Fuzzy Hybrid Decision Model for FMS Evaluation and Selection based on GRA-TOPSIS Method

Shanliang Yang, Xiao Xu, Mei Yang, Ge Li

***Abstract*—**The aim of this paper is to present a hybrid group decision model for evaluating flexible manufacturing systems(FMSs), in which the information about attribute weights is completely unknown, and the attribute values take the form of triangular fuzzy numbers. In this proposed methodology, the voting method is adopted to calculate the attribute weights by aggregating the decision-makers' attitudes and preferences on weights of each attribute. Then grey relational analysis(GRA) is combined with the concepts of TOPSIS to evaluate and select the best FMS from a set of alternatives. An illustrative example is given to demonstrate the practicality and feasibility of the proposed group decision model. The comparative study results showed that this model is an effective means for tackling FMS evaluation problems under fuzzy environment. Finally, a sensitivity analysis is performed to show the robustness of the model.

***Keywords*—**flexible manufacturing system, hybrid group decision model, the voting method, grey relational analysis(GRA), TOPSIS, sensitivity analysis

I. Introduction

Flexible manufacturing system(FMS) refers to a manufacturing system that can combine the efficiency of a mass-production line and the flexibility of a job shop to produce high-quality and competitively priced products on a group of machines[23]. The coherent meaning of FMS is the capability of manufacturing system to process a variety of different product styles simultaneously at various work stations, and product styles as well as quantities of production can be adjusted in response to customers' dynamic demands. The main components of FMS usually consist of robots, computer-controlled machines, numerical controlled machines(CNC) and other instrumentation devices. Due to the fierce competition in the market environment, manufacturing systems with fast response time and highly flexility are required. To meet the requirements of consumers, manufacturing industries have to select appropriate manufacturing strategies, manufacturing processes and equipment and so forth[23], [33]. However, it is a difficult and complex task for decision makers to evaluate wide-range of FMS alternatives and select the best one based on a set of conflicting attributes.

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FMS selection is an unstructured decision problem involving multiple factors and has been gaining more and more importance in an increasingly competitive global scenario. In recent years, a number of researchers and scholars have applied various multiple attribute decision making(MADM) methods for solving FMS selection problem[7]. MADM is an important part of modern decision science, and has been receiving great attention from researchers and practitioners over the last decades, and achieved a wealth of research results[36]. The methods of MADM usually include, Simple Additive Weighting(SAW), Analytic Hierarchy Process(AHP), the Technique for Order Preference by Similarity to Ideal Solution(TOPSIS), Data Envelopment Analysis(DEA), Grey Relational Analysis(GRA), ELECTRE(Elimination and Et Choice Translating Reality) and PROMETHEE(Preference Ranking Organization Method for Enrichment of Evaluations)[9], [15], [30].

Among these methods, TOPSIS is the most well-known MADM method introduced by Hwang and Yoon[5]. The basic concept of this method is that the chosen optimal alternative should be the one that has the shortest distance from the positive ideal solution and the farthest from the negative ideal solution. The positive ideal solution is a solution that maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria[29]. Although TOPSIS is widely applied in many fields, it has some limitations. It is reported that TOPSIS introduces two reference ideal solutions, but it does not consider the relative importance of the distances from these ideal solutions[8], [16]. Furthermore, it is not suitable for solving the MADM problems with the complicated interrelationships between multiple attributes and factors. Having to deal with FMS selection problems with interactions between the weights of attributes, the grey relational analysis(GRA) integrated with TOPSIS is adopted as the analysis tool in this paper. GRA, as an important part of grey system theory, has been proven to be very useful for dealing with poor, uncertain and insufficient information[2], [32]. It is an impact evaluation method that measures the degree of similarity or difference between two sequences based on the grade of relation[22].

The performance ratings and attribute weights in FMS selection problem are generally described by ill-defined and subjective linguistic terms[4]. In order to handle the vagueness in the assessments made by the decision makers, fuzzy set theory[34] has been incorporated into the GRA-TOPSIS method to overcome this deficiency. In addition, it is believed that groups should be able to make better decisions than individuals because of having greater collective knowledge[20], [26]. As a result, we develop a group decision model based on the voting method and fuzzy GRA-TOPSIS to evaluate alternative FMSs under a fuzzy environment, where the vagueness are dealt with linguistic terms parameterized by triangular fuzzy numbers. The voting method is used for setting attribute weights, whereas the fuzzy GRA-TOPSIS method is employed for obtaining the precise ranking of FMS alternatives.

The remainder of this paper is organized as follows. In the next section, we review the relevant literature on methods used in FMS selection. Section III introduces some basic concepts of fuzzy set theory, which will be used in the subsequent sections. In Section IV, the proposed model for FMS selection is presented and the stages are explained in detail. Section V investigates an empirical study to illustrate the applicability and potentiality of the proposed group decision model. Finally, some concluding remarks and future work are discussed in Section VI.

II. Previous Related Literature

FMS evaluation and selection is critical to the profitability of manufacturing companies in an increasingly competitive global environment, which involves the analysis of a large number of economic and technical factors[18]. However, the availability of wide-range of alternative options makes the FMS selection process a more difficult and complex task[31]. A number of researchers and practitioners have investigated the FMS selection problem by applying various MADM methods.

Chang Lin Yang and Shan Ping Chuang et al.[3] developed an integrated performance measurement model for evaluating manufacturing systems. The analytical hierarchy process(AHP) and the analytical network process(ANP) were utilized to determine the weight of each criterion when generating the performance scores. A methodology based on digraph and matrix methods was proposed by R. Venkata Rao[24] for evaluation of alternative flexible manufacturing systems. Literature [14] presented a distinct experience-based decision support system that used factual information of historical decisions to calculate confidence factors. A fuzzy-decision-tree algorithm was applied to provide a more objective approach given the evidence of previous implementation cases. Shiang Tai Liu[27] suggested a fuzzy DEA/AR method that was able to evaluate the performance of FMS alternatives when the input and output data were represented as crisp and fuzzy data.

