FMS SELECTION UNDER DISPARATE LEVEL-OF-SATISFACTION OF DECISION MAKING USING AN INTELLIGENT FUZZY-MCDM MODEL

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Abstract: This chapter outlines an intelligent fuzzy multi-criteria decision-making (MCDM) model for appropriate selection of a flexible manufacturing system (FMS) in a conflicting criteria environment. A holistic methodology has been developed for finding out the "optimal FMS" from a set of candidate-FMSs. This method of trade-offs among various parameters, viz., design parameters, economic considerations, etc., affecting the FMS selection process in an MCDM environment. The proposed method calculates the global priority values (GP) for functional, design factors and other important attributes by an eigenvector method of a pair-wise comparison. These GPs are used as subjective factor measures (SFMs) in determining the selection index (SI). The proposed fuzzified methodology is equipped with the capability of determining changes in the FMS selection process that results from making changes in the parameters of the model. The model achieves balancing among criteria. Relationships among the degree of fuzziness, level-of-satisfaction and the SIs of the MCDM methodology guide decision makers under a tripartite fuzzy environment in selecting their choice of trading-off with a predetermined allowable fuzziness. The measurement of level-of-satisfaction during making the appropriate selection of FMS is carried out.

Key words: FMS, intelligent fuzzy MCDM, global priority, sensitivity analysis, selection indices

C. Kahraman (ed.), Fuzzy Multi-Criteria Decision Making.

1. INTRODUCTION

A flexible manufacturing system (FMS) is a set of integrated computer-controlled, automated material handling equipments and numerical-controlled machine tools capable of processing a variety of part types. Due to the competitive advantages like flexibility, speed of response, quality, reduction of lead-time, reduction of labour etc., FMSs are now gaining popularity in industries.

Today's manufacturing strategy is purely a choice of alternatives. The better the choice, more will be the productivity as well as the profit maintaining quality of product and responsiveness to customers. In this era of rapid globalization, the overall objective is to purchase a minimum amount of capacity (i.e., capital investment) and utilize it in the most effective way. Although FMS is an outgrowth of existing manufacturing technologies, its selection is not often studied. It has been a focal point in manufacturing–related research since the early 1970s. FMS provides a low inventory environment with unbalanced operations unique to the conventional production environment. The process design of an FMS consists of a set of crucial decisions that are to be made carefully. It requires decision making, e.g., selection of a CNC machine tool, material handling system, or product mix. The selection of a FMS thus requires trading-off among the various parameters of the FMS alternatives. The selection parameters are conflicting in nature. High-quality management is not enough for dealing with the complex and ill-structured factors that are conflicting in nature (Buffa, 1993). Therefore, there is a need for sophisticated and applicable technique to help the decision makers for selecting the proper FMS in a manufacturing organization.

The authors, thus, propose a DSS methodology, for appropriate FMS selection, that trade off among some intangible criteria as well as cost factors to get the maximum benefit out of these conflicting-in-nature criteria. There have been many contributors to the literature on selection of proper FMS. A selective review of some of the relevant works in this area is give here. Kaighobadi and Venkatesh (1994) presented an overview and survey of research in FMSs. They also presented a definition of FMSs. Chen et al. (1998) investigated the relationship between flexibility measurements and system performance in the flexible manufacturing systems environment. The authors suggested several alternative measures for the assessment of machine flexibility and routing flexibility—two of the most important flexibility types discussed in the literature. Nagarur (1992) showed that computer integration and flexibility of the system were the two critical factors of FMS. Eight different types of flexibility were proposed by Browne et al. (1984). Each of these flexibilities contributes to overall flexibility of the system to cope with possible changes in demand structure. In addition to machine, process, product, routing, volume, expansion, operation and production flexibility as described by Browne et al. (1984). Barad and Sipper (1988) introduced another classification, i.e., transfer flexibility. Buzacott and Mandelbaum (1985) defined flexibility as the ability of a manufacturing system to cope with changing circumstances. High-level flexibility enables a manufacturing firm to provide faster response to market changes maintaining high product quality standards (Gupta and Goyal, 1989).

Flexible manufacturing provides an environment where integration effects cannot be eliminated (Lenz, 1988). If the inventory is raised, the manufacturing environment becomes that of the job shop type. On the contrary, if the operations are balanced, the environment becomes that of the transfer line. The changes in production are related to both inventory changes as well as changes in flow time. Three variables determine the amount of integration effects that result in a production process. These are inventory level, balanced loading, and flexibility. Inventory level is quantified by counting the number of parts that are active in the production process. Balanced loading can be quantified by the use of flow time. The use of flow time is to measure the balance within a production facility, and it is derived from the transfer line. The flow time provides a means to measure the balance between station loads in any type of production facility. Flexibility can be measured by the variability of the flow time. A process with greater degree of flexibility will provide less variability to the flow time.

