A Fuzzy Multiple attributes Decision-Making for the Evaluation of Advanced Manufacturing Technology

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Abstract

Evaluation of advanced manufacturing technology is very important to improving manufacturing system competitiveness, and is being increasing discussing in the literature on manufacturing system. Traditional methods of solving advanced manufacturing technology evaluation problems cannot effectively handle problems involving imprecise and subjective information. The objective of this paper is to develop a fuzzy multiple attributes decision- making model with three-stage assessment to evaluate the suitability of manufacturing technology. The evaluation problem is solved by a fusion method based on maximum entropy ordered weighted averaging operators. We also proposed a fusion method of fuzzy information, which was assessed using both linguistic and numerical scales. In addition, an interactive decision analysis is developed to make a consistent decision. When evaluating the suitability of manufacturing technology, it may be necessary to improve upon the technology, and naturally advanced manufacturing technology is seen as the best direction for improvement. The flexible manufacturing system adopted in a case study is used in this study to illustrate the computational process of the proposed method.

Keywords: Fuzzy sets, Multiple attributes analysis, Advanced manufacturing technology, Maximum entropy ordered weighted averaging operators, Three-stage assessment

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模糊多屬性決策方法應用於先進製造技術評估之研究

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摘　要

對於改善製造系統的競爭力，先進製造技術評估具有重要的策略性功能，在相關文獻的討論日益增加。針對製造技術評估問題，傳統衡量方法無法有效率地處理評估資訊中的不精確性與主觀性。本文提出一種三階段的多屬性決策模式，其中提出一種 MEOWA 運算子的模糊資訊融合方法，藉以整合語意資訊與數值資訊，適合於不確定決策環境下的製造技術適合度評估問題；此外，本法亦提出一個互動式決策分析，有助於達成決策的一致性。在評估製造技術適合度時，不僅可以發現製造技術的改善時機，更可以確定製造技術的改善方向，直到評估者滿意為止。最後，藉由個案研究之彈性製造系統評估，展示本法之運算過程。

關鍵字：模糊集合，多屬性分析，先進製造技術，MEOWA 運算子，三階段評估

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1. Introduction

Manufacturing environments recently have changed so fast that manufacturing system competitiveness has increased importance. Manufacturing firms have been investing in advanced manufacturing technologies to improve their manufacturing performance in terms of cost, quality and flexibility, in an effort to compete with other firms in the global marketplace (Karsak and Tolga, 2001). Generally, advanced manufacturing technology (AMT) represents numerous modern technologies devoted to improving manufacturing firm competitive position, including flexible manufacturing systems, computer-integrated manufacturing systems, just-in-time systems, and so on (Small and Chen, 1997). Selecting a suitable AMT is important for manufacturing firms when making capital investment decisions to improve their manufacturing performance.

In practice, while some firms that adopt these technologies report reaping considerable benefits, others have been less successful, which indicates that AMT investment remains promising but high risky (Small and Chen, 1997). Furthermore, the rapid growth of the AMT industry is now creating problems. Prospective firms now face the situation of having to decide among several AMTs, all of which are capable of performing a specific task. The development of appropriate assessment approaches is crucial to ensuring that each AMT project is assessed from the perspective of all benefits and costs (Liang and Wang, 1993; Small and Chen, 1997). The literature review has revealed difficulties in justification of the AMT investment using traditional economic technology, and a few existing methodologies have provided satisfactory solutions. Therefore, this paper presents a methodology that can be applied to the AMT evaluation problem.

From a methodological perspective, the AMT selection problem is a fuzzy multiple attribute decision-making problem involving the consideration of fuzzy assessments and the opinions of decision-makers (or experts). In the AMT selection decision problem, numerous effects (attributes) must be considered in justifying a particular manufacturing technology (Karsak and Tolga, 2001). Punniyamoorthy and Ragavan (2003) proposed a deterministic approach to decision making for technology selection, which considers both subjective and objective attributes, attributes that are also seen in Karsak and Tolga (2001). Objective attributes are defined by using appropriate numerical terms, such as

investment cost, setup time, and so on, used for assessing the quantitative effects of manufacturing technology. Since precise quantitative information may not be available or computational costs may be excessively high, these expert identified performance ratings can be 'approximate numerical values', which can be expressed by sentences such as *'approximately equal to'*, *'at least'*, or *'approximately between'* and so on (Martinez et al., 2007; Olcer and Odabasi, 2005; Perego and Rangone, 1998). Subjective attributes have qualitative definitions, e.g. process flexibility, product quality, etc., used for assessing the qualitative effects of manufacturing technology, which may be unquantifiable due to the nature of such technology. Expert opinions can be represented linguistically, using labels such as *'high'*, *'middle'*, or *'low'* etc. Consequently, with respect to multiple attribute analysis, appropriate AMT selection is difficult-to-synthesize.

