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ORIGINAL ARTICLE

A fuzzy AHP–ANN-based decision support system for machine tool selection in a flexible manufacturing cell

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Abstract In respond to new market requirements and competitive positioning of manufacturing companies and in order to provide cost effective, high performance products, there is a need for reconfigurable manufacturing systems with a view of introducing new manufacturing technologies. However one of the problems faced is how to select the alternative machines that are consistent with manufacturing goals. In this paper a decision support system is presented for machine tool selection in flexible manufacturing cell using fuzzy analytic hierarchy process (fuzzy AHP) and artificial neural network. A program is developed in the model to find the Priority weights of the Evaluation Criteria and Alternative's Ranking called PECAR for fuzzy AHP model. The artificial neural network (ANN) is used to verify the results of fuzzy AHP (PECAR program) and to predict the alternatives' ranking. A feed forward back propagation ANN is designed and trained using the results from the program. A numerical example to select the most suitable CNC machine based on data collected from a designed questionnaire is given to demonstrate the applicability of the proposed model. The result of neural net simulation is compared with the results from fuzzy AHP model. It is concluded that the proposed decision support system by combining the fuzzy AHP and ANN models can be used as a powerful tool to select the most suitable alternative machines to form the structure of a flexible manufacturing cell.

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Keywords Machine selection · Decision Support System · Flexible Manufacturing Cell · Fuzzy AHP · Artificial Neural Network

1 Introduction

Machine tool selection is an important decision-making process for many manufacturing companies. Improperly selected machines can negatively affect the overall performance of a production system. The speed, quality, and cost of manufacturing strongly depend on the type of the machine tool used. Thus, selecting the most suitable machine from an increasing number of available machines can be highly demanding [1].

One of the most important developments in factory automation is through the implementation of flexible manufacturing systems (FMS). This involves the complete manufacturing activity from the head office to the shop floor. The shop floor is composed of flexible manufacturing cells (FMC) interconnected by material transportation devices. FMC may be considered the most significant development in small batch manufacturing. The setting-up and operating costs of FMC can be a major hindrance to their large-scale implementation and use, particularly by small- and medium-sized industries [2].

Flexible manufacturing cells have been used as a tool to implement flexible manufacturing processes to increase the competitiveness of manufacturing systems. FMC represent a class of highly automated systems. The increased importance of these highly automated manufacturing systems to the survival of modern industries has resulted in growing research efforts that address many issues inherent in flexible manufacturing. One of the key issues is the problem of machine selection in an FMC [3].

Researchers have used different approaches to select the most suitable alternative machine. For example, Moon et al.

[4] proposed an integrated machine tool selection and sequencing model based on genetic algorithm. A decision support system based on analytical algorithm was developed by Abdel-Malek and Resare [5] to select machining center and robot. Cimren et al. [6] proposed the analytic hierarchy process (AHP) as a decision support system for machine tool selection. Sun et al. [7] analyzed the art of machine selection and introduced the advantage of machine tool selection based on grey relation and AHP method. Dagdeviren [8] presented an integrated approach which employs AHP and preference ranking organization method for enrichment evaluation (PROMETHEE) for the equipment selection problem. Stam and Kuula [9] described the use of AHP to aid the decision maker in selecting the appropriate technology and design in planning of an FMS. A hybrid approach, which integrates AHP with simulation techniques, was proposed by Ayag [10] to determine the best machine tool.

Wang et al. [11] proposed a fuzzy multiple attribute decision making model and simulation to assist the decision maker to deal with machine selection problem for an FMC. A decision support system was developed by Tansel Ic and Yurdakul [12] to help the decision makers in their machining center selection using fuzzy AHP and fuzzy technique for order preference by similarity to ideal solution (fuzzy TOPSIS). A fuzzy TOPSIS-based methodology was described by Onut et al. [13] for the evaluation and selection of vertical CNC machining centers for a manufacturing company. Yurdakul and Tansel Ic [14] used fuzzy TOPSIS as a multicriteria decision making approach to rank the machine tools. An intelligent approach to machine tool selection problem through fuzzy analytic process (ANP) was proposed by Ayag and Ozdemir [15]. Chtourou et al. [16] presented the development of a prototype expert system for machine selection of manufacturing systems. Lin and Yang [17] presented the development of a model using AHP for the selection of the most suitable machine using the expert system concept. Mishra et al. [18] adopted a fuzzy goal programming model of the machine tool selection and operation allocation in FMS. A fuzzy goal programming approach was presented by Chan and Swarnkar [19] to model the machine tool selection and operation allocation problem in FMS. Rai et al. [20] applied a fuzzy goal programming model using genetic algorithm to model the problem of machine tool selection and operation allocation in FMS. Alberti et al. [21] presented a decision support system for high speed milling machine tool selection using artificial neural network.

Recent research has shown that the application of artificial neural network techniques in decision making domain is very promising. ANN achieved good results in evaluating and ranking alternatives [22]. ANN has been used in many applications and research area. One of the important benefits of using ANN is the ability of generalizing variables which are obtained from a real world problem [23].

In this paper, a decision support system is developed by an artificial intelligence approach namely fuzzy—integrated with AHP and artificial neural network to select the best alternative machine. A fuzzy AHP program called PECAR is developed using MATLAB to determine the priority weights of the evaluating criteria and ranking the alternatives. A supervised artificial neural network using feed-forward back propagation algorithm is then trained using the results from the PECAR program. The program allows the decision makers to apply different scenarios by changing the input parameters and observing the results in a simple and easy way to a point that they satisfied with the selected machine which meet the manufacturing objectives.

The machine selection problem in this article has been modeled using fuzzy AHP method to cater qualitative and uncertain parameters. Decision makers' judgments are used in the selection process, and their judgments become a single value by applying methods like geometric means. However, the decision making team can decide to use this value or select a desired value among the judgments based on the manufacturing goals set by the team in selecting an alternative machine. The proposed model is combined with ANN model, firstly, to verify the results of fuzzy AHP method, and once the model is trained, it can be capable of predicting the most suitable alternative machine either with a single or group decision maker saving time and effort for the new decision making process. By this, it can be possible to overcome the difficulties that may result from establishing decision making groups. Furthermore, the trained ANN can be used to select any type of machine required for the FMC structure, unless the proposed fuzzy AHP structure remains unchanged.

Due to the complexity and uncertainty of the decision process, such a proposed approach is required to support decision makers in selecting the appropriate machine tools among the increasing number of the existing alternatives introduced by the manufacturers to the market.

