Int J Adv Manuf Technol (2007) 35:363–376
DOI 10.1007/s00170-006-0714-0

ORIGINAL ARTICLE

Development of a machine tool selection system using AHP

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Received: 7 January 2006 / Accepted: 3 July 2006 / Published online: 5 September 2006

Abstract The selection of appropriate machines is one of the most critical decisions in the design and development of an efficient production environment. In this study, we propose a decision support system for machine tool selection using an effective algorithm, the analytic hierarchy process. In the selection process, we first consider qualitative decision criteria that are related to the machine properties. Reliability and precision analyses may be included in the detailed evaluation procedure. Furthermore, the decision-maker may take into account the economical considerations through cost analysis. In addition, the robustness of the selection procedure may be evaluated using sensitivity analysis. An illustrative example of machine tool selection using the proposed methodology and the software implementation are provided.

Keywords Analytic hierarchy process · AHP · Machine tool selection · Decision support systems

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1 Introduction

Competitive market conditions as a result of globalization, limited resources, etc. force companies to make careful decisions. Any waste of resources such as money, time, workforce, etc., due to inappropriate decisions, directly increases the costs of companies, which, in turn, is reflected to the customer. Machine tool selection is very critical for companies where machining process adds vital value on the product. Machining operations are used in the manufacturing of a variety of products due to the quality, flexibility and reduced lead times that can be achieved. For the majority of remaining production operations where machining is not used as the primary manufacturing process, it is used in the manufacturing of tooling that is vital to the production, such as dies and molds. Therefore, a poor decision would result in quality, flexibility, productivity, etc., problems which could have dramatic results. This study aims at developing a systematical, accurate, fast, and practical decision-making process for machine tool selection.

A decision is a choice made from two or more alternatives. Decision-making is the process of sufficiently reducing uncertainty and doubt about alternatives to allow a reasonable choice to be made among them. Researchers have studied different decision-making problems by using different decision-making methods such as the analytic hierarchy process (AHP), fuzzy multiple-attribute decision-making model, linear and 0–1 integer programming models, genetic algorithms (GA), etc.

There are two major studies in the literature that employ the AHP approach. Lin and Yang [6] developed a model for the selection of the most suitable machine from a range of machines available for the manufacture of particular part types. In this study, there are four main criteria: machine procedures, lead time, labor cost, and operation shift; and

Table 1 Scale of relative importance

	Definition	Explanation
1	Equal importance	Two activities contribute equally
3	Weak importance of one over another	Experience and judgment slightly favor one over another
5	Essential or strong importance	...Strongly favor one over another
7	Very strong and demonstrated	...Strongly favored and its dominance demonstrated in practice
9	Absolute importance	Evidence favoring one over another is of the highest possible order
2,4,6,8	Intermediate values between adjacent scale values	

three alternatives: conventional machines, NC machines, and flexible manufacturing cells. Tabucanon et al. [11] develop a decision support framework designed to aid decision-makers in selecting the most appropriate machines for flexible manufacturing systems (FMS). The framework consists of two main stages. The first stage, called as the pre-screening stage, narrows down all possible configurations using AHP. The second stage uses a goal programming (GP) model. Oeltjenbruns et al. [8] investigate the compatibility of AHP to strategic planning in manufacturing. The objective is to develop/explore different planning alternatives ranging from extending the life of existing machinery to total replacement with a new manufacturing system and to evaluate these alternatives through economical and technological criteria. Yurdakul [14] presents a model that links machine alternatives to manufacturing strategy for machine tool selection. In this study, the evaluation of investment in machine tools can model and quantify strategic considerations by using the AHP method. On the other hand, Cheng et al. [4] claim that although AHP is an effective tool for management decision-making, it can be defective if used improperly.

Table 2 Criteria and related sub-criteria

1. Productivity	2. Flexibility	3. Safety and environment	4. Adaptability
P1. Max. speed	F1. U axis	SE1. Safety door	A1. Taper type
P2. Horse power	F2. Articulated axis	SE2. Fire extinguisher	A2. Space requirement
P3. Tool change time	F3. No of pallets	SE3. Mist collector	A3. CNC control type
P4. Number of spindles	F4. Rotary table		A4. Coolant type
P5. Rapid traverse speed	F5. Total number of tools		
P6. Cutting feed	F6. Head changer		
	F7. CNC or not?		
	F8. Index table		
	F9. Dual axis rotary table		

Table 3 Simple machining center specifications

1. General	Company name, machine name, machine type, CNC type, column style type, etc.
2. Spindle	Spindle type, spindle direction, taper number, max. speed, tower, etc.
3. Tooling	Number of tools, max. tool diameter, etc.
4. Work support	Table size, rotary table, etc.
5. Axis	Number of axis, cutting feed, rapid traverse speed, etc.
6. Dimensions and weight	Machine dimensions, machine weight, etc.

Wang et al. [13] suggest a fuzzy multiple-attribute decision-making model to assist the decision-maker in dealing with the machine selection problem for FMS. A linear 0–1 integer programming model for machine tool assignment and operation allocation in FMS is proposed by Atmani and Lashkari [2]. The model determines the optimal machine-tool combinations and assigns the operations of the part types to the machines (minimizing total costs of processing, material handling, and machine setups). Moon et al. [7] propose a model for an integrated machine tool selection and sequencing. The model, which is formulated as a 0–1 integer program, determines machine visiting sequences for all part types such that total production time for the production order is minimized and workloads among machine tools are balanced. In order to solve the model, a GA approach based on a topological sort technique is developed. Haddock and Hartshorn [5] use a decision support system (DSS) in the specific selection of a machine that is required to process specific dimensions of a part. The selection will depend on part characteristics, which are labeled in a part code and correlated with machine specifications and qualifications. The choice of

Table 4 Productivity sub-criteria pair-wise comparison

	NS	MS	TT	SP
NS	–	M		EM
MS		–		
TT	EM	S	–	M
SP		EM		–

NS Number of spindles, *MS* Maximum speed, *TT* Tool-to-tool time, *SP* Spindle power

Table 5 Numerical values corresponding to data in Table 4

	NS	MS	TT	SP
NS	1	3	0.5	2
MS	0.33	1	0.2	0.5
TT	2	5	1	3
SP	0.5	2	0.33	1

Table 7 Main criteria comparison and numerical values

	P	F		P	F
P	–	MS	P	1	4
F		–	F	1/4	1

P Productivity, *F* Flexibility

the optimal machine, vs. possible alternatives, can be made by a planner comparing the criterion measure(s). Examples of possible criteria include relative location of machines, machining cost, processing time, and availability of a machine(s).

