SELECTION OF A CNC VERTICAL MACHINE CENTRE FOR THE DESIGN OF FLEXIBLE MANUFACTURING SYSTEMS – A CASE STUDY

G. Anand[1] , Rambabu Kodali [2]& Balaji Mohan Chimakurthy[3]

Abstract: *One of the important decisions during the design of a Flexible Manufacturing Systems (FMS) is to identify and select suitable machine tools that are in-line with the organisational as well as other flexibility requirements. Selecting a suitable machine tool is of paramount importance because it involves heavy investment and a mistake in such decisions would affect the flexibilities and operations of both the FMS as well as the organisation. A review of literature related to FMS revealed that although this problem has been addressed, no paper is available, which attempted to select a suitable machine tool during the design of a FMS using an off-beat Multi-Criteria Decision-Making (MCDM) model namely, the Performance Value Analysis (PVA). Hence, in this paper, an attempt has been made to address these issues by presenting a case study in which a decision regarding the selection of a particular model of a VMC is made by using the PVA model, which considered various technical specifications and features of the available alternatives.*

Keywords: Flexible Manufacturing Systems (FMS), Vertical Machining Centre (VMC), Multi-Criteria Decision Making (MCDM) model, Performance Value Analysis (PVA), Machine Flexibility, Case study.

Nature of the Paper: Methodologies and models

Dimensions of enterprise flexibility: Manufacturing flexibility, Machine flexibility

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[1] Assistant Professor,Quantitative Methods & Operations Management (QM&OM) Area
Indian Institute of Management Kozhikode (IIMK),IIMK Campus P.O., Kunnamangalam, Kozhikode, Kerala – 673570, INDIA,anandg@iimk.ac.in
[2] Professor,Department of Mechanical Engineering ,Birla Institute of Technology & Science (BITS) Pilani, Pilani Campus,Pilani, Rajasthan – 333031, INDIA.,proframbabukodali@gmail.com, rbkodali@bits-pilani.ac.in
[3] Software Engineer,Tata Consultancy Services Limited,Desk# II-184, No. 69/2, Salarpuria G.R. Tech Park, JAL Building, Mahadevapura, K.R.Puram, Bengaluru - 560066, Karnataka, India
balaji.mohan@tcs.com, lionbalaji@gmail.com

Introduction

FMS is defined as a manufacturing system with computer-controlled workstations and material handling systems designed to manufacture more than one kind of part type in low to medium volumes to meet customer requirements (Kumar et al., 2009). According to Adam and Ebert (1999), a work station can consist of a machine or a robot that performs a particular class of tasks for which specialized tools are continuously available for one at a time use and changed quickly and automatically by computers according to unique requirements for each component as it progresses through the system. The quality of the product thus produced from a workstation is a function of the capability of the machine, the quality of maintenance and the capability of individual cutting tools, grippers, fixtures, programming, etc. Therefore, the selection of appropriate Computer Numeric Control (CNC) machine tools has become an important task in the design of FMS (Taha and Rostam, 2011). Furthermore, an improper selection can negatively affect productivity, precision, flexibility and company's responsive manufacturing capabilities (Arslan et al., 2004). On the other hand, using proper equipment can enhance the production process, provide effective utilization of manpower, increase production, and improve system flexibility, thereby improves the competitiveness of the organization. But the equipment selection problem – especially the selection of a Vertical Machining Centre (VMC) or Horizontal Machining Centre (HMC) during the design of FMS is more complex, as many conflicting attributes are to be considered during the selection process (Önüt et al, 2008). Secondly, due to the technical advancements in CNC machines and demand from industry, there has been a drastic increase in the availability of CNC machines in the market with wide range of capabilities and technical specifications (Alberti et al., 2011). Thirdly, collecting information about those machine models which are suitable to the requirements, sorting these models based on the technical data, filtering out those models which do not meet the requirements and capabilities and then finally selecting the most appropriate one among the existing alternative of machine tool is a mammoth task for the operations manager.

Although a plethora of papers are available that deal with the machine tool selection problem, only very few papers exist that addressed the decision problem of selecting the machine tools from the purchasing perspective (Alberti et al., 2011). Especially, no paper is found in the literature, which discusses about the selection of a machine tool - in particular a VMC for purchasing using an off-beat Multi-Criteria Decision-Making (MCDM) model such as Performance Value Analysis (PVA). Hence, in this paper, an attempt has been made to address this issue. The paper is arranged as follows: Section 2 deals with the literature review and identifies the research gaps, while Section 3 provides an overview of a case situation. Section 4 enumerates the algorithm of PVA and demonstrates how PVA has been used for making a decision of selecting a suitable VMC. Section 5 focuses on the results and discussion and finally, Section 6 ends with concluding remarks.

1. Literature Review

Several researchers have studied the machine tool selection problem using mathematical models, heuristic algorithms and different MCDM methods. The reviewed papers are classified into two categories – namely, papers that deal with machine selection problem in general and papers that deal with machine selection problem in a FMS environment.