Meredith and Suresh (1986) addressed justification of economic analysis and of analytical and strategic approaches in advanced manufacturing technologies. Evaluation of FMS alternatives was earlier carried out by Miltenburg and Krinsky (1987). They analyzed traditional economic evaluation techniques for the evaluation. Nelson (1986) formulated a scoring model for FMS project selection. Performance measures, viz., quality and flexibility, were also quantified in the scoring model. Use of the analytic hierarchy process (AHP) for evaluation of tangible and intangible benefits during FMS investment was reported by Wabalickis (1988). Stam and Kuula (1991) developed a two-phase decision support procedure using AHP and multi-objective mathematical programming for selection of FMS. Sambasivarao and Deshmukh (1997) presented a DSS integrating multi-attribute analysis, economic analysis and risk evaluation analysis. They have suggested AHP, TOPSIS (technique for order preference for similarity to ideal solution), and a linear additive utility model as an alternative multi-attribute analysis model. Shang and Sueyoshi (1995) formulated a model of simulation and data envelopment analysis (DEA) along with AHP for FMS selection. Karsak and Tolga (2001) proposed a fuzzy-MCDM approach for evaluation of advanced manufacturing system investments considering economic and strategic selection criteria. Karsak (2002) proposed a robust decision-making procedure for evaluating FMS using a distance-based fuzzy-MCDM philosophy.

Some researchers (Chen et al., 1998; Evans and Brown, 1989) believe that qualitative benefits cannot be considered mathematically unless one uses a knowledge-based system. This dissertation outlines a mathematical approach based on the judgmental values of a decision maker that can help decision makers in selecting the cost-effective FMS.

Abdel-Malek and Wolf (1991) propose a "measure" for the decision-making process. The said "measure" ranks different competing FMS designs according to their inherent flexibility as they relate to the maximum flexibility possible stipulated by the state-of-the-art. In developing the proposed "measure," the attributes governing the flexibility of FMS major components are defined. A notion of "strings" representing alternative production routes for different products is set forth. The method allows the integration of the eight points of flexibility stated by Browne et al. (1984) into a single comprehensive flexibility indicator.

Elango and Meinhart (1994) provide a framework for selection of an appropriate FMS using a holistic approach. The selection process considers operational and financial aspects. Furthermore, their selection process is consistent with industry, market, organizational, and other strategic needs.

A DSS for dynamic task allocation in a distributed structure for flexible manufacturing systems FMS has been developed by Trentesaux et al. (1998). An entity of the manufacturing system is considered as an autonomous agent, called the integrated management station (IMS), able to cooperate with other agents to achieve a global production program. Cooperation is performed by exchanging messages among the different agents. The characteristics of a DSS that supports multi-criteria algorithms and sensitivity tests is presented in Trentesaux et al. (1998). This DSS is integrated to each decision system of every IMS. Trentesaux et al.'s (1998) research work aims at allocating tasks in a dynamic way by proposing to the human operator a selection of possible resources.

Sarkis and Talluri (1999) disclose a model for evaluating alternative FMSs by considering both quantitative and qualitative factors. The evaluation process uses a DEA model, which incorporates both ordinal and cardinal measures. The model provides pair-wise comparisons of specific alternatives for FMSs. The consideration of both tangible and intangible factors is achieved in their methodology. The analysis of results provides both seller's and buyer's perspectives of FMS evaluation.

The decision-making process for machine-tool selection and operation allocation in a FMS usually involves multiple conflicting objectives. Rai et al.

(2002) address application of a fuzzy goal-programming concept to model the problem of machine-tool selection and operation allocation with explicit considerations given to objectives of minimizing the total cost of machining operation, material handling, and set up. The constraints pertaining to the capacity of machines, tool magazine, and tool life are included in the model. A genetic algorithm (GA)-based approach is adopted to optimize this fuzzy goal-programming model.

Advanced computing/communications technology is present in virtually all areas of manufacturing. In the near future, a totally computer-controlled manufacturing environmental will be a realistic expectation (Haddock and Hartshorn, 1989). The integration and enhancement of both computer-aided design (CAD) and computer-aided manufacturing (CAM) represents the foundations for achieving a totally integrated manufacturing system.

The requirements for increased responsiveness to market and the demands for shorter product introduction times underline the need for a coherent formal approach toward equipment selection to support the knowledge and experience of the engineers entrusted with this important task (Gindy and Ratchev, 1998). With the increasing complexity of the decision making in manufacturing system design, the search for the right structure depends on the capability of the designers to compare different solutions using common approaches in an integrated decision-making environment (Gindy and Ratchev, 1998).

Thus, machine tool selection has strategic implications that contribute to the manufacturing strategy of a manufacturing organization (Yurdakul, 2004). In such a case, it is important to identify and model the links between machine tool alternatives and manufacturing strategy (Yurdakul, 2004).

Haddock and Hartshorn (1989) present a DSS that assists in the specific selection of a machine 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 the optimal machine, versus possible alternates, is made by a planner comparing a criterion measure. Some possible criteria for selection as suggested by Haddock and Hartshorn (1989) are the relative location of machines, machining cost, processing time and availability of a machine.