In addition, Zahari Taha and Sarkawt Rostam[35] implemented a decision support system to select the best alternative machine using a hybrid approach of fuzzy analytic hierarchy process and PROMETHEE. In the research of Jia Wen Wang and Ching Hsue Cheng et al.[10], fuzzy hierarchical TOPSIS method was introduced for supplier selection, which not only was well suited for evaluating fuzziness and uncertainty problems, but also could provide more objective and accurate criterion weights. Shian Jong Chuu[25] proposed a fuzzy multiple attribute decision-making method applied in the group decision-making to improving advanced manufacturing technology selection process, and moreover, a new fusion method of fuzzy information was developed to managing information assessed in different linguistic scales and numerical scales.

A literature review has demonstrated that the FMS selection problem is a multi-attribute group decision-making problem under a fuzzy environment. Thus, an innovative group decision-making model using the voting method and fuzzy GRA-TOPSIS approach is put forward to resolve this problem.

III. Fuzzy Sets and Fuzzy Numbers

In real world situations, the descriptions of human judgments and preferences are often imprecise, vague and uncertain. Therefore, it is inadequate and impossible for modeling decision-making problems by using only crisp and exact numerical values[1], [11]. To cope with this difficulty, Zadeh introduced the fuzzy set theory in 1965 which provided a powerful tool to deal with the ambiguity of concepts associated with human judgments[34]. The fuzzy set theory has been applied in a variety of fields, for instance, artificial intelligence, computer science, control engineering, operations research and decision theory, etc.

One of the easier methods to clarify human subjective judgments is using linguistic terms. Linguistic terms are very useful in solving decision-making problems which are too complex or not well-defined to be reasonably described in conventional quantitative expressions[19]. So far, the fuzzy numbers are widely used in practical problems to represent the linguistic variables. Moreover, triangular and trapezoidal fuzzy numbers are the most common used fuzzy numbers both in theory and practice[18]. In this study, triangular fuzzy numbers are preferred for expressing linguistic terms because of their calculation easiness. In the following, some basic concepts of fuzzy set will be introduced. Furthermore, triangular fuzzy numbers and their arithmetic operations are also presented.

Definition 1 Let X be the universe which is a classical set of object, and the generic elements are denoted by x, a fuzzy subset $\tilde{A}$ in X is a set of ordered pairs:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x) | x \in X\} \tag{1}$$

where $\mu_{\tilde{A}}(x) \in [0,1]$ is called the membership function of $\tilde{A}$ and stands for the membership degree of x in $\tilde{A}$. The closer the value of $\mu_{\tilde{A}}(x)$ approaches to 1, the more x belongs to $\tilde{A}$.

Definition 2 Let $\tilde{A}$ be a fuzzy set, its membership function is $\mu_{\tilde{A}}(x) : \mathbb{R} \to [0,1]$, if

- $\tilde{A}$ is normal, i.e., $\exists x \in \mathbb{R}, \sup_x \mu_{\tilde{A}}(x) = 1$.
- $\tilde{A}$ is convex, i.e., $\forall x_1, x_2 \in X, \quad \forall \lambda \in [0,1]$, $\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda)x_2) \geqslant \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2))$.

then $\tilde{A}$ is a fuzzy number.

Definition 3 Suppose $\tilde{A}$ is a triangular fuzzy number that is defined as a triplet (a, b, c) (see Figure 1). The membership function $\mu_{\tilde{A}}(x)$ is defined as

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x \in (-\infty, a) \\ (x-a)/(b-a), & x \in (a, b) \\ (x-c)/(b-c), & x \in (b, c) \\ 0, & x \in (c, \infty) \end{cases} \tag{2}$$

where parameter b denotes the strongest grade of membership, that is, $\mu_{\tilde{A}}(b) = 1$, while a and c are the lower and upper bounds of fuzzy number $\tilde{A}$, respectively.

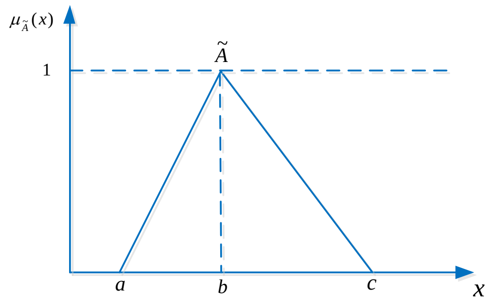

Fig. 1. Membership function of triangular fuzzy number $\tilde{A} = (a, b, c)$

After defining the triangular fuzzy number, we now discuss the basic arithmetic operations of triangular fuzzy numbers, which are based on Zadeh's Extension principle.

Definition 4 Suppose $\tilde{A} = (a_1, b_1, c_1)$ and $\tilde{B} = (a_2, b_2, c_2)$ are two triangular fuzzy numbers, then the addition, subtraction, multiplication and division operations of $\tilde{A}$ and $\tilde{B}$ can be shown as follows:

$$\begin{aligned} \tilde{A} \oplus \tilde{B} &= (a_1 + a_2,\ b_1 + b_2,\ c_1 + c_2) \\ \tilde{A} \ominus \tilde{B} &= (a_1 - c_2,\ b_1 - b_2,\ c_1 - a_2) \\ \tilde{A} \otimes \tilde{B} &= (a_1 \cdot a_2,\ b_1 \cdot b_2,\ c_1 \cdot c_2) \\ \tilde{A} \oslash \tilde{B} &= (a_1/c_2,\ b_1/b_2,\ c_1/a_2) \end{aligned} \quad (3)$$

Definition 5 Given two triangular fuzzy numbers $\tilde{A} = (a_1, b_1, c_1)$ and $\tilde{B} = (a_2, b_2, c_2)$, the vertex approach is utilized to calculate the distance between them.

$$d(\tilde{A}, \tilde{B}) = \sqrt{[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]/3} \quad (4)$$

To deal with the vagueness, ambiguity and subjectivity frequently arising from human judgments, the fuzzy set theory has been incorporated into many other MADM approaches[28], including GRA and TOPSIS method.