1.1. Papers that deal with machine selection problem in general

Lin and Yang (1996) presented a machine selection model from a range of machines for the manufacture of particular part types using the Analytic Hierarchy Process (AHP). Chen (1999) studied the problem of selecting the best machining process and equipment in a dynamic manufacturing environment using integer programming model and a heuristic algorithm. Arslan et al. (2004) proposed a DSS based on the Multi-Criteria Weighted Average (MCWA) method to rank the machines. Gopalakrishnan et al. (2004) described the design and development of a system for the selection and construction of VMC and HMC packages with a base machine and options format subject to budgetary constraints. They developed a user-friendly and object-oriented computer-based DSS system incorporating real data from a machine tool sales organization. Ayag and Ozdemir (2006) used the fuzzy AHP technique to overcome the vagueness and uncertainty while weighing the machine tool alternatives under eight main and nineteen sub-criteria. Subsequently, they carried out benefit/cost ratio analysis by using both the fuzzy AHP score and procurement cost of each alternative. Dağdeviren (2008) used the AHP method to analyze the structure of the equipment selection problem and determined the weights of criteria and later obtained the final ranking by using the PROMETHEE method. Athawale and Chakraborty (2010) evaluated the CNC machines in terms of system specifications and cost by using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. Samvedi et al. (2011) integrated the fuzzy AHP and Grey Relational Analysis (GRA) approaches for the selection of a machine tool from a given set of alternatives.

1.2. Papers that deal with machine selection problem in a FMS environment

Myint and Tabucanon (1994) proposed a decision support framework based on multiple-criteria approach for the machine selection problem of FMS. Their framework consists of two parts. The first part is called the prescreening stage, which narrows down all possible configurations by using AHP and the second stage uses Goal Programming (GP) model to find out the satisfactory candidate from the remaining short listed configurations. Similarly, Tabucanon et al. (1994) developed an intelligent Decision Support System (DSS) which combined the AHP with the rule based technique used for creating Expert Systems (ES) and used the same to select a CNC turning center for processing a family of rotational parts. Atmani and Lashkari (1998) proposed a linear, 0-1 integer programming model of the machine-tool assignment and operation allocation in a FMS, which provides an optimal plan by minimizing the total costs of operations, material handling and set-ups. Wang et al. (2000) proposed a Fuzzy Multiple-Attribute Decision-Making (FMADM) model to assist the decision-maker to deal with the machine selection problem for a Flexible Manufacturing Cell (FMC). Chan and Swarnkar (2006) noted that planning problems in FMS that need realistic modelling and quicker solution and hence they presented a fuzzy GP approach to model the machine tool selection and operation allocation problem of FMS. They also used the Ant Colony Optimization (ACO)-based approach to optimize the model. Taha and Rostam (2011) developed a DSS for machine tool selection in a FMC using fuzzy AHP and Artificial Neural Network (ANN). They developed a program to find the Priority weights of the Evaluation Criteria and Alternative's Ranking called PECAR for fuzzy AHP model, while the ANN is used to verify the results of fuzzy AHP (PECAR program) and to predict the alternatives' ranking. They demonstrated their proposed approach using a numerical example to select the most suitable CNC machine based on data collected from a designed questionnaire.

1.3. Research gaps

Thus, a review of related papers revealed that many papers have already addressed this issue of selecting the machine tool both in general as well as in FMS environment. However, the following shortcomings can be identified from this brief review:

- Although a significant number of papers that deal with the decision of selecting a suitable machine tool for purchasing/procurement are available in the former classification, not many papers were available that deal with this issue in the FMS environment.

- Most of the papers in either of the categories above utilized various MCDM models such as AHP, ANP, PROMETHEE, TOPSIS and its variants involving fuzzy approach. Other optimization methods such as 0-1 linear programming, GP, GRA, ACO, etc. were also employed. However, none of the papers have utilized PVA - a MCDM model derived based on utility value analysis.

Hence, to overcome these shortcomings, an attempt has been made in this paper to demonstrate the decision of selecting a suitable machine tool (i.e. a VMC) for purchasing using the PVA for a real-life case organization.

2. Case study

To demonstrate the use of the PVA for the selection of a VMC, a real-life case situation of a FMS Laboratory of an educational institute is presented. The name of the institute is masked and it is named as ‘ BIINTESCPI’ to avoid conflict of interests. BIINTESCPI is an all-India institute for higher education deemed to be a University by the Government of India and offers various on-campus and off-campus degree programmes in Science, Engineering and Management. It has established many laboratories in different departments to support the various degree programmes offered. The Mechanical Engineering Department is one of the oldest departments of this institute, which was started in the year 1946 and offers first degree (under graduate), higher degree (post graduate) and doctoral degree (PhD) programmes apart from carrying out cutting-edge research in various areas of Mechanical Engineering. As a part of the sponsored research project in the department, the existing FMS Laboratory has to be upgraded with additional facilities such as VMCs and HMCs. Hence, a decision of selecting a suitable machining centre has to be made considering the budgetary constraints. Although the above described case may not be from a manufacturing organization, a similar situation is more prevalent in such organisations, when they attempt to improve the competitiveness/flexibility and expand their shop floor capability by procuring additional equipments. Naturally, this problem is of prime importance as it involves huge investment. The Principal Investigator (PI) of the research project has already carried out an initial study about the different VMCs that are available in the market, based on which he has sorted and filtered the available data to identify a those models, which are meeting the requirements. The list of models considered for selection of a suitable VMC is shown in Table 1.

