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A hybrid fuzzy AHP-PROMETHEE decision support system for machine tool selection in flexible manufacturing cell

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Abstract The selection process of a suitable machine tool among the increased number of alternatives has been an important issue for manufacturing companies for years. This is because the improper selection of a machine tool may cause many problems that will affect the overall performance. In this paper, a decision support system (DSS) is presented to select the best alternative machine using a hybrid approach of fuzzy analytic hierarchy process (fuzzy AHP) and preference ranking organization method for enrichment evaluation (PROMETHEE). A MATLAB- based fuzzy AHP is used to determine the weights of the criteria and it is called program for Priority Weights of the Evaluation Criteria (PWEC), and the PROMETHEE method is applied for the final ranking. The proposed model is structured to select the most suitable computer numerical controlled (CNC) turning centre machine for a flexible manufacturing cell (FMC) among the alternatives which are assigned from a database (DB) created for this purpose. A numerical example is presented to show the applicability of the model. It is concluded that the proposed model has the capability of dealing with a wide range of desired criteria and to select any type of machine tool required for building an FMC.

Keywords Machine selection · Decision-making · CNC machines · FMC · Fuzzy AHP · PROMETHEE

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Introduction

In response to new market requirements and competitive positioning 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.

Flexible manufacturing cells (FMCs) 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 the many issues inherent in flexible manufacturing. One of the key issues is the problem of machine selection in an FMC (Venkata Rao 2007).

The selection of a suitable machine tool among the alternatives is a multiple criteria decision making (MCDM) problem (Ayag and Ozdemir 2006) and the analytic hierarchy process (AHP) method developed by Saaty (1980) has been widely used in this area. Zahedi (1986) reviewed the AHP method and its applications in decision making problems referring to major extensions and criticisms of the method.

In the conventional AHP, the crisp pair-wise comparison seems insufficient and too imprecise to capture the decision-maker (DM) judgments correctly. Therefore, fuzzy logic is introduced into the pair-wise comparison of the AHP to compensate for this deficiency in the conventional AHP and the technique is called fuzzy AHP (Ayag 2005).

Fuzzy set theory is basically a theory of classes with unsharp boundaries. What is important to recognize is that any crisp theory can be fuzzified by generalizing the concept of a set within that theory to the concept of a fuzzy set (Zadeh 1994). The key idea of fuzzy set theory (Zadeh 1978) is that an element has a degree of membership in a fuzzy set which is defined by a membership function.

Recently several methods of MCDM have been proposed to select the best alternatives. The PROMETHEE method is one of them (Behzadian et al. 2010) which was developed by Brans and extended by Brans and Vincke (1985).

Time and effort saving as well as easiness and applicability of decision making models are important factors for decision-makers. Hence, taking into account these factors, the proposed decision support model in this paper can be applied to solve the decision making problem of machine tool selection. The application of fuzzy AHP alone is cumbersome with the increased number of evaluation criteria and entails lengthy and laborious pairwise comparisons for the alternatives with respect to each criterion. To solve this deficiency, the PROMETHEE method is integrated into the model. In this method, the criteria weights are controlled by providing a specific preference function with its thresholds for each criterion to take into account the constraints of selecting an alternative machine tool for an application. In PROMETHEE, the evaluation criteria can be classified into two types: cost nature and benefit nature by using min/max functions. The method with its tools, geometrical analysis for an interactive aid (GAIA) plane, walking weights, stability intervals, multiple comparisons and preference flows enables the decision-maker to control the process by using real data of the alternatives' characteristics in the evaluation table and changing the criteria weights to see their effects on the final ranking. A feedback of the weights found by using fuzzy AHP method and new weights found by applying if-what scenarios will be provided to the decision-maker to make a final decision to select an alternative which is consistent with the goal set by decision-maker.

In this paper, a decision support system (DSS) is presented to select the best alternative machine using a hybrid approach of MATLAB based-fuzzy analytic hierarchy process (fuzzy AHP) and PROMETHEE. The MATLAB based-fuzzy AHP is used to determine the weights of the criteria and it is called the Priority Weights of the Evaluation Criteria (PWEC) program, and the PROMETHEE method is used for the ranking of the alternatives. This is followed by a GAIA plane to identify conflicts between criteria and to group the alternatives, and a sensitivity analysis of if-what scenarios by changing the criteria weights. The proposed model is structured to select the best CNC turning centre machine among the alternatives, which are assigned from a database created for this purpose, as a block building to form the structure of an FMC. A numerical example is presented to show the applicability of the model.

The reminder of the paper is organized as follows: In the section "Literature review", the related literatures are reviewed. The proposed methodology is described in the section "Proposed model". In the section "Fundamental concepts of fuzzy AHP and PROMETHEE", the basics of the two methods are presented, followed by an illustrative example to demonstrate the applicability of the model. The section "Discussions and implications" clarifies the purpose of the study and how the problem is solved and discusses the results. Finally the last section is the "Conclusion".

Literature review

Machine tool selection has been a very important issue for manufacturing firms for years. This is because the improper selection of a machine tool can cause many problems affecting the overall performance and its responsive manufacturing capabilities. Researchers have used different approaches to select the most suitable alternative machine. For example, Cimren et al. (2007) proposed AHP as a decision support system (DSS) for machine tool selection using an effective algorithm. Sun et al. (2008) analysed the art of machine selection, and introduced the advantage of machine tool selection based on grey relation and AHP method. Dagdevrin (2008) presented an integrated approach which employs AHP and PROMETHEE for the equipment selection problem. Chang (2010) applied AHP and technique for order preference by similarity to ideal solution (TOPSIS) to construct a collaborative decision making model for predicting the yield of a wire saw machine for wafer slicing process in the fabrication of photovoltaic cells. The evaluation weights were determined by the AHP, and the optimal performing machine was identified by TOPSIS. A DSS was developed by Arslan et al. (2004) in which a multi-criteria weighted average (MCWA) using hierarchy tree is used in decision making. A visual interactive decision support framework using AHP is described by Stam and Kuula (1991) to aid the DM in selecting the appropriate technology and design in planning of a flexible manufacturing system (FMS). A DSS based on analytical algorithm was developed by Abdel-Malek and Resare (2000) to select machining centres and robots. Moon et al. (2002) proposed an integrated machine tool selection and sequencing model based on genetic algorithm. Liu (2008) utilized data envelopment analysis (DEA) as a multi criteria tool for the evaluation of FMS. In the aforementioned literature, the use of AHP in the selection process is insufficient to capture the decision makers' judgements correctly in finding criteria weights and alternatives' ranking. Therefore, other methods are integrated with AHP.

