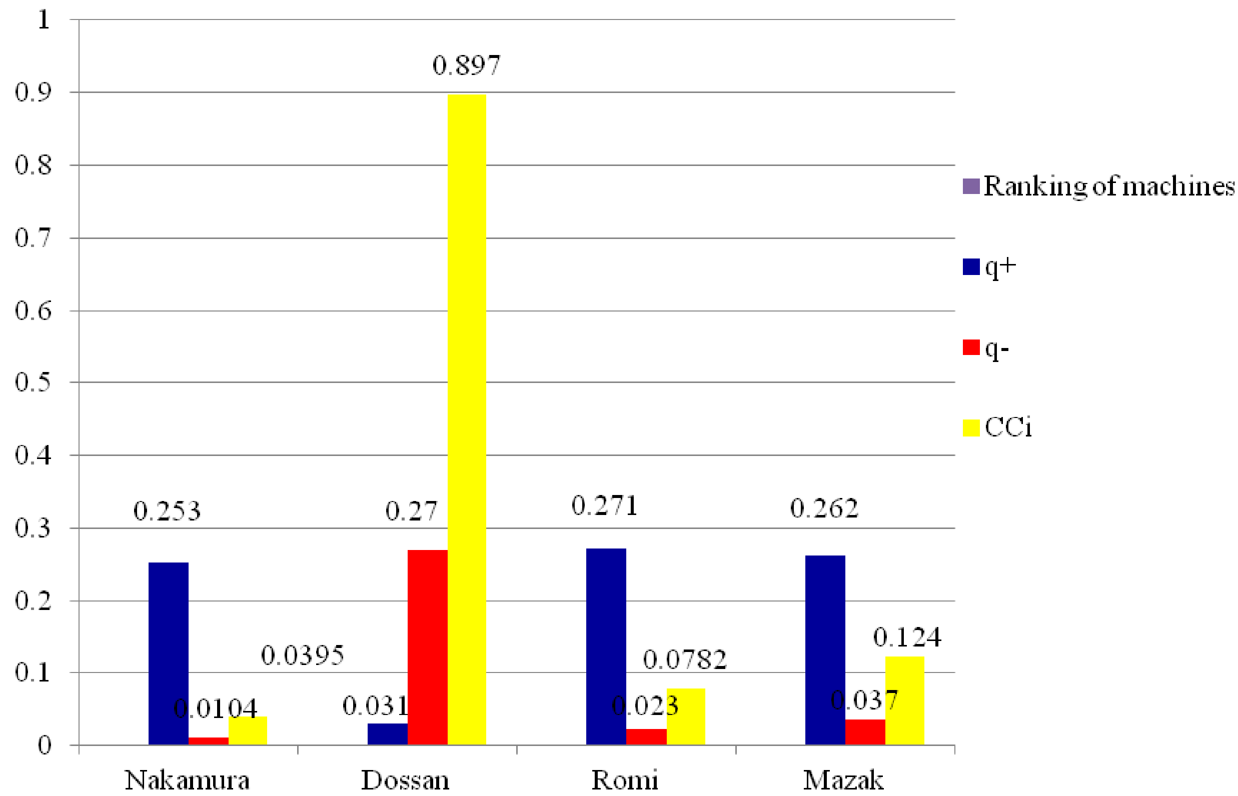

Figure 5. Ranking of alternatives

Discussion

Decision-making is the hard and time-consuming process involving the attributes in uncertain manufacturing environment. The purpose of this study is to build an approach to support decision-makers in machine tool selection problem based on the expert's judgments. An integrated approach of fuzzy AHP and TOPSIS is proposed for decision-making in machine tool selection. In particular, AHP uses the pair-wise comparisons to determine the weights of attributes. The conventional AHP, however, cannot describe the expert's judgments due to the uncertainty. Thus, fuzzy logic is employed to integrate into AHP to obtain the result more accurately. Moreover, the most advantage of fuzzy logic is to use the fuzzy linguistic preference relation to obtain the pair-wise comparison matrix with minimal questions, which is required to answer by experts. Therefore, the integration of fuzzy AHP and TOPSIS to rank the alternatives is useful for the decision-making process with the incomplete information. For instance, we need 7(7-1)/2 comparison among attributes and 7*4(4-1)/2 comparisons for machine tools to each attribute in AHP method. Thus, the total number of comparisons is 7(7-1)/2+7*4(4-1)/2=63. However, when the integration of consistent fuzzy AHP and TOPSIS is used to make the decision, the number of the pair-wise comparisons needed is (7-1)=6.

Besides, the disadvantage of this approach is to determine the experts, who have an experience in the industry. The result accuracy depends on the level of experience of expert.

Therefore, the group decision-making and the interactions of the attributes are suggested for future research to obtain a decision more effectively.

Conclusions

Decision-making is a difficult process involving the uncertain, imprecise, in completed information. In this study, the integration of fuzzy AHP and TOPSIS with the support of the fuzzy linguistic preference relation is proposed as the effective and simple tool to solve the imprecise, vague, intangible information for multi-attribute decision-making. The result highlights that Dossan is the best alternative in implementation of the manufacturing systems.

Appendix

Fuzzy Reference Relations

Definition 1: A fuzzy positive matrix $\tilde{A} = (\tilde{a}_{ij})$ is reciprocal $\Leftrightarrow \tilde{a}_{ji} = \tilde{a}_{ij}^{-1}$ [21,18,22].