Table 1: List of models considered for selection of a suitable VMC

S. No.	1	2	3	4	5	6	7
Models / Alternatives	VMC400	VMC500	VMC800S	VMC800	VCM800	KODI40	KODI40V80

Since, purchasing a new machine tool for the FMS is expensive and the relative investments tend to be irreversible, careful consideration of various factors / attributes / elements / criteria / specifications / performance indicators (in short, it will be called as 'decision criteria' for the sake of simplicity) is required before a decision can be made. Generally, these criteria can be broadly classified into two categories: quantitative and qualitative. In this case, since the PI has already vetted some of the decision criteria, it is assumed that the qualitative aspects such as maintainability, degree of service available, popularity of the supplier, etc. were considered during the initial screening itself. Hence, they are not considered separately in this analysis. Once the models were identified as shown above; quotations, brochures, manuals, trade literature, booklets containing technical specification, etc. were obtained from reputed vendors and known sources of vendors, who deal with the above models. Furthermore, it should also be remembered here that the identified models have similar functionalities as per the requirements. Hence, the goal is to obtain the 'best value for the money' by selecting a model, which is superior in terms of technological aspects, features, etc. from the available alternatives. Various documents mentioned earlier were used by the PI and two of his colleagues from the same department to identify the decision criteria for comparisons individually. The team members had around 10 years of industrial experience and 36 years of teaching experience on an average. Once the list of decision criteria was received from them individually, it was consolidated by eliminating duplicate criteria through brain storming sessions. Table 2 shows the list of decision criteria, from which it can be found that these criteria are highly quantitative in nature. Hence, PVA has been utilized, as it one of the rarely used MCDM models, which can efficiently process the quantitative data and give the best results based on the performance and value. In the next section, the algorithm of PVA is illustrated in a step-by-step manner.

3. Selection of a VMC using PVA

The PVA model is well received in literature (Arbel and Seidman, 1984; D'Angelo et al., 1996a; D'Angelo et al., 1996b, D'Angelo et al., 1998). It is a revised version of utility value analysis, which considers the direct / indirect and quantitative / qualitative elements and aggregates the weight values of such multiple criteria to arrive at a decision. Various researchers have used this model for diverse applications especially in the field of manufacturing systems, supply chains, etc. Kodali et al. (2004) used it for justification of world-class manufacturing systems; Sangwan (2006) applied it in the area of green manufacturing systems to justify the same, while Gurmurthy and Kodali (2008) justified the implementation of lean manufacturing systems in a case organization. Karthik (2006) utilized this model to select suppliers for designing robust supply chains, while Routroy (2009) demonstrated the application of the same for selection of third party logistics service providers. Very recently, Soni and Kodali (2010) have used PVA as part of an internal benchmarking exercise while assessing the supply chain performance.

To demonstrate the PVA, the input from PI as well as two of his colleagues was used. One of the authors was given the task of collecting the data. The team members were asked to compare each alternative with respect to the decision criteria identified earlier. The data obtained from them were fed into the PVA algorithm, which is described in detail in the following section.

3.1. Algorithm

Step 1. Define the problem and determine the objective.

The problem in this case is to select a suitable VMC for expanding the capability of the laboratory. The objective of this problem is to select a VMC, which performs better in all aspects such as features, technical specifications, cost, etc. for the given budgetary constraints.

Step 2. Identify the alternatives (a_i) available. The alternatives considered are already shown is Table 1.

Step 3. Determine the decision criteria (c_j) that govern the problem. The details regarding the same are presented in Table 2.

Step 4. Classify the decision criteria into significant categories.

This was carried out by the team based on their domain knowledge using brainstorming sessions. The decision criteria were classified into the following significant categories: Table and Pallet (TP), Operating Characteristics (OC), Machine Features (MF) and Standard Accessories (SA).

Table 2: List of decision criteria and its categorization

S. No.	Attributes / Criteria / Performance indicators / Decision factors / Elements	Notation	Direct/ Indirec	Significan t category
1.	Maximum allowable weight on pallet in Kg	MAXPW T	▲	TP
2.	Maximum stroke in X-direction in mm	STKXAX	▲	OC
3.	Maximum stroke in Y-direction in mm	STKYAX	▲	OC
4.	Maximum stroke in Z-direction in mm	STKZAX	▲	OC
5.	Maximum feed rate in X-direction in mm/min	CFRXAX	▲	OC
6.	Maximum feed rate in Y-direction in mm/min	CFRYAX	▲	OC
7.	Maximum feed rate in Z-direction in mm/min	CFRZAX	▲	OC
8.	Rapid feed rate in X-direction in mm/min	RFRXAX	▲	OC
9.	Rapid feed rate in Y-direction in mm/min	RFRYAX	▲	OC
10.	Rapid feed rate in Z-direction in mm/min	RFRZAX	▲	OC
11.	Maximum spindle speed in rpm	MXSSPD	▲	OC
12.	Spindle motor power in kW	SPMPOW	▼	MF
13.	Clamping area length in mm	CALEN	▲	TP
14.	Clamping area width in mm	CAWIDT	▲	TP
15.	Tool holding capacity of automatic tool changer	NOOTOL	▲	SA
16.	Maximum tool dia. that can be held when all pockets are full in mm	TOLDIA	▲	SA
17.	Maximum tool dia. that can be held when all pockets are empty in mm	TDWATL	▲	SA
18.	Maximum tool length that can be held in mm	TOLLEN	▲	SA
19.	Maximum tool weight in Kg	TOLWGT	▲	SA
20.	Tool change time in seconds	TCTIME	▼	SA
21.	Number of pallets	NOOPAL	▲	TP
22.	Machine length in mm	MACLEN	▼	MF
23.	Machine width in mm	MACWI D	▼	MF
24.	Machine height in mm	MACHG T	▼	MF
25.	Machine weight in Kg	MACWG T	▼	MF

▲ – Highest value is considered as the best (Direct)

▼ – Lowest value is considered as the best (Indirect)

Step 5. Classify the elements into direct (performance grows while the measure increases) and indirect categories (performance grows while the measure decreases).

