

# A model for selecting suitable dispatching rule in FMS based on fuzzy multi attribute group decision making

Mohammad Ali Kashfi · Mehrdad Javadi

Received: 14 October 2014 / Accepted: 4 February 2015 / Published online: 25 February 2015  
© German Academic Society for Production Engineering (WGP) 2015

**Abstract** Flexible manufacturing systems (FMSs) have received increasing attention in recent decades as they conduct manufacturing in most productive and effective way, but productive output of such a system is closely related to internal and external criteria. FMS scheduling is the most affected area by these criteria, therefore, selecting appropriate and suitable scheduling types or dispatching rules, with respect to system criteria, is a crucial decision point for decision makers. According to the literature, many papers and researches have published to handle this problem in different methods such as mathematical programming, simulation, heuristic, and other similar techniques, but utilization of most of these methods is generally time-consuming, complex with some problems while performing, especially at a condition that a system requires decision making by a group of experts with a range of varied criteria. According to these issues, in this paper, fuzzy multi attribute decision making approach is used to develop a combined fuzzy analytical hierarchical process and fuzzy technique for order of preference by similarity to ideal solution group decision making model. This model is developed in three main stages and 13 steps and considers a group of decision makers' evaluations to select the most suitable dispatching rule among a set of alternatives, with respect to real time criteria. Applying this model is simple, fast and considers all decision criteria and prevents system tardiness and idle time.

**Keywords** FMS · Dispatching rule · FMADM · Fuzzy AHP · Fuzzy TOPSIS · Group decision making

## 1 Introduction

Manufacturing systems often face with several issues that require appropriate and real-time decisions. In today's competitive market, the flexibility and responsiveness to the market demands of these systems is an essential requirement. Therefore, the introduction of flexible manufacturing systems (FMSs) has had a strong positive impact on manufacturing technology [1]. An FMS consists of a group of machining centers, interconnected by means of an automated material handling and storage system, and controlled by an integrated computer system. It is designed to combine the efficiency of a high-production line and the flexibility of a job shop to best suit the batch production of mid-volume and mid-variety products [2]. Over the past several years flexible manufacturing has increased in popularity due to its potential advantages: quicker response to market changes, reduction in work-in-process, high inventory turnover and high levels of productivity [3]. Owing to its highly automated nature, a typical FMS has a high investment cost. Hence, it becomes necessary to select the best configuration at the design stage, and, more importantly, to identify the most efficient scheduling rules at the operational stage [1]. Scheduling plays a vital role in the production control of an FMS, which involves several real-time decisions, such as part type and machine selection, resource allocation, machine allocation, and tool loading. The primary objective of an effective scheduling system is to produce the right parts, at the right time, at a competitive cost, by minimizing overhead and operating costs, subject to satisfying demand for the enterprise's products [4].

---

M. A. Kashfi (✉) · M. Javadi  
School of Industrial Engineering, Islamic Azad University,  
South Tehran Branch, P.O.Box:1151863411, Tehran, Iran  
e-mail: st\_m\_kashfi@azad.ac.ir

M. Javadi  
e-mail: m\_javadi@azad.ac.ir

Therefore, the development of FMS scheduling strategy remains one of the most important areas of research. Scheduling in an FMS environment is more complex and difficult than in a conventional manufacturing environment. This is primarily due to versatile machines, which are capable of performing many different operations resulting in many alternative routes for part types, and also due to the systems capacity for simultaneous part processing [5]. Scheduling systems of FMS may be considered in at least two categories: 1. Medium-term scheduling systems, 2. Short-term scheduling systems [6]. Medium-term scheduling systems have been implemented through material requirements planning (MRP) systems. The short-term scheduling system is a real time decision system in which dispatching rules are widely used to dynamically control part movement. Dispatching rules are used for job sequencing and define priorities of the operations, especially in real-time environment. When a machine becomes available for processing, an operation that can be processed on the machine must be assigned to it. If two or more operations are ready to be processed on the same machine, one of the operations has to be selected according to a dispatching rule. A dispatching rule is associated with a machine and selects the next part to be serviced from a set of parts awaiting processing at the machine. For example, a first in-first out (FIFO) rule selects the part which first entered the queue at a machine as the next part to be serviced [6]. The real-time decision system should select a dispatching rule which best suits the selected performance criteria in the next short time period. Many dispatching rules, such as shortest processing time (SPT), minimum slack time (Slack), and FIFO, have been developed in related researches which each one would be used in different conditions. But in a dynamic manufacturing environment of an FMS, selection of suitable dispatching rules for each machine could improve FMS performance by adapting dispatching to the unique situation at each machine. It is known that FMS scheduling can not be affected by only a few criteria; in place of this, many criteria and system parameters affect scheduling problem, so system performance parameters are naturally affected [7]. Many dispatching rules are proposed in the literature, and the choice of a suitable dispatching rule depends on the nature of the scheduling problem and the performance measure of interest. Since the scheduling environment is dynamic, the nature of the scheduling problem will change over time, therefore, the dispatching rule must also change over time. Decision makers usually have to measure all the pros and cons and strike a balance in their planning of the systems [7]. Since now, many different ways are developed to solve the FMS dispatching rule selection problems, but selecting the suitable method is still a challenge for decision-makers and planners. This process should be done according to the

comparing system conditions, performance measures, and the selected values of the system criteria such as mean flow time, mean tardiness, work-in-process inventory, production rate and other performance criteria. Because of the variety of dispatching rules and different weights of criteria in different conditions, it is demanded to develop a model for selecting the suitable dispatching rule with respect to system conditions in a FMS [8]. It is also to be considered the linguistic and imprecise aspect of system information and planners opinions in the decision making process. To handle this, the fuzzy logic is an appropriate approach. The major advantage of using fuzzy logic is that the vagueness and imprecision of many relevant effects can be explicitly considered. This is important because the decision maker has inexact information about the effects not due to uncertainty, which can be modelled using probability theory, but rather to imprecision. Fuzzy set theory can take explicit account of this imprecision and effectively combine it with more precise items of information. [1]