The proposed decision support system is structured to select the most suitable CNC turning center machine among the alternatives, which are assigned from the database created for this purpose, as a block building to form the structure of an FMC. A numerical example based on data collected by questionnaire is presented to demonstrate the applicability of the model. A comparison is made between the results from the fuzzy AHP model and the ANN model.

The integration of fuzzy AHP (PECAR program) and ANN for machine tool selection and by using the trained neural network to predict the alternatives' ranking in this paper is a significant contribution of the proposed approach in comparison to others in the literature.

The remainder of the paper is arranged as follows: Section 2 described the proposed model. The concept of fuzzy AHP

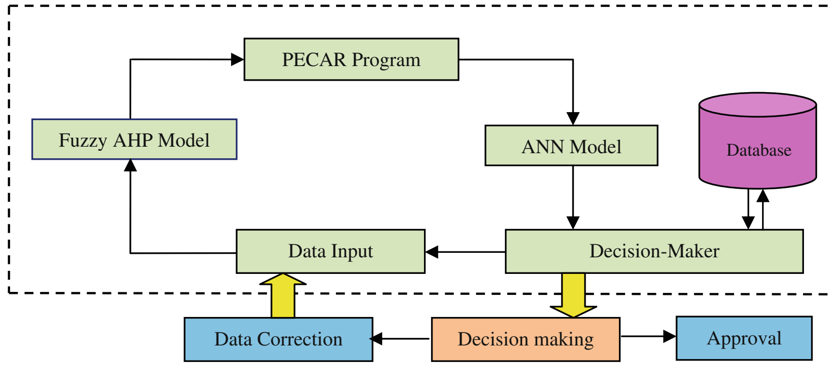


Fig. 1 Scheme of the proposed model

and ANN is introduced in Section 3. Section 4 contains a numerical example followed by discussion in Section 5, and conclusions are made in Section 6.

Table 1 Turning center machine specifications

Turning center	
1. Work envelope	
Main spindle	Operating type
	Turning diameter
	Turning length
	Maximum swing
	Std. chuck diameter
	Standard collect
	Bar capacity
	Spindle direction
2. Components	
Headstock spindle	Std. nose
	Std. bore
	Top RPM
	Index increment
	Horse power
	No. of headstock spindle
3. Tooling	
Carrier	No. of turning tools
	Square shank diameter
	Round shank diameter
	No. of rotary tools
	Live tool shank diameter
	Rotary HP
	Rotary RPM
	No. of carriers
4. Axes specification	
	No. of standard axes
	No. of optional axes
5. General	
	Machine weight
	Floor layout
	Mill/drill function

2 Fuzzy AHP–ANN model

2.1 Model structure

The structure of the proposed model is shown in Fig. 1. The required data are initially prepared and entered into the PECAR program. The criteria are then weighted, and the alternatives are ranked. The results are used to design, train, and after that to simulate the artificial neural network (ANN) model. The approval of these results and final decision is made by the decision maker (DM).

The basic accepted criteria (Table 1) in the model are extracted from reviewed literature and the interviews for the CNC experts. The hierarchy construction used in the model is shown in Fig. 2. The figure shows the hierarchy diagram of the main criteria and criteria used to select the machine tool. At the top level (Level 1), the goal of the model is defined which is to select the most suitable CNC machine tool for an FMC among the alternatives at the bottom level, assigned from a database created for this purpose. To achieve this objective, a number of main criteria (Level 2) and criteria (Level 3) are defined in the figure. Both Level 2 and 3 detail the specifications of CNC turning center machines. Assigning the main criteria and criteria for any particular machine selection problem is strongly dependent on the objectives of building the FMC and the manufacturing goals of the company.

2.2 PECAR program

To find the priority weights of the evaluation criteria and ranking the selected alternatives by the fuzzy AHP model, a program called PECAR is developed using MATLAB. Among the features of the program is the capability of using unlimited number of evaluation criteria and alternatives and can be used for individual decision making or team decision making. Also, it is time-saving and flexible. The program allows the decision maker to use various values of confidence level and index of optimism to

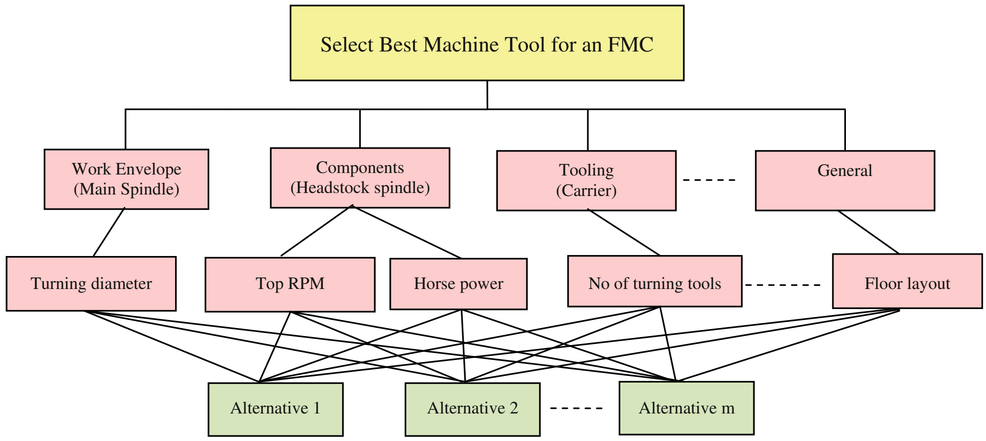


Fig. 2 Hierarchy structure

see their effects on the results. The program steps are structured as follows:

1. Data input—the following data are required from decision maker(s) to start the program:
   - The number of decision makers participating in the selection process
   - The preferred number of evaluation criteria (n)
   - The number of initially preferred alternatives (m) assigned from the created database
   - The value of confidence level (α) between the range [0, 1]
   - The value of index of optimism (λ) between the range [0, 1]
   - Inserting the decision makers' preference score of evaluation criteria using fuzzy numbers, individually for each participated decision maker to establish fuzzy comparison matrix for the criteria
   - Inserting the decision makers' comparison score of alternatives with respect to each criterion using fuzzy numbers, individually for each participated decision maker to establish fuzzy comparison matrices for the alternatives
2. Calculations:
   - Finding the lower limit and upper limit of fuzzy numbers with their reciprocals
   - Finding the α-cut matrices for criteria and alternatives
   - Normalizing the produced matrices from the previous step
   - Calculating the maximum eigen value (λmax)
   - Calculating the consistency index (CI) for each matrix
   - Finding the matrix random index (RI)
   - Calculating and checking the consistency ratio for each matrix
3. Outputs:
   - Criteria weights for each decision-maker participated in the decision making process
   - Alternatives' weights for each participated decision maker

2.3 Database

A database (DB) of 118 CNC turning center machine was created using Microsoft Excel and incorporating real data from machine tool sales organization [24–27]. The structure is as shown in Table 1.