Most of the identified criteria fall under the 'direct' category, as the performance of these criteria needs to be at its maximum as the measures increases. For instance, it is always desirable to have the 'maximum allowable weight on the pallet (MAXPWT)' to be higher, so that it can process multiple work pieces at any given time. Same holds good for other elements such as speed, feed rate, etc. Hence, an 'up arrow' is used to represent the same. On the other hand, there are certain elements such as 'motor power', whose value should be less, as it is not desirable to have higher energy consumption. Hence, a 'down arrow' is used to represent the same. Categorization of different elements into 'direct' and 'indirect' category is also shown in Table 2.

Step 6. Form the performance matrix, i.e., co-efficient e_{ij} related to the decision criterion c_j ($j = 1, 2, \ldots J$) and the alternative a_i ($i = 1, 2, \ldots I$)

As mentioned earlier, the data for each of the decision elements for each of the alternative VMCs were extracted from the brochures, data sheets, technical literature and other documents sent by the vendors. Table 3 shows a sample performance matrix for the elements under the significant category 'Operating Characteristics (OC)'.

Step 7. Quantify the qualitative attributes using the scale of 1 to 10, where 1 represents very low, 3 means low, 5 means medium, 7 means high, and 9 means very high.

Since no qualitative elements were available in this decision problem, this step was skipped.

Step 8. Assign absolute weight values (w_j) on a suitable scale (say 1 to 10) for each decision criterion reflecting the normative judgment of the decision maker.

The importance of each decision criterion was determined by the decision makers. The team members were asked to rate the importance of each criterion and the rounded average of the same in the form of integers is entered in table. For instance, the importance weight value for 'maximum spindle speed (MXSSPD)' is determined to be 6 and the same is entered in the 2nd column of Table 3.

Table 3. Sample performance matrix for the significant category 'Operating Characteristics (OC)'

Criteria (c_j)	**Weight values (w_i)**	**Performance coefficients (e_{ij}) for alternatives (a_i)**						
		VMC400	**VMC500**	**VMC800S**	**VMC800**	**VCM800**	**KODI40**	**KODI40V.80**
STKXAX	7	400	520	710	760	710	560	800
STKYAX	7	400	450	450	500	450	410	510
STKZAX	7	420	420	450	450	450	460	510
CFRXAX	7	2000	10000	5000	5000	10000	5000	5000
CFRYAX	7	2000	10000	5000	5000	10000	5000	5000

Criteria (c_j)	Weight values (w_i)	Performance coefficients (e_{ij}) for alternatives (a_i)						
		VMC400	VMC500	VMC800S	VMC800	VCM800	KODI40	KODI40V.80
CFRZAX	7	2000	10000	5000	5000	10000	5000	5000
RFRXAX	7	10000	12000	20000	20000	20000	20000	24000
RFRYAX	7	10000	12000	20000	20000	20000	20000	24000
RFRZAX	7	10000	12000	20000	20000	20000	12000	18000
MXSSPD	6	4000	6000	6000	8000	6000	4000	4000

Step 9. Form the normalized performance matrix. This matrix helps in transforming the initial performance measure into a score/weight for easier interpretation. It is based on the value function f_j, which is obtained for each decision criterion (c_j) as per the following steps:

i) Direct category (when performance increases while the measure increases)

$$p_{ij} = \frac{e_{ij}}{\max(e_j)} \quad (1)$$

for each alternative a_i related to attribute c_j

ii) Indirect category (when performance grows while the measure decreases)

$$p_{ij} = \frac{\min(e_j)}{e_{ij}} \quad (2)$$

for each alternative a_i related to attribute c_j

A sample normalized performance matrix for the criteria under the significant category – 'Standard Accessories (SA)' is shown in Table 4. Consider the e_{ij} coefficients for the alternatives corresponding to the element 'tool holding capacity of automatic tool changer NOOTOL'. Since, this criterion is under direct category, the maximum among these values is selected – i.e., 24, which is the maximum tool holding capacity for VMC 500, VMC 800, VMC 800S and VCM 800. Now, using the f_j function for direct category (i.e., Equation 1), the p_{ij} values are calculated for each of the alternatives under that particular criterion. Hence, it is 12/24 = 0.5 for VMC 400, 0.833 for KODI 40 and KODI 40V.80, while it is 1 for the remaining alternatives. In the case 'tool change time in seconds (TCTIME)', which fall under the indirect category, the minimum among these values is selected – i.e., 3 for both KODI 40 and KODI 40V.80. Hence, as per the f_j function for indirect category (i.e., Equation 2), the p_{ij} value for VMC 400 is obtained as 3/8 = 0.375, while it is 1 for both KODI 40 and

KODI 40V.80. In a similar manner, the p_{ij} values of decision criteria for other alternatives are obtained.