Tabucanon et al. (1994) propose an approach to the design and development of an intelligent DSS that is intended to help the selection process of alternative machines for FMS. The process consists of a series of steps starting with an analysis of the information and culminating in a conclusion—a selection from several available alternatives and verification of the selected alternative to solve the problem. The approach combines the AHP technique with the rule-based technique for creating expert systems (ESs). This approach determines the architecture of the computer-based environment necessary for the decision support software system to be created. It includes the AHP software package (Expert Choice), Dbase III + DBMS, Expert System shell (EXSYS), and Turbo Pascal compiler (for the external procedural programs). A prototype DSS for a fixed domain, namely a CNC turning center that is required to process a family of rotational parts, is developed. Tabucanon et al.'s (1994) methodology helps the user to find the most "satisfactory" machine on the basis of several objective as well as subjective attributes.

Flexible manufacturing cells (FMCs) have been used as a tool to implement flexible manufacturing processes to increase the competitiveness of manufacturing systems (Wang et al., 2000). In implementing an FMC, decision makers encounter the machine selection problem, including attributes, e.g., machine type, cost, number of machines, floor space, and planned expenditures (Wang et al., 2000). Wang et al. (2000) propose a fuzzy multiple-attribute decision-making (FMADM) model to assist the decision maker to deal with the machine selection problem for an FMC realistically and economically. In their work, the membership functions of weights for those attributes are determined in accordance with their distinguishability and robustness when the ranking is performed.

AHP is widely used for tackling FMS selection problems due to the concept's simplicity and efficiency (Sambasivarao and Deshmukh, 1997). But AHP, as it is, do not take into consideration tangible factors, such as cost factors (Saaty, 1980, 1986, 1990). Thus, there is a need to allow cardinal factors in AHP to make the model robust and more efficient. In this chapter, a robust MCDM procedure is proposed using AHP that incorporates qualitative as well as quantitative measures for the FMS selection problem. The methodology proposed is very useful first to quantify the intangible factors in a strong manner and then to find out the best among member alternatives depending on their cost factors.

Some researchers believe that qualitative benefits cannot be considered mathematically unless one uses a knowledge-based system (Chen et al., 1998; Evans and Brown, 1989). This chapter outlines a fuzzified intelligent approach based on the judgmental values of the decision maker in selecting the most cost-effective FMS. One objective of this chapter is to find out fuzziness patterns of FMS selection decisions having a disparate level-of-satisfaction of the decision makers. Another objective is to provide a robust, quantified monitor of the level of satisfaction among decision makers and to calibrate these levels-of-satisfaction against decision makers' expectations.

2. FMS SELECTION PROBLEM

As a first step in testing the MCDM model proposed in the previous chapter, the authors have illustrated an example with FMS selection. Six different types of objective cost components have been identified for the selection problem. The total costs of each alternative are nothing, but the objective factor costs (OFCs) of the FMSs (refer to Table 1). The task is to select the best candidate-FMS among five candidate-FMSs.

Table 1. Cost Factor Components

FMS/OFCs	S_1	S_2	S_3	S_4	S_5
1. Cost of Acquisition	1.500	0.800	1.300	1.00	0.900
2. Cost of Installation	0.075	0.061	0.063	0.053	0.067
3. Cost of Commissioning	0.063	0.052	0.055	0.050	0.061
4. Cost of Training	0.041	0.043	0.046	0.042	0.040
5. Cost of Operation	0.500	0.405	0.420	0.470	0.430
6. Cost of Maintenance	0.500	0.405	0.420	0.470	0.430
Total Cost (OFC)	2.239	1.431	1.949	1.669	1.550
Objective Factor Measure (OFM_i)	0.154	0.241	0.177	0.206	0.222

The subjective attributes influencing the selection of FMS are shown in Table 2. The study consists of five different attributes, viz., flexibility in pick-up and delivery, flexibility in the conveying system, flexibility in automated storage and retrieval system, life expectancy/payback period, and tool magazine changing time. One may consider other attributes appropriate to selection of FMS. The attributes influencing the FMS selection problem are shown in Table 2.

Table 2. Attributes Influencing the FMS Selection Problem

Factor I	Factor II	Factor III	Factor IV	Factor V
Flexibility in pick-up and delivery	Flexibility in conveying system	Flexibility in automated storage and retrieval system	Life expectancy/pay back period	Tool magazine changing time

The MATLAB® fuzzy toolbox has been used in this work wherein a logical intelligent rule has been coded in M-file suitably using the designed MF.

3. SIMULATION USING MATLB®

The most important task for a decision maker is the selection of the factors. Thorough representation of the problem indicating the overall goal, criteria, sub-criteria (if any), and alternatives in all levels maintaining the sensitivity to change in the elements is a vital issue. The number of criteria or alternatives in the proposed methodology should be reasonably small to allow consistent pair-wise comparisons.