Obviously much real world knowledge is fuzzy rather than precise. In AMT ranking/selection problems, assessment data employed in multiple attribute decision making problems are generally fuzzy linguistic, numerical, or some mixture of thereof. Hence, a useful decision-making model is to provide the ability to handle multiple fuzzy assessments, that is, by aggregating the information of multiple attributes. This study attempts to establish a useful decision-making model by using fuzzy multiple attributes analysis to improve the AMT selection process.

Therefore, this study proposes a decision-making model based on fuzzy multiple attributes analysis to assess the suitability of AMT alternatives. In the proposed method, we have developed a new fuzzy fusion method of fuzzy information for managing information assessed using both linguistic and numerical scales. Fusion of fuzzy assessment data is performed by maximum entropy ordered weighted averaging (MEOWA) operators. The remainder of this paper is organized as follows. Section 2 provides a literature review focused on methods used in AMT selection, decision-making with fuzzy multiple attributes analysis, and linguistic assessments used in the decision-making. Section 3 then presents a fuzzy fusion method. A fuzzy multiple attribute decision-making model for evaluating an appropriate AMT is proposed in Section 4. The process aggregates each parameter assessed by an individual, and aggregates the results to determine the final ranking order. In Section 5, an example using a case of leading Taiwanese bicycle manufacturers is used to illustrate the computational

process of the proposed method. Finally, the last section summarizes this research.

2. Literature Review

This section reviews the literature on justification techniques for AMT, decision-making with fuzzy multiple attributes analysis, and linguistic assessments used in the decision-making.

2.1 Justification techniques for AMT

Numerous precision-based methods of AMT evaluation have recently been developed. These deterministic justification techniques are classified into economic, analytical, strategic and integrated approaches (Naik and Chakravarty, 1992). These methods deviate from one another mainly because to the treatment of qualitative effects being based on crisp evaluation, i.e. the evaluation values must be precise. However, in real life, the assessments of performance ratings for subjective attributes (or the importance grades of all attributes) are generally expressed via fuzzy linguistic assessment (Zadeh, 1975). Therefore, the primary problem of the above methods is that they are based on accurate measurement and crisp evaluation.

Traditional approaches of solving AMT selection problems cannot effectively handle problems involving imprecise and subjective information. In fact, most decision-makers (or experts) view performance ratings for subjective attributes as linguistic labels, such as high, middle, and low, etc. Since Zadeh (1965) introduced fuzzy sets theory to deal with vagueness problems, linguistic labels have been used in approximate reasoning within the fuzzy sets theory framework to handle imprecise data and vague linguistic expression. Several researchers have utilized fuzzy multiple attributes decision-making (FMADM) models for AMT selection problems. Perego and Rangone (1998) presented reviews of the application of FMADM theory to AMT selection. FMADM techniques belong to three categories: (1) fuzzy goal methodology, (2) fuzzy linguistic methods, and (3) fuzzy hierarchical models. Karsak and Tolga (2001) proposed a FMADM method for evaluating advanced manufacturing system investments. The proposed approach applied fuzzy discounted cash flow analysis and linguistic assessments of decision makers to the economic (objective) criterion and strategic (subjective) criteria, respectively. Abdel-Kader and Dugdale (2001) proposed a

FMADM model for the evaluation of AMT investments. The proposed model applied the mathematics of analytical hierarchy process and fuzzy sets theory to aggregate the two major dimensions of financial attribute and non-financial attributes, respectively. Moreover, Punniyamoorthy and Ragavan (2003) proposed a strategic decision-making model for AMT selection, which considered objective and subjective factors. Regarding the intangible benefits arising from subjective attributes, a range of evaluated values is taken and three different levels are considered within the range. This study modeled a technology selection problem defined into a multiple attributes scenario, and proposed a decision-making model with a new fuzzy fusion method for resolving manufacturing technology evaluation problems.