Table 4. Sample normalized performance matrix for the elements under the significant category – 'Standard Accessories (SA)'

Criteria (c_j)	Direct/ Indirect	Weight values (w_i)	Normalized performance coefficient values (p_{ij}) for alternatives (a_i)						
			VMC400	**VMC500**	**VMC800S**	**VMC800**	**VCM800**	**KODI40**	**KODI40V.80**
NOOTOL	▲	7	0.500	1.000	1.000	1.000	1.000	0.833	0.833
TOLDIA	▲	4	0.800	0.800	1.000	1.000	0.600	0.800	0.800
TDWATL	▲	3	0.781	1.000	1.000	1.000	0.938	0.781	0.781
TOLLEN	▲	4	0.667	1.000	1.000	1.000	0.833	0.833	0.833
TOLWGT	▲	3	0.600	0.800	1.000	1.000	0.800	0.800	0.800
TCTIME	▼	5	0.375	0.750	0.600	0.600	0.750	1.000	1.000

Step 10. Obtain the relative weight value for each criterion (c_j) from absolute weight value (w_j) using Equation 3:

$$\overline{W_j} = \frac{w_j}{\sum w_j} \quad \text{such that } \sum \overline{W_j} = 1 \tag{3}$$

To obtain the relative weight values, the weight values obtained for all the decision criteria (not just the criteria under a particular significant category) were summed up. It was found to be 132. For instance, the importance weight value of 'maximum tool weight in Kg (TOLWGT)' is found to be '3'. Hence, using Equation 3, its relative weight value is calculated as 3/132, which is equal to 0.023. Similarly, the relative weight values for other criteria were calculated, which are shown in Table 5.

Step 11. Obtain partial performance measure Z_{ij} by multiplying the relative weight values $\overline{W_j}$ of decision criterion to the normalized coefficient value for each of its alternatives (p_{ij})

$$Z_{ij} = p_{ij} \times \overline{W_j} \quad (\text{i} = 1, 2, \ldots \text{I}) \tag{4}$$

For example, the partial performance measure (Z_{ij}) for 'tool holding capacity of automatic tool changer (NOOTOL)' is obtained as follows: the relative weight values obtained in the earlier step (i.e., 0.053) is multiplied with the corresponding normalized coefficient values of alternatives (p_{ij}), which are 0.5, 1, 1, 1, 1, 0.833 and 0.833 respectively for each of the alternatives (see Table 4). Hence, for VMC 400, the partial performance measure is calculated as 0.053 * 0.5 = 0.027. Similarly, the values for other criteria were obtained, which are shown in Table 5.

Table 5: Partial performance measures for alternatives

Criteria	**Relative weight values** $\overline{W_j}$	**Partial performance measures (Z_{ij}) for alternatives (a_i)**						
		VMC400	**VMC500**	**VMC800S**	**VMC800**	**VCM800**	**KODI40**	**KODI40V.80**
MAXPWT	0.061	0.030	0.042	0.061	0.061	0.061	0.036	0.061
STKXAX	0.053	0.027	0.034	0.047	0.050	0.047	0.037	0.053
STKYAX	0.053	0.042	0.047	0.047	0.052	0.047	0.043	0.053
STKZAX	0.053	0.044	0.044	0.047	0.047	0.047	0.048	0.053
CFRXAX	0.053	0.011	0.053	0.027	0.027	0.053	0.027	0.027
CFRYAX	0.053	0.011	0.053	0.027	0.027	0.053	0.027	0.027
CFRZAX	0.053	0.011	0.053	0.027	0.027	0.053	0.027	0.027
RFRXAX	0.053	0.022	0.027	0.044	0.044	0.044	0.044	0.053
RFRYAX	0.053	0.022	0.027	0.044	0.044	0.044	0.044	0.053
RFRZAX	0.053	0.027	0.032	0.053	0.053	0.053	0.032	0.048
MXSSPD	0.045	0.023	0.034	0.034	0.045	0.034	0.023	0.023
SPMPOW	0.045	0.040	0.045	0.040	0.040	0.040	0.040	0.040
CALEN	0.030	0.019	0.022	0.027	0.027	0.027	0.029	0.030
CAWIDT	0.030	0.024	0.030	0.027	0.027	0.027	0.024	0.030
NOOTOL	0.053	0.027	0.053	0.053	0.053	0.053	0.044	0.044
TOLDIA	0.030	0.024	0.024	0.030	0.030	0.018	0.024	0.024
TDWATL	0.023	0.018	0.023	0.023	0.023	0.021	0.018	0.018
TOLLEN	0.030	0.020	0.030	0.030	0.030	0.025	0.025	0.025
TOLWGT	0.023	0.014	0.018	0.023	0.023	0.018	0.018	0.018
TCTIME	0.038	0.014	0.028	0.023	0.023	0.028	0.038	0.038
NOOPAL	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
MACLEN	0.030	0.030	0.023	0.026	0.025	0.025	0.029	0.022
MACWID	0.030	0.030	0.022	0.017	0.018	0.017	0.027	0.018
MACHGT	0.015	0.014	0.012	0.013	0.013	0.013	0.015	0.013
MACWGT	0.015	0.015	0.010	0.008	0.012	0.011	0.015	0.012
Overall measure (N_j)	**1.000**	**0.579**	**0.809**	**0.819**	**0.842**	**0.883**	**0.756**	**0.831**

Step 12. Aggregate the partial performance measures for each alternative to obtain the overall measure (N_i) of alternative (a_i). In other words, sum the values of Z_{ij} to obtain the overall measure.

$$N_i = \sum_{j=1}^{J} Z_{ij} \qquad (5)$$

For instance, under VMC 800, the partial performance measures such as 0.061, 0.047, …, 0.012 are summed up to obtain the overall measure of 0.805. Similarly, the overall measures for other alternatives are calculated, which are shown in Table 5.

Step 13. Rank the alternatives (a_i) in accordance with decreasing value of N_i.