A machine tool selection problem similar to ours is addressed by Arslan et al. [1] and a multi-criteria weighted average approach is proposed. In this study, we present an AHP-based decision support methodology. In addition, reliability, precision, and cost analyses are used to help the decision-maker reach an accurate solution. Criteria set defined by the decision-maker may be further improved using sensitivity analysis.

The remainder of the paper is organized as follows: Section 2 briefly discusses multi-criteria decision-making and describes AHP and revised AHP approaches. The problem setting is introduced in section 3. The details of the methodology utilizing an illustrative example are presented in section 4. Section 5 gives concluding remarks and insights for future research. The implementation of the proposed methodology through software developed using Visual Basic is included in the Appendix.

2 Multi-criteria decision-making: background

Multiple criteria decision-making (MCDM) is one of the most well known branches of decision-making. It refers to making decisions in the presence of multiple, usually conflicting, objectives. The basic idea behind MCDM is the construction of a decision tree using a selection of criteria relevant to a particular decision and the weighting/scoring of the criteria and the alternatives for each different criterion. Triantaphyllou [12] claims that MCDM is divided into multi-objective decision-making (MODM) and multi-attribute decision-making (MADM). On the other hand, MCDM is also classified based on the number of decision-makers involved: single or group decision-makers. Each method uses numerical techniques to help decision-makers choose among a discrete set of alternatives. In the decision-making problem, the first step is deciding the best MCDM method.

Alternatives, attributes, criteria, sub-criteria, weights of importance, and decision matrix are the main concepts related to MCDM. Weighted sum model, weighted product model, AHP, revised AHP, Electre, and Topsis are well-known MCDM methods used in the literature. In this paper, AHP and revised AHP methods are briefly summarized and the interested reader is referred to Triantaphyllou [12] for details of the other methods.

AHP is a method introduced by Saaty [9] to determine the priority of a set of alternatives and the relative importance of attributes in a multi-criteria decision-making problem. In this approach, the decision-maker carries out simple pair-wise comparison judgments, which are then used to develop overall priorities for ranking the alternatives (see Table 1).

The most important task in decision-making is to determine the appropriate factors to be included in the hierarchic structure. Hierarchy is the ordering of parts or elements of a whole from the highest to the lowest. In the construction of the hierarchy tree, one should use sufficient information to accurately represent the decision-making problem. Also, the elements of comparison should be homogeneous. A hierarchy may be divided into sub-hierarchies sharing only a common topmost element.

The AHP approach consists of the following four stages:

1. Decompose the problem into a systematic hierarchical structure. This hierarchical structure attempts to decompose an unstructured problem into several integrated dimensions (or components or elements).
2. Employ the pair-wise comparison method. The decision-maker will compare each of the paired elements in

Table 6 Normalized and average values

	NS	MS	TT	SP	AVG
NS	0.260	0.272	0.245	0.307	0.271
MS	0.086	0.090	0.098	0.076	0.088
TT	0.521	0.454	0.491	0.461	0.482
SP	0.130	0.181	0.163	0.153	0.157

Table 8 Normalized and average values for main criteria

	P	F	AVG
P	0.8	0.8	0.8
F	0.2	0.2	0.2

$S_{Productivity}$=0.8, $S_{Flexibility}$=0.2

Table 9 Machine alternatives

Name	Company	TY	MS	AA	TTT	NS	UA	MSP	NT	HC
V1	X	MC	3150	Opt.	32	1	None	35	80	Std.
V2	X	MC	4000	None	20	1	None	25	30	Std.
V3	X	MC	6000	None	18	1	None	25	30	None
M1	Y	MC	7000	None	6	1	None	15	40	None
M2	Y	MC	5000	None	10	1	None	27	40	None
M3	Y	MC	8000	None	15	1	None	10	20	None

MC Machining center, *TY* Type, *MS* Maximum speed, *AA* Articulated axis, *TTT* Tool-to-tool time, *RTS* Rapid traverse speed, *UA* U axis, *NS* Number of spindles, *NT* Number of tools, *HC* Head changer

the matrices that form the questionnaire. Saaty [9] recommends the use of a nine-point scale as described in Table 1. Then, an approximate weight vector is calculated. At the end of this step, the weights of the objectives are determined.

3. Carry out the consistency measure. The consistency measure is used to screen out the inconsistency of responses (refer to Triantaphyllou [12] for details in consistency).
4. Use the relative weights for different purposes. For decision-making that involves a set of scenarios or alternatives, the weighted criteria will be scored by the decision-maker so that the total score can be calculated.

Belton and Gear [3] claim that a ranking inconsistency can occur when AHP is used. They propose the revised AHP method where the data are normalized by dividing the largest entry in each column to reach to the desired solution. The details of the above steps with the normalization procedure are provided in section 4 with an illustrative example of the machine selection process.

3 Problem setting

3.1 Decision criteria

In the problem addressed, there are four main categories, each having different requirements. These four main criteria with the corresponding sub-criteria are shown in Table 2. For example, productivity depends on six sub-criteria such as speed, horsepower, cutting feed, etc., while flexibility depends on nine sub-criteria. Safety and environment is also considered as an important criterion especially for satisfying regulations and standards. Adaptability is the suitability of machine to the existing environment or system.

In addition to these main and sub-criteria, some machine features such as machine type, manufacturer, column construction, axis, number of ranges, etc. are also considered to allow the decision-maker to eliminate undesired machines.

3.2 Classification of machines (database structure)

For selecting the best machine, creating a large database, which includes a large number of the machines available in the market, is the first and most important step. Before entering machines into a defined database, the fields should be determined and defined. These fields should contain machine features that are standard in the market. Therefore, a standard classification scheme is crucial for constructing the database frame (see Table 3).

In the database, the general field defines the basic information about the machines. Spindle contains information about the spindle. Tooling specifies the number of tools, tool diameter, tool change time, head changer, etc., that are necessary to measure machine tool performance. Work support deals with the place where workpiece stands. Axis information of the machines is stored in the axis specification. In the last field, physical information such as dimensions, weight, etc. is stored.