IV. Hybrid Group Decision Model for FMS Selection using fuzzy GRA-TOPSIS

In this section, a new hybrid group decision model is introduced for the evaluation and selection of alternative FMSs. The proposed model comprises of three stages: (1) Identify the evaluation attributes to be used in the decision model; (2) Determine the attribute weights using the voting method; (3) Obtain the precise ranking of alternative FMSs based on fuzzy TOPSIS integrated with GRA technique. The detailed procedures of hybrid group decision model for FMS evaluation can be described as follows.

Step 1 The first step of proposed hybrid model is to identify the pertinent evaluation attributes and alternative flexible manufacturing systems. The hierarchical structure of FMS selection is established with three levels. The objective is at the first level, while evaluation attributes are at the second level and alternative FMSs are on the third level.

Step 2 After the approval of hierarchical structure for FMS evaluation, this fuzzy multiple attribute decision-making problem could be concisely constructed in matrix format as

$$\tilde{\mathbf{D}} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} X_1 & X_2 & \dots & X_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix} \end{array} \quad (5)$$

$$\tilde{w} = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n) \quad (6)$$

where $A_1, A_2, \dots, A_m$ are possible alternatives to be selected, $X_1, X_2, \dots, X_n$ denote the evaluation attributes which measure the performance of alternatives, $\tilde{x}_{ij}$ represents the fuzzy performance rating of the ith alternative A_i versus the jth attribute X_j and $\tilde{w}_j$ is the weight of attribute X_j. In this paper, $\tilde{x}_{ij}, \forall i, j$ and $\tilde{w}_j, j = 1, 2, \dots, n$ are assessed in linguistic terms described by triangular fuzzy numbers, i.e., $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}), \tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$.

Step 3 A group of k experts is established to consider and evaluate the importance weights of the attributes. Supposed that members of the decision group are as follows

$$\mathbf{E} = (E_1, E_2, \dots, E_k) \quad (7)$$

In addition, different voting power weights are assigned to each group member according to their professional titles, given by

$$\tilde{\lambda} = (\tilde{\lambda}_1, \tilde{\lambda}_2, \dots, \tilde{\lambda}_k) \quad (8)$$

where $\tilde{\lambda}_t$ expressed by triangular fuzzy number represents the voting power weight of the tth decision maker. The definition of different professional titles and their corresponding triangular fuzzy scales are listed in Table I. For example, if the tth expert owns the title of associate professor, then his/her voting power weight is $\tilde{\lambda}_t = (0.6, 0.7, 0.8)$.

Step 4 Every group member provides his/her qualitative assessment with respect to each attribute using the linguistic scale presented in Table II. The fuzzy collective opinion matrix for all experts can be expressed as

$$\tilde{\mathbf{W}}^* = \begin{array}{c} \\ E_1 \\ E_2 \\ \vdots \\ E_k \end{array} \begin{array}{c} \begin{array}{cccc} X_1 & X_2 & \dots & X_n \end{array} \\ \begin{bmatrix} \tilde{w}^*_{11} & \tilde{w}^*_{12} & \dots & \tilde{w}^*_{1n} \\ \tilde{w}^*_{21} & \tilde{w}^*_{22} & \dots & \tilde{w}^*_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{w}^*_{k1} & \tilde{w}^*_{k2} & \dots & \tilde{w}^*_{kn} \end{bmatrix} \end{array} \quad (9)$$

TABLE I. Triangular fuzzy scale for the voting weight of each expert

Professional title	Triangular fuzzy scale
Assistant Research Fellow	(0.0, 0.1, 0.2)
Research Fellow	(0.2, 0.3, 0.4)
Senior Research Fellow	(0.4, 0.5, 0.6)
Associate Professor	(0.6, 0.7, 0.8)
Professor	(0.8, 0.9, 1.0)

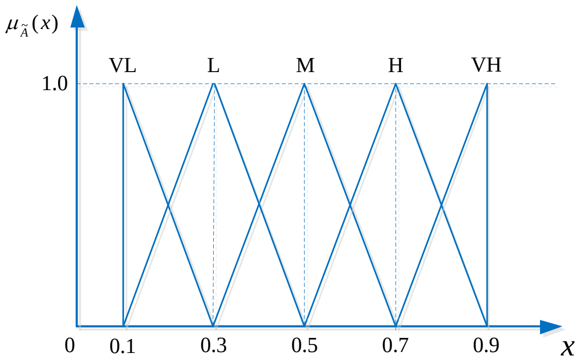

Fig. 2. Fuzzy membership function of the linguistic scale

where $\tilde{w}_{tj}^*$ indicates the fuzzy weight of the jth attribute assessed by the tth evaluator. The semantic of the linguistic terms in Table II is provided by triangular fuzzy numbers defined on the interval [0.1, 0.9], which are characterized by membership functions as shown in Figure 2. For example, the linguistic variable 'VL' can be represented by the triangular fuzzy number (0.1, 0.1, 0.3).

Step 5 To integrate all the expert opinions, Eq.(10) is adopted to aggregate the subjective judgements of k experts for obtaining the fuzzy weight $\tilde{w}_j$ of attribute X_j.

$$\tilde{w}_j = \sum_{t=1}^{k} \tilde{\lambda}_t \otimes \tilde{w}_{tj}^*, j = 1, 2, \ldots, n \tag{10}$$

$\tilde{\lambda}_t, t = 1, 2, \ldots, k$ and $\tilde{w}_{tj}^*, \forall t, j$ are all parameterized triangular fuzzy numbers. To ensure that the ranges of $\tilde{w}_j, j = 1, 2, \ldots, n$ belong to the interval [0, 1], the normalized fuzzy weights of attributes can be acquired by

$$\tilde{w}_j = (w_{j1}/\max_j w_{j3}, w_{j2}/\max_j w_{j3}, w_{j3}/\max_j w_{j3}) \tag{11}$$