In this paper, we developed a model based on fuzzy multi attribute decision making (FMADM) approach. The model is a combination of fuzzy analytical hierarchical process (FAHP) and technique for order of preference by similarity to ideal solution (TOPSIS) techniques to meet the solution for dispatching rule selection problem in an FMS which considers evaluations of a group of decision makers. The paper is set out as follows: in Sect. 2 literature review is presented. Section 3 outlines the main concepts of this paper: dispatching rules, fuzzy multi attribute decision making, fuzzy AHP and fuzzy TOPSIS. Section 4 we explained the methodology of model procedure to select suitable dispatching rules. A numerical example is presented in Sect. 5 to clarify the model and finally conclusions are given in Sect. 6.

## 2 Literature review

Several studies have been conducted on the issue of FMS scheduling and dispatching rule in recent past decades. According to these studies, dispatching rule selection for a specific manufacturing system can be studied by employing mathematical programming, simulation, heuristic, and other similar techniques [7]. Kumar et al. [9] optimized FMS scheduling by taking into account the precedence constraints that minimize the make span. Gupta et al. [3] explored the applicability of multi criterion approaches to the production scheduling problems of an FMS and review the pertinent literature on FMS scheduling involving multiple objectives. Reddy et al. [4] have demonstrated a mechanism for the dynamic selection of group heuristics from several candidate alternatives by exploiting real time information from the Flexible Manufacturing System

(FMS). Low et al. [5] use one of the multiple objective decision making methods, a global criterion approach. They develop a multi objective model for solving FMS scheduling problems with consideration of three performance measures, namely minimum mean job flow time, mean job tardiness, and minimum mean machine idle time, simultaneously. In addition methods based on simulated annealing, tabu search and hybrid heuristics, which are a combination of two common local search methods, are also proposed for solving the addressed FMS scheduling problems. Chan et. al [1] have studied fuzzy multi criteria decision-making techniques for evaluating scheduling rules. In their study, a framework for evaluation of combinations of scheduling rules has been developed using a fuzzy multi criteria decision making technique and a simulation model was employed in order to illustrate the effectiveness of their approach. Lee [11] proposed a fuzzy-rule-based system for an adapting scheduling, which dynamically selects and applies the most suitable strategy according to the current state of scheduling environment. An application of their proposed method to a job dispatching problem in a hypothetical FMS was completed to show the effectiveness of their proposed model. Shih and Sekiguchi [12] proposed a fuzzy inference-based scheduling decision for FMS with multiple objectives. The objectives have different and dynamic preference levels. It is inferred that the changes in the production environment may be sensed by environmental variables. The detected changes are input in a fuzzy inference mechanism, which outputs the current preference levels of all objectives. A multiple criteria scheduling decision is then made, using the partitioned combination of the preference levels. Domingos and Politano [13] proposed an online scheduling procedure based on fuzzy logic, whose main characteristic is shop floor tasks scheduling using production rules of an expert to meet several measures of performance. Chan et. al [14] presented a real-time fuzzy expert system to scheduling parts for an FMS. First, some vagueness and uncertainties in scheduling rules are indicated and then, a fuzzy logic approach is proposed to improve the system performance by considering multiple performance measures. This approach focuses on characteristics of the system's status, instead of parts, to assign priorities to the parts waiting to be processed. The above studies concentrate on improving scheduling procedure in FMS, but there are few papers focusing on selecting suitable dispatching rules with respect to system criteria. The most extensively studied scheduling system criteria were minimization of flow time and maximization of system use [3]. Smith et al. [15] stated the most important system criteria as: Minimizing lateness/tardiness, Minimizing make span, Maximizing system/machine use, Minimizing Work In Process (WIP), Maximizing

throughput, Minimizing average flow time and Minimizing maximum lateness/tardiness. Petroni and Rizzi [16] presented a fuzzy logic tool to rank flow shop dispatching rules under multiple performance criteria. This tool is detailed with reference to a significant industrial case of a major company operating in the boilermaker industry. The results show that the approach is robust and effective in providing a practical guide to scheduling practitioners in choosing priorities dispatching rules when there are multiple objectives. Subramanian et al. [10] proposed a fuzzy scheduler that uses the prevailing conditions in the job shop to select dynamically the most appropriate dispatching rule from several candidate rules. This method is applied to a formal test bed job shop problem and a much larger problem that is representative of a real industrial problem. The results indicate that the fuzzy scheduler is effective. Sadinezhad et al. [8] developed a model for selecting the best dispatching rule with respect to criteria and system conditions. They developed an analytical network process (ANP) model to consider the inner dependencies among criteria. Finally, they apply the proposed model to prove the applicability of the model. Yazgan [7] developed an ANP model based on benefit, opportunity, cost, and risk. The model is based on a multiple criteria decision making process which contains different performance criteria, details of FMS information, a company's strategic criteria, and different well-known dispatching rules. In addition, that fuzziness of information was also considered in the evaluation process. Ravi et al. [17] proposed a simulation model of a random flexible manufacturing system aimed at solving scheduling problems. The model is written using a proven, powerful modeling methodology, SLAM II and can be used interactively. It offers five alternative scheduling rules, but other rules could be incorporated if required. Most of these papers have concentrated on developing variant models of dispatching rules and their application in FMS, with respect to different multi criterion conditions. Selecting the most appropriate and suitable rule among the different type of rules, is also a challenging problem for system operators and planners, especially in a dynamic and online manufacturing and their related tools and methods systems such as FMS. This decision is influenced by system criteria, decision maker's opinion and manufacturing priorities. Considering this issue that most of the opinions are linguistic, applying fuzzy logic is a perfect approach. As a result, developing a method with respect to multi criteria condition and fuzzy environment of system, to enhance the decision making process is vital. The literature review shows the deficiencies of existing methods for the process of selecting dispatching rule with respect to fuzzy and multi criterion conditions of the system. In this paper, fuzzy multi attribute decision making approach is used. A