Table 10 Normalized machine values

Name	Company	MS	AA	TT	NS	UA	SP	NT	HC
V1	X	0.095	1	0.316	0.166	0	0.255	0.333	1
V2	X	0.120	0	0.198	0.166	0	0.182	0.125	1
V3	X	0.180	0	0.178	0.166	0	0.182	0.125	0
M1	Y	0.211	0	0.059	0.166	0	0.109	0.166	0
M2	Y	0.150	0	0.099	0.166	0	0.197	0.1666	0
M3	Y	0.241	0	0.148	0.166	0	0.072	0.083	0

Table 11 Productivity scores for each alternative

Name	Company	MS (Score)	TT(Score)	NS(Score)	SP(Score)
V1	X	0.095*0.007	0.316*0.385	1*0.217	0.255*0.126
V2	X	0.120*0.007	0.198*0.385	1*0.217	0.182*0.126
V3	X	0.180*0.007	0.178*0.385	1*0.217	0.182*0.126
M1	Y	0.211*0.007	0.059*0.385	1*0.217	0.109*0.126
M2	Y	0.150*0.007	0.099*0.385	1*0.217	0.197*0.126
M3	Y	0.241*0.007	0.148*0.385	1*0.217	0.072*0.126

3.3 Decision methodology

The machine selection problem deals with selecting the best machine among a large number of alternatives under user-defined decision criteria. In the proposed methodology, AHP is used to rank machines from best to worst. In AHP, typically the alternatives are compared. In our approach, however, we perform pair-wise comparisons of the decision criteria only since it is obviously not tractable to compare each machine with all other machines with respect to each criterion due to the larger number of machine alternatives.

AHP enables the user to determine the criteria weights by using comparison matrices. Although the determination of the criteria weights in multi-criteria weighted average method is critically important, AHP offers simple approach. For our machine selection problem, the hierarchy tree consists of three levels: Level 1 contains the goal, which is the selection of the best machine; Level 2 contains four main criteria; and Level 3 consists of sub-criteria based on the machine specifications.

3.4 Application environment

The proposed methodology is implemented as a computerized DSS using the Visual Basic (VB) programming language. VB is a distinctly different language providing powerful features such as graphical user interfaces, event handling, and access to Win32 API, object-oriented features, error handling, structured programming, and much more. Microsoft Access is selected as the database management system. Using Microsoft Access, all information can be managed from a single database file. In addition, a Web-based application is also implemented using Java. The software implementation is described in the Appendix.

Table 12 Total scores and the ranking

Name	Company	Total score	Rank (AHP)
V1	X	0.321	1
V2	X	0.242	2
V3	X	0.144	3
M1	Y	0.122	4
M2	Y	0.115	5
M3	Y	0.092	6

4 Methodology and an illustrative example

We propose a decision support methodology for machine tool selection using the AHP technique. Once a short list of the best-fitting machines is obtained, precision and reliability analyses as well as the cost analysis on the so-obtained machine ranking may also be conducted in the second stage with the additional information from the manufacturers. Furthermore, the robustness of the selection procedure may be evaluated using sensitivity analysis. In what follows is the outline of the methodology with an illustrative real-world example.

4.1 Obtaining the machine ranking using AHP

Stepwise procedure to obtain criteria scores using AHP is as follows:

Step 1 Select main criteria: Suppose, the decision-maker selects productivity and flexibility.

Step 2 Select sub-criteria: Productivity has six sub-criteria. Among these six, maximum speed, main spindle power, tool change time, and number of spindles are selected.

Step 3 Compare selected sub-criteria to calculate the score: For this comparison, the decision-maker asks the question, “How important is the maximum speed compared to the main spindle power?” The answer to questions such as this one can only be answered by someone who has a very good knowledge of the application where the machine will be used. For the speed vs. power question, the machining strategy, part material, and geometry need to be considered. For example, for some materials with low machinability, higher productivity can be better obtained by taking heavy cuts at lower speeds instead of higher speeds which would not result in practical tool lives. On the other hand, if the part has very thin

Table 13 Cost values for alternatives

Name	Life	%i	PC	A_1	A_2	A_3	A_4	A_5
V1	3	5	90K	10K	15K	18K		
V2	4	5	60K	4K	7K	9K	12K	
V3	2	5	70K	20K	25K			
M1	3	5	80K	28K	32K	36K		
M2	5	5	50K	7K	9K	11K	14K	16K
M3	3	5	95K	33K	35K	35K		

PC Purchasing cost, A_j=Annual cost for year j

and flexible sections which may deflect and vibrate due to deep and heavy cuts, then shallow cuts with high spindle speeds would result in a much better surface quality, tolerance integrity, and high productivity. The decision-maker uses the following rates of importance: E=Equal (1), EM=Equal-Moderate (2), M=Moderate (3), MS=Moderate-Strong (4), S=Strong (5), SVS=Strong-Very Strong (6), VS=Very Strong (7), VSEX=Very Strong–Extreme (8), EX=Ex treme (9).

Step 4 Construct pair-wise comparison matrix for sub-criteria: Each rate of importance has an equivalent numerical value as given above. These rates are replaced in Table 4 by their equivalent numerical values as shown in Table 5.

Step 5 Normalize the pair-wise comparison matrix by dividing the values in each column by the column sum (see Table 6).

Step 6 Calculate the scores (the relative weights) of the criteria by taking the average value of each row. The scores of the sub-criteria of productivity are as follows: $s_{P/NS}$=0.271, $s_{P/MS}$=0.088, $s_{P/TT}$=00.482, $s_{P/SP}$=0.157.

These steps are repeated for the other criterion (flexibility) and related sub-criteria selected (articulated axis, head changer, total # of tools and U axis, in our example).

Step 7 Compare selected main criteria to calculate the score: Productivity and flexibility are compared as shown in Table 7.

Table 14 Cost analysis results

Name	Annual cost ($)	Rank
M2	22.7K	1
V1	24.7K	2
V2	47.2K	3
V3	60K	4
M1	61.2K	5
M3	69.1K	6

Step 8 Calculate scores for the main criteria as in steps 5 and 6 (see Table 8). Then, each pair-wise comparison (for both main and sub-criteria) consistency is examined.

Step 9 Calculate the overall score for criteria by multiplying main criteria score with sub-criteria score. For example, total score of cutting feed and spindle power are calculated as follows:

$$S_{Maximum\ Speed} = s_{P/Maximum\ Speed} \times s_{Productivity}$$
$$= 0.088 \times 0.8 = 0,070 S_{Main\ Spindle\ Power}$$
$$= s_{P/Main\ Spindle\ Power} \times S_{Productivity}$$
$$= 0.157 \times 0.8 = 0,126$$

At the end of this procedure, the decision-maker's qualitative preferences are converted into numerical values. Then, the best machine will be selected among the machines in the database. The decision-maker may eliminate some alternatives by setting constraints on machines such as power, machine type, manufacturer, etc. After an alternative set is determined, scores are applied to these alternatives.

