Flexible Manufacturing System Selection under Disparate
Level-of-Satisfaction of Decision Maker using Intelligent
Fuzzy-MCDM Model

Arijit Bhattacharya¹, Ajith Abraham² and Pandian Vasant³

¹Embark Initiative Post-Doctoral Research Fellow
School of Mechanical & Manufacturing Engineering
Dublin City University
Glasnevin, Dublin 9, Ireland.
arijit.bhattacharya2005@gmail.com

²Norwegian Center of Excellence
Center of Excellence for Quantifiable Quality of Service
Norwegian University of Science and Technology
O.S. Bragstads plass 2E, NO-7491
Trondheim, Norway.
ajith.abraham@ieee.org

³Universiti Teknologi Petronas
31750 Tronoh, BSI, Perak DR, Malaysia
pvasant@gmail.com

Abstract: This Chapter outlines an intelligent fuzzy-MCDM model for appropriate selection of Flexible Manufacturing System (FMS) in conflicting criteria environment. A holistic methodology has been developed for finding out the “optimal FMS” from a set of candidate-FMSs. This method trade-offs among various parameters, viz., design parameters, economic considerations, etc., affecting the FMS selection process in multi-criteria decision-making environment. The proposed method calculates the global priority values (GP) for functional, design factors and other important attributes by eigen-vector method of pair-wise comparison. These GPs are used as Subjective Factor Measures (SFM) in determining 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 selection indices (SI) of the MCDM methodology guide decision-makers (DM) under tripartite fuzzy environment in selecting their choice trading-off with a pre-determined allowable fuzziness. The measurement of level-of-satisfaction during making the appropriate selection of FMS is carried out.

1. Introduction
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-a-days 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 globalisation the overall objective is to purchase a minimum amount of capacity (i.e., capital investment) and utilize it in the most effective way. Though FMS is an
outgrowth of existing manufacturing technologies, its selection is not oft studied. It has been a focal point in manufacturing related research since early 1970s. FMS provides a low inventory environment with unbalanced operations unique to the conventional production environment. Process design of FMS consists of a set of crucial decisions that are to be made carefully. It requires decision-making, e.g., selection of CNC machine tool, material handling system, product mix, etc. 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 [4]. 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-offs 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 given here. Kaighobadi and Venkatesh [12] presented an overview and survey of research in FMSs. They also presented a definition of FMSs. Chen et al. [6] 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 [18] 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 [3]. 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 laid down by Browne et al., Barad and Sipper [2] introduced another classification, i.e., transfer flexibility. Buzacott and Mandelbaum [5] 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 [9].

Flexible manufacturing provides an environment where integration effects cannot be eliminated [15]. 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. There are three variables that 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 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 [16] addressed justification of economic analysis, analytical and strategic approaches in advanced manufacturing technologies. Evaluation of FMS alternatives was earlier carried out by Miltenburg and Krinsky [18]. They analyzed traditional economic evaluation techniques for the evaluation. Nelson [19] formulated a scoring model for FMS project selection. Performance measures, viz., quality and flexibility were also quantified in the scoring model. Use of analytic hierarchy process (AHP) for evaluation of tangible and intangible benefits during FMS
investment was reported by Wabalickis [31]. Stam and Kuula [27] developed a two-phase decision support procedure using AHP and multi-objective mathematical programming for selection of FMS. Sambasivarao and Deshmukh [24] 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 linear additive utility model as alternative multi-attribute analysis model. Shang and Sueyoshi [26] formulated a model of simulation and data envelopment analysis (DEA) along with AHP for FMS selection. Karsak and Tolga [14] proposed a fuzzy multi criteria decision-making (MCDM) approach for evaluation of advanced manufacturing system investments considering economic and strategic selection criteria. Karsak [13] proposed a robust decision-making procedure for evaluating FMS using distance-based fuzzy MCDM philosophy.