combined fuzzy AHP-TOPSIS model is developed to empower decision making systems to help FMS planners, operators or intelligent decision maker systems, to select the most suitable dispatching rule.

### 3 Concepts

#### 3.1 FMS dispatching rules

Dispatching rules are used for job sequencing and define priorities of the operations and is used to generate production schedules for operations in job shop manufacturing systems, especially for real-time scheduling. Dispatching rules can be classified in a different way. Blackstone et al. [18] divided traditional dispatching rules into four categories: Process time (e.g., shortest processing time, shortest remaining process time, shortest processing time plus setup time, etc.), Due date (e.g., earliest due date, critical ratio, minimum slack time, etc.) and Part characteristics (e.g., random, FIFO, etc.) and Hybrid of the previous two or three. Moser and Engel [19] classified the dispatching rules as follows: Static or dynamic and a priori or a posteriori. As we are focusing on real-time scheduling in this paper, Table 1 shows some of dynamic dispatching rules included in the real-time scheduling mechanism according to Montazeri and Van Wassenhove research [20].

#### 3.2 Fuzzy multi attribute decision making

The multiple attribute decision making (MADM) refers to an approach of problem solving that is employed to solve problems involving selection from among a finite number of alternatives. An MADM method is a procedure that specifies how attribute information is to be processed in order to arrive at a choice. Tzeng and Hwang [21] summarized the procedures of MADM in five main steps according to the Dubois and Pradeas:

1. Define the nature of the problem;
2. Construct a hierarchy system for its evaluation;
3. Select the appropriate evaluation model;
4. Obtain the relative weights and performance score of each attribute with respect to each alternative;
5. Determine the best alternative according to the synthetic utility values, which are the aggregation value of relative weights, and performance scores corresponding to alternatives.

The methods of MADM include, weighted sum method (WSM), weighted product method (WPM), TOPSIS, AHP and etc. According to the literature, the classical MADM methods, both deterministic and random processes, cannot effectively handle decision making problems with imprecise and linguistic information. Thus, fuzzy multi attribute decision making (FMADM) approach were developed to handle linguistic evaluations of decision makers. In this

**Table 1** Type of dynamic dispatching rules

Dispatching rule	Explanation
1. SIO	Select the job with the shortest imminent operation time
2. LIO	Select the job with the longest imminent operation time
3. SRPT	Select the job with the shortest remaining processing time
4. LRPT	Select the job with the longest remaining processing time
5. SDT	Select the job with the smallest ratio obtained by dividing the processing time of the imminent operation by the total processing time for the part
6. SMT	Select the job with the smallest value obtained by multiplying the processing time of the imminent operation by the total processing time for the part
7. LDT	Select the job with the largest ratio obtained by dividing the processing time of the imminent operation by the total processing time for the part
8. LMT	Select the job with the largest value obtained by multiplying the processing time of the imminent operation by the total processing time for the part
9. FRO	Select the job with the fewest number of remaining operations
10. MRO	Select the job with the largest number of remaining operations
11. FIFO	Select the job according to first in, first out
12. SLACK	Select the job with the least amount of slack
13. SLACK/RO	Select the job with the smallest ratio of slack time to the number of remaining operations
14. SSLACK/RO	Select the job with the smallest ratio of static slack time to the number of remaining operations
15. SLACK/TP	Select the job with the smallest ratio of the job slack time to the total processing time
16. SLACK/RP	Select the job with the smallest ratio of the job slack time to the remaining processing time

approach, instead of a crisp value, FMADM methods use a range of value to incorporate the decision maker's uncertainty [22]. The aim of this paper is to choose an alternative among a set of alternatives under conflicting judgments and uncertainty conditions. Hence, the fuzzy AHP and TOPSIS methods are used together. Both TOPSIS and AHP are logical decision making approaches and deal with the problem of choosing an alternative from a set of candidate alternatives which are characterized in terms of some attributes [22]. Fuzzy AHP is utilized for determining the weights of the criteria. Then, ranking of the alternative is determined by the help of TOPSIS method.