The DB can be updated as new technologies of CNC machines are introduced to the market. However, some machine specifications, like cost, cannot be easily provided and updated due to manufacturers' policies for providing the machine price only upon purchasing and not for research purposes.

3 The concepts of fuzzy AHP and ANN models

3.1 Fuzzy AHP

In the conventional AHP method first developed by Saaty [28], pairwise comparisons for each level with respect to the goal of the best alternative selection are conducted using a nine-point scale.

Due to the vagueness and uncertainty on judgments of decision makers, crisp pairwise comparison in the conventional AHP seems insufficient and too imprecise to capture the decision makers' judgments correctly. Therefore, fuzzy logic is introduced into the pairwise comparison of the AHP to compensate for this deficiency in the conventional AHP, and the technique is called fuzzy AHP. The key idea of fuzzy set theory is that an element has a degree of membership in a fuzzy set which is defined by a membership function. The most commonly used range for expressing the degree of membership function is the unit interval [0, 1]. A fuzzy set contains elements that have different degrees of membership in it [29].

Different types of fuzzy membership functions have been used in fuzzy logic. However, three types are most common: monotonic, triangular, and trapezoidal. Because the fuzzy set is a convex function, the trapezoidal function or triangular function approaches the convex function well [30].

The triangular fuzzy numbers are more convenient in applications due to their computational simplicity, and they are useful in promoting representation and information processing in a fuzzy environment [31].

The characteristics and membership function of the triangular fuzzy number $\mu_{\tilde{A}}(x) = (\ell, m, u)$ are expressed by Eq. 1 [32]:

$$\mu_{\tilde{A}}(x) = \begin{cases} (x-\ell)/(m-\ell), & \ell \le x \le m \\ (u-x)/(u-m), & m \le x \le u \\ 0, & \text{Otherwise} \end{cases} \tag{1}$$

By introducing the α-cut and defining the interval of confidence at confidence level α, the triangular fuzzy number can be characterized as [30]:

$$\forall\, \alpha \in [0,1]$$

$$\tilde{A}_\alpha = [\ell_\alpha, u_\alpha] = [(m-\ell)\,\alpha + \ell,\ u - (u-m)\,\alpha] \tag{2}$$

The α-cut is known to incorporate the experts or decision maker(s) confidence over his/her preference or the judgments.

The AHP method can be considered in terms of an eigenvector method in which the eigenvector corresponding to the largest eigenvalue of the pairwise comparisons matrix provides the relative priorities of the factors. The fuzzy eigenvector is solved by using the triangular fuzzy number and interval arithmetic as follows:

1. The crisp numbers are replaced by triangular fuzzy numbers, to indicate the relative strength of the elements in the judgment matrix as:

$$\widetilde{A} = \begin{bmatrix} 1 & \widetilde{a}_{12} & \dots & \dots & \widetilde{a}_{1n} \\ \widetilde{a}_{21} & 1 & \dots & \dots & \widetilde{a}_{2n} \\ . & . & \dots & \dots & . \\ . & . & & & . \\ . & . & \dots & \dots & . \\ \widetilde{a}_{n1} & \widetilde{a}_{n2} & \dots & \dots & 1 \end{bmatrix} \tag{3}$$

where

$$\widetilde{a}_{ij} = \begin{cases} \widetilde{1},\ \widetilde{3},\ \widetilde{5},\ \widetilde{7},\ \widetilde{9} & i > j \\ 1, & i = j \\ \widetilde{1}^{-1},\ \widetilde{3}^{-1},\ \widetilde{5}^{-1},\ \widetilde{7}^{-1},\ \widetilde{9}^{-1}, & i < j\} \end{cases} \tag{4}$$

2. A fuzzy eigenvalue $\widetilde{\lambda}$ is a fuzzy number solution to:

$$\widetilde{A}\,\widetilde{x} = \widetilde{\lambda}\,\widetilde{x} \tag{5}$$

$\widetilde{A}$ is a n-by-n fuzzy matrix and $i\,\widetilde{x}$ is a nonzero n-by-1 fuzzy eigenvector containing the fuzzy numbers. Fuzzy arithmetic is used for all the operations.

3. Fuzzy multiplication and addition are performed by using interval arithmetic and α-cuts. For all $0<\alpha\le 1$ and all i, j, the equations are:

$$\tilde{a}^{\alpha}_{ij} = [\tilde{a}^{\alpha}_{ij\ell},\ \tilde{a}^{\alpha}_{iju}] \tag{6}$$

$$\tilde{x}_{\alpha i} = [\tilde{x}^{\alpha}_{i\ell},\ \tilde{x}^{\alpha}_{iu}] \tag{7}$$

$$\tilde{a}^{\alpha}_{i1\ell}\ x^{\alpha}_{i\ell} + \ldots\ldots + \tilde{a}^{\alpha}_{in\ell}\ x^{\alpha}_{n\ell\ell} = \lambda\ x^{\alpha}_{i\ell} \tag{8}$$

$$\tilde{a}^{\alpha}_{i1u}\,x^{\alpha}_{iu} + \ldots\ldots + \tilde{a}^{\alpha}_{inu}\,x^{\alpha}_{nu} = \lambda\,x^{\alpha}_{iu} \tag{9}$$

4. The degree of satisfaction can be estimated from the decision maker by index of optimism λ, where its value range is 0<λ<1. The larger the index λ, the higher the degree of satisfaction:

$$\tilde{a}^{\alpha}_{ij} = \lambda\ a^{\alpha}_{iju} + (1-\lambda)\ a^{\alpha}_{ij\ell}\ \ ,\ \forall\ \lambda \in [0,1] \tag{10}$$

5. The matrix $\widetilde{A}$ is reconstructed by using the $\widetilde{a}^{\alpha}_{ij}$ equation above, and the degree of satisfaction can be estimated setting the index of optimism λ and fixing α. Therefore:

$$\widetilde{A} = \begin{bmatrix} 1 & \widetilde{a}^{\alpha}_{12} & \dots & \dots & \widetilde{a}^{\alpha}_{1n} \\ \widetilde{a}^{\alpha}_{21} & 1 & \dots & \dots & \widetilde{a}^{\alpha}_{2n} \\ . & . & \dots & \dots & . \\ . & . & \dots & \dots & . \\ \widetilde{a}^{\alpha}_{n1} & \widetilde{a}^{\alpha}_{n2} & \dots & \dots & 1 \end{bmatrix} \tag{11}$$