2.2 Decision-making with fuzzy multiple attributes analysis

Decision-making is a usual human activity. It basically involves selecting the most preferred alternative(s) from a finite set of alternatives in order to achieve certain predefined objectives (or goals). A literature review of AMT evaluation demonstrates that the AMT selection problem is a multi-attribute decision-making problem in a fuzzy environment, and involves considering multiple attributes decision-making.

In the decision-making problems under uncertainty, a decision maker can provide imprecise or linguistic preference information. For example, when attempting to qualify qualitative phenomenon related to human perception, or precise quantitative information may not be stated, natural language is frequently used rather than numerical values (Herrera and Herrera-Viedma, 2000). Hence, the linguistic approach appears to be an important tool for providing a decision-making framework that incorporates the vagueness and imprecision inherent in AMTs justification and selection. An effective means of expressing attributes including process flexibility, product quality, required investment cost and reduction in setup time, which cannot be assessed using either crisp values or random process, is using linguistic variables or fuzzy numbers (Karsak and Tolga, 2001).

A decision maker frequently faces the problem of identifying a solution from a finite set of alternatives. Multiple attribute decision-making (MADM) deals with the problem of selecting an alternative from a set of alternatives characterized by multiple attributes. The selected alternative is that which is the most preferred among all the

relevant attributes (or predefined objectives). Clearly, the classical MADM methods, both deterministic and random processes, cannot effectively handle decision-making problems with imprecise and linguistic information, and thus FMADM methods were developed.

FMADM methods basically involve two phases before to achieve a decision (Roubens, 1997): aggregation and exploitation. The aggregation phase combines the performance ratings for all attributes with respect to each alternative. The exploitation phase ranks the alternatives with respect to the global aggregated performance ratings. Various methods exist for solving these two main phases of FMADM. The literature contains numerous applications of FMADM to different aspects of selection problems with vague data, e.g., robot selection (Liang and Wang, 1993), propulsion system selection (Olcer and Odabasi, 2005), advanced manufacturing systems selection (Karsak and Tolga, 2001; Perego and Rangone, 1998), etc. Furthermore, there are a great number of FMADM methods related to evaluation, such as manufacturing flexibility (Chuu, 2005), engineer evaluation (Martinez et al., 2007) and so on.

In a fuzzy environment, a multiple attribute decision-making problem considered in this study composes the following elements: Let $A=\{A_1, A_2, \cdots, A_m\}$ comprise a finite set of alternatives (courses of AMT), and moreover let there be a finite set of attributes $C=\{C_1, C_2, \cdots, C_k\}$, where these attributes are classified as subjective attributes $\{C_1, C_2, \cdots, C_s\}$ and objective attributes $\{C_{s+1}, C_{s+2}, \cdots, C_k\}$. A general procedure for decision-making with fuzzy multiple attributes analysis requires three major stages (Herrera et al., 2005): first, the opinions (or evaluations) from experts should be unified. The second stage then aggregates unified opinions to form a collective opinion for each alternative. This opinion is usually a fuzzy number or linguistic label, and is used to order the alternatives. The third stage involves selecting preferred alternative(s) based on their ranking order. Therefore, a new AMT selection method based on fuzzy multiple attribute decision-making is developed in the three stages of this procedure.

2.3 Linguistic assessments

The linguistic assessment is an approximate method based on linguistic variables. The concept of linguistic variables is extremely useful in dealing with decision situations, which are too complex or ill-defined to be reasonably described using

conventional quantitative expressions (Zadeh, 1975). A linguistic variable is one whose values are not numbers but rather words or sentences in a natural or artificial language (Zimmermann, 1996). For example, the opinions of experts regarding subjective or objective attributes for an alternative can be linguistic labels or approximate numerical values, respectively.