### 3.3 Fuzzy AHP

The AHP is one of the most widely-used MADM methods. It was originally developed by saaty [29] which is assisting decision maker to set criteria priorities. AHP is a powerful method to solve complex decision problems. Any complex problem can be decomposed into several sub-problems using AHP in terms of hierarchical levels where each level represents a set of criteria or attributes relative to each sub-problem. The AHP method is a multi criteria method of analysis based on an additive weighting process, in which several relevant attributes are represented through their relative importance [24]. By reducing complex decisions to a series of one-on-one comparisons, then synthesizing the results, AHP not only helps decision makers arrive at the best decision, but also provides a clear rationale that it is the best. AHP uses both the linguistic assessments and numerical values for the alternative selection problem having multi level hierarchical structure. The advantages of AHP include its ability to make both qualitative and quantitative decision attributes commensurable and its flexibility with regard to the setting of objectives. However, Yang and Chen [25] have pointed out deficits of AHP:

1. AHP method is mainly used in nearly crisp-information decision applications;
2. AHP method creates and deals with a very unbalanced scale of judgment;
3. AHP method does not take into account the uncertainty associated with the mapping of human judgment to a number of natural language;
4. Ranking of the AHP method is rather imprecise;
5. The subjective judgment by perception, evaluation, improvement and selection based on preference of decision-makers have great influence on the AHP results.

Considering these deficits, several researchers integrate fuzzy theory with AHP to improve the uncertainty and handle linguistic evaluations of decision makers [24].

Laarhoven and Pedrycz [30] were the first who developed saaty's AHP method in fuzzy environment and their new method provides more realistic results than non-fuzzy AHP. In this approach, instead of a crisp value, FMADM methods use a range of value to incorporate the decision maker's uncertainty.

### 3.4 Fuzzy TOPSIS

TOPSIS, is another method of MADM which was proposed by Hwang and Yoon [31] in 1981, is an efficient method in dealing with the tangible attributes and the number of alternatives to be assessed. The main idea came from the concept of the compromise solution to choose the best alternative nearest to the positive ideal solution and farthest from the negative ideal solution. Then, choose the best one of sorting, which will be the best alternative. TOPSIS gives a solution that is not only closest to the hypothetically best, but which is also farthest from the hypothetically worst. However, TOPSIS method needs an efficient procedure to find out the relative importance of different attributes with respect to the objective and AHP provides such a procedure [21–23, 26–29]. Fuzzy AHP and fuzzy TOPSIS are supplement methods which empower decision making process under uncertainty conditions.

## 4 Model methodology

In this paper the proposed methodology to select suitable dispatching rule is consist of 3 main stages: (1) problem definition, (2) weight evaluation using fuzzy AHP, (3) determining best alternatives using fuzzy TOPSIS. Each stage in this procedure is also contains several steps which are described as below:

Stage 1. Construction of hierarchy:

The first step of the proposed model is to determine all the important criteria and their relationship of the decision problem in the form of a hierarchy. This step is crucial because the selected criteria can influence the final choice. The hierarchy is structured from the top (the overall goal of the problem) through the intermediate levels (criteria and sub-criteria on which subsequent levels depend) to the bottom level (the list of alternatives).

*Step 1:* Set up the hierarchical system by decomposing the problem into a hierarchy of interrelated elements.

The typical fuzzy AHP decision problem consists of (1) a number of alternatives,  $A = \{a_i | i = 1, 2, \dots, m\}$  (2) a set of evaluation criteria,  $C = \{c_j | j = 1, 2, \dots, n\}$ , (3) a linguistic judgment  $r_{ij}$  representing the relative importance of each pair criteria, and (4) a weighting vector,  $W = (w_1, w_2, \dots, w_n)$ .

Stage 2. Fuzzy AHP computations:

In this methodology we use Geometric Mean Method which was developed by Buckley [28] for fuzzy AHP approach. Based on this approach the steps are:

Step 2: Obtain the fuzzy evaluation matrix for each decision maker as follows:

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \dots & \tilde{a}_{1j} & \dots & \tilde{a}_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{i1} & \dots & \tilde{a}_{ij} & \dots & \tilde{a}_{in} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{ni} & \dots & \tilde{a}_{nj} & \dots & \tilde{a}_{nn} \end{bmatrix} \quad (1)$$

where  $\tilde{a}_{ij} \odot \tilde{a}_{ij}$ ,  $\tilde{a}_{ij} \cong \tilde{w}_i/\tilde{w}_j$  and all  $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$  are triangular fuzzy numbers with  $l_{ij}$  the lower and  $u_{ij}$  the upper limit and  $m_{ij}$  is the point where the membership function  $\mu(x) = 1$ . The importance weights of various criteria and the ratings of alternatives are considered as linguistic variables and expressed in positive triangular fuzzy numbers in Tables 2, 3.

In order to use further equations, we have to know that according to the characteristics of triangular fuzzy numbers and the extension principle put forward by Zadeh [29], the operational laws of triangular fuzzy numbers,  $\tilde{M}_1 = (l_1, m_1, u_1)$  and  $\tilde{M}_2 = (l_2, m_2, u_2)$  are as follows:

1. Addition of two fuzzy numbers:

$$\tilde{M}_1 \oplus \tilde{M}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (2)$$

**Table 2** Linguistic variables for the importance weight of each criterion

Linguistic scale	Triangular fuzzy number
Very low (VL)	(0, 0.1, 0.2)
Low (L)	(0.1, 0.2, 0.3)
Medium low (ML)	(0.2, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.6)
Medium high (MH)	(0.5, 0.7, 0.8)
High (H)	(0.7, 0.8, 0.9)
Very high (VH)	(0.8, 1.0, 1.0)

**Table 3** Linguistic variables for the alternatives ratings

Linguistic scale	Triangular fuzzy number
Very poor (VP)	(0, 1, 2)
Poor (P)	(1, 2, 3)
Medium poor (MP)	(2, 4, 5)
Fair (F)	(4, 5, 6)
Medium good (MG)	(5, 7, 8)
Good (G)	(7, 8, 9)
Very good (VG)	(8, 10, 10)

2. Multiplication of two fuzzy numbers:

$$\tilde{M}_1 \otimes \tilde{M}_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (3)$$

3. Inverse matrix of fuzzy numbers:

$$\tilde{M}_1 \otimes \tilde{M}_1^{-1} \cong \left( \frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1} \right) \quad (4)$$

Step 3: Converting variables to fuzzy numbers: Convert the linguistic variables into triangular fuzzy numbers to construct fuzzy decision matrix and determining the fuzzy weight of each criterion.