The overall measure for each of the alternatives shows the preference of alternatives among the decision makers. Hence, they are arranged either in decreasing or increasing order for the ease of interpretation. The results of the ranking are shown in Table 6.

Table 6: Ranking of alternatives

Rank	1	2	3	4	5	6	7
Alternatives	VCM800	VMC800	KODI40V80	VMC800S	VMC500	KODI40	VMC400

Step 14. Perform the significant category analysis by setting the weights of each decision criterion that are different from the significant category being considered to zero. Carry out steps 8 to 13 and repeat step 14 for all significant categories.

For instance, if we consider the significant category TP, it includes 4 elements. The weight values for the degree of importance of the criteria as given earlier by the decision makers, the performance values (e_{ij}) in the performance matrix and the normalized performance matrix for the alternatives for those criteria under this significant category are retained (see Table 7a and 7b).

Table 7. Significant category analysis for the category – Table and Pallets (TP)

Table 7a. Initial performance matrix and absolute weight values for decision criteria

Decision criteria / factors / elements	**Weight values**	**Performance coefficients (e_{ij}) for alternatives (a_i)**						
(c_j)	**(w_i)**	**VMC400**	**VMC500**	**VMC800S**	**VMC800**	**VCM800**	**KODI40**	**KODI40V.80**
MAXPWT	8	250	350	500	500	500	300	500
CALEN	4	600	700	860	860	860	900	950
CAWIDT	4	400	500	460	460	460	410	510

NOOPAL	3	2	2	2	2	2	2	2

Table 7b. Normalized performance matrix and relative weight values for decision criteria

Decision criteria / factors / elements	**Weight values**	**Normalized coefficients for alternatives**						
(c_j)	**(wi)**	**VMC400**	**VMC500**	**VMC800S**	**VMC800**	**VCM800**	**KODI40**	**KODI40V.80**
MAXPWT	0.421	0.500	0.700	1.000	1.000	1.000	0.600	1.000
CALEN	0.211	0.632	0.737	0.905	0.905	0.905	0.947	1.000
CAWIDT	0.211	0.784	0.980	0.902	0.902	0.902	0.804	1.000
NOOPAL	0.158	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 7c. Partial performance measures and overall measures for the alternatives

Decision criteria / factors / elements	**Weight values**	**Partial performance measures (Z_{ij}) for alternatives (a_i)**						
(c_j)	**(wi)**	**VMC400**	**VMC500**	**VMC800S**	**VMC800**	**VCM800**	**KODI40**	**KODI40V.80**
MAXPWT	0.421	0.211	0.295	0.421	0.421	0.421	0.253	0.421
CALEN	0.211	0.133	0.155	0.191	0.191	0.191	0.199	0.211
CAWIDT	0.211	0.165	0.206	0.190	0.190	0.190	0.169	0.211
NOOPAL	0.158	0.158	0.158	0.158	0.158	0.158	0.158	0.158
Overall measure (N_j)	**1.000**	**0.667**	**0.814**	**0.959**	**0.959**	**0.959**	**0.779**	**1.000**

Once again, the relative weight values for the degree of importance of criteria under this category were calculated. Based on these relative weight values and normalized performance matrix values, the partial performance measures for each of the alternatives for those criteria under this significant category are calculated. Apart from this, the aggregated performance measures for all the alternatives are obtained by summing the partial performance measures for each decision elements as shown in Table 7c. Table 7 shows a sample significant category analysis for the category – Table and Pallets (TP). The above mentioned steps are repeated for the remaining significant categories. A summary of the significant category analysis and the total performance analysis is shown in Table 8.

Table 8. Aggregated indices for the alternatives

Alternatives	Significant Category Analysis				Total performance analysis
	TP	**OC**	**MF**	**SA**	
VMC400	0.667	0.453	0.951	0.592	0.579
VMC500	0.814	0.771	0.819	0.898	0.809
VMC800S	0.959	0.757	0.761	0.923	0.819
VMC800	0.959	0.795	0.782	0.923	0.842
VCM800	0.959	0.909	0.772	0.834	0.883
KODI40	0.779	0.670	0.926	0.850	0.756
KODI40V80	1.000	0.794	0.767	0.850	0.831

Step 15. Take the decision based on the overall aggregated partial performance measures and the aggregated performance measures of significant categories (see Tables 6 to 8).

The details regarding the decision taken are presented in the next section.

4. Results and discussion

Highly user-friendly software for the PVA model is developed in VC^{++} to aid the user in inputting the decision criteria, performance coefficients, weights etc. and computing the partial performance measures for all criteria. It also aids in carrying out the significant category analysis. However, all these calculations can be carried out using spreadsheet packages such as Microsoft Excel. The decision can be taken based on the Figures 1 and 2 and Tables 6 to 8. As seen from Tables 6 and 8, for the current situation, the model VCM800 is considered to be the best alternative, as it has scored the maximum performance value of 0.883 among the alternatives considered. It is closely followed by VMC 800, KODI40V.80. However, Figure 1 shows that the best alternative (VCM 800) has not performed well for the all decision criteria. In the case of 'number of pallets (NOOPAL)', all the alternatives had the same performance, while in the case 'machine weight in Kg (MACWGT)', all the alternatives had varied performance and in particular the alternative KODI40V.80 has performed better than the VCM 800 for this criteria. But, based on a consolidated analysis of all the elements, it was found that VCM 800 is the best alternative.