Intelligent approaches such as fuzzy logic, neural network, and expert system are widely used to support decision-making in machine tool selection. Yurdakul and Tansel Ic (2009) used fuzzy TOPSIS as a MCDM approach to rank the machine tools. A fuzzy TOPSIS based methodology has been described by Onut et al. (2008) for evaluation and selection of vertical CNC machining centres for a manufacturing company. An intelligent approach to machine tool selection problem through fuzzy analytic network process (ANP) was proposed by Ayag and Ozdemir (2009). A DSS was developed by Tansel Ic and Yurdakul (2009) to help the decision makers in their machining centre selection using fuzzy AHP or fuzzy TOPSIS. Wang et al. (2000) proposed a fuzzy multiple attribute decision making model and simulation to assist the decision maker to deal with the machine selection problem for an FMC. A fuzzy goal programming approach is presented by Chan and Swarnkar (2006) to model the machine tool selection and operation allocation problem in FMS. A fuzzy goal programming model using genetic algorithm was applied by Rai et al. (2002) to model the problem of machine tool selection and operation allocation in FMS. Mishra et al. (2006) adopted a fuzzy goal programming model of the machine tool selection and operation allocation in FMS. Karsak and Kuzgunkaya (2002) presented a fuzzy multiple objective programming approach to facilitate decision making in the selection of a FMS. Alberti et al. (2009) presented a DSS for high speed milling machine tool selection using artificial neural network. Chtourou et al. (2005) presented the development of a prototype expert system for the machine selection of manufacturing systems. Lin and Yang (1996) presented the development of a model using the AHP for the selection of the most suitable machine using the expert system concept. A DSS was developed by Norrie et al. (1989) for planning in flexible manufacturing using a consortium knowledge-based system utilizing expert systems. Keung et al. (2001) addressed the problem of multiple machine tool selection and job scheduling on a flexible machining workstation under tool sharing environment. Both problems are solved simultaneously using genetic algorithm.

Simulation modelling is used with other techniques for the same purpose. A hybrid approach which integrates AHP with simulation techniques was proposed by Ayag (2007) to determine the best machine tool. AHP, simulation modelling and group technology (GT) are combined for the proposed design of a cellular and FMS by Chan and Abhary (1996). Chan et al. (2000) reported an integrated approach for the automatic design of FMS using simulation and MCDM techniques. Aly and Subramaniam (1993) presented the development of a DSS for the design of FMS using simulation. A unified framework based on AHP, simulation and accounting procedure was proposed by Shang and Sueyoshi (1995) to facilitate decision making in the design and planning of FMS.

Several methods of MCDM have been proposed in recent years to select the best alternatives. The PROMETHEE method is one of them which was developed by Brans and extended by Brans and Vincke (1985). The method is applied in different areas such as manufacturing and assembly, hydrology and water management, environment management, chemistry, etc. This method is applicable with a GAIA plane descriptive tool which provides a valuable tool for the DM to discriminate the criteria expressing similar or conflicting preferences, as well as the quality of each alternative on the different criteria (Behzadian et al. 2010).

In the reviewed literature, the researchers used fuzzy AHP, fuzzy ANP or fuzzy TOPSIS either separately or integrated with other methods like simulation and genetic algorithm. In using fuzzy numbers to represent subjective pairwise comparisons of criteria and alternatives with respect to each criterion, the DM faces difficulties due to the lengthy process of pairwise comparisons of the selected criteria and preferred alternatives. In this paper, this deficiency is solved by the PWEC program (fuzzy AHP) to weigh the criteria using the decision maker's preference score and integrated with PROMETHEE to rank alternatives instead of using fuzzy numbers in pairwise comparison constructions for alternatives with respect to each criterion. We believe that, this is a significant contribution of the proposed approach where it is easy and flexible to use and clear for decision making judgements. Furthermore, the model allows for if-what scenarios by changing the weights of criteria and observing their effects on alternatives' ranking. Also, the model can be used to identify conflicts between criteria, to group the alternatives, and to observe the quality of the alternatives with respect to each criterion.

Proposed model

Model structure

In this paper, we employed a hybrid approach of fuzzy AHP and PROMETHEE using MATLAB programming to assist the DM in the selection of the most suitable machine tool from several alternatives. The structure of the proposed model is shown in Fig. 1. The required data is initially prepared and entered into the MATLAB-based fuzzy AHP model. The criteria are then weighted. The final ranking of the alternatives is done by PROMETHEE, followed by an analysis of the results. The approval of these results and final decision is made by the DM.

The basic accepted criteria in the model are extracted from reviewed literature and machine tool manufacturers (Table 1). The hierarchy structure used in the model is shown in Fig. 2.