Some researchers [6, 8] believe that qualitative benefits cannot be considered mathematically unless one uses knowledge-based system. This dissertation outlines a mathematical approach based on the judgmental values of decision-maker that can help DMs in selecting the cost-effective FMS.

Abdel-Malek and Wolf [1] propose a “measure” for 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. [3] into a single comprehensive flexibility indicator.

Elango and Meinhart [7] provide a framework for selection of an appropriate FMS using a holistic approach. The selection process considers operational and financial aspects. Further, 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. [29]. An entity of the manufacturing system is considered as an autonomous agent, called Integrated Management Station (IMS), able to cooperate with other agents to achieve a global production program. Co-operation 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. [29]. This DSS is integrated to each decision system of every IMS. Trentesaux et al.’s [29] research work aims at allocating tasks in a dynamic way by proposing to the human operator a selection of possible resources.

Sarkis and Talluri [25] disclose a model for evaluating alternative FMSs by considering both quantitative and qualitative factors. The evaluation process utilizes 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 provide both seller's and buyer's perspectives of FMSs evaluation.

The decision-making process for machine-tool selection and operation allocation in a FMS usually involves multiple conflicting objectives. Rai et al. [20] 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 [11]. The integration and further 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 underlie the need for a coherent formal approach towards equipment selection to support the knowledge and experience of the engineers entrusted with this important task [10]. With the increasing complexity of the decision-making in manufacturing system design, the search for the right structure depends upon the capability of the designers to compare different solutions using common approaches in an integrated decision-making environment [10].

Thus, machine tool selection has strategic implications that contribute to the manufacturing strategy of a manufacturing organization [33]. In such a case, it is important to identify and model the links between machine tool alternatives and manufacturing strategy [33].

Haddock and Hartshorn [11] 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 labelled 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 [11] are the relative location of machines, machining cost, processing time and availability of a machine.

Tabucanon et al. [28] 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 (ES). 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 centre that is required to process a family of rotational parts, is developed. Tabucanon et al.’s [28] methodology helps the user to find the most "satisfactory" machine on the basis of several objective as well as subjective attributes.

Flexible manufacturing cells (FMC) have been used as a tool to implement flexible manufacturing processes to increase the competitiveness of manufacturing systems [32]. In implementing an FMC, DMs encounter the machine selection problem including attributes, e.g. machine type, cost, number of machines, floor space and planned expenditures [32]. Wang et al. [32] propose a fuzzy multiple-attribute decision-making (FMADM) model to assist the DM 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 [24]. But AHP, as it is, do not take into consideration tangible factors, such as cost factors [21, 22, 23]. Thus, there is a need to allow cardinal factors in AHP to make the model robust and more efficient. In this paper, a robust MCDM procedure is proposed using AHP that incorporates qualitative as well as quantitative measures for FMS selection problem. The methodology proposed is very useful first to quantify the intangible factors in a well manner and then to find out the best among member alternatives depending upon their cost factors.

Some researchers believe that qualitative benefits cannot be considered mathematically unless one uses knowledge-based system [6, 8]. The present paper outlines a fuzzified intelligent approach based on the judgmental values of decision-maker in selecting the most cost-effective FMS. One objective of the present paper is to find out fuzziness patterns of FMS selection decisions having disparate level of satisfaction of the DMs. Another objective is to provide a robust, quantified monitor of the level of satisfaction among DMs and to calibrate these levels of satisfaction against DMs’ 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 best candidate-FMS among five candidate-FMSs.