However, in the real world, the linguistic approach is appropriate for application to many decision situations; restated, while a decision maker cannot generally specify precise numerical values they can take the form of linguistic variables or fuzzy numbers because (1) a decision should be made to experience time pressure and lack of knowledge or data (Weber, 1987); (2) numerous attributes are subjective or intangible owing to being unquantifiable in nature (Zadeh, 1975); (3) as for objective attributes, precise quantitative or non-monetary information may not be stated because it is either unavailable or too costly to compute (Herrera and Herrera-Viedma, 2000). This approach allows the representation of expert information more directly and adequately (Herrera et al., 1996). Therefore, the linguistic approach is used in different fields, and decision-making includes numerous approaches based on linguistic information.

In applying a linguistic approach to AMT selection, since numerous attributes have been considered in evaluating AMT suitability, these attributes can be identified by considering specific manufacturing system requirements. In general, the attributes are classified as subjective and objective. For each subjective attribute, expert opinions regarding individual alternative can be linguistic terms (labels), which are characterized by trapezoidal fuzzy numbers. For objective attributes, expert opinions are expressed as approximate numerical values characterized with trapezoidal fuzzy numbers.

As mentioned above, in order to establish the decision matrix for experts, decision-makers (or experts) express their opinions (or preferences) for each alternative with respect to each attribute. With respect to each alternative, the performance ratings and importance grade for each subjective attribute should be rated scored on a linguistic term set (or linguistic scale). The strongest assessment is assigned the highest (or lowest) label *'Definitely high'* (or *'Definitely low'*) on a linguistic scale. The elements of the term set determine the granularity of the uncertainty. Furthermore, let $S=\{s_0, s_1, \cdots, s_T\}$ be a finite and totally ordered term set with an odd cardinal, where the middle term represents 'average', i.e., a probability of 'approximately 0.5', and the remaining terms

are ordered symmetrically around it, and exhibit the following properties (Herrera et al., 1995).

1. The set is ordered: $s_i \geqq s_j$ if $i \geqq j$.
2. The negation operator is defined as Neg(s_i) = s_j such that $j = T - i$.
3. The maximization operator is Max (s_i, s_j) = s_i if $s_i \geqq s_j$.
4. The minimization operator is Min (s_i, s_j) = s_j if $s_i \geqq s_j$.

For example, a linguistic scale comprising seven terms S_1 could be represented as follows:

$S_1 = \{ s_0 = DL, s_1 = VL, s_2 = L, s_3 = M, s_4 = H, s_5 = VH, s_6 = DH \}$

where *DL* = Definitely Low, *VL* = Very Low, *L* = Low, *M* = Middle, *H* = High, *VH* = Very High, *DH* = Definitely High.

The semantic of the terms of the linguistic scale is provided by fuzzy numbers defined on the interval *[0, 1]*, which are characterized by membership functions. The use of linguistic variables increases the flexibility and reliability of decision maker evaluations, but complicates the aggregation of the linguistic labels. Generally, two main approaches are used to aggregate and compare linguistic terms in decision-making: the first approach uses the associated membership functions, while the second calculates linguistic labels directly. Most methods belong to the first approach. Among these methods, Chen and Hwang (1992) presented a numerical approximation system that individually transforms linguistic terms according to their corresponding fuzzy numbers. As for the other methods, the introduction of the linguistic ordered weighted averaging (LOWA) method by Herrera et al. (1995) opened the way to act by direct computation on labels. The LOWA operators are based on the ordered weighted averaging (OWA) operators defined by Yager (1988) and on the convex combination of linguistic labels defined by Delgado et al. (1993). Chuu (2005) proposed a modified LOWA operator with a maximum entropy weighting vector for assessing manufacturing flexibility. This study thus applies a new fuzzy fusion method based on linguistic assessments for AMT evaluation.

3. Fusion of Fuzzy Information

In the fuzzy assessment of AMT, fuzzy numbers are very useful in improving information representation and processing in a fuzzy environment. Trapezoidal (or triangular) fuzzy numbers have been used to characterize linguistic labels (or

approximate numerical values) used in approximate reasoning. The trapezoidal fuzzy numbers are chosen for application considering their intuitive representation, ease in computation, and good enough to capture the vagueness of fuzzy assessment (Herrera *et al.*, 1996; Karsak and Tolga, 2001; Olcer and Odabasi, 2005). Let a fuzzy number A be a special fuzzy subset of a universal set X with membership function $\mu_A(x)$, which is a continuous mapping from each element x in X to a real number in the interval $[0, 1]$. This study assumes that a trapezoidal fuzzy number $B=(n_1, n_2, n_3, n_4)$ is represented by the membership function $\mu_B(x)$ given below.