PWEC program

In order to find the criteria weights, a program called PWEC is developed in the model using MATLAB. Among the prominent feature of the program is the capability of using unlimited number of criteria, and it is fast and flexible in application. The program also allows the DM to use various

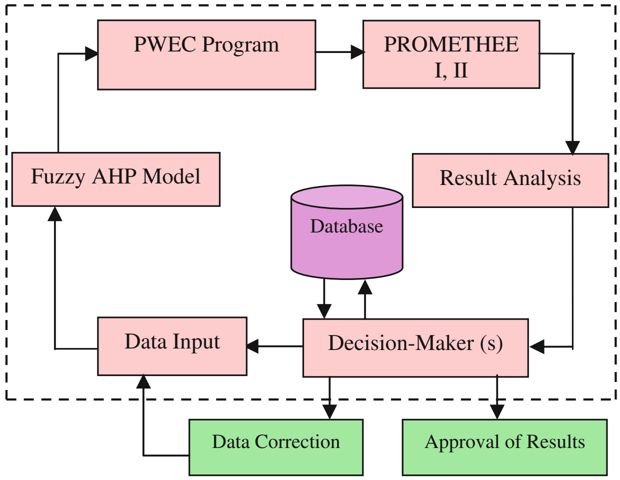

Fig. 1 Scheme of the proposed model

Table 1 Turning Centre Specifications

Turning centre	
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

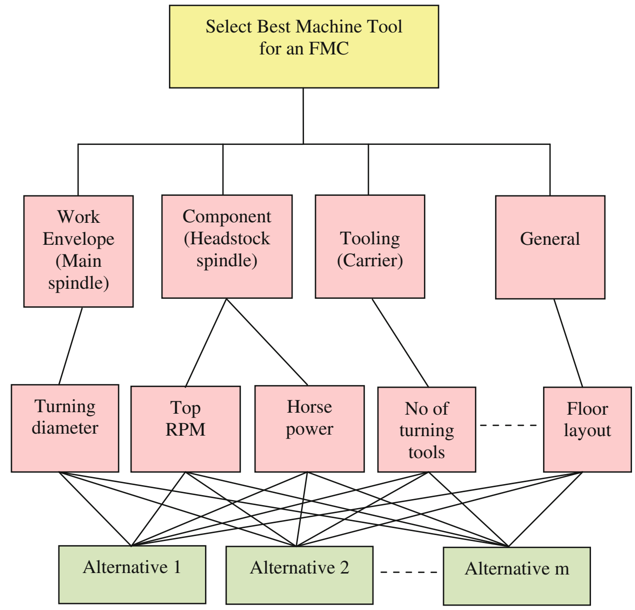

Fig. 2 Hierarchy structure

numbers of confidence level and index of optimism in the [0, 1] range to show their effects on the results. The program structure is as follows:

- Inserting:
  - The preferred number of evaluation criteria (n).
  - The value of the confidence level (α).
  - The index of optimism (λ).
- Inserting the DM preference score of evaluation criteria using triangular fuzzy numbers (TFNs).
- Finding the lower limit (l) and upper limit (u) of TFNs with their reciprocals.
- Finding the α-cut matrix.
- Normalizing the produced matrix.
- Finding the column vector of the evaluation criteria.
- Calculating the maximum eigen value (λ_{max}).
- Calculating the consistency index (CI).
- Finding the matrix random index (RI).
- Calculating the matrix consistency ratio (CR).
- Printing: Criteria's priority weights, λ_{max}, CI, RI, and CR.

Database structure

A database (DB) of 118 CNC turning centre was created using Microsoft Excel and incorporating real data from machine tool sales organization (e.g. Mazak; Nakamura; Romi; Doosan).

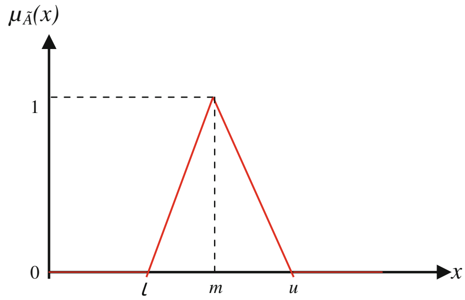

Fig. 3 The membership function of the triangular fuzzy number $\tilde{A}$

Fundamental concepts of fuzzy AHP and PROMETHEE

Fuzzy AHP

In the conventional AHP method first developed by Saaty (1980), pair-wise 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 judgements of decision-makers, crisp pair-wise comparison in the conventional AHP seems insufficient and too imprecise to capture the decision-makers judgments correctly. Therefore, fuzzy logic is introduced into the pair-wise 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 (Zadeh 1978) 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 (Ayag 2005).

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 approximate the convex function well (Lee 1995).

Triangular fuzzy numbers (TFNs) are more suitable in applications due to their computational simplicity and they are useful in promoting presentation and information processing in a fuzzy environment and successfully applied in various applications (Tang 2009).

A fuzzy number $\tilde{A}$ on R is a TFN if it is membership function $x \in \tilde{A}$, $\mu_{\tilde{A}}(x)$: $R \to [0, 1]$ is equal to as follows: (see Fig. 3)

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

The algebraic operations of TFNs can be performed as follows (Zadeh 1965; Chang and Wang 2009):

- Addition of two fuzzy numbers:

$$(l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (2)$$

- Subtraction of two fuzzy numbers:

$$(l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \quad (3)$$

- Multiplication of two fuzzy numbers:

$$(l_1, m_1, u_1) \times (l_2, m_2, u_2) = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (4)$$

- Division of two fuzzy numbers:

$$(l_1, m_1, u_1) \,/\, (l_2, m_2, u_2) = (l_1/u_2, m_1/m_2, u_1/l_2) \quad (5)$$

- Inversion:

$$(l, m, u)^{-1} = (1/u, 1/m, 1/l) \quad (6)$$

- Multiplication of any real number α:

$$\alpha \times (l, m, u) = (\alpha l, \alpha m, \alpha u) \quad (7)$$

By introducing the α-cut and defining the interval of confidence at confidence level α, the TFN can be characterized as (Lee 1995):

$$\forall \alpha \in [0, 1]$$
$$\tilde{A}\alpha = [l\alpha, u\alpha] = [(m-l)\,\alpha + l, u - (u-m)\,\alpha] \quad (8)$$

The α-cut is known to incorporate the experts or decision-makers 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 TFN number and interval arithmetic as follows:

(1) The crisp numbers are replaced by TFNs, to indicate the relative strength of the elements in the judgment matrix as:

$$\breve{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \dots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & 1 \end{bmatrix} \quad (9)$$

where:

$$\tilde{a}_{ij} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} & i > j \\ 1 & i = j \\ \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1} & i < j \end{cases} \tag{10}$$

(2) A fuzzy eigenvalue $\tilde{\lambda}$ is a fuzzy number solution to:

$$\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x} \tag{11}$$

$\tilde{A}$ is a n-by-n fuzzy matrix and $\tilde{x}$ is a non-zero 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:

$$\tilde{a}_{ij}^{\alpha} = \left[a_{ijl}^{\alpha}, a_{iju}^{\alpha}\right] \tag{12}$$

$$\tilde{x}_{i}^{\alpha} = \left[\tilde{x}_{il}^{\alpha}, \tilde{x}_{iu}^{\alpha}\right] \tag{13}$$

$$a_{i1l}^{\alpha}x_{il}^{\alpha} + \cdots + a_{inl}^{\alpha}x_{nl}^{\alpha} = \lambda x_{il}^{\alpha} \tag{14}$$

$$a_{i1u}^{\alpha}x_{iu}^{\alpha} + \cdots + a_{inu}^{\alpha}x_{nu}^{\alpha} = \lambda x_{iu}^{\alpha} \tag{15}$$

(4) The degree of satisfaction can be estimated from the DM by index of optimism λ. The larger the index λ is, the higher the degree of satisfaction is:

$$\tilde{a}_{ij}^{\alpha} = \lambda \tilde{a}_{iju}^{\alpha} + (1 - \lambda)\, \tilde{a}_{ijl}^{\alpha}, \quad \forall \lambda \in [0, 1] \tag{16}$$

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

$$\breve{A} = \begin{bmatrix} 1 & \tilde{a}_{12}^{\alpha} & \cdots & \tilde{a}_{1n}^{\alpha} \\ \tilde{a}_{21}^{\alpha} & 1 & \cdots & \tilde{a}_{2n}^{\alpha} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{a}_{n1}^{\alpha} & \tilde{a}_{n2}^{\alpha} & \cdots & 1 \end{bmatrix} \tag{17}$$

The five TFNs are defined with the corresponding intensity of importance as shown in Fig. 4 (Li and Huang 2009).

The lower limit (l) and upper limit (u) of the fuzzy numbers with respect to α are defined by the following (Ayag and Ozdemir 2006):

$$\left.\begin{array}{ll} \tilde{1}_{\alpha} = [1, 3 - 2\alpha] & \\ \tilde{3}_{\alpha} = [1 + 2\alpha, 5 - 2\alpha], & \tilde{3}_{\alpha}^{-1} = [1/(5 - 2\alpha), 1/(1 + 2\alpha)] \\ \tilde{5}_{\alpha} = [3 + 2\alpha, 7 - 2\alpha], & \tilde{5}_{\alpha}^{-1} = [1/(7 - 2\alpha), 1/(3 + 2\alpha)] \\ \tilde{7}_{\alpha} = [5 + 2\alpha, 9 - 2\alpha], & \tilde{7}_{\alpha}^{-1} = [1/(9 - 2\alpha), 1/(5 + 2\alpha)] \\ \tilde{9}_{\alpha} = [7 + 2\alpha, 11 - 2\alpha], & \tilde{9}_{\alpha}^{-1} = [1/(11 - 2\alpha), 1/(7 + 2\alpha)] \end{array}\right\} \tag{18}$$

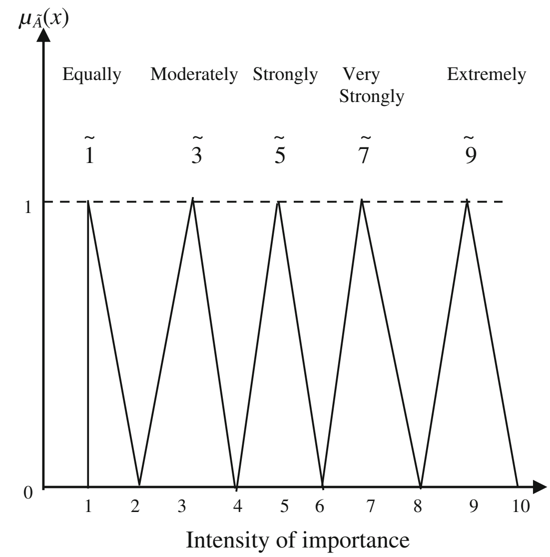

Fig. 4 Fuzzy membership function

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

$$\text{CI} = (\lambda_{\max} - n)/(n - 1) \tag{19}$$

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 (1980).

So, the matrix consistency ratio is calculated using:

$$\text{CR} = \text{CI/RI} \tag{20}$$

A CR of 0.1 or less is considered acceptable.

The PROMETHEE method

The evaluation table is the starting point of the PROMETHEE method (Albadvi et al. 2007). In this table, the alternatives are evaluated on the different criteria. The application requirements of the method are:

(1) Priority weights of the criteria.
(2) Preference functions.

PROMETHEE is based on the extensions of the nation of criterion and it is simple and easily understood by the DM. This extension is based on the introduction of a preference function (P) giving the preference of the DM for an action (alternative) a with regard to b. This function is defined separately for each criterion; its value between [0,1]. For two particular actions (a) and (b), the preference function of (a)