Step 6 The normalization of fuzzy decision matrix is performed by applying the linear scale transformation method since it preserves the property that the values of converted triangular fuzzy numbers will be scaled into [0, 1]. Hence, the normalized fuzzy decision matrix denoted by $\tilde{\mathbf{R}}$ could be identified as

$$\tilde{\mathbf{R}} = [\tilde{r}_{ij}]_{m\times n}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{12}$$

$$\tilde{r}_{ij} = \begin{cases} (a_{ij}/c_j^+, b_{ij}/c_j^+, c_{ij}/c_j^+), & j \in J^+ \\ (a_j^-/c_{ij}, a_j^-/b_{ij}, a_j^-/a_{ij}), & j \in J^- \end{cases} \tag{13}$$

TABLE II. LINGUISTIC SCALE FOR THE IMPORTANT WEIGHT OF EACH ATTRIBUTE

Linguistic term	Triangular fuzzy scale
Very Low(VL)	(0.1, 0.1, 0.3)
Low(L)	(0.1, 0.3, 0.5)
Medium(M)	(0.3, 0.5, 0.7)
High(H)	(0.5, 0.7, 0.9)
Very High(VH)	(0.7, 0.9, 0.9)

where $c_j^+ = \max_i c_{ij}, a_j^- = \min_i a_{ij}$, J^+ is associated with benefit attributes and J^- is associated with cost attributes.

Step 7 The weighted normalized fuzzy decision matrix $\tilde{\mathbf{V}}$ can be computed by multiplying the normalized fuzzy decision element and the aggregative fuzzy weight of each attribute, which is defined as

$$\tilde{\mathbf{V}} = [\tilde{v}_{ij}]_{m\times n}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \tag{14}$$

where $\tilde{v}_{ij} = \tilde{w}_j \otimes \tilde{r}_{ij}$ and $\tilde{v}_{ij}, \forall i, j$ are positive triangular fuzzy numbers.

Step 8 After completing the performance normalization of various attribute scales, the fuzzy positive ideal solution(FPIS, A^+) and fuzzy negative ideal solution(FNIS, A^-) can be defined as two referential sequences

$$\begin{aligned} A^+ &= \{(\max_i \tilde{v}_{ij} | j \in J^+), (\min_i \tilde{v}_{ij} | j \in J^-)\} \\ &= \{\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_j^+, \ldots, \tilde{v}_n^+\} \end{aligned} \tag{15}$$

$$\begin{aligned} A^- &= \{(\min_i \tilde{v}_{ij} | j \in J^+), (\max_i \tilde{v}_{ij} | j \in J^-)\} \\ &= \{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_j^-, \ldots, \tilde{v}_n^-\} \end{aligned} \tag{16}$$

Considering that the ranges of decision elements $\tilde{v}_{ij}, \forall i, j$ belong to the closed interval [0, 1], it satisfies that $\tilde{v}_{J^+}^+ = \tilde{v}_{J^-}^- = (1, 1, 1)$ and $\tilde{v}_{J^+}^- = \tilde{v}_{J^-}^+ = (0, 0, 0)$ where J^+ is associated with benefit attributes and J^- is associated with cost attributes.

Step 9 To take each of the alternatives to be the comparative sequence in order to obtain the distances between A_i and two referential sequences, which are given as Eq.(17) and Eq.(18) respectively

$$\Delta_{ij}^+ = |A^+(j) - A_i(j)| = |\tilde{v}_j^+ - \tilde{v}_{ij}| = d(\tilde{v}_j^+, \tilde{v}_{ij}) \tag{17}$$

$$\Delta_{ij}^- = |A^-(j) - A_i(j)| = |\tilde{v}_j^- - \tilde{v}_{ij}| = d(\tilde{v}_j^-, \tilde{v}_{ij}) \tag{18}$$

where Δ_{ij} indicates the distance of the ith alternative A_i to the ideal solution with respect to the jth attribute X_j, and $d(\tilde{v}_A, \tilde{v}_B)$ denotes the distance measurement between two triangular fuzzy numbers $\tilde{A}$ and $\tilde{B}$.

Step 10 The grey relational coefficient of each alternative to the two referential sequences can be calculated as follows

$$\gamma_{ij}^+ = \frac{\min_i \min_j \Delta_{ij}^+ + \zeta \max_i \max_j \Delta_{ij}^+}{\Delta_{ij}^+ + \zeta \max_i \max_j \Delta_{ij}^+} \tag{19}$$

$$\gamma_{ij}^- = \frac{\min_i \min_j \Delta_{ij}^- + \zeta \max_i \max_j \Delta_{ij}^-}{\Delta_{ij}^- + \zeta \max_i \max_j \Delta_{ij}^-} \tag{20}$$

Grey relational coefficient is used for determining how close each alternative is to the ideal solution. Here, $\zeta \in [0, 1]$ is the distinguishing coefficient, which generally takes 0.5.

Step 11 The grey relational grade about the ith alternative A_i and the fuzzy positive ideal solution A^+ can be determined as

$$S_{i^+} = \frac{1}{n}\sum_{j=1}^{n}\gamma_{ij}^{+}, i = 1, 2, \ldots, m \quad (21)$$

Similarly, the grey relational grade about the ith alternative A_i and the fuzzy negative ideal solution A^- can be obtained as

$$S_{i^-} = \frac{1}{n}\sum_{j=1}^{n}\gamma_{ij}^{-}, i = 1, 2, \ldots, m \quad (22)$$

The grey relational grade represents the level of correlation between the referential sequence and the comparative sequence.

Step 12 Once the S_{i^+} and S_{i^-} of each alternative have been calculated successfully, a relative closeness coefficient is defined to determine the final ranking order of all alternatives which is calculated as

$$C_{i^*} = S_{i^+}/(S_{i^+} + S_{i^-}), 0 < C_{i^*} < 1 \quad (23)$$

It is obvious that a greater value of C_{i^*} indicates a higher priority of the alternative FMS. Therefore, the ranking order of all alternatives can be obtained, and the best one is selected from a set of feasible alternatives, according to the C_{i^*} value.