The five triangular fuzzy numbers and their reciprocal scale are defined with the corresponding membership function as shown in Table 2 [33]. The lower limit (ℓ) and upper limit (u) of the fuzzy numbers with respect to α are defined by the following [34]:

$$\left.\begin{array}{l} \widetilde{1}^{\alpha} = [1, 3-2\alpha] \\ \widetilde{3}^{\alpha} = [1+2\alpha, 5-2\alpha],\quad \widetilde{3}^{\alpha-1} = [1/5-2\alpha, 1/1+2\alpha] \\ \widetilde{5}^{\alpha} = [3+2\alpha, 7-2\alpha],\quad \widetilde{5}^{\alpha-1} = [1/7-2\alpha, 1/3+2\alpha] \\ \widetilde{7}^{\alpha} = [5+2\alpha, 9-2\alpha],\quad \widetilde{7}^{\alpha-1} = [1/9-2\alpha, 1/5+2\alpha] \\ \widetilde{9}^{\alpha} = [7+2\alpha, 11-2\alpha],\quad \widetilde{9}^{\alpha-1} = [1/11-2\alpha, 1/7+2\alpha] \end{array}\right\} \tag{12}$$

Table 2 Definition and membership functions of fuzzy numbers

Fuzzy number	Definition	Membership function	Reciprocal scale
$\widetilde{1}$	Equally important	(1,1,2)	(1/2,1,1)
$\widetilde{3}$	Moderately important	(2,3,4)	(1/4,1/3,1/2)
$\widetilde{5}$	Strongly important	(4,5,6)	(1/6,1/5,1/4)
$\widetilde{7}$	Very strongly important	(6,7,8)	(1/8,1/7,1/6)
$\widetilde{9}$	Extremely important	(8,9,10)	(1/10,1/9,1/8)
$\widetilde{2}, \widetilde{4}, \widetilde{6}, \widetilde{8}$	Intermediate values		

6. Calculating the overall priority weight for each alternative (AW) by multiplying the vector of criteria weight (CW) by the matrix of alternative evaluation weights (AEW) using the equation below:

$$AW_k = \sum_{i=1}^{n} CW_i \times AEW_{ik} \tag{13}$$

where n=number of criteria, m=number of alternatives, and k=1, 2,…, m.

In order to identify the consistency ratio of a matrix, first, the matrix consistency index (CI) is found by:

$$CI = (\lambda_{max} - n)/(n-1) \tag{14}$$

The consistency index of a randomly generated reciprocal matrix with reciprocal forces is called the random index (RI) and is calculated using the matrix order (n) and the table explained by Saaty [28].

So, the matrix consistency ratio (CR) is calculated using:

$$CR = CI/RI \tag{15}$$

A consistency ratio of 0.1 or less is considered acceptable.

3.2 ANN

Neural networks attempt to model human intuition by simulating the physical process upon which intuition is based, that is, by simulating the process of adaptive biological learning. It learns through experience, and is able to continue learning as the problem environment changes [35]. ANN operates by simulating the ability of biological neural systems to perform complex decision making tasks [36].

ANNs can be classified into two major categories: supervised and unsupervised ANNs. In supervised ANNs, there is usually a decision maker who can provide some feedback in terms of evaluating the given set of training patterns, while the unsupervised ANNs do not require the external evaluator [37]. Supervised learning systems are generally more flexible in the design of hidden layers [38].

ANN architecture is generally described as an arrangement of interconnected nodes organized into three groups input, hidden, and output. The most commonly used approach to ANN learning is the feed-forward back propagation algorithm. The parameters of the model such as the choice of input nodes, number of hidden layers, number of hidden nodes (in each hidden layer), and the form of transfer functions are problem-dependent and often require trial and error to find the best model for a particular application [39].

There is no exact rule to decide the number of the hidden layers. There are four methods of selecting the number of hidden nodes (NHN) [22, 23]. The four methods are dependent on: the number of input nodes (IN), the number of output nodes (ON), and the number of samples (SN):

$$NHN1 = (IN \text{ x } ON)^{1/2} \tag{16}$$

$$NHN2 = \frac{1}{2}(IN + ON) \tag{17}$$

$$NHN3 = \frac{1}{2}(IN + ON) + (SN)^{1/2} \tag{18}$$

$$NHN4 = 2(IN) \tag{19}$$

In this paper, a supervised feed forward back propagation ANN is designed, and values from the fuzzy AHP model (PECAR program), where the priority weights of criteria and alternatives are determined, are then used in training stage. The designed ANN consists of three layers: an input layer, a hidden layer, and an output layer. In the designed stage, the input–output sets for all participated decision makers are prepared where the priority weights of the evaluation criteria are used for input values and the priority weights of the alternatives are used as target (output) values.

As for the number of the hidden nodes in the hidden layer, Eqs. 16–19 are used to find out the number and design different network models for training.

The prepared input–output sets mentioned above are then split into two parts: part one is used for training the neural network and the second part, where they are not used in training stage, is used to test the ANN model.