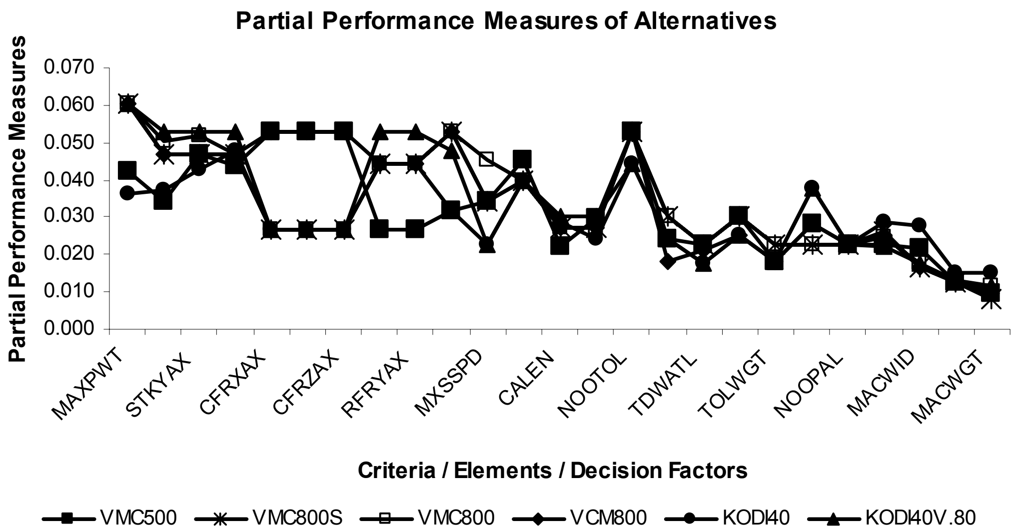

Figure 1. Partial performance measure for the alternatives

From Figure 2, which shows the summary of significant category analysis, it was found that KODI40V.80 has performed better in the category of TP, while VMC 400 has scored the lowest. On the other hand, VMC 400 outscored other alternatives under the significant category – 'Machine Features (MF)'. VCM 800 was considered to be the best in the significant category – 'Operating Characteristics (OC)', while both VMC800S and VMC 800 performed better than any of the other alternatives in the case of significant category – 'Standard Accessories (SA)'. Thus, PVA also helps in understanding the best alternatives for each of the significant category. If the decision makers are interested in one particular significant category alone, then it also helps them to make/change the decision accordingly. However, in this case, considering the overall performance for all the decision criteria and the significant categories, VCM 800 has performed better than any of the other alternatives and hence it is considered to be the best for the case organization.

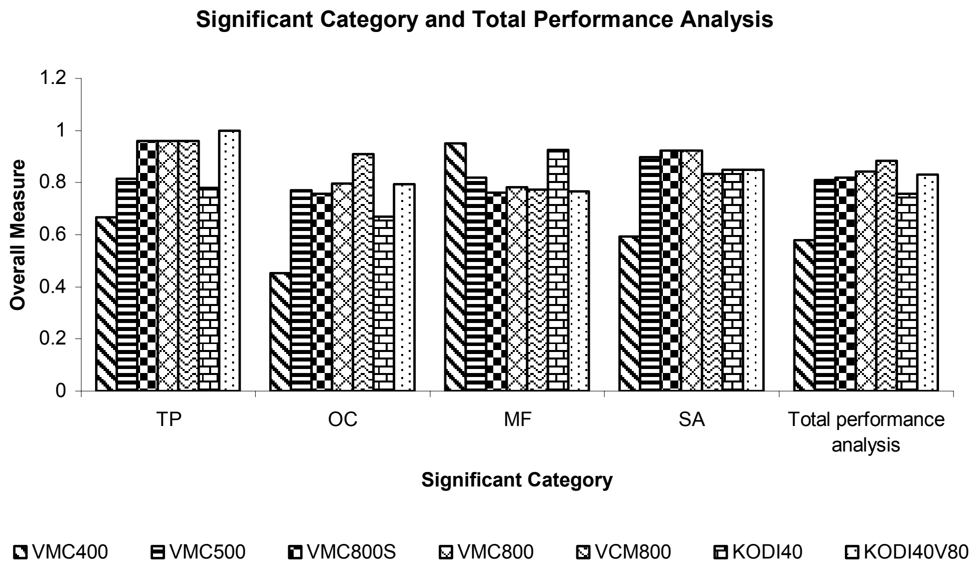

Figure 2. Significant category and total performance analysis of alternatives

5. Conclusions

The paper started with the claim that 'one of the important decisions in the design of FMS is to select a suitable VMC or HMC' for purchasing. However, based on the literature review, it was found that adequate importance is not given to this decision especially in the literature of FMS. Since, selecting a suitable VMC or HMC can affect various flexibilities of the FMS, it is imperative that such decisions are made after careful consideration of various decision criteria. Hence, in this paper, an attempt has been made to present a systematic method for 'selection of a suitable VMC' for a case situation using a rarely used MCDM model called PVA. The entire algorithm was demonstrated in a step-by-step manner and it was found that VCM 800 was found to be a better alternative for the case organization for the given situation. It is believed that the case study and the accompanying demonstration of the PVA algorithm would help the managers in making a better decision apart from providing them sufficient confidence in their decision making process, as PVA can act as a decision support system too.