As decision making requires multiple perspectives from different people, most organizational decisions for FMS evaluation are made in groups. To make the group decision-making process as efficient and effective as possible, the voting method is employed in this paper to determine the appropriate attribute weights. Meanwhile, the definition of grey relational coefficient of GRA method is introduced to replace the definition of general distance in conventional TOPSIS under fuzzy environment. As a result, the proposed model can overcome the problem of inconsistent ranking of alternative FMSs, and it can also efficiently grasp the ambiguity in human judgments and preferences for evaluation attributes.

V. Illustrative Example for Evaluating FMSs

In this section, to illustrate the feasibility and potentiality of the proposed hybrid group decision model for solving FMS evaluation problems, an empirical case of evaluating alternative FMSs(adapted from literature[12]) is considered. The aforementioned methodology is applied to solve this FMS selection problem to make the proposed group decision model more understandable.

A. Identify Necessary Attributes for FMS Evaluation Problem

For this FMS selection problem, the available information is adapted from Karsak and Kuzgunkaya's research[12]. Karsak and Kuzgunkaya had presented an illustrative problem for evaluating FMSs using a fuzzy multiple objective programming approach. In this paper, the FMS selection problem consists of four attributes and eight alternative FMSs, as shown in Table III and Table IV. Among these four attributes, reduction in labor cost(RLC) and reduction in work-in-process(RWP) are benefit attributes(where higher values are desirable), whereas, capital and maintenance cost(CMC) and floor space used(FSU) are cost attributes(where lower values are desirable).

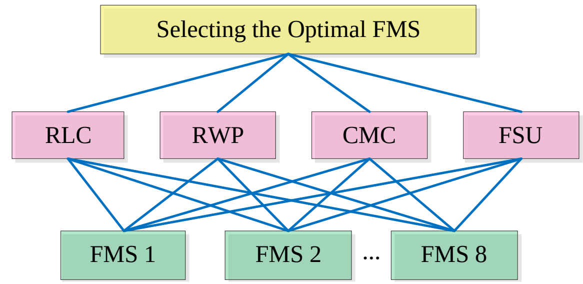

Fig. 3. Hierarchical structure for FMS selection problem

The evaluation attributes and alternative FMSs are arranged in a hierarchical structure as depicted in Figure 3. There are three levels in the decision hierarchy for this FMS selection problem. The overall goal of the decision process defined as "Selecting the optimal FMS" is at the top level. The four attributes are at the second level and eight FMS alternatives are at the third level of the hierarchy.

B. Calculate the fuzzy weights of attributes using the voting method

Initially, the expert group is formed with the following members: $\mathbf{E} = (E_1, E_2, E_3, E_4, E_5)$. Next, the group members are asked to express their assessments of importance weights for each evaluation attribute by casting a vote according to the linguistic scales shown in Table II. The linguistic assessments for all experts and their professional titles are presented in Table V.

Then the fuzzy collective opinion matrix for all experts is constructed by converting the linguistic evaluation(shown in Table V) into triangular fuzzy numbers, as shown in Table VI. From steps 3-5 of the proposed method, an aggregative fuzzy weight value for each attribute can be obtained as

$$\begin{aligned}\tilde{w} =&[(0.2909, 0.5182, 0.8182), (0.2667, 0.5182, 0.7939),\\ &(0.4606, 0.7424, 1.0000), (0.0970, 0.2091, 0.4788)]\end{aligned}$$

C. Determine the ranking order of alternative FMSs based on fuzzy GRA-TOPSIS

Use step 6 to compute the fuzzy normalized fuzzy decision matrix, as shown in Table VII. The next step of the analysis is to find out the weighted normalized fuzzy decision matrix using Eq.(14), and the calculated results are listed in Table VIII. Due to the fact that triangular fuzzy numbers fall into the range of [0, 1], two referential sequences of fuzzy positive ideal solution A^+ and fuzzy negative ideal solution A^- can be identified as

$$A^+ = [(1, 1, 1), (1, 1, 1), (0, 0, 0), (0, 0, 0)]$$

TABLE III. FMS evaluation attributes and their definitions

Attribute	Definition of the Attribute
RLC	Reduction in labor cost (%)
RWP	Reduction in work-in-process(WIP) (%)
CMC	Capital and maintenance cost (\$ 1,000)
FSU	Floor space used (sq. ft.)

TABLE IV. EVALUATION ATTRIBUTES AND ALTERNATIVES FOR FMS SELECTION[12]

Alternatives	RLC	RWP	CMC	FSU
A_1	(25, 30, 35)	(20, 23, 26)	(1400, 1500, 1800)	(4000, 5000, 6000)
A_2	(16, 18, 20)	(7, 13, 16)	(1100, 1300, 1500)	(5500, 6000, 6500)
A_3	(10, 15, 20)	(10, 12, 16)	(750, 950, 1150)	(6000, 7000, 8000)
A_4	(23, 25, 27)	(12, 20, 22)	(800, 1200, 1300)	(3500, 4000, 4500)
A_5	(12, 14, 16)	(10, 18, 25)	(850, 950, 1050)	(1500, 3500, 5500)
A_6	(14, 17, 20)	(13, 15, 20)	(1000, 1250, 1500)	(3500, 5250, 7000)
A_7	(17, 23, 27)	(13, 18, 23)	(900, 1100, 1300)	(2500, 3000, 3500)
A_8	(12, 16, 20)	(5, 8, 12)	(1400, 1500, 1600)	(2000, 3000, 4000)

TABLE V. LINGUISTIC ASSESSMENTS GIVEN BY EXPERTS AND THEIR TITLES

Experts	RLC	RWP	CMC	FSU	Professional title
E_1	VL	M	VH	M	Research Fellow
E_2	M	L	H	L	Associate Professor
E_3	M	M	VH	VL	Professor
E_4	M	VH	M	L	Senior Research Fellow
E_5	H	M	H	VL	Professor