Matrix 1 is the decision matrix based on the judgmental values from different judges. Matrices 2 to 6 show comparisons of the weightages for each attribute. Matrix 7 consolidates the results of the earlier tables in arriving at the composite weights, i.e., SFM_i values, of each of the alternatives.

$$D = \begin{bmatrix} 1 & 5 & 3 & 4 & 5 \\ \frac{1}{5} & 1 & \frac{1}{3} & \frac{1}{2} & 1 \\ \frac{1}{3} & 3 & 1 & 3 & 5 \\ \frac{1}{4} & 2 & \frac{1}{3} & 1 & 3 \\ \frac{1}{5} & 1 & \frac{1}{5} & \frac{1}{3} & 1 \end{bmatrix}$$

Matrix 1. Decision matrix (I.R. = 4.39%)

$$A_1 = \begin{bmatrix} 1 & 3 & 2 & 5 & 4 \\ \frac{1}{3} & 1 & \frac{1}{3} & 5 & 2 \\ \frac{1}{2} & 3 & 1 & 4 & 3 \\ \frac{1}{5} & \frac{1}{5} & \frac{1}{4} & 1 & \frac{1}{3} \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{3} & 3 & 1 \end{bmatrix}$$

Matrix 2. Pair-wise comparison matrix for 'F_1' (I.R. = 4.48%)

$$A_2 = \begin{bmatrix} 1 & 7 & 3 & 5 & 6 \\ \frac{1}{7} & 1 & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} \\ \frac{1}{3} & 4 & 1 & 3 & 4 \\ \frac{1}{5} & 3 & \frac{1}{3} & 1 & 2 \\ \frac{1}{6} & 2 & \frac{1}{4} & \frac{1}{2} & 1 \end{bmatrix}$$

Matrix 3. Pair-wise comparison matrix

$$A_3 = \begin{bmatrix} 1 & 4 & 1 & 3 & 7 \\ \frac{1}{4} & 1 & \frac{1}{4} & \frac{1}{2} & 5 \\ 1 & 4 & 1 & 2 & 7 \\ \frac{1}{3} & 2 & \frac{1}{2} & 1 & 3 \\ \frac{1}{7} & \frac{1}{5} & \frac{1}{7} & \frac{1}{3} & 1 \end{bmatrix}$$

Matrix 4. Pair-wise comparison matrix for F_2 (I.R. = 3.32%) for F_3 (I.R. = 1.88%)

$$A_4 = \begin{bmatrix} 1 & \frac{1}{3} & 5 & 3 & 6 \\ 3 & 1 & 5 & 7 & 6 \\ \frac{1}{5} & \frac{1}{5} & 1 & 2 & 3 \\ \frac{1}{3} & \frac{1}{7} & \frac{1}{2} & 1 & 2 \\ \frac{1}{6} & \frac{1}{6} & \frac{1}{3} & \frac{1}{2} & 1 \end{bmatrix}$$

Matrix 5. Pair-wise comparison matrix

$$A_5 = \begin{bmatrix} 1 & \frac{1}{3} & 5 & 7 & 4 \\ 3 & 1 & 5 & 6 & 4 \\ \frac{1}{5} & \frac{1}{5} & 1 & 2 & \frac{1}{2} \\ \frac{1}{7} & \frac{1}{6} & \frac{1}{2} & 1 & \frac{1}{3} \\ \frac{1}{4} & \frac{1}{4} & 2 & 3 & 1 \end{bmatrix}$$

Matrix 6. Pair-wise comparison matrix for F_4 (I.R. = 6.22%) and for F_5 (I.R. = 6.87%)

$$G = \begin{bmatrix} 0.471 & 0.076 & 0.259 & 0.131 & 0.063 \\ 0.408 & 0.512 & 0.366 & 0.273 & 0.305 \\ 0.159 & 0.051 & 0.104 & 0.501 & 0.458 \\ 0.279 & 0.246 & 0.338 & 0.103 & 0.074 \\ 0.050 & 0.117 & 0.151 & 0.075 & 0.047 \\ 0.103 & 0.075 & 0.040 & 0.047 & 0.116 \end{bmatrix}$$

Matrix 7. Final matrix to find out Global Priority

In the proposed methodology, the unit of OFC is US$, whereas the objective factor measure (OFM) is a non dimensional quantity. Correspondingly, the SI is also a non-dimensional quantity. The higher the SI values, the better would be the selection. The value of the objective factor decision weight (α) lies between 0 and 1. For α = 0, SI = SFM; i.e., selection is solely dependent on subjective factor measure values found from AHP and SFM values dominate over OFM values. There is no significance of considering the cost factor components for α = 0. For α = 1, SI = OFM; i.e., OFM values dominate over the SFM values, and the FMS selection is dependent on OFM values only. For α = 1, the cost factors get priority over the other factors. Keeping this in mind, the values of α are taken in between 0 and 1. To verify the practicality and effectiveness of the final outcome of the proposed methodology, sensitivity analysis is done.

The basic fuzzified equation governing the selection process is recalled once again. It is to be remembered that the Eq. (1) (Wabalickis, 1988) uses MF as depicted by Eq. (2).

$$\tilde{\mathrm{LSI}}_i\Big|_{\alpha=\alpha_{\mathrm{SFM}_i}} = \mathrm{LSI}_L + \left(\frac{\mathrm{LSI}_U - \mathrm{LSI}_L}{\gamma}\right)\ln\frac{1}{C}\left(\frac{A}{\alpha_{\mathrm{LSI}_i}} - 1\right) \tag{1}$$

$$\mu(x) = \begin{cases} 1 & x < x^a \\ 0.999 & x = x^a \\ \dfrac{B}{1+Ce^{\gamma x}} & x^a < x < x^b \\ 0.001 & x = x^b \\ 0 & x > x^b \end{cases} \tag{2}$$

The intelligent decision algorithm generates the coefficients of the fuzzy constraints in the decision variables. The rule first declares a function C_j and assigns the constants in the MF. The aim is to produce a rule that works well on previously unseen data, i.e., the decision rule should "generalize" well. An example is appended below:

```
function [cj] = mpgen(cj0,cj1,gamma,mucj)
B = (0.998 / ((0.001 × exp(gamma)) − 0.999));
A=0.999 × (1 + B);
cj=cj0 + ((cj1 − cj0) / gamma) × (log((1 / B) × ((A / mucj) − 1)));
```

The rule supports this work by allowing the call to the function to contain a variable, which is automatically set to different values as one may request. The logical way in which the intelligent fuzzy-MCDM acts as an agent in the entire system includes many *if − else* rules.