$$\mu_B(x) = \begin{cases} (x-n_1)/(n_2-n_1), & n_1 \le x \le n_2, \\ 1, & n_2 \le x \le n_3, \\ (x-n_4)/(n_3-n_4), & n_3 \le x \le n_4, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

with $n_1 \le n_2 \le n_3 \le n_4$. The x in interval $[n_2, n_3]$ yields the maximal grade of $\mu_B(x)$, i.e., $\mu_B(x)=1$, which is the most likely value of the evaluation data. Meanwhile, the n_1 and n_4 comprise the lower and upper limits of the available area for the evaluation data, respectively, which are used to reflect the fuzziness of the evaluation data.

Therefore, following the decision process for managing multi-granularity linguistic information (Herrera *et al.*, 2000], but considering our particular decision context, i.e., to handle compatibility between approximate numerical values and linguistic labels, this study presents a fusion method of fuzzy information, which is performed in two phases:

1. Making the information uniform.
2. Computing the collective information.

They are analyzed in the following subsections.

3.1 Making the information uniform

For handling all the fuzzy data, the expert fuzzy assessments must be converted into a basic linguistic scale (Herrera *et al.*, 2000). Each assessment value is defined as a fuzzy set on the basic linguistic scale. With respect to the assessments made by linguistic labels in the linguistic scale, let $S=\{s_0, s_1, \cdots, s_T\}$ and $V=\{v_0, v_1, \cdots, v_G\}$ be two linguistic scales, such that $G \ge T$. A transformation function θ_{SV} is then defined as

(Herrera *et al.*, 2000]:

$\theta_{SV} : S \rightarrow F(V),$

$\theta_{SV}(s_i)=\{(u_{ij}, v_j)/j \in \{0, 1, \cdots, G\}\}$ for $s_i \in S,$

$$u_{ij} = \max_x min\{\mu_{si}(x), \mu_{vj}(x)\}, \qquad (2)$$

where $F(V)$ denotes the set of fuzzy sets defined in V, which is a basic linguistic scale, and $\mu_{si}(x), \mu_{vj}(x)$ represents the membership functions of the fuzzy sets associated with the labels s_i and v_j, respectively.

As mentioned above, all the information sources using the same scale (*[0,1]*) are considered. Regarding the fuzzy assessments assessed by approximate numerical values, the transformation function also appropriately implemented to converting the standardized fuzzy assessments, the ranges of which belong to *[0, 1]*, into a basic linguistic scale. The max-min operation has been used in θ_{SV}, because it is a classical tool for setting the degree of matching between fuzzy sets (Zimmermann, 1996). The following subsection presents how to obtain the collective assessments for each attribute (or expert).

3.2 Computing the collective information

The converted information (performance rating) provided by experts for each alternative with respect to attribute is defined as the fuzzy set on the basic linguistic scale V. The collective performance rating of an alternative is then obtained by aggregating these fuzzy sets. The collective performance rating is also a new fuzzy set defined on V. This paper considers the MEOWA operator as the aggregation operator. An MEOWA operator is used because is not only feasible but also effective. It is elicited as follows.

The OWA operators introduced by Yager (1988) provide a family of aggregation operators lying between the '*and*' and the '*or*', and a unified framework for decision making under uncertainty. With respect to the OWA operator weights, Yager (1988) also provided two measures, namely *'orness'* and *'dispersion (or entropy)'*. The orness is a value that lies in *[0,1]*, and measures the degree to which the aggregation resembles an '*or*' operation, and can be considered a gauge of decision-maker optimism. The more closely the orness of an OWA operator approaches the *'or'* operator, the more the optimistic decision-maker is about obtaining the best solution. The dispersion measures the degree to which all the aggregates are equally used. In the framework of multiple

attribute decision-making under uncertainty, the OWA operators can be provided for aggregating the attributes associated with some linguistic fuzzy quantifiers (Kacprzyk, 1986), such as *'as many as possible'*, *'most'*, *'average'*, *'almost all' 'at least half'*, etc., used to determine the weights. In decision-making, linguistic fuzzy quantifiers are used to indicate a fusion strategy for guiding the process of aggregating expert opinions.