Step 4: Aggregate group evaluations: Construct fuzzy comparison pairwise matrix after aggregating the evaluation fuzzy numbers according to Eq. 5. In this step, to aggregate decision makers evaluation results, use the following algorithm based on geometric mean method proposed by Buckley [28] :

$$l_i = \left\{ \prod_{j=1}^k l_{ijk} \right\}^{\frac{1}{k}}, m_i = \left\{ \prod_{j=1}^k m_{ijk} \right\}^{\frac{1}{k}}, u_i = \left\{ \prod_{j=1}^k u_{ijk} \right\}^{\frac{1}{k}} \quad (5)$$

Where  $(l_{ijk}, m_{ijk}, u_{ijk})$  is the fuzzy evaluation of group members  $k, (k = 1, 2, \dots, k)$ .

Step 5: Calculate the geometric means of fuzzy comparison values of each criterion via Eq. 6, here  $\tilde{r}_{ij}$  represents triangular values.

$$\tilde{r}_{ij} = \left\{ \prod_{j=1}^n \tilde{a}_{ij} \right\}^{\frac{1}{n}} \quad (6)$$

Step 6: Find the relative fuzzy normalized weight  $w_j$  of each criterion, the fuzzy weights of each criterion can be found in Eq. 7:

**Table 4** Methodology structure of the model

Methodology steps
Stages 1 and 2: Fuzzy AHP
1. Setup hierarchical structure
2. Construct fuzzy evaluation matrix (Eq. 1)
3. Convert variables into fuzzy numbers (Table 2)
4. Aggregate decision makers evaluation fuzzy numbers (Eq. 5)
5. Calculate geometric means of each criterion (Eq. 6)
6. Find relative fuzzy normalized weight of each criterion (Eq. 7)
Stages 3: Fuzzy TOPSIS
7. Construct aggregated fuzzy rating matrix (Eqs. 5, 8 and Table 3)
8. Calculate normalized fuzzy decision matrix (Eq. 9)
9. Calculate weighted normalized fuzzy decision matrix (Eq. 10)
10. Determine FPIS and FNIS (Eqs. 11, 12)
11. Obtain separation measures (Eqs. 13, 14)
12. Calculate the coefficient closeness (Eq. 15)
13. Determine ranking order and select the best alternative

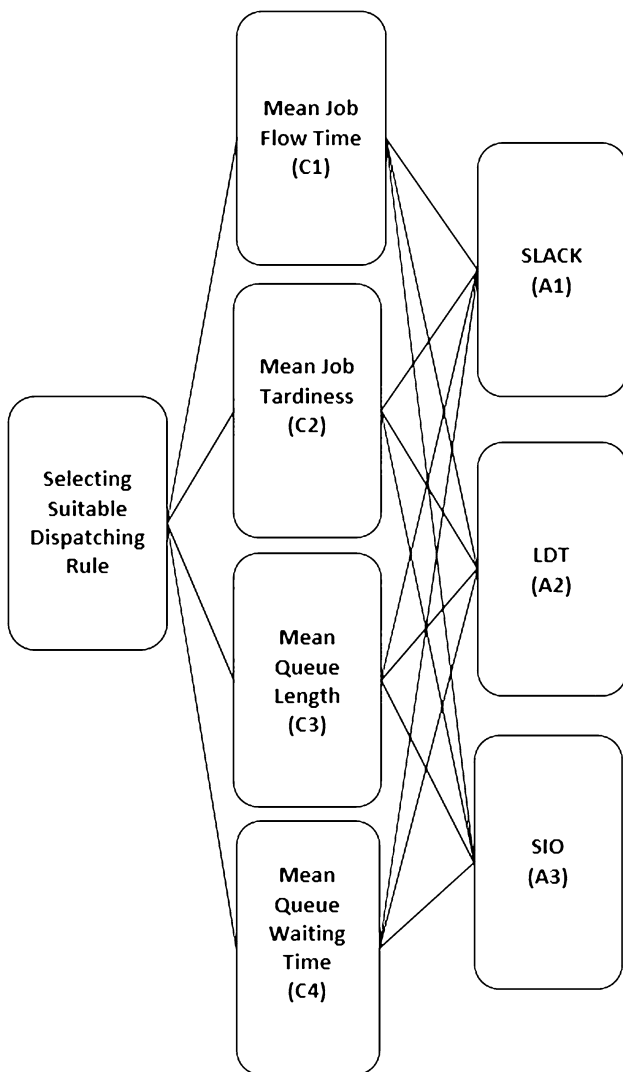


Fig. 1 Hierarchical structure of decision problem

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_j) \tag{7}$$

Stage 3. Fuzzy TOPSIS computations:

Given a set of alternatives,  $A = \{a_i | i = 1, 2, \dots, m\}$ , and a set of criteria,  $C = \{c_j | j = 1, 2, \dots, n\}$ , where  $X = \{x_{ij} | i = 1, 2, \dots, n, j = 1, 2, \dots, m\}$  denotes the set of alternatives ratings and  $W = \{w_j | i = 1, 2, \dots, m\}$  is the set of importance weights, the problem could be expressed in matrix format as

$$\tilde{A} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \dots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix}, \tilde{W} = [\tilde{w}_1 \quad \tilde{w}_2 \quad \dots \quad \tilde{w}_n] \tag{8}$$

where,  $\tilde{x}_{ij}, \forall i, j$  and  $\tilde{w}_{ij}, j = 1, 2, \dots, n$ , are described by triangular fuzzy numbers,  $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$  and  $\tilde{w}_j = (\tilde{w}_1, \tilde{w}_2, \tilde{w}_3)$  and  $\tilde{w}_j$  is derived by Eq. 7 in step 6.

Step 7: Construct fuzzy rating matrix of alternatives with respect to criteria and each decision maker evaluation using Table 3 and then construct aggregated fuzzy rating matrix according to fuzzy linguistic evaluations.

Step 8: Calculate normalized fuzzy decision matrix  $\tilde{R}$  by Eq. 9:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n}, i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \tag{9}$$

where  $\tilde{r}_{ij} = (\frac{l_i}{c_j^*}, \frac{m_i}{c_j^*}, \frac{u_i}{c_j^*})$  and  $c_j^* = \max_i c_{ij}$

Step 9: Calculate weighted normalized decision matrix  $\tilde{V}$  by Eq. 10:

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \tag{10}$$

where  $\tilde{v}_{ij} = \tilde{r}_{ij} \odot \tilde{w}_j$

Table 5 Fuzzy linguistic evaluation matrix with respect to the goal

	DM1				DM2				DM3			
	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>
C <sub>1</sub>	–	VH	H	L	–	H	H	ML	–	MH	H	ML
C <sub>2</sub>	–	–	MH	H	–	–	H	H	–	–	M	H
C <sub>3</sub>	–	–	–	M	–	–	–	ML	–	–	–	MH
C <sub>4</sub>	–	–	–	–	–	–	–	–	–	–	–	–

Table 6 Aggregated fuzzy comparison matrix

	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>
C <sub>1</sub>	(1.000, 1.000, 1.000)	(0.654, 0.824, 0.896)	(0.700, 0.800, 0.900)	(0.159, 0.317, 0.422)
C <sub>2</sub>	(1.116, 1.213, 1.529)	(1.000, 1.000, 1.000)	(0.519, 0.654, 1.629)	(0.700, 0.800, 0.900)
C <sub>3</sub>	(1.111, 1.250, 1.429)	(0.614, 1.529, 1.926)	(1.000, 1.000, 1.000)	(0.342, 0.519, 1.339)
C <sub>4</sub>	(2.371, 3.150, 6.300)	(1.111, 1.250, 1.429)	(0.747, 1.926, 2.924)	(1.000, 1.000, 1.000)

According to the weighted normalized fuzzy decision matrix, we know that the elements  $\tilde{v}_{ij}; \forall i, j$  are normalized positive triangular fuzzy numbers and their ranges belong to the closed interval  $[0; 1]$ .

*Step 10:* Determine the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) as follows:

$$FPIS = \tilde{A}^+ = \{\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+\} \\ = \{(max_j \tilde{v}_{ij} \mid i \in I), (min_j \tilde{v}_{ij} \mid i \in J)\}, \tag{11}$$

$$FNIS = \tilde{A}^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-\} \\ = \{(min_j \tilde{v}_{ij} \mid i \in I), (max_j \tilde{v}_{ij} \mid i \in J)\}, \tag{12}$$

*Step 11:* Obtain the separation measures. The separation of each alternative from the ideal one is given by euclidean distance by the following equations:

$$\tilde{d}_i^+ = \left( \sum_{i=1}^n (\tilde{v}_{ij} - \tilde{v}_{ij}^+) \right)^{1/2}, \quad i = 1, 2, \dots, m \tag{13}$$

$$\tilde{d}_i^- = \left( \sum_{i=1}^n (\tilde{v}_{ij} - \tilde{v}_{ij}^-) \right)^{1/2}, \quad i = 1, 2, \dots, m \tag{14}$$

*Step 12:* Calculate the coefficient closeness to the ideal solution ( $CC_i$ ). The closeness coefficient ( $CC_i$ ) represents the distances to fuzzy positive ideal solution,  $\tilde{A}^+$ , and the fuzzy negative ideal solution,  $\tilde{A}^-$  simultaneously. The closeness coefficient of each alternative is calculated as

$$CC_i = \frac{\tilde{d}_i^-}{(\tilde{d}_i^+ + \tilde{d}_i^-)} \tag{15}$$

*Step 13:* A set of alternatives is made in the descending order in this step, according to the preference value indicating the most preferred and least preferred feasible solutions. Obviously, an alternative  $A_i$  is closer to the  $FPIS(\tilde{A}^+)$  and farther from  $FNIS(\tilde{A}^-)$  as  $CC_i$  approaches to 1. Therefore, according to the closeness coefficient, we can determine the ranking order of all alternatives and select the best one among a set of feasible alternatives. Table 4, illustrates the model methodology in stages and steps, using combined fuzzy AHP-TOPSIS approach.