TABLE VI. FUZZY COLLECTIVE OPINION MATRIX OF DECISION-MAKERS AND THEIR VOTING WEIGHTS

Experts	RLC	RWP	CMC	FSU	Voting power weight
E_1	(0.1, 0.1, 0.3)	(0.3, 0.5, 0.7)	(0.7, 0.9, 0.9)	(0.3, 0.5, 0.7)	(0.2, 0.3, 0.4)
E_2	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)	(0.5, 0.7, 0.9)	(0.1, 0.3, 0.5)	(0.6, 0.7, 0.8)
E_3	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)	(0.7, 0.9, 0.9)	(0.1, 0.1, 0.3)	(0.8, 0.9, 1.0)
E_4	(0.3, 0.5, 0.7)	(0.7, 0.9, 0.9)	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)	(0.4, 0.5, 0.6)
E_5	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)	(0.5, 0.7, 0.9)	(0.1, 0.1, 0.3)	(0.8, 0.9, 1.0)

TABLE VII. THE NORMALIZED FUZZY DECISION MATRIX FOR ALTERNATIVE FMSS

FMSs	RLC	RWP	CMC	FSU
A_1	(0.7143,0.8571,1.0000)	(0.7692,0.8846,1.0000)	(0.4167,0.5000,0.5357)	(0.2500,0.3000,0.3750)
A_2	(0.4571,0.5143,0.5714)	(0.2692,0.5000,0.6154)	(0.5000,0.5769,0.6818)	(0.2308,0.2500,0.2727)
A_3	(0.2857,0.4286,0.5714)	(0.3846,0.4615,0.6154)	(0.6522,0.7895,1.0000)	(0.1875,0.2143,0.2500)
A_4	(0.6571,0.7143,0.7714)	(0.4615,0.7692,0.8462)	(0.5769,0.6250,0.9375)	(0.3333,0.3750,0.4286)
A_5	(0.3429,0.4000,0.4571)	(0.3846,0.6923,0.9615)	(0.7143,0.7895,0.8824)	(0.2727,0.4286,1.0000)
A_6	(0.4000,0.4857,0.5714)	(0.5000,0.5769,0.7692)	(0.5000,0.6000,0.7500)	(0.2143,0.2857,0.4286)
A_7	(0.4857,0.6571,0.7714)	(0.5000,0.6923,0.8846)	(0.5769,0.6818,0.8333)	(0.4286,0.5000,0.6000)
A_8	(0.3429,0.4571,0.5714)	(0.1923,0.3077,0.4615)	(0.4688,0.5000,0.5357)	(0.3750,0.5000,0.7500)

$$A^- = [(0,0,0),(0,0,0),(1,1,1),(1,1,1)]$$

Next, using Eq.(17) and Eq.(18), the distance of each candidate from two referential sequences A^+ and A^- with respect to each attribute can be calculated. The result is depicted in Table IX. Then the grey relational coefficient and grey relational grade of each FMS alternative can be derived by using Eqs.(19)-(22), as shown in Table X. Here, this example used the distinguishing coefficient $\zeta = 0.5$ to calculate the grey relational coefficient. Once the grey relational grades are determined, the relative closeness coefficient can be computed by Eq.(23), with the final results being listed in Table XI. According to the relative closeness coefficient, the ranking of all alternative FMSs in descending order is given as

$$A_1 \succ A_4 \succ A_2 \succ A_7 \succ A_6 \succ A_3 \succ A_8 \succ A_5$$

To validate the results obtained using the fuzzy GRA-TOPSIS model, fuzzy SAW[17] and fuzzy TOPSIS[6] are applied to solve the same numerical example as two comparable methods. In addition, the weights of FMS evaluation attributes are considered the same for these two comparable methods, which is calculated using the voting method for the realistic comparison of the results of all the methods. The final ranking results derived using the methodology of fuzzy SAW, fuzzy TOPSIS and fuzzy GRA-TOPSIS are shown in Figure 4. A comparison result indicates that the ranking results obtained using fuzzy TOPSIS method and fuzzy GRA-TOPSIS method are more or less the same, while fuzzy SAW method has a great discrimination in the ranking of the same FMS alternatives. All of the three methods suggest A_1 is the best choice and A_4 is the second best choice. But the ranking results for the other FMS alternatives using fuzzy SAW method is significantly different from the other two methods. Fuzzy SAW method is believed to be less reliable because different ranking results will be obtained when different ranking methods are applied for ranking fuzzy numbers. Although the results of fuzzy TOPSIS method almost corroborate with those derived by the fuzzy GRA-TOPSIS method, the relative importance of the distance from A^+ and A^- is not considered in fuzzy TOPSIS method. This shortcoming is overcome through the grey relational coefficient of the fuzzy GRA-TOPSIS model. Therefore, the proposed fuzzy GRA-TOPSIS model is proved to be more effective for the ranking and selection of FMS alternatives.

The group decision-making process will be finished if the group of experts accept the evaluation results. Otherwise, the group experts have to modify their linguistic assessments for each attribute until the final decision is considered as consistent and acceptable. After detailed analysis of this case study, FMS A_1 is recommended by the group as the best performer among

TABLE VIII. THE WEIGHTED NORMALIZED FUZZY DECISION MATRIX FOR ALTERNATIVE FMSS

FMSs	RLC	RWP	CMC	FSU
A_1	(0.2078,0.4442,0.8182)	(0.2051,0.4584,0.7939)	(0.1919,0.3712,0.5357)	(0.0242,0.0627,0.1795)
A_2	(0.1330,0.2665,0.4675)	(0.0718,0.2591,0.4886)	(0.2303,0.4283,0.6818)	(0.0224,0.0523,0.1306)
A_3	(0.0831,0.2221,0.4675)	(0.1026,0.2392,0.4886)	(0.3004,0.5861,1.0000)	(0.0182,0.0448,0.1197)
A_4	(0.1912,0.3701,0.6312)	(0.1231,0.3986,0.6718)	(0.2657,0.4640,0.9375)	(0.0323,0.0784,0.2052)
A_5	(0.0997,0.2073,0.3740)	(0.1026,0.3587,0.7634)	(0.3290,0.5861,0.8824)	(0.0264,0.0896,0.4788)
A_6	(0.1164,0.2517,0.4675)	(0.1333,0.2990,0.6107)	(0.2303,0.4455,0.7500)	(0.0208,0.0597,0.2052)
A_7	(0.1413,0.3405,0.6312)	(0.1333,0.3587,0.7023)	(0.2657,0.5062,0.8333)	(0.0416,0.1045,0.2873)
A_8	(0.0997,0.2369,0.4675)	(0.0513,0.1594,0.3664)	(0.2159,0.3712,0.5357)	(0.0364,0.1045,0.3591)