For example, suppose there are six machine alternatives (see Table 9). There are records for each alternative on the database that contain machine features that are used to calculate the score such as machine name, type, manufacturer, maximum speed, etc. The score of a machine is calculated as follows: First, we determine the related property fields in the database that depend on the selected sub-criteria. Then, we normalize these values by dividing them to the largest value. In this step, limits may be imposed on the largest values that can be used for

Table 15 Pair-wise comparison matrix for reliability

	BFR	RDS
BFR	–	S
RDS		–

Table 16 Machine ranking according to reliability analysis

Name	BFR	RDS	Rank (reliability)
V1	0.9	0.7	1
V3	0.8	0.8	2
M2	0.7	0.7	3
M1	0.6	0.8	4
V2	0.6	0.7	5
M3	0.5	0.9	6

Table 18 Precision values for alternatives

Name	AP	TS
V1	0.9	0.6
V2	0.7	0.8
V3	0.8	0.9
M1	0.6	0.8
M2	0.5	0.7
M3	0.8	0.9

normalization in order to eliminate problems resulting from very high field values due to exceptional cases. Third, we determine which machine specification is the best by multiplying the criteria score by related values on the machine data. Finally, we calculate the total score by summing up the calculated values for each machine alternative. The machine with the highest score is selected as the best machine.

In the example, eight database fields are related to the criteria selected by the decision-maker. These values are normalized by dividing the highest as it is seen in the Table 10. The scores of the sub-criteria of productivity are as follows: $s_{P/NS}$=0.271, $s_{P/CF}$=0.088, $s_{P/TT}$=00.482, $s_{P/SP}$=0.157. The scores that are calculated as a result of AHP are multiplied by the values in the related fields. For productivity, the score of each alternative is calculated as in Table 11. After calculating the flexibility scores for machines, the total score is found by adding the productivity and flexibility scores. According to these scores, machines are ranked from highest score (the best) to the lowest (the worst) as illustrated in Table 12.

4.2 Cost analysis

Most decision-making problems can be accomplished by more than one alternative. In general, the alternatives being considered require the investment of different amounts of capital and their annual revenues and cost may vary. Sometimes the alternatives may have different useful lives. Because different levels of investment normally produce varying economic outcomes, an analysis is performed to determine which one of mutually exclusive alternatives is preferable and, consequently, how much capital should be invested.

Three methods are described to analyze cash flows that are used to determine economic advantages of an alternative. The present worth (PW) method is based on the concept of equivalent worth of all cash flows relative to some base or beginning point in time called the present. The future worth is based on the equivalent worth of all cash inflows and outflows at the end of planning horizon (study period) at an interest rate. The annual worth (AW) of a project is an equal annual series of dollar amounts for stated study period that is equivalent to the cash inflows and outflows at an interest rate (Sullivan et al. [10]). The economic analysis of the mutually exclusive alternatives for an engineering project must be done on a comparable basis.

Since various economic factors such as machine life, purchasing cost, manufacturing cost, and interest rate affect the cost of a machine tool, the combination of the present and annual worth methods are used for the cost analysis. A_{kt} is the annual cost of machine k in the year t, i is the annual interest rate, P_k is the net present value of the machine k, AW_k annual worth of machine k, OC_{kt} is the operational cost of machine k in year j, MC_{kt} is the maintenance cost of machine k in year t, and n_k is the life of machine k. (t=0, 1, ..., n_k). The annual worth of machine k is:

$$AW_k = \frac{1}{P_k}\left(\frac{(1+i)^n - 1}{i(1+i)^n}\right) \quad (1)$$

where

$$P_k = A_{k0}(1+i)^0 + A_{k1}(1+i)^1 + A_{k2}(1+i)^2 +,,, + A_{kn}(1+i)^n \quad (2)$$

Then, the annual cost of machine k can be calculated as:

$$A_{kj} = AW_k + OC_{kj} + MC_{kj} \quad (3)$$

For the machines in our example, suppose the cost values in Table 13 hold.

Table 17 Pair-wise comparison matrix for precision

	AP	TS
AP	–	M
TS		–

Table 19 Machine ranking according to precision analysis

Name	Precision rank
V3	1
M3	2
V1	3
V2	4

Table 20 Comparisons for sensitivity analysis

	P	F		P	F
P	–	S	P	–	VS
F		–	F		–

If the cost calculation method is used for the machines above, the cost values and ranking are found as in Table 14.

4.3 Reliability analysis

Reliability is the statistical measure of the probability that a mechanical element will not fail in use. The methodology that is proposed for machine tool selection uses reliability analysis considering the estimated reliability values of the machines. In the first stage, AHP is performed according to two criteria; bearing failure rate (BFR) and reliability of drive system (RDS), and criteria weights are obtained. In the next stage, reliability values for each candidate machine are defined. Finally, the machines are ranked based on criteria weights and reliability values.

After performing AHP for the data in Table 15, the criteria weights are calculated as: S_{BFR}=0.8333, S_{RDS}=0.1667. The machines are then ranked as illustrated in Table 16.

4.4 Precision analysis

In order to rank machines according to their precision, three steps are followed. First, there are four main criteria about machine precision: axis precision (AP), repeatability (R), static and dynamic rigidity (SDR), and thermal stability (TS). Then, AHP is performed on these selected criteria in order to find the decision-maker preferences. In the next stage, precision values for each machine in the candidate set are defined as shown in Table 17. In the final stage, precision scores are calculated using criteria weights and reliability values and the machines are ranked according to their precision scores (see Tables 18 and 19).

Table 21 New machine ranking as a result of sensitivity analysis

Name	AHP rank for strong	Very strong
M2	1	1
M1	2	3
V1	3	2
V3	4	4
V2	5	6
M3	6	5

Table 22 Resulting rankings

Name	AHP Rank	Cost rank	Reliability rank	Precision rank
M2	1	1	3	6
M1	2	5	4	5
V1	3	3	5	3
V3	4	4	2	1
V2	5	2	1	4
M3	6	6	6	2

4.5 Sensitivity analysis

The rate of change in the output of a model caused by the changes of the model inputs is estimated by sensitivity analysis methods. In decision-making problems, sensitivity analysis provides the decision-maker with the ability to determine how critical each factor is. As a result of sensitivity analysis, the question, "how sensitive is the actual ranking of the alternatives to the changes in the current weights of the decision criteria?", is answered.