OWA operators have been applied numerous fields, including neural networks, decision-making, data base systems, learning systems and fuzzy logic controllers, communication networks, and so on, as described by Yager (1993). To determine OWA operator weights, O'Hagan (1988) developed a maximum entropy approach, which formulates the problem as a constraint nonlinear optimization model with a predefined degree of orness as its constraint and the entropy as its objective function. The resultant weights and OWA operators are termed the maximum entropy weights and MEOWA operators, respectively. Filev and Yager (1995) examined the analytical properties of MEOWA operators and proposed a two-step process for obtaining the maximum entropy weights that generate some prescribed orness without having to solve the constraint nonlinear optimization problem. In practice, Chuu (2005) also proposed a fuzzy multi-attribute decision-making model based on MEOWA operators for evaluating manufacturing flexibility. These studies thus showed that using the maximum entropy method to determine MEOWA operator weights is both feasible and effective.

An MEOWA operator of dimension n is a mapping:

$\Phi : R^n \rightarrow R$

which has an associated maximum entropy weighting vector $W^* = [w_1^*, w_2^*, \cdots, w_n^*]$, with $w_i^* \in [0, 1]$ and $\sum_{i=1}^{n} w_i^* = 1$ such that

$$\Phi(a_1, a_2, \cdots; a_n) = \sum_{J=1}^{n} w_j^* b_j , \qquad (3)$$

where b_j is the jth largest element in the collection $\{a_1, a_2, \cdots, a_n\}$.

An algorithm for calculating W^* is as follows (Filev and Yager, 1995; Kacprzyk, 1986; Yager, 1988):

Step1: Determine a non-decreasing proportional linguistic fuzzy quantifier Q for representing the fuzzy majority over decision makers or attributes, as follows,

$$Q(r) = \begin{cases} 0 & \text{if } r < a, \\ (r-a)/(b-a) & \text{if } a \leqq r \leqq b, \\ 1 & \text{if } r > b, \end{cases} \quad (4)$$

with $a, b, r \in [0, 1]$. Some non-decreasing proportional linguistic fuzzy quantifiers are typified by terms *'most'*, *'at least half'*, and *'as many as possible'*, the respective parameters (a, b) of which are $(0.3, 0.8)$, $(0, 0.5)$ and $(0.5, 1)$, respectively,

Step 2: Compute the weighting vector W,

$$W(i) = Q(i/n) - Q((i-1)/n), \text{ for } i = 1, 2, \cdots, n. \quad (5)$$

Step 3: Compute the *orness* value α,

$$\alpha = \left(\sum_{i=1}^{n} (n-i)\, W(i)\right) / (n-1). \quad (6)$$

Step 4: Compute the W^*, using the two-step process.

4-1: Find a positive solution h^* of the algebraic equation,

$$\sum_{i=1}^{n} \left((n-i)/(n-1) - \alpha\right) h^{(n-i)} = 0. \quad (7)$$

4-2: Obtain W^* from the following equation, using $\beta^* = (n-1) \ln h^*$,

$$W^*(i) = \frac{e^{\beta^* \times ((n-i)/(n-1))}}{\sum_{j=1}^{n} e^{\beta^* \times ((n-j)/(n-1))}}, \text{ for } i = 1, 2, \cdots, n. \quad (8)$$

4. Evaluating the Suitability of AMT

This section presents a new AMT selection method using fuzzy multi-attribute decision-making to overcome above problems. This method enables the experts' fuzzy assessments with the linguistic and numerical scales can be considered in the aggregation process. An algorithm is developed in three main stages, as follows:

1. Qualitative assessment stage.
2. Quantitative evaluation stage.
3. Selection stage.

The first stage assesses the qualitative effects of AMT with respect to subjective attributes. With respect to objective attributes, the second stage evaluates the quantitative effects of AMT. The last stage aggregates the assessments, ranks the alternatives, and make a decision. A committee of experts (decision-makers) is responsible for evaluating the suitability of alternatives. To establish the assessment data

for the committee, experts express their opinions regarding each alternative with respect to each attribute.

4.1 Qualitative assessment stage

This stage aims to obtain the weighted performance ratings versus subjective attributes, and then convert them to yield the fuzzy assessment vectors.