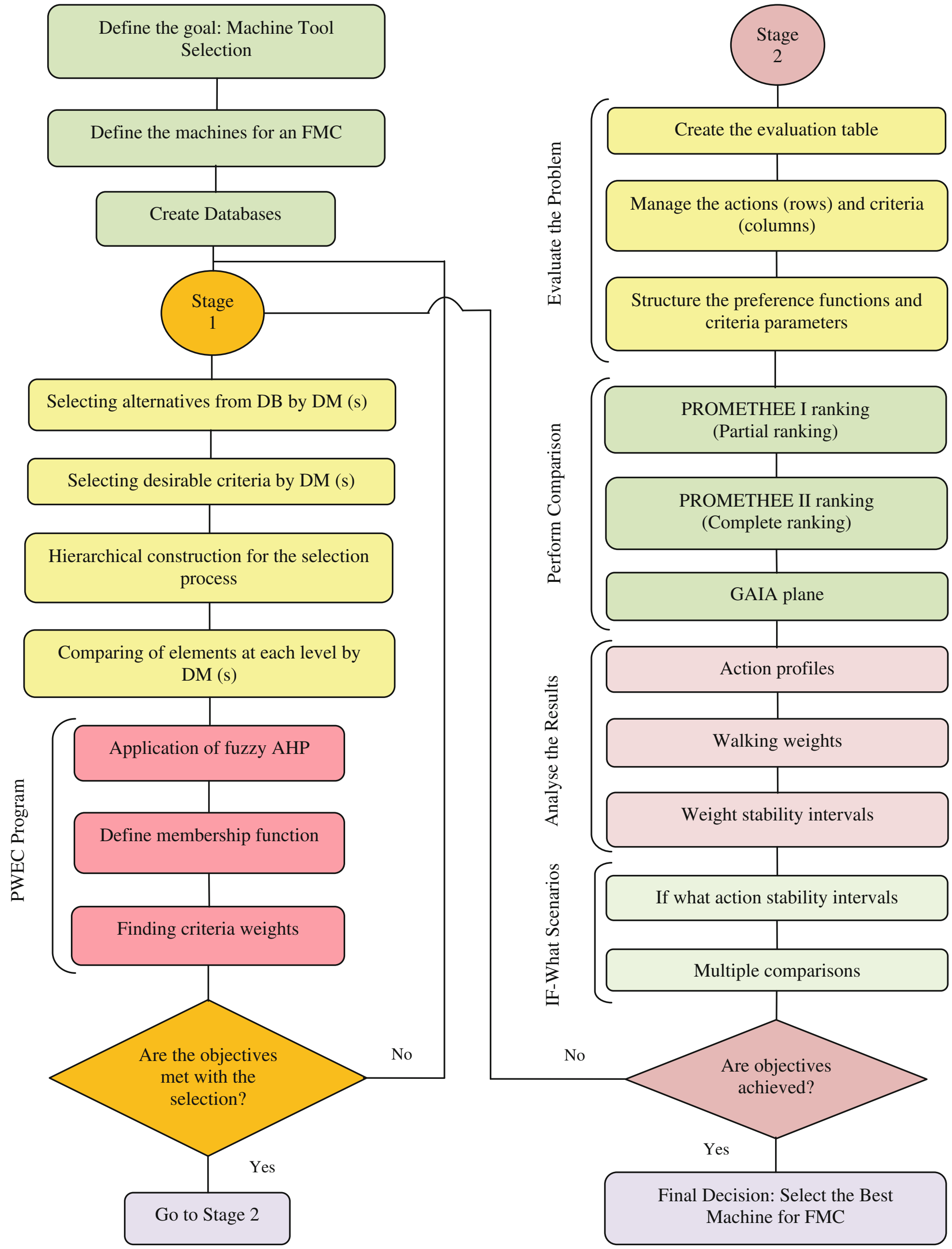

Fig. 5 Flow chart of the proposed model

with regard to (b) can be defined as (Brans and Vincke 1985):

$$P(a,b) = \begin{cases} 0 & \text{if} \quad f(a) \le f(b) \\ P[f(a), f(b)] & \text{if} \quad f(a) > f(b) \end{cases} \qquad (21)$$

Six types of preference function are proposed by Brans and Vincke (1985): usual criterion, level criterion, U-criterion, V-criterion, criterion with linear preference and indifference area, and Gaussian criterion. The thresholds ι, m, p, q, r, s and σ can possibly be determined interactively between the decision-maker and the analyst.

In PROMETHEE two techniques PROMETHEE I and PROMETHEE II are used for solving the ranking problem:

(1) PROMETHEE I: Ranking the action by a partial pre order using the following equations:
Preference Index:

$$\pi(a,b) = \left(\frac{1}{k}\right) \sum_{h=1}^{k} P_h(a,b) \qquad (22)$$

Table 2 Input data

Evaluation criteria	
Work envelope/ turning diameter (WE/Dia)	
Headstock spindle /top RPM (HS/rpm)	
Tooling / no. of turning tools (NT)	
Number of axes (NA)	
Machine weight (MW)	
Floor layout (FL)	
Horse power (HP)	
Confidence level: $\alpha = 0.5$	
Index of optimism: $\lambda = 0.5$	

Outgoing flow:

$$\Phi^{+}(a) = \sum_{x \in k} \pi(a, x) \tag{23}$$

Incoming flow:

$$\Phi^{-}(a) = \sum_{x \in k} \pi(x, a) \tag{24}$$

(2) PROMETHEE II: Ranking the actions by a total pre-order using:
Net flow:

$$\Phi(a) = \Phi^{+}(a) - \Phi^{-}(a) \tag{25}$$

A software called Decision Lab (2000) supports this method and also sensitivity analysis on the results is possible in the software using GAIA plane, walking weights, etc.

In this paper, a two stage model was used for machine tool selection. In stage 1 the fuzzy AHP was used with the PWEC program to find out the criteria weights, while in stage 2 the Decision Lab software is used for the final ranking of the alternatives and analysis. The flow chart of the two stages is shown in Fig. 5.

Illustrative example

In this section, the hybrid approach of fuzzy AHP and PROMETHEE presented in this paper is demonstrated via a numerical example to prove the approach's applicability. Suppose that a decision has to be made on the most suitable CNC turning centre machine from several alternatives. Experts on CNC machines participated in the selection process.

The steps that would have to be taken are:

- Assigning the evaluation criteria.
- Selecting the alternative machines from the established database.
- Approval of the decision hierarchy.
- Assigning the preference score for the selected criteria.
- Defining the confidence level α and the index of optimism λ.
- Defining the preference function with its thresholds for each criterion.
- Assessment of the results according to the firm's goal and final decision making.