There are two closely related sensitivity analysis problems. In the first problem, the sensitivity analysis approach determines the smallest change in current weights of the criteria, which can alter the existing ranking of the alternatives (called *problem1*). In the second problem, it is determined how critical the performance measures of the alternatives are in the ranking of the alternatives (called *problem2*). Triantaphyllou [12] discusses the solution methodologies for two problems.

One of the critical aspects of the proposed methodology is the assignment of the comparison values. Comparison values can take values between "Equal" and "Extreme", and sometimes the user may not be absolutely sure in the correct assignment of a value. Sensitivity analysis is used to examine the effects of different comparison values on AHP. In this part of the decision methodology, a typical question such as, "If I assign *moderate* instead of *strong*, how will my machine ranking be changed?", is answered. First of all, comparison values are increased step by step. This "Strong" value is increased one step and the change in machine ranking is examined. The comparison value at which the machine ranking is changed is taken as a break point. Then the original pair-wise comparison value is decreased step by step until the machine ranking changes. The comparison value at which the machine ranking is changed is taken as another break point.

In the example, we assume that productivity is stronger than flexibility. This strong value is increased one step and then checked whether the machine ranking is changed. For example, equal-strong value is given instead of strong and it is checked to see if the machine ranking is changed. If not, it is decreased one more step, to equal, and so on. As a

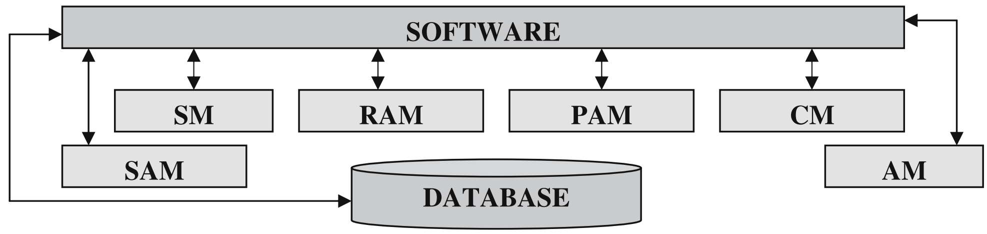


Fig. 1 Structure of the DSS

result of sensitivity analysis, the following new machine ranking list is found (Tables 20 and 21).

4.6 Final selection

After cost, reliability, and precision analysis, the decision-maker is faced with four machine rankings. According to their preference, they will select the best machine. For example, technical properties of the machine can be more important than the cost, and also the decision-maker would like to buy a more reliable machine. At this point, to make the best selection, the decision-maker should define their needs clearly. There are constraints in this decision-making problem such as budget, available space in manufacturing area, precision values, power needs, flexibility of the machines, etc. The aim of the decision-maker should be to select the best machine that satisfies these constraints. The resulting rankings of our methodology aim at supporting the decision-maker in making their final selection as shown in Table 22.

5 Conclusions and future research

Selecting the most suitable machine from the increasing number of available machines in the market is a challenging task. Productivity, precision, flexibility, and responsive manufacturing capabilities of the company depend on the machine properties. In this study, the machine tool selection problem is addressed and an AHP-based methodology is proposed. Machine properties and main and sub-decision criteria are investigated to apply the proposed methodology.

The major contribution of this study is combining the AHP-based selection methodology with reliability, precision, and cost analyses to evaluate several alternatives and make an accurate decision. The proposed methodology is very flexible in the sense that it can be applied to other types of selection problems, e.g., selection of a vehicle, hardware, appliances, etc.

Our methodology may be considered as a part of the process planning system. The approach may be integrated into the overall manufacturing planning system. The proposed decision methodology may also be used to select

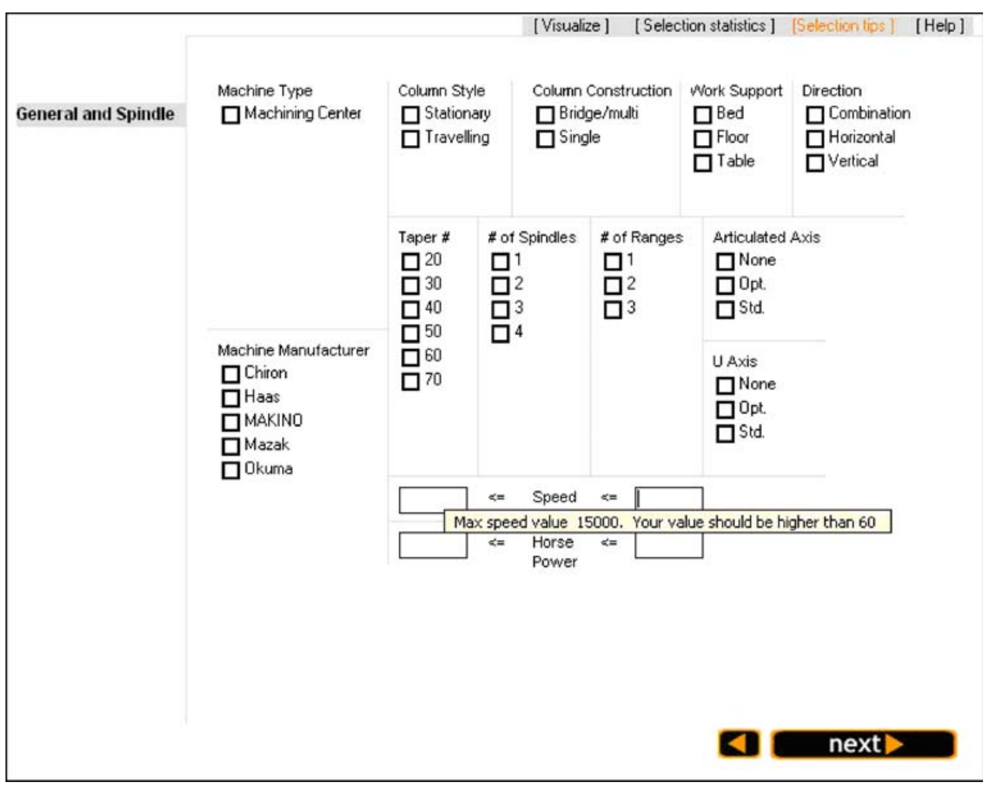


Fig. 2 Machine tool selection database search

Fig. 3 Main criteria selection for AHP

the appropriate tools for machining, the material handling system, robots, materials, etc. Such an integration will construct an intelligent computer-assisted process planning system that enables the design and control of the overall manufacturing activities. The authors are currently investigating the application of this system as a future study.