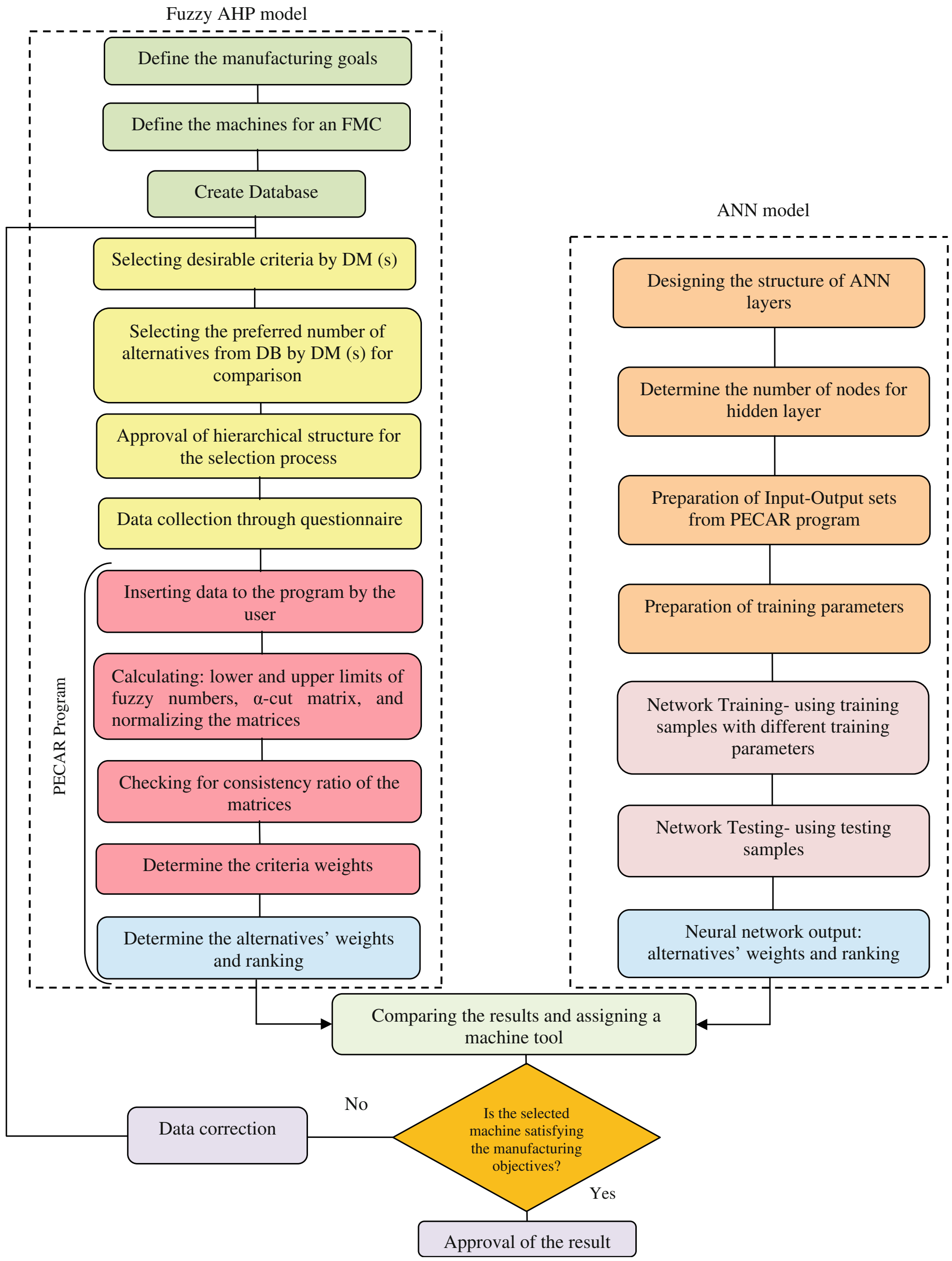
In the training stage, the model is trained with different training parameters of epoch, learning rate, and momentum coefficient and different activation functions. Then, the different models are tested, and the outputs from the network simulation will be the alternatives' weights and ranking for each participated decision maker.

Results from the ANN model are then compared with fuzzy AHP model.

In the proposed model, the ANN model is used to verify the results of the fuzzy AHP model and to predict the alternatives ranking. On the other hand, once the neural network is trained, it can be used to predict the alternatives ranking with any input–output set of judgments from decision maker(s).

The flowchart of the proposed model is shown in Fig. 3. The figure shows a two-stage model for machine tool selection. In stage one, the fuzzy AHP is applied using the developed PECAR program to find out the criteria weights and the alternatives' weights and ranking, while in stage two, the ANN is applied using MATLAB 7.4 (R2007a) software.

Fig. 3 Flowchart of the proposed model



4 Numerical example

In this section, the decision support system of fuzzy AHP and ANN presented in this paper is demonstrated via a numerical example to prove the approach's applicability. Five experts on CNC machines participated in the selection process.

The initial steps performed by the experts in selecting the most suitable CNC turning machine are:

- assigning the evaluation criteria,
- selecting the alternative machines from the established database, and
- approval of the decision hierarchy.

There are a number of criteria as explained in Table 1, in order to select the most suitable machine tool among the available alternatives in the market. In this study, the selected criteria are extracted from literature and interviews for the CNC experts participated in the case study presented in this section. The experts have decided ten evaluation criteria based on their experiences. However,

Table 3 Input data

Evaluation criteria
Turning diameter (TD)
Turning length (TL)
Std. chuck diameter (SCD)
Bar capacity (BC)
Top rpm (RPM)
Horse power (HP)
No. of turning tools (NTT).
Std. number of axes (SNA)
Machine weight (MW)
Floor layout (FL)
Alternatives, CNC turning center machines (TCM): Doosan, Mazak, Nakamura, Romi
Number of participated decision makers
Confidence level: α=0.5 (default value)
Index of optimism: λ=0.5 (default value)

Table 4 Fuzzy comparison matrix for the criteria

	TD	TL	SCD	BC	RPM	HP	NTT	SNA	MW	FL
TD	1	$\tilde{3}$	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{7}^{\wedge}-1$	$\tilde{7}^{\wedge}-1$
TL	$\tilde{3}^{\wedge}-1$	1	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{7}^{\wedge}-1$	$\tilde{7}^{\wedge}-1$
SCD	$\tilde{3}$	$\tilde{3}$	1	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{7}^{\wedge}-1$
BC	$\tilde{5}$	$\tilde{5}$	$\tilde{3}$	1	$\tilde{3}$	$\tilde{1}$	$\tilde{5}$	$\tilde{1}$	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$
RPM	$\tilde{3}$	$\tilde{3}$	$\tilde{3}$	$\tilde{3}^{\wedge}-1$	1	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{7}^{\wedge}-1$
HP	$\tilde{5}$	$\tilde{5}$	$\tilde{3}$	$\tilde{3}^{\wedge}-1$	$\tilde{3}$	1	$\tilde{5}$	$\tilde{1}$	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$
NTT	$\tilde{3}$	$\tilde{5}$	$\tilde{3}$	$\tilde{3}^{\wedge}-1$	$\tilde{3}$	$\tilde{3}^{\wedge}-1$	1	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$
SNA	$\tilde{5}$	$\tilde{5}$	$\tilde{3}$	$\tilde{3}^{\wedge}-1$	$\tilde{3}$	$\tilde{1}^{\wedge}-1$	$\tilde{5}$	$\tilde{1}$	$\tilde{3}^{\wedge}-1$	$\tilde{3}^{\wedge}-1$
MW	$\tilde{7}$	$\tilde{7}$	$\tilde{5}$	$\tilde{3}$	$\tilde{5}$	$\tilde{3}$	$\tilde{5}$	$\tilde{3}$	1	$\tilde{3}^{\wedge}-1$
FL	$\tilde{7}$	$\tilde{7}$	$\tilde{7}$	$\tilde{3}$	$\tilde{7}$	$\tilde{3}$	$\tilde{5}$	$\tilde{3}$	$\tilde{3}$	1