Definition 2: A fuzzy positive matrix $\tilde{A} = (\tilde{a}_{ij})$ is consistent $\Leftrightarrow \tilde{a}_{ij} \otimes \tilde{a}_{jk} \approx \tilde{a}_{ik}$ [21,18].

Proposition 1 [18,17,23]: Consider a set of alternatives, $X = \{x_1, x_2, ..., x_n\}$ associated with a fuzzy reciprocal preference matrix $\tilde{A} = (\tilde{a}_{ij})$ with $\tilde{a}_{ij} \in [1/9, 9]$ and the corresponding fuzzy reciprocal linguistic preference relation $\tilde{P} = (\tilde{p}_{ij})$ with $\tilde{p}_{ij} \in [0,1]$.

a) $p_{ij}^{L} + p_{ji}^{R} = 1, \forall i, j \in \{1, 2, ..., n\}$ (9)

b) $p_{ij}^{M} + p_{ji}^{M} = 1, \forall i, j \in \{1, 2, ..., n\}$ (10)

c) $p_{ij}^{R} + p_{ji}^{L} = 1, \forall i, j \in \{1, 2, ..., n\}$ (11)

Proposition 2 [18,17,23]: For a reciprocal fuzzy reference relation $\tilde{P} = (\tilde{p}_{ij}) = (p_{ij}^{L}, p_{ij}^{M}, p_{ij}^{R})$ to be consistent, the following statement must be equivalent:

a) $p_{ij}^{L} + p_{jk}^{L} + p_{ki}^{R} = \frac{3}{2}, \forall i < j < k.$ (12)

b) $p_{ij}^{M} + p_{jk}^{M} + p_{ki}^{M} = \frac{3}{2}, \forall i < j < k.$ (13)

c) $p_{ij}^{R} + p_{jk}^{R} + p_{ki}^{L} = \frac{3}{2}, \forall i < j < k.$ (14)

d) $p_{i(i+1)}^{L} + p_{(i+1)(i+2)}^{L} + \cdots + p_{(j-1)j}^{L} + p_{ji}^{R} = \frac{j-i+1}{2}, \forall i < j.$ (15)

e) $p_{i(i+1)}^{M} + p_{(i+1)(i+2)}^{M} + \cdots + p_{(j-1)j}^{M} + p_{ji}^{M} = \frac{j-i+1}{2}, \forall i < j.$ (16)

f) $p^R_{i(i+1)} + p^R_{(i+1)(i+2)} + \cdots + p^R_{(j-1)j} + p^L_{ji} = \frac{j-i+1}{2}, \forall i < j.$ (17)

If the entries of the design matrix or the values of the matrix $\tilde{P} = (\tilde{p}_{ij}) = (p^L_{ij}, p^M_{ij}, p^R_{ij})$ are not in the interval [0,1] but fall in a interval [-c, 1+c], (c>0), the obtained fuzzy numbers would need to be transformed by using transform function to preserve the reciprocity and addictive consistency; namely $f:[-c,1+c] \to [0,1]$.

$$f(x^{L,M,R}) = \frac{x^{L,M,R} + c}{1+2c} \quad (18)$$

Table A1. Previous Research Works of Machine Selection Problem

Author	Year	Objective	Methodology
Z.Ayag, G.G.Ozdemir	2006	MTS	FuzzyAHP
Z.Taha and S. Rostam	2011	MTS	FuzzyAHP&ANN
Semih Onut et al	2008	MTS	FuzzyAHP&FuzzyTOPSIS
Z. Ayag	2007	MTS	AHP&Simulation
Z. Taha, S. Rostam	2011	MTS	FuzzyAHP&PROMETHEE
S.Myint& Tabucanon	1994	MTS	AHP&GP,sensitivityanalysis
M. Yurdakul	2004	MTS	AHP&ANP
A. Samvedi et al	2012	MTS	FuzzyAHP&GRA
O. Duran, J. Aguilo	2008	MTS	FuzzyAHP
M. Dagdeviren	2008	E.Sel	AHP&PROMETHEE
V. Paramasivam et al	2011	E.Sel	AHP&ANP
M. T. Tabucanon et al	1994	MTS	AHP&ES
Yusuf Tansel Ic et al	2012	MTS	AHP
Y.T. Ic, M. Yurdakul	2009	MTS	FuzzyAHP&FuzzyTOPSIS
ZC. Lin, CB. Yang	1996	MTS	AHP
M. R. Abdi	2009	MTS	FuzzyAHP&sensitivity
Jiyang Qi	2010	MTS	FuzzyAHP

Notation

FMS: **F**lexible **M**anufacturing **S**ystem

FMC: **F**lexible **M**anufacturing **C**ell

GP : **G**oal **P**rogramming.

ANP: **A**nalytic **N**etwork **P**rocess

AHP: **A**nalytic **H**ierarchy **P**rocess

ES : **E**xpert **S**ystem.

TOPSIS: **T**echnique for **O**rder **P**reference by **S**imilarity to **I**deal **S**olution

PROMETHEE: **P**reference **R**anking **O**rganization **METH**od for **E**nrich **E**valuation

MTS: **M**achine **T**ool **S**election

E.Sel: **E**quipment **Sel**ection

ANN: **A**rtificial **N**eural **N**etworks.

GRA: **G**rey **R**elational **A**nalysis.

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