Appendix: Software implementation

The proposed methodology is implemented using Visual Basic and Microsoft Access. The exemplary database includes specifications of 236 machine tools. The developed software consists of six modules as shown in Fig. 1. Selection (SM), sensitivity analysis (SAM), reliability analysis (RAM), precision analysis (PAM) and cost analysis (CM) modules are used for the decision process while the sixth module (AM) is used for administrative purposes, define/update a machine, manufacturer, or user and to manage default values for each user.

In order to use the software, the decision-maker should login by entering username, password, and user type. Login option lets decision-makers keep track of her decision activities.

Selection

This module enables the decision-maker to select the most appropriate machine according to his or her preferences. SM uses AHP methodology in order to rank machines as described earlier.

In this module, the decision-maker may load predefined selection preferences or may add their favorite machines to the candidate list.

In the first step of the decision process, the decision-maker defines machine options about general machine properties, spindle specifications, tooling, and work support, axis and machine dimensions. In this step, the decision-maker may determine the power requirement using process models in the literature (Arslan et al. [1]). The aim of the decision support system is to guide the decision-maker in order to make good decisions. This software also has a capability of redirecting users. For example, if the speed value of the available machines is between 60 and 15,000 and the user enters 59, they get a warning. At the end of this step, the decision-maker obtains the machine alternatives meeting her desired specifications (Fig. 2).

After filtering all machines according to desired machine options, the user chooses the required main criteria to apply AHP. After determining the main criteria, the decision-maker selects sub-criteria related to these main criteria and then makes comparisons by using qualitative values for desired sub-criteria (Figs. 3, 4 and 5).

In the last step, the user compares the main criteria. As a result of the selection process, the machines are ranked from the best to the worst, as seen in Fig. 6. The first machine in the ranking is the best machine under the