References

1. Adam E.E. and Ebert R.J. (1999). Production and Operations Management, Prentice-Hall, New Delhi.
2. Alberti M., Ciurana J., Rodríguez C.A. and Özel T. (2011). Design of a decision support system for machine tool selection based on machine characteristics and performance tests, *Journal of Intelligent Manufacturing*, 22(2):263-277.
3. Arbel A. and Seidman A. (1984). Performance evaluation of flexible manufacturing systems, *IEEE Transactions on Systems, Man, and Cybernetics*, 14(4): 606-617.
4. Arslan M.C., Çatay B. and Budak E. (2004). A decision support system for machine selection, *Journal of Manufacturing Technology Management*, 15(1):101-109.
5. Athawale V.M. and Chakraborty S. (2010). A TOPSIS Method-based Approach to Machine Tool Selection, Proceedings of the 2010 International Conference on Industrial Engineering and Operations Management (IEOM 2010): 9-10 January 2010, Dhaka, Bangaladesh, available online at: http://www.iieom.org/paper/124%20Chakraborty.pdf, accessed on 24 October 2011.
6. Atmani A. and Lashkari R.S. (1998). A model of machine tool selection and operation allocation in flexible manufacturing systems, *International Journal of Production Research*, 36(5):339-1349.
7. Ayag Z. and Özdemir R.G. (2006). A fuzzy AHP approach to evaluating machine tool alternatives, *Journal of Intelligent Manufacturing*, 17(2): 179-190.
8. Chan F.T.S. and Swarnkar R. (2006). Ant colony optimization approach to a fuzzy goal programming model for a machine tool selection and operation allocation problem in an FMS, *Robotics and Computer-Integrated Manufacturing*, 22(4): 353-362.
9. Chen M. (1999). A heuristic for solving manufacturing process and equipment selection problems, *International Journal of Production Research*, 37(2):359-374.
10. D'Angelo A., Gastaldi M. and Levialdi N. (1996a). Dynamic analysis of the performance of a flexible manufacturing system: a real case application, *Computer Integrated Manufacturing Systems*, 9(2): 101-110.
11. D'Angelo A., Gastaldi M. and Levialdi N. (1996b). Multicriteria evaluation model for flexible manufacturing system design, *Computer Integrated Manufacturing Systems*, 9(3): 171-178.
12. D'Angelo A., Gastaldi M. and Levialdi N. (1998). Performance analysis of a flexible manufacturing system: A statistical approach, *International Journal of Production Economics*, 56-57(1): 47-59.
13. Dağdeviren M. (2008). Decision making in equipment selection: an integrated approach with AHP and PROMETHEE, *Journal of Intelligent Manufacturing*, 19(4): 397-406.
14. Gopalakrishnan B., Yoshii T. and Dappili S.M. (2004). Decision support system for machining center selection, *Journal of Manufacturing Technology Manag*ement, 15(2):144-154.
15. Gurumurthy A. and Kodali R. (2008). A multi-criteria decision-making model for the justification of lean manufacturing systems, *International Journal of Management Science and Engineering Management*, 3(2):100-118.
16. Karthik V.N. (2006). An integrated supplier selection methodology for designing robust supply chains, Proceedings of IEEE International Conference on Management of Innovation and Technology (ICMIT 2006): 21-23 June, Singapore, pp.906-910.
17. Kodali R., Sangwan K.S. and Sunnapwar V.K. (2004). Performance value analysis for the justification of world-class manufacturing systems, *Journal of Advanced Manufacturing Systems*, 3(1):85-102.

18. Kumar R.M.S., Asokan P. and Kumanan S. (2009). Artificial immune system-based algorithm for the unidirectional loop layout problem in a flexible manufacturing system, *International Journal of Advanced Manufacturing Technology*, 40(5-6):553-565.
19. Lin Z.C. and Yang C.B. (1996). Evaluation of machine selection by the AHP method, *Journal of Materials Processing Technology*, 57(3-4):253-258.
20. Myint S. and Tabucanon M.T. (1994). A multiple-criteria approach to machine selection for flexible manufacturing systems, *International Journal of Production Economics*, 33(1-3):121-131.
21. Önüt S., Kara S.S. and Efendigil T. (2008). A hybrid fuzzy MCDM approach to machine tool selection, *Journal of Intelligent Manufacturing*, 19(3): 443-453.
22. Routroy S. (2009). Selection of third party logistics provider in supply chain, *International Journal of Services Technology and Management*, 12(1):23-34.
23. Samvedi A., Jain V. and Chan F.T.S. (2011). An integrated approach for machine tool selection using fuzzy analytical hierarchy process and grey relational analysis, *International Journal of Production Research*, DOI:10.1080/00207543.2011.560906.
24. Sangwan K.S. (2006). Performance value analysis for justification of green manufacturing systems, *Journal of Advanced Manufacturing Systems*, 5(1):59-74.
25. Soni G. and Kodali R. (2010). Internal benchmarking for assessment of supply chain performance, *Benchmarking: An International Journal*, 17(1):44-76.
26. Tabucanon M.T., Batanov D.N. and Verma D.K. (1994). Decision support system for multicriteria machine selection for flexible manufacturing systems, *Computers in Industry*, 25(2):131-143.
27. Taha Z. and Rostam S. (2011). A fuzzy AHP–ANN-based decision support system for machine tool selection in a flexible manufacturing cell, *International Journal of Advanced Manufacturing Technology,* 57(5-8): 719-733.
28. Wang T.Y., Shaw C.F. and Chen Y.L. (2000). Machine selection in flexible manufacturing cell: a fuzzy multiple attribute decision-making approach, *International Journal of Production Research*, 38(9):2079-2097.