The priority weights of the selected criteria are determined using the PWEC program and the final ranking of the alternatives is found by applying the Decision-Lab (2000) software as follows:

Step (1): Preparing the input data to PWEC program (Table 2).
Step (2): Replacing the crisp numbers given by the DM by TFNs and the fuzzy comparison matrix is established as shown in Table 3.
Step (3): Reconstructing the fuzzy comparison matrix and introducing the α-cut matrix by applying Eqs. (16) and (18). The resulting matrix is generated by the PWEC program as shown in Table 4.
Step (4): Normalizing the matrix from step (3) and finding the criteria weights by finding the column vector (eigen vector). The resulting matrix is shown in Table 5 and the criteria weights are shown in Table 6.
Step (5): Assigning the alternative machines—CNC turning centre machine (TCM)—from the created DB: Mazak, Nakamura, Romi, and Doosan.
Step (6): Establishing the evaluation table and assigning the preference function for each criterion as in Table 7.
Step (7): By applying the Decision-Lab 2000 software, the PROMETHEE I calculates the positive and negative preference flows Φ^{+} and Φ^{-} for each alternative and alternative ranking as in Fig. 6.

PROMETHEE II provides the complete ranking of the alternatives by calculating the net flow Φ. The result is shown in Fig. 7.

So, the final ranking of the alternatives is:

TCM1: Nakamura machine,
TCM2: Mazak machine,
TCM3: Doosan Infracore machine, and
TCM4: Romi machine.

Table 3 Fuzzy comparison matrix for the criteria

	WE/Dia	HS/rpm	NT	NA	MW	FL	HP
WE/Dia	1	$\tilde{3}$	$\tilde{5}$	$\tilde{5}$	$\tilde{7}$	$\tilde{5}$	$\tilde{3}^{-1}$
HS/rpm	$\tilde{3}^{-1}$	1	$\tilde{3}$	$\tilde{5}$	$\tilde{7}$	$\tilde{7}$	$\tilde{3}^{-1}$
TS	$\tilde{5}^{-1}$	$\tilde{3}^{-1}$	1	$\tilde{3}$	$\tilde{5}$	$\tilde{7}$	$\tilde{5}^{-1}$
NA	$\tilde{5}^{-1}$	$\tilde{5}^{-1}$	$\tilde{3}^{-1}$	1	$\tilde{3}$	$\tilde{3}$	$\tilde{3}^{-1}$
MW	$\tilde{7}^{-1}$	$\tilde{7}^{-1}$	$\tilde{5}^{-1}$	$\tilde{3}^{-1}$	1	$\tilde{3}$	$\tilde{7}^{-1}$
FL	$\tilde{5}^{-1}$	$\tilde{7}^{-1}$	$\tilde{7}^{-1}$	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	1	$\tilde{9}^{-1}$
HP	$\tilde{3}$	$\tilde{3}$	$\tilde{5}$	$\tilde{3}$	$\tilde{7}$	$\tilde{9}$	1

Table 4 α-Cut matrix

	WE/Dia	HS/rpm	NT	NA	MW	FL	HP
WE/Dia	1.000	3.000	5.000	5.000	7.000	5.000	0.375
HS/rpm	0.375	1.000	3.000	5.000	7.000	7.000	0.375
TS	0.208	0.375	1.000	3.000	5.000	7.000	0.208
NA	0.208	0.208	0.375	1.000	3.000	3.000	0.375
MW	0.145	0.145	0.208	0.375	1.000	3.000	0.145
FL	0.208	0.145	0.145	0.375	0.375	1.000	0
HP	3.000	3.000	5.000	3.000	7.000	9.000	1.000

Table 5 Normalized matrix

	WE/Dia	HS/rpm	NT	NA	MW	FL	HP
WE/Dia	0.1943	0.3810	0.3395	0.2817	0.2305	0.1429	0.1513
HS/rpm	0.0729	0.1270	0.2037	0.2817	0.2305	0.2000	0.1513
TS	0.0405	0.0476	0.0679	0.1690	0.1646	0.2000	0.0840
NA	0.0405	0.0265	0.0255	0.0563	0.0988	0.0857	0.1513
MW	0.0283	0.0185	0.0141	0.0211	0.0329	0.0857	0.0588
FL	0.0405	0.0185	0.0099	0.0211	0.0123	0.0286	0
HP	0.5830	0.3810	0.3395	0.1690	0.2305	0.2571	0.4034

Table 6 Criteria weights

Weights:
- HP = 0.3376
- WE/Dia = 0.2459
- HS/rpm = 0.1810
- NT = 0.1105
- NA = 0.0692
- MW = 0.0371
- FL = 0.0187

$\lambda_{max} = 7.7752$

CI = 0.1292

RI = 1.32

CR = 0.0979

Step (8): The GAIA plane (Fig. 8) and walking weights (Fig. 9) are then drawn.

The GAIA plane shown in Fig. 8 is used to identify conflicts between criteria and to group the alternatives. In this plane the criteria are represented by axis and the alternatives by points. The criteria expressing similar preferences on the data are oriented in the same direction, while conflicting criteria are pointing in opposite directions. We can observe from the figure, for example, that the HP and diameter is in strong conflict with the tools.

It is also possible to observe the quality of the alternatives with respect to the criteria. For our example, the Nakamura machine is good with tools as they are allocated in the same quarter (fourth quarter), and similarly Mazak is good with work envelop/turning diameter as they are in the same quarter (second quarter).

The walking weights (Fig. 9) allow the DM to perform if-what scenarios to modify the criteria weights and to observe the resulting modifications of the alternatives' ranking.

From Fig. 9, the weight distribution of the selected criteria for our example is 25, 18, 11, 7, 4, 2, 34%, and from the upper part of the figure one can easily observe that the Nakamura dominates the other alternatives.