### 5 Numerical example

To clarify the developed model, a numerical example is presented here. In this paper, selecting suitable dispatching rule considered as the decision problem. According to the literature, we consider 4 main criteria for this problem: mean job flow time ( $C_1$ ), mean job tardiness ( $C_2$ ), mean queue length ( $C_3$ ) and mean queue waiting time ( $C_4$ ). Considering dispatching rules in Table 1, we determine 3 alternatives, SLACK ( $A_1$ ), LDT ( $A_2$ ) and SIO ( $A_3$ ). We also consider a group of decision makers (DM) consist of 3 planners, contributing in evaluation procedure. We start the process by setting up hierarchical structure of the decision problem as shown in Fig. 1, then, according to Table 2, we consider all decision makers evaluations of criteria importance using linguistic weighting variables, as shown in Table 5. In next steps the linguistic evaluations converted into triangular fuzzy numbers and then aggregated fuzzy decision matrix is constructed as shown in Table 6. Geometric means and importance weights of criteria are calculated as shown in Table 7.

**Table 7** Geometric means and importance weights of criteria

	$\tilde{r}_i$	$\tilde{w}_i$
$C_1$	(0.519, 0.676, 0.764)	(0.093, 0.162, 0.237)
$C_2$	(0.798, 0.893, 1.223)	(0.144, 0.214, 0.379)
$C_3$	(0.695, 0.998, 1.385)	(0.125, 0.240, 0.429)
$C_4$	(1.184, 1.695, 2.265)	(0.213, 0.398, 0.702)

**Table 8** The rating of alternatives with respect to criteria

	$C_1$			$C_2$			$C_3$			$C_4$		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
$A_1$	G	G	V	G	G	G	FG	G	VG	VG	MG	VG
$A_2$	MG	MG	MH	G	VG	G	G	MG	G	F	MG	G
$A_3$	F	G	F	MG	F	VG	MP	MP	F	G	G	VG

**Table 9** Fuzzy comparison matrix of alternatives

	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	(7.319, 8.618, 9.322)	(7.000, 8.000, 9.000)	(6.073, 7.368, 8.143)	(6.542, 8.243, 8.963)
$A_2$	(5.593, 7.319, 8.320)	(7.319, 8.618, 9.322)	(6.257, 7.652, 8.653)	(5.192, 6.542, 7.56)
$A_3$	(4.820, 5.848, 6.868)	(5.429, 7.047, 7.830)	(2.52, 4.309, 5.313)	(7.319, 8.618, 9.322)
Weight	(0.093, 0.162, 0.237)	(0.144, 0.214, 0.379)	(0.125, 0.24, 0.429)	(0.213, 0.398, 0.702)



**Table 10** Fuzzy weighted normalized decision matrix

	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	(0.076, 0.156, 0.246)	(0.112, 0.191, 0.381)	(0.085, 0.197, 0.39)	(0.156, 0.366, 0.702)
$A_2$	(0.056, 0.127, 0.211)	(0.113, 0.198, 0.379)	(0.084, 0.197, 0.399)	(0.119, 0.280, 0.569)
$A_3$	(0.066, 0.138, 0.237)	(0.114, 0.220, 0.432)	(0.046, 0.150, 0.332)	(0.227, 0.500, 0.953)

**Table 11** Closeness coefficient and alternatives ranking

	$\tilde{d}_j^+$	$\tilde{d}_j^-$	$CC_i$	Rank
$A_1$	0.299	0.287	0.490	2
$A_2$	0.462	0.209	0.312	3
$A_3$	0.093	0.520	0.849	1

This step forward, fuzzy TOPSIS steps are used, according to decision makers evaluations. The rating of each alternative with respect to each criterion is shown in Table 8. Then, aggregated fuzzy decision matrix is constructed after converting linguistic evaluations to fuzzy triangular numbers, as shown in Table 9. In the next steps we construct fuzzy weighted normalized matrix in Table 10, and then closeness of coefficients and ranking for each alternative are derived as presented in Table 11. According to the results, alternative  $A_3$  has the highest  $CC_i$  and is ranked as the first alternative, therefore it is the most suitable dispatching rule. The example results, show that the alternative order would be:

$$A_3 \succ A_1 \succ A_2$$

### 6 Conclusion

Selecting a dispatching rule in flexible manufacturing systems (FMS) is an important problem for planners and decision makers. It could be a more challenging problem while considering various criteria and system performance parameters. This paper describes the procedure of selecting suitable dispatching rule in FMS based on fuzzy multiple attribute group decision making approach. In this approach we have suggested a combination of fuzzy AHP and TOPSIS group decision making model which helps in the selection of a suitable dispatching rule among available alternatives. AHP method is used to assign weights of each criterion and TOPSIS is used to determine final ranking of alternatives. The model is developed in 3 main stages and 13 steps. On the first stage, the hierarchical structure of decision problem is constructed, in next stage the fuzzy AHP method is used with respect to evaluation results of a group of decision makers or experts to determine the importance weight of each criterion and finally in the third

stage, the fuzzy TOPSIS method used to rank the alternative which helps decision makers to select the most suitable one. A numerical example presented to clarify the procedure of this model. The great advantage of this model is that it considers all criteria and all decision makers evaluations with no limitation, under uncertainties of the decision making process. The model is appropriate to use in real time decision making process to select the most suitable dispatching rule in an FMS. It also decreases the idle time and system tardiness. For further researches, it is suggested to apply this model in different real FMS systems and compare the result to other models. The outputs will result in the identification of possible deficiencies of the proposed model and may lead to some improvements. There is also a good research area to apply this model with other approaches which are introduced in the literature review.