TABLE IX. DISTANCES OF EACH ALTERNATIVE FMS FROM A^+ AND A^- VERSUS EACH ATTRIBUTE

	Distance of A_i from A^+				Distance of A_i from A^-			
FMS	RLC	RWP	CMC	FSU	RLC	RWP	CMC	FSU
A_1	0.5685	0.5679	0.3923	0.1107	0.5507	0.5424	0.6491	0.9136
A_2	0.7242	0.7466	0.4835	0.0822	0.3200	0.3220	0.5832	0.9327
A_3	0.7592	0.7407	0.6913	0.0745	0.3027	0.3196	0.4693	0.9401
A_4	0.6290	0.6425	0.6231	0.1282	0.4366	0.4566	0.5261	0.8977
A_5	0.7812	0.6513	0.6404	0.2816	0.2535	0.4906	0.4602	0.8263
A_6	0.7358	0.6817	0.5209	0.1240	0.3138	0.4001	0.5664	0.9082
A_7	0.6604	0.6457	0.5835	0.1781	0.4220	0.4618	0.5199	0.8619
A_8	0.7475	0.8181	0.3964	0.2169	0.3080	0.2326	0.6392	0.8448

TABLE X. RESULTS OF GREY RELATIONAL COEFFICIENT FOR FMS EVALUATION PROBLEM

	FPIS				FNIS			
FMS	RLC	RWP	CMC	FSU	RLC	RWP	CMC	FSU
A_1	0.4947	0.4950	0.6035	0.9304	0.6884	0.6940	0.6279	0.5078
A_2	0.4267	0.4185	0.5418	0.9843	0.8893	0.8872	0.6671	0.5009
A_3	0.4139	0.4206	0.4395	1.0000	0.9093	0.8898	0.7480	0.4983
A_4	0.4659	0.4599	0.4685	0.9001	0.7750	0.7583	0.7054	0.5137
A_5	0.4063	0.4561	0.4608	0.7001	0.9711	0.7315	0.7553	0.5420
A_6	0.4224	0.4434	0.5200	0.9073	0.8964	0.8076	0.6779	0.5098
A_7	0.4522	0.4585	0.4872	0.8236	0.7877	0.7541	0.7098	0.5276
A_8	0.4181	0.3941	0.6004	0.7725	0.9031	1.0000	0.6335	0.5344

TABLE XI. RELATIVE CLOSENESS COEFFICIENT AND RANKING ORDER OF ALTERNATIVE FMSS

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
S_{i+}	0.6309	0.5928	0.5685	0.5736	0.5058	0.5733	0.5554	0.5463
S_{i-}	0.6295	0.7361	0.7614	0.6881	0.7500	0.7229	0.6948	0.7677
C_{i*}	0.5005	0.4461	0.4275	0.4546	0.4028	0.4423	0.4442	0.4157
Rank	1	3	6	2	8	5	4	7

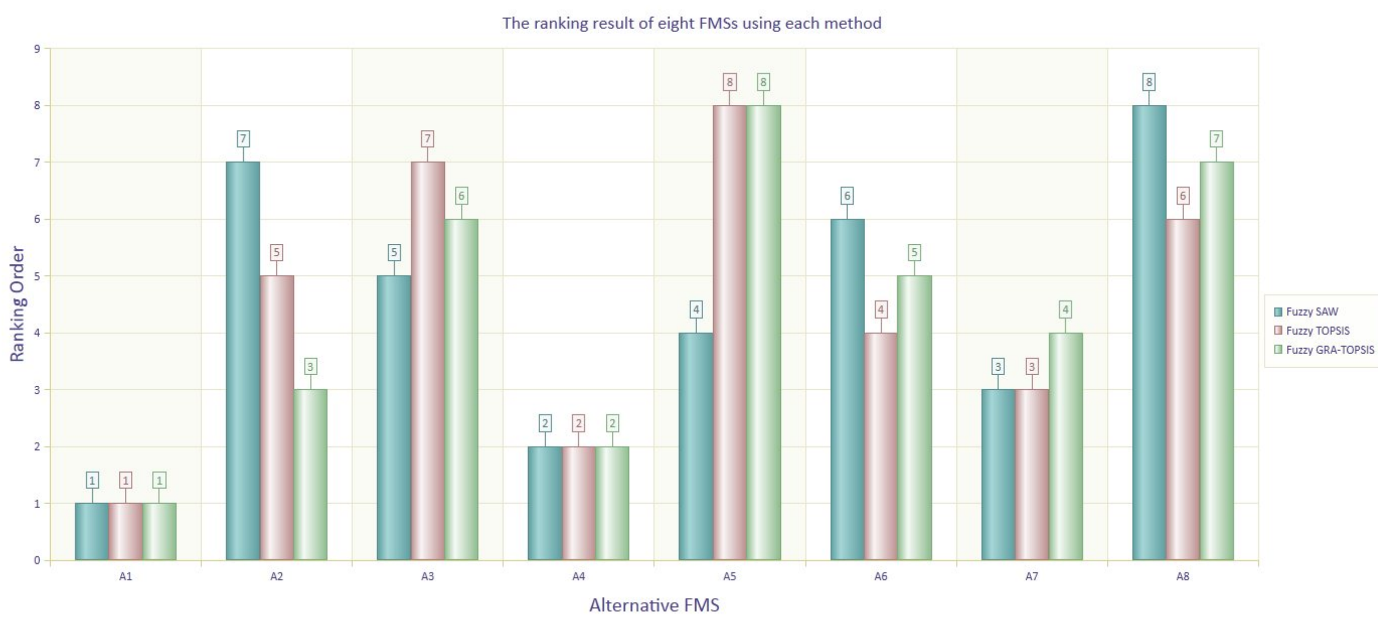

Fig. 4. The ranking results of FMS alternatives using each method

these alternatives.