Table 5 Fuzzy comparison matrix for the alternatives with respect to the first criteria—turning diameter (TD)

TD	Nakamura	Mazak	Romi	Doosan
Nakamura	1	$\tilde{7}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$	$\tilde{5}^{\wedge}-1$
Mazak	$\tilde{7}$	1	$\tilde{5}$	$\tilde{3}$
Romi	$\tilde{5}$	$\tilde{5}^{\wedge}-1$	1	$\tilde{1}^{\wedge}-1$
Doosan	$\tilde{5}$	$\tilde{3}^{\wedge}-1$	$\tilde{1}$	1

Table 6 α-Cut matrix for the criteria

	TD	TL	SCD	BC	RPM	HP	NTT	SNA	MW	FL
TD	1.0000	3.0000	0.3750	0.2083	0.3750	0.2083	0.3750	0.2083	0.1458	0.1458
TL	0.3750	1.0000	0.3750	0.2083	0.3750	0.2083	0.2083	0.2083	0.1458	0.1458
SCD	3.0000	3.0000	1.0000	0.3750	0.3750	0.3750	0.3750	0.3750	0.2083	0.1458
BC	5.0000	5.0000	3.0000	1.0000	3.0000	1.5000	3.0000	1.5000	0.3750	0.3750
RPM	3.0000	3.0000	3.0000	0.3750	1.0000	0.3750	0.3750	0.3750	0.2083	0.1458
HP	5.0000	5.0000	3.0000	0.7500	3.0000	1.0000	3.0000	1.5000	0.3750	0.3750
NTT	3.0000	5.0000	3.0000	0.3750	3.0000	0.3750	1.0000	0.3750	0.3750	0.2083
SNA	5.0000	5.0000	3.0000	0.7500	3.0000	0.7500	3.0000	1.0000	0.3750	0.3750
MW	7.0000	7.0000	5.0000	3.0000	5.0000	3.0000	3.0000	3.0000	1.0000	0.3750
FL	7.0000	7.0000	7.0000	3.0000	7.0000	3.0000	5.0000	3.0000	3.0000	1.0000

Table 7 α-Cut matrix for the alternatives

(TD)	Nakamura	Mazak	Romi	Doosan
Nakamura	1.0000	0.1458	0.2083	0.2083
Mazak	7.0000	1.0000	5.0000	3.0000
Romi	5.0000	0.2083	1.0000	0.7500
Doosan	5.0000	0.3750	1.5000	1.0000

Table 8 Normalized matrix for the criteria

	TD	TL	SCD	BC	RPM	HP	NTT	SNA	MW	FL
TD	0.0254	0.0682	0.0130	0.0207	0.0144	0.0193	0.0194	0.0181	0.0235	0.0443
TL	0.0095	0.0227	0.0130	0.0207	0.0144	0.0193	0.0108	0.0181	0.0235	0.0443
SCD	0.0762	0.0682	0.0348	0.0373	0.0144	0.0347	0.0194	0.0325	0.0336	0.0443
BC	0.1270	0.1136	0.1043	0.0996	0.1148	0.1390	0.1552	0.1300	0.0604	0.1139
RPM	0.0762	0.0682	0.1043	0.0373	0.0383	0.0347	0.0194	0.0325	0.0336	0.0443
HP	0.1270	0.1136	0.1043	0.0747	0.1148	0.0927	0.1552	0.1300	0.0604	0.1139
NTT	0.0762	0.1136	0.1043	0.0373	0.1148	0.0347	0.0517	0.0325	0.0604	0.0633
SNA	0.1270	0.1136	0.1043	0.0747	0.1148	0.0695	0.1552	0.0866	0.0604	0.1139
MW	0.1778	0.1591	0.1739	0.2988	0.1914	0.2780	0.1552	0.2599	0.1611	0.1139
FL	0.1778	0.1591	0.2435	0.2988	0.2679	0.2780	0.2586	0.2599	0.4832	0.3038

Table 9 Normalized matrix for the alternatives

(TD)	Nakamura	Mazak	Romi	Doosan
Nakamura	0.0556	0.0843	0.0270	0.0420
Mazak	0.3889	0.5783	0.6486	0.6050
Romi	0.2778	0.1205	0.1297	0.1513
Doosan	0.2778	0.2169	0.1946	0.2017

Table 10 Criteria weight for the first decision maker's judgment

TD	TL	SCD	BC	RPM	HP	NTT	SNA	MW	FL
0.0266	0.0196	0.0395	0.1158	0.0489	0.1087	0.0689	0.1020	0.1969	0.2731

CR=0.0885<0.1, acceptable

the proposed model is not restricted to those criteria only. It can be used for others and for unlimited number of criteria as long as meets company goals for purchasing a machine tool.

A questionnaire based on the proposed hierarchy structure was formulated using fuzzy numbers. The next step for the decision makers are:

- assigning the preference score for the evaluation criteria, and
- comparing the alternatives with respect to each evaluation criterion.

After the data have been collected from the decision makers, 55 matrices for the evaluation criteria and the alternatives' comparisons are built.

The priority weights of the selected criteria and the weights and ranking of the alternatives based on fuzzy AHP model are determined using the PECAR program as follows:

Step 1. Preparing the input data to PECAR program (Table 3)

Step 2. Replacing the crisp numbers given by the decision makers by triangular fuzzy numbers. To simplify the application procedure of the proposed approach, the first decision maker's preference scores are presented. The established fuzzy comparison matrices for the evaluation criteria and the alternatives are shown in Tables 4 and 5, respectively.

Step 3. Reconstructing the fuzzy comparison matrices and introducing the α-cut matrix by applying Eqs. 10 and 12. The resulting matrices are generated by the PECAR program as shown in Tables 6 and 7.

Step 4. Normalizing the matrices from the step (3) and finding the criteria weights and alternatives' weights by finding the column vector (eigen vector). The resulting matrices are shown in Tables 8 and 9.

Step 5. The criteria weights and alternatives' weights for the first decision maker are shown in Tables 10 and 11.