3.1 Fuzzy Sensitivity of the MCDM Model

In a real-life situation, the decision environments rarely remain static. Therefore, it is essential to equip the proposed decision-making model with the capability to determine changes in the selection process that results from making changes in the parameters of the model. So, the dynamic behavior of the optimal selection found from the proposed methodology can be checked through the fuzzy-sensitivity plots.

Among all the FMSs, FMS_1 has the highest SI value when the objective factor decision weight lies between 0.33 and 1.00. However, FMS_2 would be preferred to other FMS candidate-alternatives when the value of level-of-satisfaction lies between 0.00 and 0.33.

The appropriate value of the level-of-satisfaction is to be selected cautiously. The reason behind this is as follows. The higher the α value, the dominance of the SFM_i values will be higher. The lower the α value, more will be the dominance of cost factor components, and subsequently, the intangible factors will get less priority.

Table 3 illustrates the final ranking based on the proposed model. From the Table 3 and Figures 16 to 20 ranking of the candidate-alternatives is $FMS_1 \succ FMS_2 \succ FMS_3 \succ FMS_5 \succ FMS_4$, i.e., FMS_1 is the best alternative at decision maker's level-of-satisfaction $\alpha = 0.42$. Table 3 is a clear indication of accepting the proposed methodology for the selection problem in a conflicting-criteria environment.

Relationship between the degree of fuzziness, γ, versus level-of-satisfaction (α) has been depicted for all candidate-FMSs by Figures 1 to 5. This is a clear indication that the decision variables allow the MCDM model to achieve a higher level-of-satisfaction with a lesser degree of fuzziness. Figures 6 to 10 and 11 to 15 delineate SI indices versus level-of-satisfaction (α) and SI indices versus degree of fuzziness (γ), respectively.