<table>
<thead>
<tr>
<th>OFCs</th>
<th>FMS→</th>
<th>S₁</th>
<th>S₂</th>
<th>S₃</th>
<th>S₄</th>
<th>S₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Cost of Acquisition</td>
<td>1.500</td>
<td>0.800</td>
<td>1.300</td>
<td>1.000</td>
<td>0.900</td>
<td></td>
</tr>
<tr>
<td>2. Cost of Installation</td>
<td>0.075</td>
<td>0.061</td>
<td>0.063</td>
<td>0.053</td>
<td>0.067</td>
<td></td>
</tr>
<tr>
<td>3. Cost of Commissioning</td>
<td>0.063</td>
<td>0.052</td>
<td>0.055</td>
<td>0.050</td>
<td>0.061</td>
<td></td>
</tr>
<tr>
<td>4. Cost of Training</td>
<td>0.041</td>
<td>0.043</td>
<td>0.046</td>
<td>0.042</td>
<td>0.040</td>
<td></td>
</tr>
<tr>
<td>5. Cost of Operation</td>
<td>0.500</td>
<td>0.405</td>
<td>0.420</td>
<td>0.470</td>
<td>0.430</td>
<td></td>
</tr>
<tr>
<td>6. Cost of Maintenance</td>
<td>0.060</td>
<td>0.070</td>
<td>0.065</td>
<td>0.054</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>Total Cost (OFC)</td>
<td>2.239</td>
<td>1.431</td>
<td>1.949</td>
<td>1.669</td>
<td>1.550</td>
<td></td>
</tr>
<tr>
<td>Objective Factor Measure (OFMᵢ)</td>
<td>0.154</td>
<td>0.241</td>
<td>0.177</td>
<td>0.206</td>
<td>0.222</td>
<td></td>
</tr>
</tbody>
</table>

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 conveying system, flexibility in automated storage and retrieval system, life expectancy / pay back period and tool magazine changing time. One may consider other attributes appropriate to selection of FMS.

<table>
<thead>
<tr>
<th>Factor I</th>
<th>Factor II</th>
<th>Factor III</th>
<th>Factor IV</th>
<th>Factor V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flexibility in pick-up and delivery</td>
<td>Flexibility in conveying system</td>
<td>Flexibility in automated storage and retrieval system</td>
<td>Life expectancy / pay back period</td>
<td>Tool magazine changing time</td>
</tr>
</tbody>
</table>

Table 2. Attributes influencing the FMS selection problem
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 MATLAB®

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 judgemental values from different judges. Matrices 2 to 6 show comparisons of the weightages for each of the attribute. Matrix 7 consolidates the results of the earlier tables in arriving at the composite weights, i.e., SFM values, of each of the alternatives.

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

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

Matrix 2. Pair-wise comparison matrix for ‘F₁’ (I.R. = 4.48%)

\[
A₁ = \begin{bmatrix}
1 & 3 & 2 & 5 & 4 \\
\frac{1}{3} & 1 & \frac{1}{3} & 5 & 2 \\
\frac{1}{2} & 3 & 1 & 4 & 3 \\
\frac{1}{5} & \frac{1}{5} & 1 & 1 & \frac{1}{3} \\
\frac{1}{4} & \frac{1}{4} & \frac{1}{3} & 3 & 1 \\
\end{bmatrix}
\]

Matrix 3. Pair-wise comparison matrix for F₂ (I.R. = 3.32%)

\[
A₂ = \begin{bmatrix}
1 & 7 & 3 & 5 & 6 \\
\frac{1}{7} & 1 & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} \\
\frac{1}{3} & 4 & 1 & 3 & 4 \\
\frac{1}{5} & 3 & \frac{1}{3} & 1 & 2 \\
\frac{1}{6} & 2 & \frac{1}{4} & \frac{1}{2} & 1 \\
\end{bmatrix}
\]

Matrix 4. Pair-wise comparison matrix for F₃ (I.R. = 1.88%)

\[
A₃ = \begin{bmatrix}
1 & 4 & 1 & 3 & 7 \\
\frac{1}{4} & 1 & \frac{1}{4} & \frac{1}{2} & 5 \\
\frac{1}{4} & 1 & 4 & 1 & 2 \\
\frac{1}{3} & 2 & \frac{1}{2} & 1 & 3 \\
\frac{1}{7} & \frac{1}{5} & \frac{1}{1} & \frac{1}{3} & 1 \\
\end{bmatrix}
\]