Step 6. Repeating the steps from (1) to (5) for the remaining decision makers (number 2 to number 5). The final results for the alternatives weights and ranking for the five decision makers are shown in Table 12.

Table 11 Alternatives weight for the first decision maker's judgments with respect to the first criteria

Nakamura	Mazak	Romi	Doosan
0.0522	0.5552	0.1698	0.2227

CR=0.0883<0.1, acceptable

The results from the fuzzy AHP model are used to design and train the proposed ANN model. The next steps are to find the alternatives weights and ranking using the ANN model as follows:

Step 1. The priority weights of 10 criteria are used for input values of the ANN model, and the priority weights of the 4 alternatives are used as a target.

Step 2. Designing the model using feed-forward back propagation algorithm with different number of hidden nodes, seven (7), ten (10), and twenty (20), extracted by using Eqs. 16–19.

Step 3. Training the model with different training parameters of epoch, learning rate, and momentum coefficient using different activation functions (Table 13). The mean square error (MSE) value is used as the stop criteria.

Step 4. Testing the model by using four samples for training and one sample for testing. Table 14 shows the outputs from the network simulation for the best three models.

Table 12 Alternatives' weights and ranking for all decision makers

	Alternatives			
	Nakamura	Mazak	Romi	Doosan
DM 1	0.3562	0.2493	0.1765	0.2180
DM 2	0.3003	0.3464	0.2384	0.1149
DM 3	0.1680	0.1398	0.2483	0.4439
DM 4	0.3823	0.2462	0.1639	0.2075
DM 5	0.4326	0.2170	0.1364	0.2141
Overall weight	0.3278	0.2397	0.1927	0.2396
Ranking	(1)	(2)	(4)	(3)

Table 13 ANN model parameters

	Input Nodes	Hidden Nodes	Output Nodes	Training Function	Transfer Function	Learning Rate	Momentum Coefficient	Epochs	Performance
Net 1									
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	500	0.00299097
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	700	0.00181654
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	900	0.00153206
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	1,000	0.00144041
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	1,200	0.00128544
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	1,400	0.00115173
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	1,600	0.00103381
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	1,800	0.00092932
	10	7	4	TRAINGDM	TANSIG	0.08	0.12	2,000	0.000836605
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	500	0.0591698
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	700	0.0566604
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	900	0.0559833
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	1,000	0.0557935
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	1,200	0.0554875
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	1,400	0.0552199
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	1,600	0.0549691
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	1,800	0.0547277
	10	7	4	TRAINGDM	SEGMOID	0.08	0.12	2,000	0.0544926
Net 2									
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	500	0.01931560
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	700	0.01604010
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	900	0.01085440
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	1,000	0.00716578
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	1,200	0.00286233
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	1,400	0.00184469
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	1,600	0.00144726
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	1,800	0.00119344
	10	10	4	TRAINGDM	TANSIG	0.08	0.12	2,000	0.00100192
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	500	0.1040790
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	700	0.0823511
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	900	0.0640950
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	1,000	0.0574991
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	1,200	0.0486394
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	1,400	0.0420318
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	1,600	0.0373017
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	1,800	0.0338974
	10	10	4	TRAINGDM	SEGMOID	0.08	0.12	2,000	0.0311363
Net 3									
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	500	0.001434200
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	700	0.000317409
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	900	7.35832E−005
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	1,000	3.597E−005
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	1,200	8.84475E−006
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	1,400	2.25537E−006
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	1,600	5.94434E−007
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	1,800	1.6118E−007
	10	20	4	TRAINGDM	TANSIG	0.08	0.12	2,000	4.47221E−008

Table 13 (continued)

Input Nodes	Hidden Nodes	Output Nodes	Training Function	Transfer Function	Learning Rate	Momentum Coefficient	Epochs	Performance
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	500	0.0204383
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	700	0.0192826
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	900	0.0185244
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	1,000	0.0182481
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	1,200	0.0178252
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	1,400	0.0175074
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	1,600	0.0172463
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	1,800	0.0170168
10	20	4	TRAINGDM	SEGMOID	0.08	0.12	2,000	0.0168055

From Table 13, it is clear that the best performance for each of the used models has been achieved with the TANSIG transfer function (Figs. 4, 5, and 6).

The comparison of the outputs from the fuzzy AHP model (Table 12) and from the ANN model (Table 14) is made, and the result is shown in Table 15.

From the table, one can obviously observe that the ranking of the alternatives for both fuzzy AHP model and ANN model are the same, starting with Nakamura the first alternative, followed by Mazak and Doosan, and lastly Romi.

The performance of the combined fuzzy AHP–ANN approach is compared with using fuzzy AHP and ANN alone as shown in Table 16. It can be seen from the table that the results for applying ANN alone are clearly differed in both weighting and ranking. Here, Mazak is the first alternative followed by Nakamura and Doosan where almost they have the same weight, and it is difficult to decide to choose one of them, and the last alternative is Romi.

These results clearly show the accuracy and power of the proposed fuzzy AHP which is based on the developed PECAR program and the ANN model. So, the proposed decision support system by combining the fuzzy AHP and ANN in this work can be used as an active tool to select the most suitable alternative machines.

5 Discussion

The selection of a most desirable machine tool to be consistent with the manufacturing goals is a multicriteria decision making problem and needs objectivity judgments from experts. In view of this, a multicriteria decision support system to cater qualitative and uncertain parameter is required.

The benefit of computer-based systems is to facilitate the selection process in terms of effort and time-saving for decision makers.

In this study, a hybrid approach utilizing the fuzzy logic and artificial neural network was presented for solving machine tool selection in an FMC. In the fuzzy AHP model, the fuzzy logic is introduced to the pairwise comparisons of the AHP to capture the decision-maker judgments correctly using PECAR program. The computerized model is fast in application and allows the user to vary the input parameters to show their effects on the results. Furthermore, it can be used for group decision making or single decision maker.