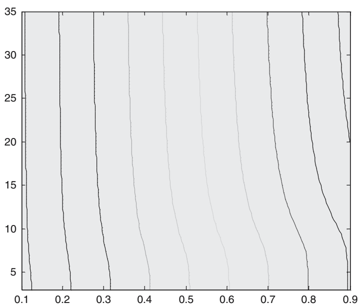

Figure 1. Fuzziness (γ) vs. α contour plot for FMS_1

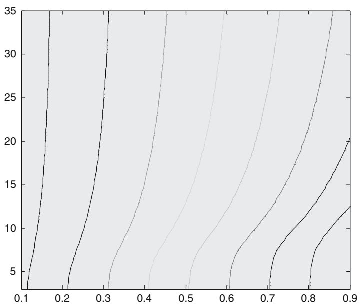

Figure 2. Fuzziness (γ) vs. α contour plot for FMS_2

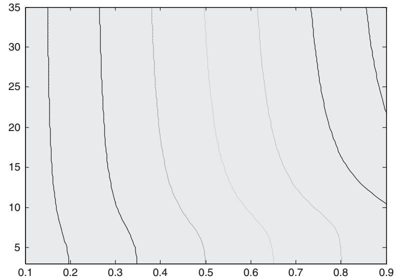

Figure 3. Fuzziness (γ) vs. α contour plot for FMS_3

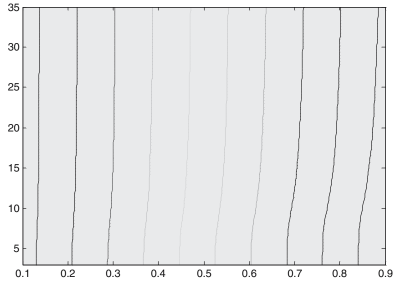

Figure 4. Fuzziness (γ) vs. α contour plot for FMS_4

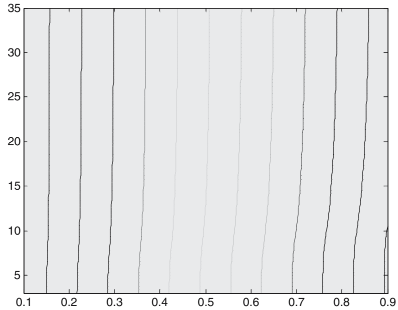

Figure 5. Fuzziness (γ) vs. α contour plot for FMS_5

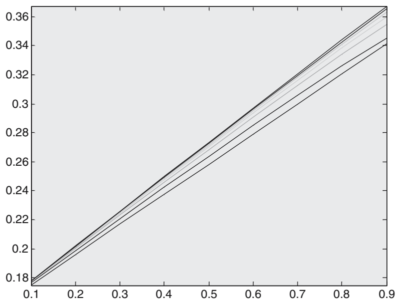

Figure 6. SI vs. α contour plot for FMS_1

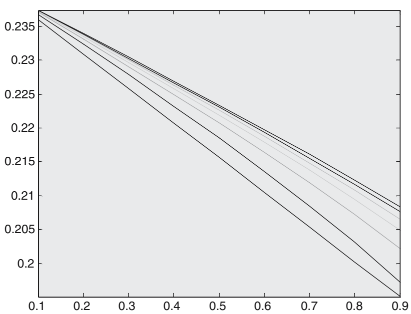

Figure 7. SI vs. α contour plot for FMS_2

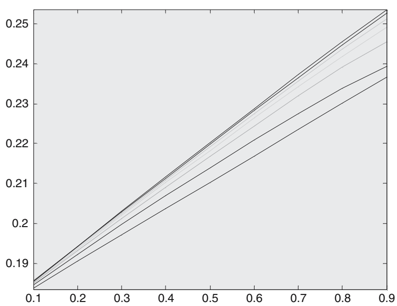

Figure 8. SI vs. α contour plot for FMS_3

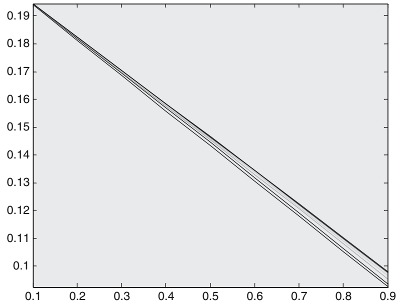

Figure 9. SI vs. α contour plot for FMS_4

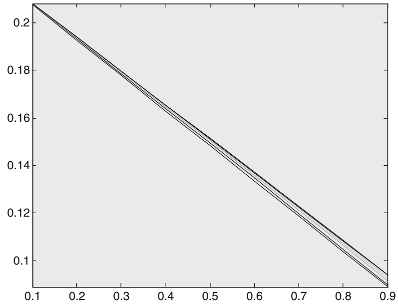

Figure 10. SI vs. α contour plot for FMS_5

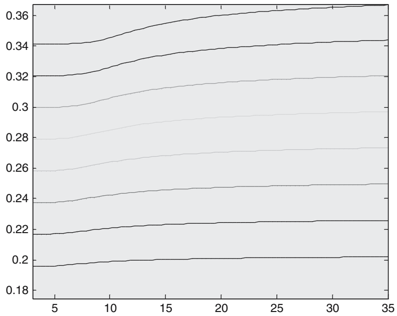

Figure 11. SI vs. γ contour plot for FMS_1

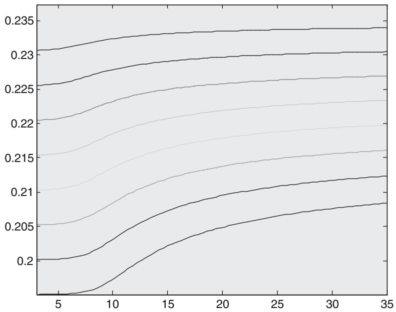

Figure 12. SI vs. γ contour plot for FMS_2

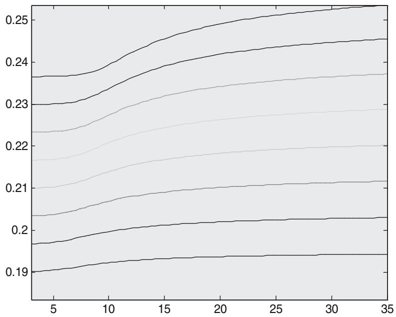

Figure 13. SI vs. γ contour plot for FMS_3

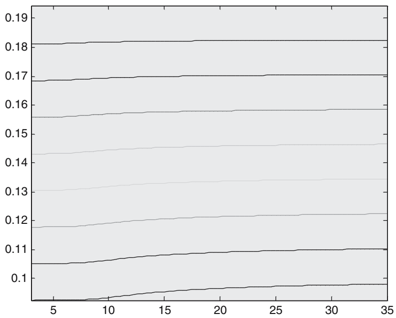

Figure 14. SI vs. γ contour plot for FMS_4

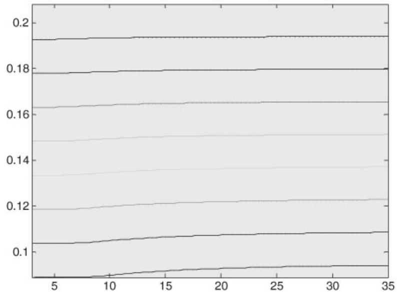

Figure 15. SI vs. γ contour plot for FMS_5

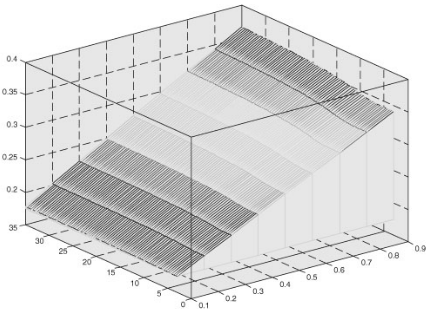

Figure 16. Fuzzy-sensitivity for FMS_1

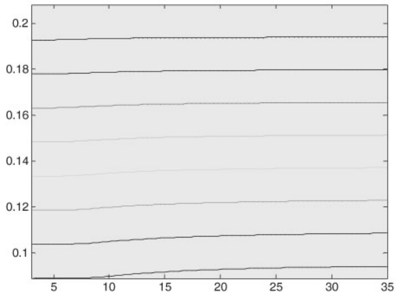

Figure 17. Fuzzy-sensitivity for FMS_2

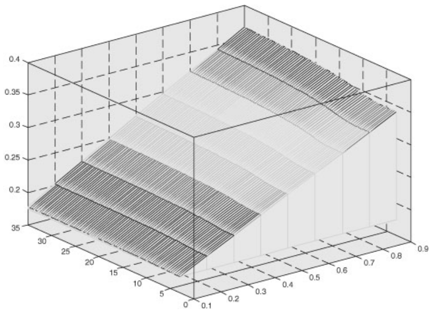

Figure 18. Fuzzy-sensitivity for FMS_3

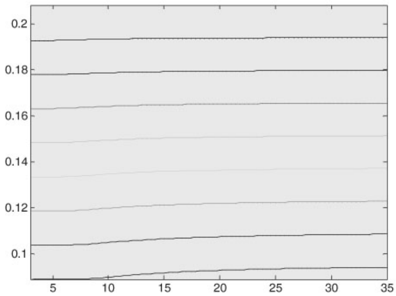

Figure 19. Fuzzy-sensitivity for FMS_4

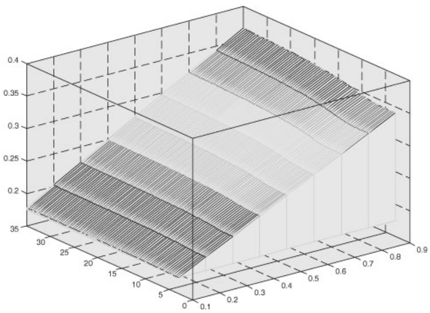

Figure 20. Fuzzy-sensitivity for FMS_5

Combining the plots as illustrated in Figures 1−15, one gets Figures 16−20. These figures elucidate 3-D mesh and contour plots. Basically Figures 16−20 illustrate fuzzy-sensitivity indicating relationships among SI indices, γ and α. Furthermore, from these plots, it is seen that the decision variables, as defined in Eq. (1), allow the MCDM model to achieve a higher level-of-satisfaction (α) with a lesser degree of fuzziness (γ).

Table 3. Ranking of the Systems

Candidate-FMS	SIi	Rank #
FMS1	0.249	#1
FMS2	0.224	#2
FMS3	0.210	#3
FMS4	0.155	#5
FMS5	0.162	#4

According to Table 3, the best alternative is FMS1 with the selection index of 0.249. The worst alternative is FMS4 with the selection index of 0.155.

4. GENERAL DISCUSSIONS AND CONCLUSION