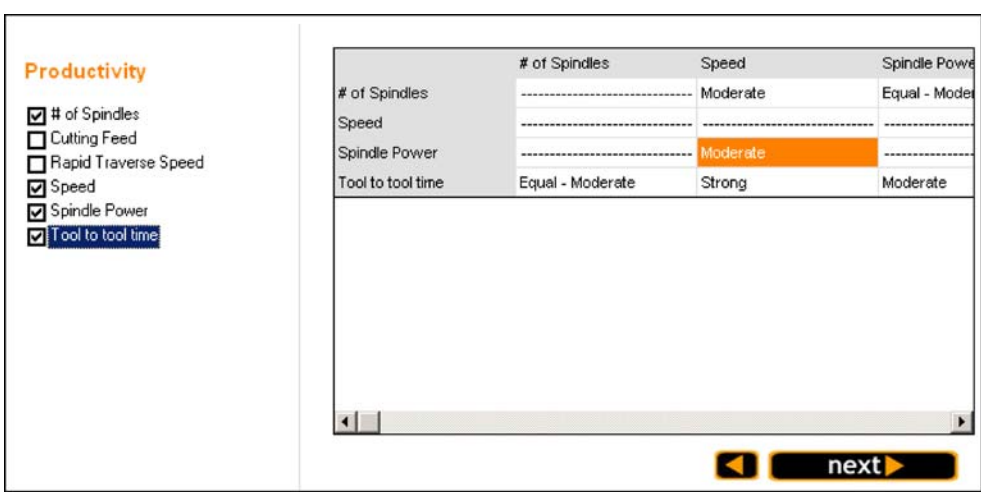


Fig. 4 Pair-wise comparison for the sub-criteria

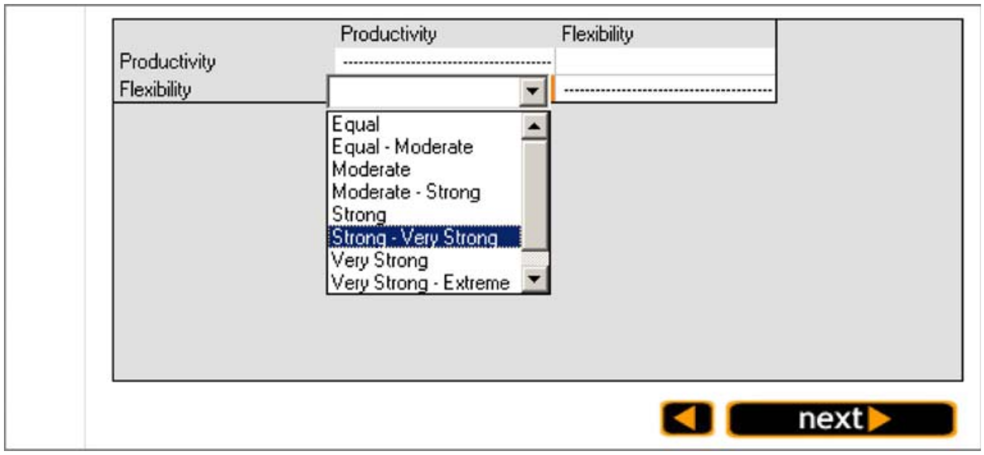


Fig. 5 Pair-wise comparison for the main-criteria

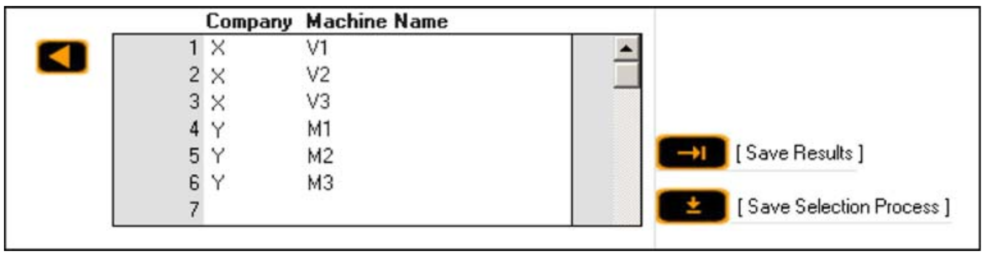


Fig. 6 Machine tool selection results

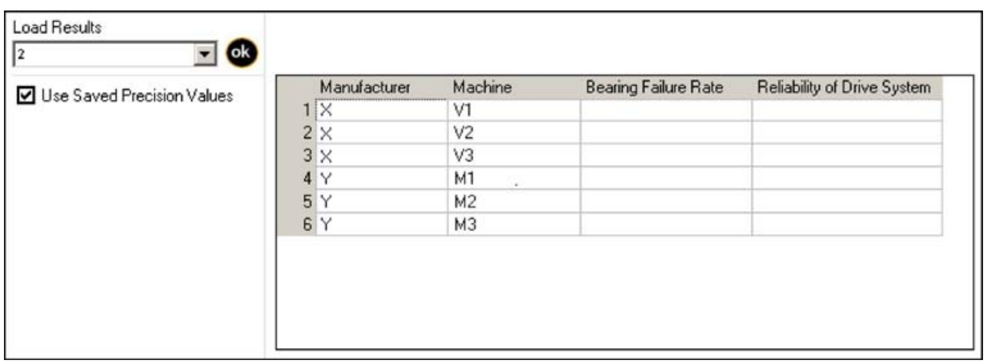


Fig. 7 Reliability analysis step 1 and 2

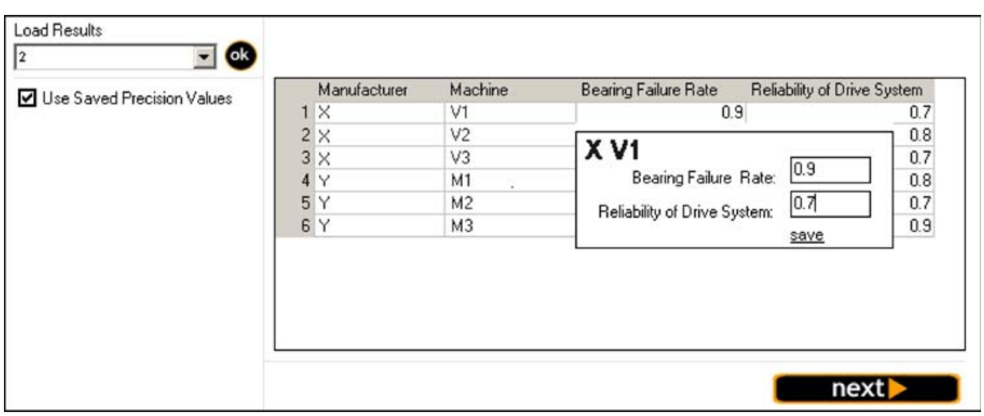


Fig. 8 Reliability analysis step 3

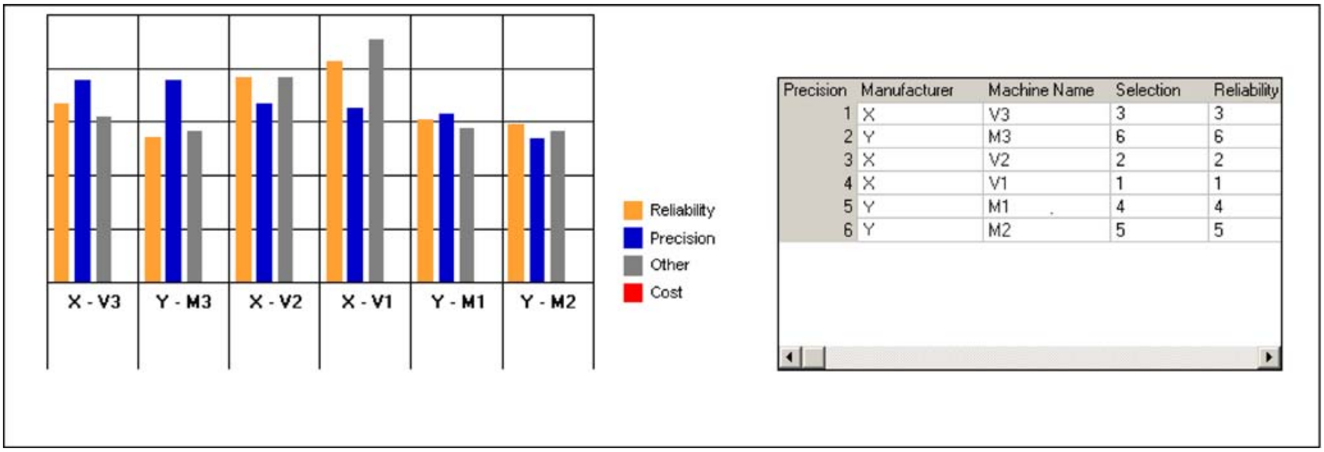
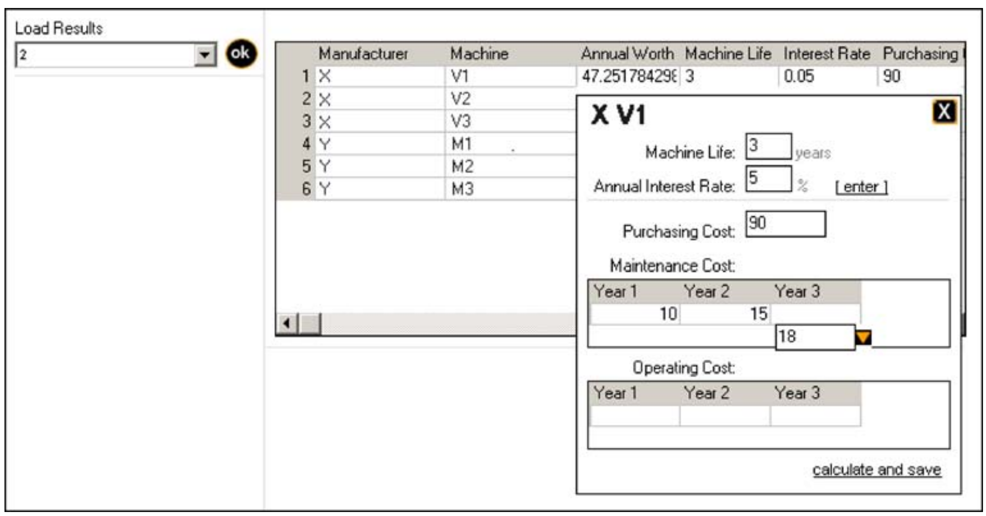