The model performance highly depends on the experts' experience in selecting the evaluation criteria and assigning the preferred number of alternatives from the database. Therefore, the managements are in need to be careful in assigning the decision makers for the selection

Table 14 Network simulation results from ANN model

Alternative weight				Network model	Transfer function	Epochs	Performance
Nakamura	Mazak	Romi	Doosan				
0.35486	0.24887	0.17593	0.21734	10-7-4	TANSIG	2,000	0.000836605
0.38871	0.2615	0.17724	0.21136	10-10-4	TANSIG	2,000	0.00100192
0.35633	0.24922	0.17644	0.21791	10-20-4	TANSIG	2,000	4.47221E−008

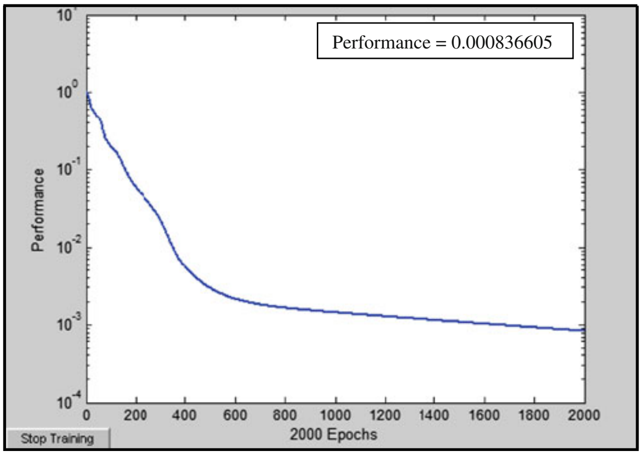


Fig. 4 Performance curve for (10-7-4) model

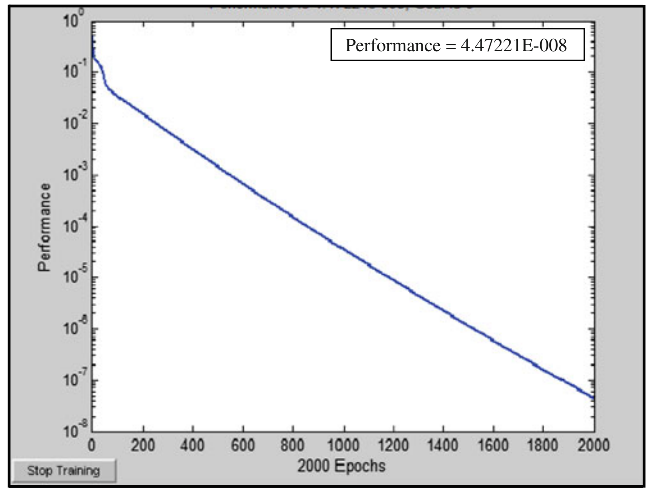


Fig. 6 Performance curve for (10-20-4) model

process. On the other hand, updating the database as new technologies introduced to the markets is another valuable source to increase the model's performance.

In this study, the fuzzy model was verified and compared with a developed ANN model. As the number of training data samples is increased, the ANN model can train faster and learn the selection problem very well. It seems from the comparison of outputs for ANN model and the output desired that the network is learnt.

Furthermore, once the network is trained, it can be used for predicting alternatives weights by either team decision making or single decision maker saving time and effort for the new decision making process.

6 Conclusions

This paper proposed a decision support system to select the most suitable alternative machines to achieve manufacturing objectives for companies that are planning to build a flexible manufacturing cell using fuzzy AHP and ANN.

The vagueness and uncertainty on judgments of decision makers in the conventional AHP are solved in the model by introducing fuzzy logic to the pairwise comparison of the AHP.

A user-friendly PECAR program is developed in the model which gives flexibility, easiness, and time- and effort-saving for the selection process. The program is used to find the priority weights of the selected criteria and assigned alternatives. It has the capability for using unlimited number of the criteria and the ability to change the values of confidence level and index of optimism to show their effects on the criteria weights providing a clear view to decision maker on criteria judgments and alternatives' ranking.

From the comparison between the fuzzy AHP results and the predicted results by the ANN model, it appears that the proposed decision support system is able to select the most appropriate machine tool.

In summary, the proposed DSS can be used as a powerful system for machine tool selection, and it is not

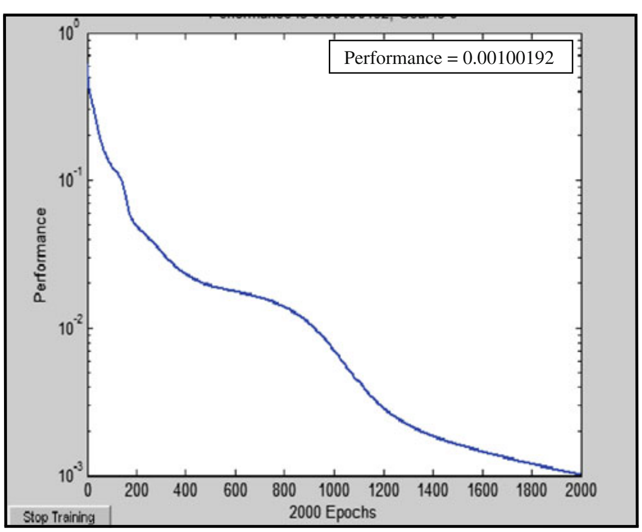


Fig. 5 Performance curve for (10-10-4) model

Table 15 Comparison between Fuzzy AHP and ANN models

	Alternative weight			
	Nakamura	Mazak	Romi	Doosan
Fuzzy AHP (desired)	0.35620	0.24930	0.17650	0.21800
Fuzzy AHP (overall weight)	0.32780	0.23970	0.19270	0.23960
ANN model (10-7-4)	0.35486	0.24887	0.17593	0.21734
ANN model (10-10-4)	0.38871	0.2615	0.17724	0.21136
ANN model (10-20-4)	0.35633	0.24922	0.17644	0.21791

Table 16 Comparison between combined fuzzy AHP–ANN, fuzzy AHP, and ANN methods

Machine alternative	Fuzzy AHP	ANN with fuzzy AHP	ANN without fuzzy AHP
Nakamura	0.35620 (1)	0.35633 (1)	0.25008 (2)
Mazak	0.24930 (2)	0.24922 (2)	0.29991 (1)
Doosan	0.21800 (3)	0.21791 (3)	0.24980 (3)
Romi	0.17650 (4)	0.17644 (4)	0.19996 (4)

limited to CNC turning center selection and can be applied to other type of machines of the FMC structure.

As a future research, the scope of this work can be expanded in different directions. One direction for example is to develop a fuzzy-based approach to select CNC machines and tool options and to allocate the operation of parts to the selected machine to achieve an optimal performance measure for an FMC. Another direction is that, by adopting fuzzy rules for obtaining the weight of each objective for a manufacturing system, the machine selection approach can be further improved. The mentioned directions are our ongoing research topics. Also, by combining the fuzzy logic and ANN, we would like to extend the future research direction to find out the optimal cutting speed and feed rate for the selected machines.

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