This chapter outlined an intelligent fuzzy-MCDM model for appropriate selection of an FMS in a conflicting criteria environment. The proposed method calculates the GP for functional, design factors and other important attributes by eigenvector method of pair-wise comparison. These GPs are used as SFMs in determining SI.

In a real-life situation, the decision environments rarely remain static. So, the dynamic behavior of the optimal selection found from the proposed methodology has been checked through the fuzzy-sensitivity plots. Figures 16−20 teach an interesting phenomenon that is found in nature. At a lower level-of-satisfaction (α), the chances of getting involved in a higher degree of fuzziness (γ) increase. Therefore, a decision maker's level-of-satisfaction should be at least moderate in order to avoid higher degree of fuzziness while making any kind of decision using the proposed MCDM model delineated in the previous chapter.

The methodology proposed is very useful first in quantifying the intangible factors in a strong manner and then in finding out the best among the alternatives depending upon their cost factors. Contrary to the traditional way of selection using discounted cash flow (DCF), this methodology is a sound alternative to apply under an unstructured environment. The fuzzy-sensitivity strengthens the validity of the proposed methodology. It verifies the practicability as well as the effectiveness of the proposed DSS method.

It is not possible for an individual to consider all the factors related to FMS as follows:

- FMSs are available in a wide range,
- Performance standards of the systems are not uniform, and
- Expression of capabilities and performance attributes among manufacturers are inconsistent and incommensurable.

Thus, a decision-making expert system may help the decision maker in selecting the most cost-effective FMS considering the conflicting-in-nature factors of the systems.

The selection problem of FMS is complex due to the high capital costs involved and to the presence of multiple conflicting criteria. One can reduce investment and maintenance costs, increase equipment utilization, increase efficiency, as well as improve facilities layout by selecting the right system suitable for the operations to be carried out.

REFERENCES

Abdel-Malek, L., and Wolf, C., 1991, Evaluating flexibility of alternative FMS designs A comparative measure, *International Journal of Production Economics*, **23**(1–3)**:** 3–10.

Barad, M., and Sipper, D., 1988, Flexibility in manufacturing systems: definitions and petri net modeling, *International Journal of Production Research*, **26:** 237–248.