Fig. 9 Precision analysis results

Fig. 10 Cost analysis: defining machine costs



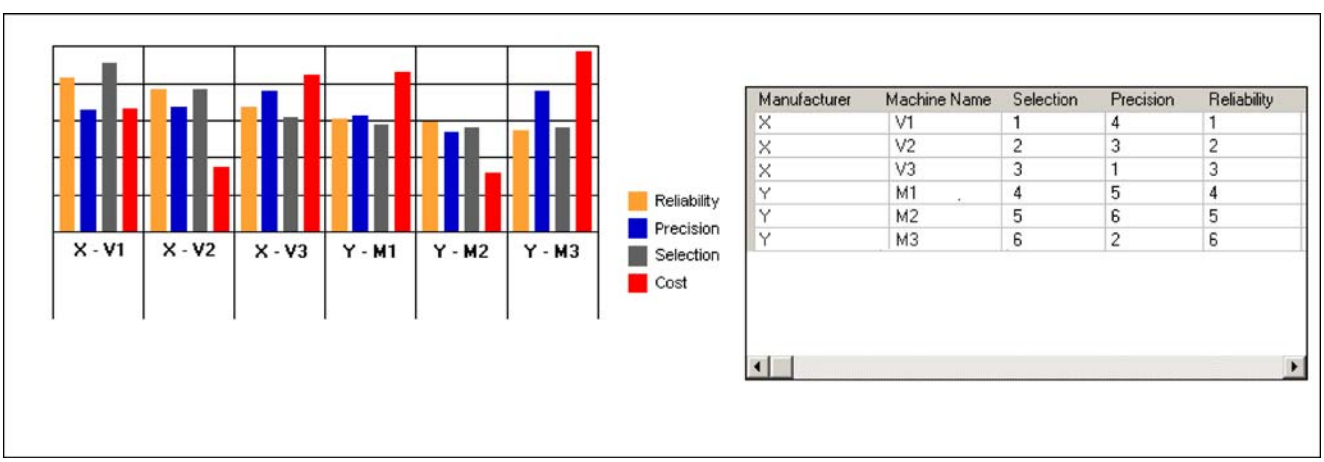


Fig. 11 Report module

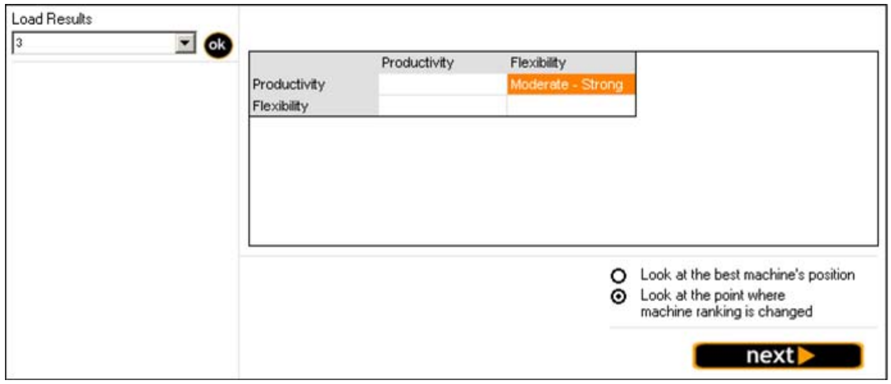


Fig. 12 Sensitivity analysis: Step 1

desired requirements of machine properties, main and sub-criteria. The user can save this result list and the values they assign during the selection process. These saved property values are used at the beginning of the selection process. At this point, the decision-maker can add the desired machines to the candidate list to save them.

Reliability analysis

In the reliability analysis part, the user first selects the preferred machine results from the saved machine list or the candidate list. After loading the list, the user performs AHP on the reliability criteria to obtain weights. Then, the reliability values are defined for each machine on the list. As a result, another ranking with respect to the reliability is obtained (Figs. 7 and 8).

Precision analysis

The precision analysis module performs in the same way as the reliability analysis module. At the end, the machines are ranked according to precision values. The report includes the ranking of machines based on precision values as well as previous AHP methodology and reliability analysis (Figs. 9 and 10).

Cost analysis

Cost analysis is used to evaluate alternatives considering cost values such as purchasing cost, operational cost, and maintenance cost by using the proposed methodology depicted in section 4 (Fig. 11).

Reports

Machine tool selection part has a report section as seen in Fig. 12. If all analyses are applied, four machine rankings are obtained. According to these rankings, the decision-maker may make the final decision and/or add selected machine(s) to the candidate list.

Sensitivity analysis

The decision-maker analyzes main pair-wise comparison values of selection in the sensitivity analysis module (Fig. 13).

First, the user loads the desired machine results. Then, they define the number of machines on which the analysis is to be performed. Finally, the selection preferences are loaded. There are two analysis options: (i) the change in the top ranked machine, (ii) the change in machine ranking.

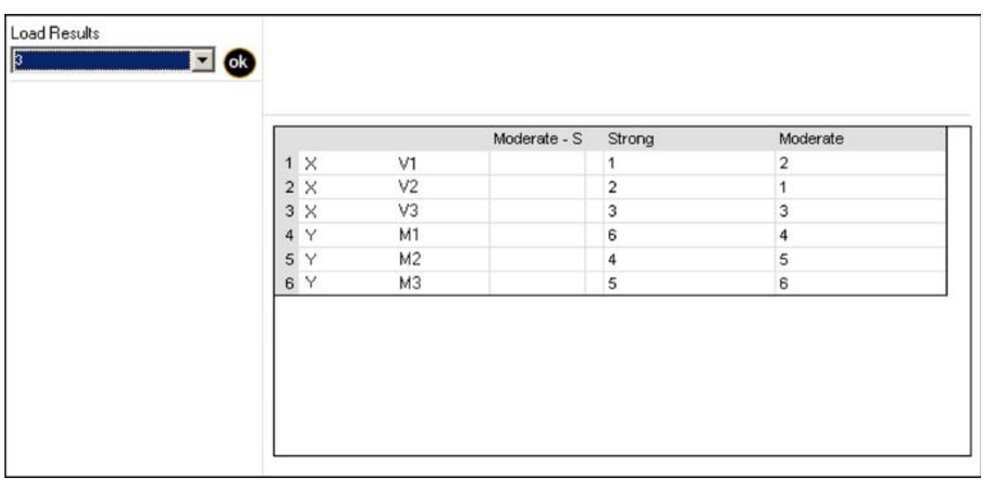


Fig. 13 Sensitivity analysis results

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