### References

1. Chan FTS, Chan HK, Kazerooni A (2002) A fuzzy multi-criteria decision-making technique for evaluation of scheduling rules. *Int J Adv Manuf Technol* 20(2):103–113
2. Chan FT, Chan HK (2004) A comprehensive survey and future trend of simulation study on FMS scheduling. *J Intell Manuf* 15(1):87–102
3. Gupta YP, Evans GW, Gupta MC (1991) A review of multi-criterion approaches to FMS scheduling problems. *Int J Prod Econ* 22(1):13–31
4. Reddy K, Xie N, Subramaniam V (2004) Dynamic scheduling of flexible manufacturing systems. <http://dspace.mit.edu/handle/1721.1/3903>
5. Low C, Yip Y, Wu TH (2006) Modelling and heuristics of FMS scheduling with multiple objectives. *Comput Oper Res* 33(3):674–694
6. Ishii N, Talavage JJ (1994) A mixed dispatching rule approach in FMS scheduling. *Int J Flex Manuf Syst* 6(1):69–87
7. Yazgan HR (2011) Selection of dispatching rules with fuzzy ANP approach. *Int J Adv Manuf Technol* 52(5–8):651–667
8. Sadi-Nezhad S, Didehkhani H, Seyedhosseini SM (2008) Developing a fuzzy ANP model for selecting the suitable dispatching rule for scheduling a FMS. In: *IEEE international conference on industrial engineering and engineering management, 2008. IEEM 2008*, pp 405–409
9. Kumar AS, Veeranna V, Durga BP, Dattatraya BS (2010) Optimization of FMS scheduling using non-traditional techniques. *Int J Eng Sci Technol* 2:7289–7296
10. Subramaniam V, Ramesh T, Lee GK, Wong YS, Hong GS (2000) Job shop scheduling with dynamic fuzzy selection of dispatching rules. *Int J Adv Manuf Technol* 16(10):759–764

11. Lee KK (2008) Fuzzy rule generation for adaptive scheduling in a dynamic manufacturing environment. *Appl Soft Comput* 8(4): 1295–1304
12. Shih HM, Sekiguchi T (1999) Fuzzy inference-based multiple criteria FMS scheduling. *Int J Prod Res* 37(10):2315–2333
13. Domingos JC, Politano PR (2003) On-line scheduling for flexible manufacturing systems based on fuzzy logic. In: *IEEE international conference on systems, man and cybernetics, 2003*, vol 5, pp 4928–4933
14. Chan FT, Chan HK, Kazerooni A (2003) Real time fuzzy scheduling rules in FMS. *J Intell Manuf* 14(3–4):341–350
15. Smith ML, Ramesh R, Dudek RA, Blair EL (1986) Characteristics of US flexible manufacturing systems—a survey. In: *Proceedings of the second ORSA/TIMS conference on flexible manufacturing systems*. Butterworth/Heinmann, pp 477–486
16. Petroni A, Rizzi A (2002) A fuzzy logic based methodology to rank shop floor dispatching rules. *Int J Prod Econ* 76(1):99–108
17. Ravi T, Lashkari RS, Dutta SP (1991) Selection of scheduling rules in FMSs: a simulation approach. *Int J Adv Manuf Technol* 6(3):246–262
18. Blackstone JH, Phillips DT, Hogg GL (1982) A state-of-the-art survey of dispatching rules for manufacturing job shop operations. *Int J Prod Res* 20(1):27–45
19. Moser M, Engell S (1992) A survey of priority rules for FMS scheduling and their performance for the benchmark problem. In: *Proceedings of the 31st IEEE conference on decision and control*, pp 392–397
20. Montazeri M, Van Wassenhove LN (1990) Analysis of scheduling rules for an FMS. *Int J Prod Res* 28(4):785–802
21. Tzeng GH, Huang JJ (2011) *Multiple attribute decision making: methods and applications*. CRC Press, Boca Raton
22. Kahraman C (2008) *Fuzzy multi-criteria decision making: theory and applications with recent developments*, vol 16. Springer, Berlin
23. Vaidya OS, Kumar S (2006) Analytic hierarchy process: an overview of applications. *Eur J Oper Res* 169(1):1–29
24. Sun CC (2010) A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods. *Expert Syst Appl* 37(12):7745–7754
25. Yang CC, Chen BS (2004) Key quality performance evaluation using fuzzy AHP. *J Chin Inst Ind Eng* 21(6):543–550 Chicago
26. Chen SJJ, Hwang CL, Beckmann MJ, Krelle W (1992) *Fuzzy multiple attribute decision making: methods and applications*. Springer, New York
27. Davies MA (1994) A multi criteria decision model application for managing group decisions. *J Oper Res Soc*, pp 47–58
28. Buckley JJ (1985) Fuzzy hierarchical analysis. *Fuzzy Sets Syst* 17(3):233–247
29. Saaty TL (2000) *Fundamentals of decision making and priority theory with the analytic hierarchy process*, vol 6. Rws Publications, Pittsburgh
30. Van Laarhoven PJM, Pedrycz W (1983) A fuzzy extension of Saaty's priority theory. *Fuzzy Sets Syst* 11(1):199–227
31. Hwang CL, Yoon K (1981) *Multiple attribute decision making: methods and applications, a state of the art survey*. Springer, New York