Browne, J., Dubois, D., Rathmill, K., Sethi, S.P., and Stecke, K.E., 1984, Classification of flexible manufacturing systems, *FMS Magazine*, **2:** 114–117.

Buffa, E.S., 1993, *Modern Production/Operations Management*, Wiley Eastern Limited, New Delhi.

Buzacott, J.A., and Mandelbaum, M., 1985, Flexibility and productivity in manufacturing systems, *Proceedings of the Annual IIE Conference*, Los Angeles, CA, pp. 404–413.

Chen, Y., Tseng M.M., and Yien, J., 1998, Economic view of CIM system architecture, *Production Planning & Control*, **9**(3)**:** 241–249.

Elango, B., and Meinhart, W.A., 1994, Selecting a flexible manufacturing system: a strategic approach. *Long Range Planning*, **27**(3)**:** 118–126.

Evans, G.W., and Brown, P.A., 1989, A multi objective approach to the design of flexible manufacturing systems, in *Proceedings of International Industrial Engineering Conference on Manufacturing and Societies*, pp. 301–305.

Gupta, Y.P., and Goyal, S., 1989, Flexibility of manufacturing systems: concepts and measurements, *European Journal of Operational Research*, **43:** 119–135.

Gindy, N.N.Z., and Ratchev, S.M., 1998, Integrated framework for machining equipment in selection of CIM, *International Journal of Computer Integrated Manufacturing*, **11**(4)**:** 311–325.

Haddock, J., and Hartshorn, T.A., 1989, A decision support system for specific machine selection, *Computers & Industrial Engineering*, **16**(2)**:** 277–286.

Kaighobadi, M., and Venkatesh, 1994, Flexible manufacturing systems: an overview, *International Journal of Operations and Production Management*, **14**(4)**:** 26–49.

Karsak, E.E., 2002, Distance-based fuzzy MCDM approach for evaluating flexible manufacturing system alternatives, *International Journal of Production Research*, **40**(13)**:** 3167–3181.

Karsak, E.E., and Tolga, E., 2001, Fuzzy multi-criteria decision-making procedure for evaluating advanced manufacturing system investments, *International Journal of Production Economics*, **69:** 49–64.

Lenz, J.E., 1988, *Flexible Manufacturing, Benefits For The Low-Inventory Factory*, Marcel Dekker, Inc., New York.

Meredith, J.R., and Suresh, N.C., 1986, Justification techniques for advanced manufacturing technologies, *International Journal of Production Research*, **24:** 1043–1057.

Miltenburg, G.J., and Krinsky, I., 1987, Evaluating flexible manufacturing systems, *IEEE Transactions*, **19:** 222–233.

Nagarur, N., 1992, Some performance measures of flexible manufacturing systems, *International Journal of Production Research*, **30:** 799–809.

Nelson, C.A., 1986, A scoring model for flexible manufacturing systems project selection, *European Journal of Operational Research*, **24:** 346–359.

Rai, R., Kameshwaran, S., and Tiwari, M.K., 2002, Machine-tool selection and operation allocation in FMS: solving a fuzzy goal-programming model using a genetic algorithm, *International Journal of Production Research*, **40**(3)**:** 641–665.

Saaty, T.L., 1980, *The Analytical Hierarchy Process*, McGraw-Hill, New York.

Saaty, T.L., 1990, How to make a decision: the analytic hierarchy process, *European Journal of Operational Research*, **48**(1)**:** 9–26.

Saaty, T.L., 1986, Exploring optimization through hierarchies and ratio scales, *Socio-Economic Planning Sciences*, **20**(6)**:** 355–360.

Sambasivarao, K.V., and Deshmukh, S.G., 1997, A decision support system for selection and justification of advanced manufacturing technologies, *Production Planning and Control*, **8:** 270–284.

Sarkis, J., and Talluri, S., 1999, A decision model for evaluation of flexible manufacturing systems in the presence of both cardinal and ordinal factors, *International Journal of Production Research*, **37**(13)**:** 2927–2938.

Shang, J., and Sueyoshi, T., 1995, A unified framework for the selection of a flexible manufacturing system, *European Journal of Operational Research*, **85:** 297–315.

Stam, A., and Kuula, M., 1991, Selecting a flexible manufacturing system using multiple criteria analysis, *International Journal of Production Research*, **29:** 803–820.

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.

Trentesaux, D., Dindeleux, R., and Tahon, C., 1998, A multicriteria decision support system for dynamic task allocation in a distributed production activity control structure. *International Journal of Computer Integrated Manufacturing*, **11**(1)**:** 3–17.

Vasant, P., Bhattacharya, A., and Barsoum, N. N., 2005, Fuzzy patterns in multi-level of satisfaction for MCDM model using smooth *S*-Curve MF, in:, *Lecture Notes in Artificial Intelligence*, Wang, L. and Jin, Y., (eds.), Springer-Verlag: Berlin, **3614:** 1294–1303.

Wabalickis, R.N., 1988, Justification of FMS with the analytic hierarchy process, *Journal of Manufacturing Systems*, **7:** 175–182.

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.

Yurdakul, M., 2004, AHP as a strategic decision-making tool to justify machine tool selection, *Journal of Materials Processing Technology*, **146**(3)**:** 365–376.