Table 7 Evaluation table

WE/Dia.	HS/rpm	NT	NA	MW	FL	HP	
Max/ min	Max	Max	Max	Max	Min	Min	Max
Weight	0.245	0.181	0.1105	0.0692	0.0371	0.0187	0.3376
Pref. function	Level	Level	Gaussian	Gaussian	U-shape	V-shape	Level
Indiffed. threshold	8	5,000	–	–	15,000	–	20
Prefernce threshold	12	6,000	–	–		10,000,000	25
Gaussian threshold	–	–	12	4	–	–	–
Unit	Inch	rpm	–	–	Ibs	10^3 Inch^3	–
Nakamura tome	7.48	5,000	24	9	26,400	1,074.52	15
Doosan infracore	9.5	6,000	12	8	1,6534	921.188	20
Romi	11.02	6,000	12	4	19,000	2,620.8	25
Mazak	16.93	4,000	12	6	2,4250	1,881.49	30

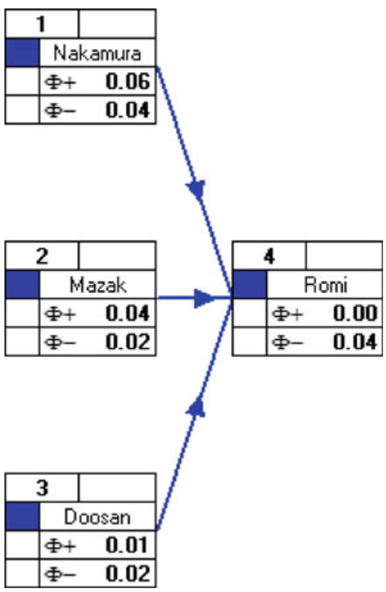

Fig. 6 PROMETHEE I partial ranking for the alternatives

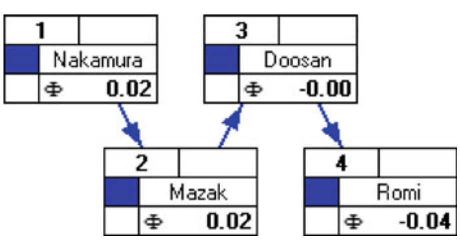

Fig. 7 PROMETHEE II complete ranking for the alternatives

To perform if-what scenario the weights are changed (by 50% of the original weights) as in Fig. 10 and the new results are 40, 14, 9, 6, 3, 1, 27% where now the Mazak dominates the other alternatives which clearly differs from the previous results. Such a sensitivity analysis tool is valuable for the DM.

Discussions and implications

In this study, the fuzzy AHP has been integrated with PROMETHEE to construct a hybrid decision support system to select the most suitable CNC machine among the alternatives available in the market.

The two stages of the proposed approach are explained in detail in Fig. 5. In stage 1, fuzzy AHP through PWEC program was used to weigh the criteria by building the fuzzy comparison matrix shown in Table 3. Tables 4 and 5 show the procedure for finding the criteria weights tabulated in Table 6.

The criteria weights are then incorporated with real data from manufacturers to establish the evaluation table (Table 7) as explained in stage 2. The PROMETHEE method was applied to rank the alternatives as in Figs. 6 and 7.

From Table 6 it can be seen that only the criteria are weighted not the alternatives. This is a prominent feature of the proposed approach which saves the decision making processing time by ranking the alternatives using PROMETHEE instead of using fuzzy numbers in constructing pairwise comparisons for alternatives with respect to each criterion which may produce vagueness and uncertainty to capture the decision maker's judgements adequately due to long process and large number of comparison matrices for alternatives with respect to each criterion. For example if we have 7 criteria and 4 alternatives, we need to establish an additional 7 matrices each of (4 × 4) elements for alternatives' comparisons.

Figure 8 shows a plane which identifies the conflicts between the criteria (e.g. diameter with tools) and the quality of alternatives with respect to each criterion (e.g. Nakamura is good with tools).

Figures 9 and 10 show the walking weights which assist the decision-maker to perform if-what scenarios. For the case study presented here, after changing the original criteria weights given by decision-makers, as in Fig. 10, it can