Matrix 5. Pair-wise comparison matrix for F₄ (I.R. = 6.22%)

\[
A₄ = \begin{bmatrix}
1 & \frac{1}{3} & 5 & 3 & 6 \\
\frac{1}{5} & \frac{1}{5} & 1 & 2 & 3 \\
\frac{1}{7} & \frac{1}{5} & \frac{1}{3} & 1 & 2 \\
\frac{1}{6} & \frac{1}{6} & \frac{1}{7} & \frac{1}{3} & 1 \\
\frac{1}{7} & \frac{1}{6} & \frac{1}{7} & \frac{1}{3} & \frac{1}{4} \\
\frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} \\
\frac{1}{2} & \frac{1}{2} & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\
\frac{1}{4} & \frac{1}{4} & \frac{1}{3} & \frac{1}{3} & \frac{1}{4} \\
\frac{1}{2} & \frac{1}{2} & \frac{1}{3} & \frac{1}{3} & \frac{1}{4} \\
\frac{1}{7} & \frac{1}{6} & \frac{1}{7} & \frac{1}{3} & \frac{1}{4} \\
\frac{1}{6} & \frac{1}{6} & \frac{1}{7} & \frac{1}{3} & \frac{1}{4} \\
\frac{1}{7} & \frac{1}{6} & \frac{1}{7} & \frac{1}{3} & \frac{1}{4} \\
\frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} \\
\frac{1}{2} & \frac{1}{2} & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\
\frac{1}{4} & \frac{1}{4} & \frac{1}{3} & \frac{1}{3} & \frac{1}{4} \\
\end{bmatrix}
\]

Matrix 6. Pair-wise comparison matrix for F₅ (I.R. = 6.87%)
In the proposed methodology, the unit of Objective Factor Cost (OFC) is US $, whereas Objective Factor Measure (OFM) is a non-dimensional quantity. Correspondingly, the SI is also a non-dimensional quantity. Higher the SI values, the better would be the selection. The value of objective factor decision weight ($\alpha$) lies between 0 and 1. For $\alpha = 0$, 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 $\alpha = 0$. For $\alpha \approx 1$, SI = OFM, i.e., OFM values dominate over the SFM values and the FMS selection is dependent on OFM values only. For $\alpha = 1$, the cost factors get priority than the other factors. Keeping this in mind, the values of $\alpha$ 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 equation (1) [31] uses the membership function (MF) as depicted by equation (2).

$$L_{Si} = L_{Si_L} + \left( \frac{L_{Si_U} - L_{Si_L}}{\gamma} \right) \ln \frac{1}{C} \left( \frac{A}{\alpha_{L_{Si_I}}} - 1 \right)$$  \hspace{1cm} (1)