D. Sensitivity analysis

The aim of sensitivity analysis is to determine how different values of an independent variable will carry an impact on a particular dependent variable under a set of assumptions[13], [21]. In general, a sensitivity analysis is performed on MADM problems to check the ranking reversal of the candidates by changing the assigned weights of evaluation attributes. Therefore, this study uses the concepts of sensitivity analysis to investigate the impact of distinguishing coefficient on the final ranking order of alternative FMSs obtained using the fuzzy GRA-TOPSIS method. The sensitivity of the degree of the relative closeness coefficient is analysed with the different distinguishing coefficient ζ which varies from 0.1 to 1.0 with an interval of 0.1, and the results are shown in Figure 5 and Figure 6.

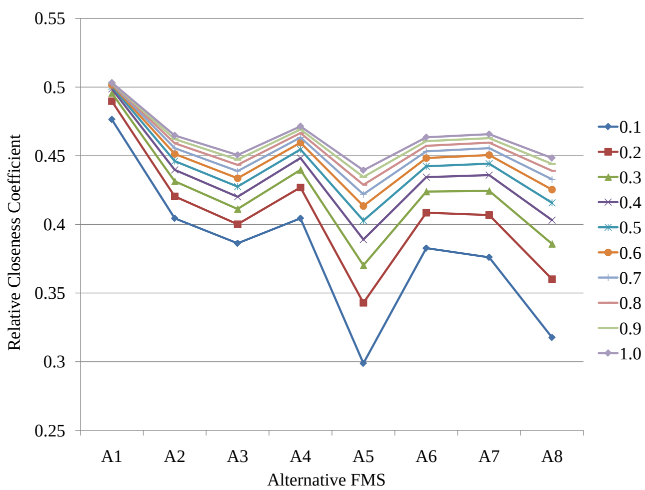

Fig. 5. Variation analysis of C_{i^*} value for alternative FMS with change of distinguishing coefficient

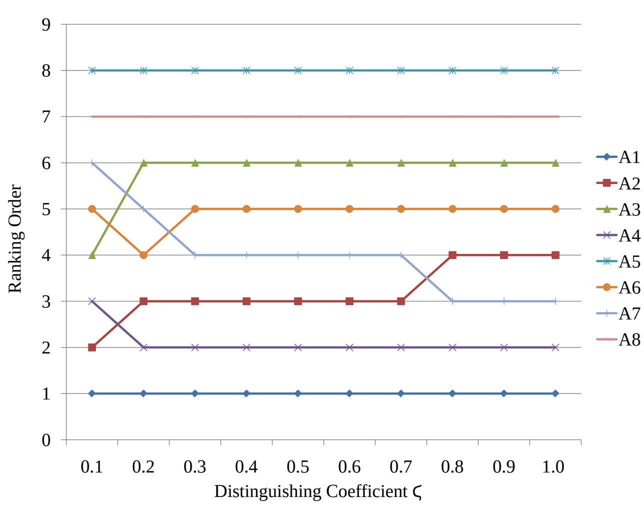

Fig. 6. An effect of distinguishing coefficient on ranking order of FMS alternatives

The results of sensitivity analysis depicted in Figure 5 and Figure 6 indicate that the effect of distinguishing coefficient ζ on final ranking order of FMS alternatives using fuzzy GRA-TOPSIS is minor. It can be observed that the ranking sequence of FMS alternatives A_1, A_5 and A_8 remain the same, no matter what value the distinguishing coefficient is. There is a slight change in ranking order of the other alternatives when the distinguishing coefficient varies greatly. However, FMS alternative A_1 is ranked first and A_5 is ranked last for every value of distinguishing coefficient. In addition, a similar ranking order is obtained for distinguishing coefficient values from 0.3 to 0.7, which indicates that the results obtained using the fuzzy GRA-TOPSIS is non-sensitive within a certain range. This allows us to draw a logical conclusion that the developed hybrid decision model is robust.

VI. Conclusion and Future Research

The expanding competitiveness due to the globalization has dramatically increased the need for manufacturers to produce high-quality products efficiently and respond to changes quickly. Flexible manufacturing systems provide the means to arrive at a solution consistent with industrial goals and objectives. To help address the issue of evaluation and selection of alternative FMSs where the information available is subjective and imprecise, an effective fuzzy GRA-TOPSIS method applied in the group decision-making model is developed. The proposed model is intended to enhance group decision-making, promote consensus and provide invaluable analysis aids.

In this paper, the voting method is integrated into the group decision-making model to obtain the appropriate attribute weights by aggregating multiple fuzzy linguistic preferences of a group of experts. The assessments of a group of experts are considered to be more objective and unbiased than those individually evaluated. Then the fuzzy GRA-TOPSIS method is employed to determine the final ranking order of alternative FMSs. We also present a case study to illustrate the applicability and potentiality of the proposed group decision model. It has been shown that the proposed model could help a group of decision makers to think comprehensively and systematically about FMS selection problem and improve the quality of decision-making process. In addition, a comparative study is used to examine the rationality of the results of the proposed method. Moreover, a sensitivity analysis is performed to demonstrate the robustness of the proposed model.

In future research, various MADM techniques such as ELECTRE, PROMETHEE and VIKOR could be applied comparatively along with fuzzy set theory to select the best FMS alternative. And our work will also focus on the application of the proposed hybrid model in the similar decision problems, such as material selection, weapon system selection, and location selection.

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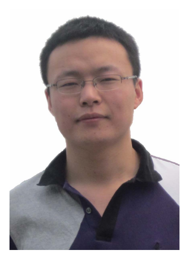

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