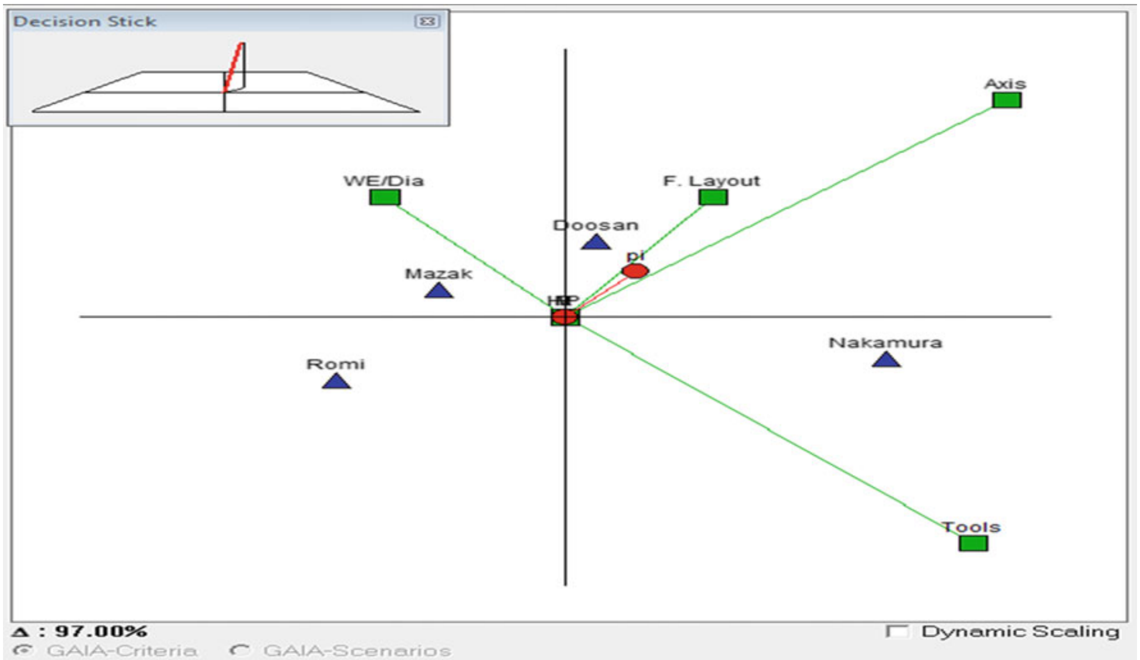

Fig. 8 GAIA plane

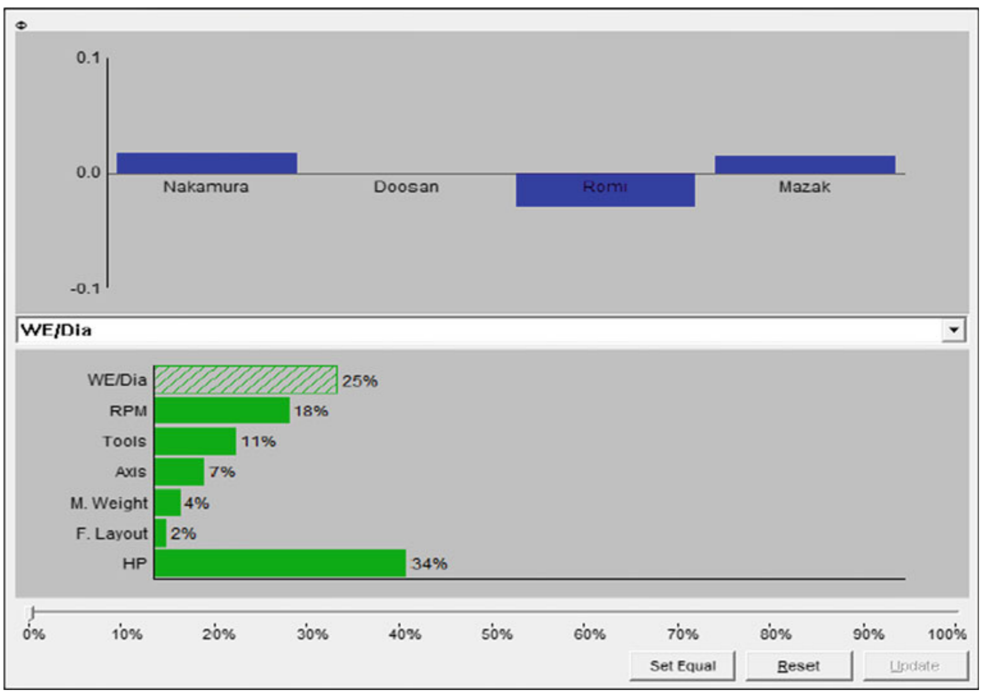

Fig. 9 Walking weights

be seen that a new classification of alternatives' ranking is presented where Mazak is the first alternative which clearly differs from the previous ranking in Fig. 9 where Nakamura is the first. Also we can observe a new distribution of criteria weights. In Fig. 9, HP dominates other criteria while in Fig. 10 the diameter dominates the others. Such tools help the decision makers to analyse the results and take the decision toward either data corrections for a new ranking of alternatives or the approval of the existing results.

Conclusion

The vagueness and uncertainty on judgments of the decision-maker (s) is solved in the model by introducing the fuzzy

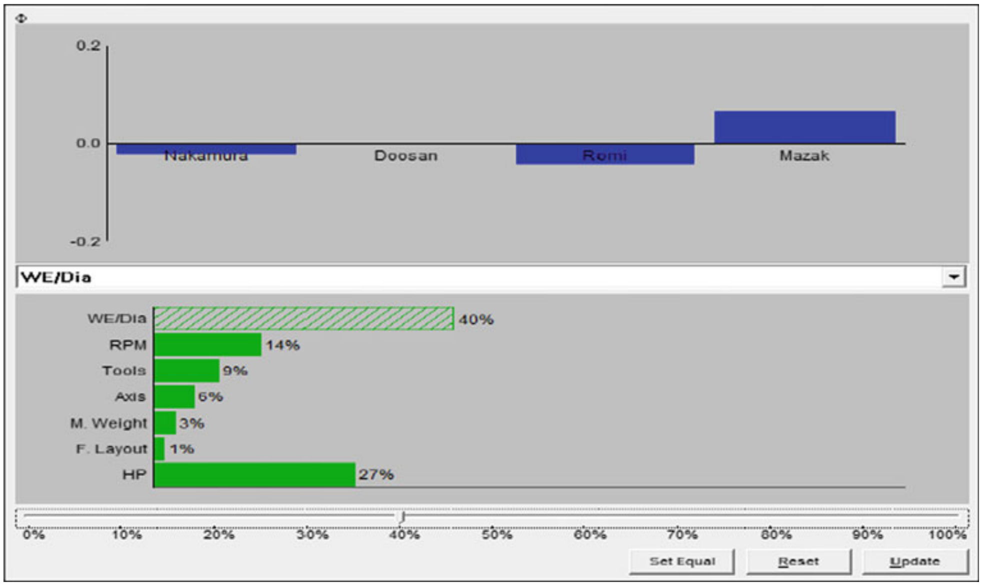

Fig. 10 New walking weights performing if-what scenario

AHP integrated with a flexible PWEC program to find the priority weights of the selected criteria. The program has the capability for using unlimited numbers of 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 the decision-maker on criteria judgments.

The PROMETHEE method enables a sensitivity analysis of if-what scenario to the decision-making process which is influenced by the weights allocated to the criteria and the problem is solved by user-friendly PWEC program.

The decision support system proposed in this paper is not limited to CNC turning centre selection and may be applied to other type of machines of the FMC structure.

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