$$\mu(x) = \begin{cases} 
1 & x < x^a \\
0.999 & x = x^a \\
\frac{B}{1 + Ce^{-x}} & x^a < x < x^b \\
0.001 & x = x^b \\
0 & x > x^b 
\end{cases}$$ \hspace{1cm} (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:

```matlab
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)*((1/B)*log((1/B)*((A/mucj)-1)));```

Matrix 7. Final matrix to find out Global Priority

$$G = \begin{bmatrix} 
0.471 & 0.076 & 0.259 & 0.131 & 0.063 \\
0.408 & 0.512 & 0.366 & 0.273 & 0.305 \\
0.159 & 0.051 & 0.104 & 0.501 & 0.458 \\
0.279 & 0.246 & 0.338 & 0.103 & 0.074 \\
0.050 & 0.117 & 0.151 & 0.075 & 0.047 \\
0.103 & 0.075 & 0.040 & 0.047 & 0.116 \\
\end{bmatrix}$$
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 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 behaviour of the optimal selection found from the proposed methodology can be checked through the fuzzy-sensitivity plots.

Amongst all the FMSs, FMS\textsubscript{1} has the highest SI value when objective factor decision weight lies between 0.33 and 1.00. However, FMS\textsubscript{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 following. The higher the $\alpha$ value, the dominance of the SFM\textsubscript{i} values will be higher. The lower the $\alpha$ 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\textsubscript{1}$\succ$ FMS\textsubscript{2}$\succ$ FMS\textsubscript{3}$\succ$ FMS\textsubscript{5}$\succ$ FMS\textsubscript{4}, i.e., FMS\textsubscript{1} is the best alternative at DM’s level of satisfaction $\alpha = 0.42$. The Table 3 is a clear indication of accepting the proposed methodology for the selection problem in conflicting-criteria environment.

Relationship between the degree of fuzziness, $\gamma$, versus level-of-satisfaction ($\alpha$) 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 ($\alpha$) and SI indices versus degree of fuzziness ($\gamma$) respectively.

![Figure 1. Fuzziness ($\gamma$) vs. $\alpha$ contour plot for FMS\textsubscript{1}](image1.png)

![Figure 2. Fuzziness ($\gamma$) vs. $\alpha$ contour plot for FMS\textsubscript{2}](image2.png)
Figure 3. Fuzziness ($\gamma$) vs. $\alpha$ contour plot for FMS$_3$

Figure 4. Fuzziness ($\gamma$) vs. $\alpha$ contour plot for FMS$_4$

Figure 5. Fuzziness ($\gamma$) vs. $\alpha$ contour plot for FMS$_5$

Figure 6. SI vs. $\alpha$ contour plot for FMS$_1$

Figure 7. SI vs. $\alpha$ contour plot for FMS$_2$

Figure 8. SI vs. $\alpha$ contour plot for FMS$_3$
Figure 9. SI vs. $\alpha$ contour plot for FMS$_4$

Figure 10. SI vs. $\alpha$ contour plot for FMS$_5$

Figure 11. SI vs. $\gamma$ contour plot for FMS$_1$

Figure 12. SI vs. $\gamma$ contour plot for FMS$_2$

Figure 13. SI vs. $\gamma$ contour plot for FMS$_3$

Figure 14. SI vs. $\gamma$ contour plot for FMS$_4$
Combining the plots as illustrated in Figures 1 to 15, one gets Figures 16 to 20. These figures elucidate 3-D mesh and contour plots. Basically Figures 16 to 20 illustrate fuzzy-sensitivity indicating relationships among SI indices, $\gamma$ and $\alpha$. Further, from these plots it is seen that the
decision variables, as defined in equation (1), allow the MCDM model to achieve a higher level-of-satisfaction ($\alpha$) with a lesser degree of fuzziness ($\gamma$).

<table>
<thead>
<tr>
<th>Candidate-FMS</th>
<th>$S_{1i}$</th>
<th>Rank #</th>
</tr>
</thead>
<tbody>
<tr>
<td>FMS$_1$</td>
<td>0.249</td>
<td>#1</td>
</tr>
<tr>
<td>FMS$_2$</td>
<td>0.224</td>
<td>#2</td>
</tr>
<tr>
<td>FMS$_3$</td>
<td>0.210</td>
<td>#3</td>
</tr>
<tr>
<td>FMS$_4$</td>
<td>0.155</td>
<td>#5</td>
</tr>
<tr>
<td>FMS$_5$</td>
<td>0.162</td>
<td>#4</td>
</tr>
</tbody>
</table>

### 4. General Discussions and Conclusion

Figures 16 to 20 teach an interesting phenomenon which is found in nature. At lower level-of-satisfaction ($\alpha$) the chances of getting involved higher degree of fuzziness ($\gamma$) increase. Therefore, a DM’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 well 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 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 ----

(i) FMSs are available in wide range,
(ii) performance standards of the systems are not uniform, and
(iii) 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 the presence of multiple conflicting criteria. One can reduce investment and maintenance costs, increase equipment utilization, efficiency as well as improve facilities layout by selecting the right system suitable for the operations to be carried out.

### References