In the fuzzy linguistic assessment, let S be an appropriate linguistic scale chosen by the committee be used for the qualitative assessment versus subjective attributes. For alternative A_i, the symbols W_t and R_{it} are linguistic labels belonging to S, and are used to denote the importance grade and related performance rating for subjective attribute C_t, respectively, according to the assessment data of experts ($i = 1, 2, \cdots, m; t = 1, 2, \cdots, s$). This work applies a convex combination of linguistic labels through direct computation; restated, the independence of the type of membership functions being used (Delgado *et al.*, 1993; Herrera *et al.*, 1995]. Consequently, the weighted rating X_{it} is also a linguistic label belonging to S, which is calculated by Equations *(9)* and *(10)*, as follows:

$$X_{it} = C^2(W_t, R_{it}) = w_1 \otimes s_b \oplus (1- w_1) \otimes s_a = s_c,\ s_b, s_a \in S\ (b \geqq a)$$
$$\text{for } i=1, 2, \cdots, m, t=1, 2, \cdots, s, \qquad (9)$$

such that

$$c = Min\ (T, a + round\ (w_1 \times (b - a))), \qquad (10)$$

where $\otimes$ denotes the general product of a linguistic label by a positive real number, $\oplus$ represents the general addition of linguistic labels, and *'round'* is a usual round operation.

For handling the fuzzy information, all the linguistic weighted ratings are transformed into their corresponding fuzzy numbers with linguistic scale S, after which these corresponding fuzzy numbers are converted into a basic linguistic scale. Therefore, each weighted rating can be defined as a fuzzy set on the basic linguistic scale. This paper considers a basic linguistic scale V_1 with 11 labels $v_0, v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9, v_{10}$, which are treated as trapezoidal fuzzy numbers with membership function $\mu(x)$, as shown in Table 1. Finally, using Equation *(2),* the corresponding fuzzy numbers of X_{it} are converted into the basic linguistic scale V_1. Thus the fuzzy assessment vector on V_1, $F(X_{it})$ can be formed as follows:

$$F(X_{it}) = (u(X_{it}, v_0), u(X_{it}, v_1), \cdots, u(X_{it}, v_{10})) \quad \text{for } i=1,2,\cdots,m,\ t=1,2,\cdots,s. \qquad (11)$$

Table 1. Linguistic variables and fuzzy numbers of basic linguistic scale

Linguistic variable	Fuzzy number
v_0：Definitely low（DL）	（0.0, 0.0, 0.0, 0.1）
v_1：Extra low（EL）	（0.0, 0.1, 0.1, 0.2）
v_2：Very low（VL）	（0.1, 0.2, 0.2, 0.3）
v_3：Low（L）	（0.2, 0.3, 0.3, 0.4）
v_4：Slightly low（SL）	（0.3, 0.4, 0.4, 0.5）
v_5：Middle（M）	（0.4, 0.5, 0.5, 0.6）
v_6：Slightly high（SH）	（0.5, 0.6, 0.6, 0.7）
v_7：High（H）	（0.6, 0.7, 0.7, 0.8）
v_8：Very high（VH）	（0.7, 0.8, 0.8, 0.9）
v_9：Extra high（EH）	（0.8, 0.9, 0.9, 1.0）
v_{10}：Definitely high（DH）	（0.9, 1.0, 1.0, 1.0）

4.2 Quantitative evaluation stage

During the second stage, the objective attributes can be classified into benefit and cost attributes. Regarding objective attributes, since precise quantitative information may be unavailable, and since evaluating this information is expensive, quantitative effects of AMT are evaluated by management using approximate numerical values, and then identified by experts. In this study these estimated performance ratings are generally expressed in sentence form as *'approximately between'*. To ensure compatibility among the various numerical scales, all the estimated values must be converted into a comparable scale. This stage attempts to obtain the weighted ratings versus objective attributes, and then convert them to yield the fuzzy assessment vectors.

During this stage, the conversion is performed by linear scale transformation as defined by Hsu and Chen (1997), since this transformation preserves the property that the ranges of standardized trapezoidal fuzzy numbers belong to *[0, 1]*. Let a trapezoidal fuzzy number $W_t=(a_t, b_t, c_t, d_t)$ be used to denote the importance grade for objective attribute C_t assigned by experts, and let $H_{it}=(e_{it}, g_{it}, h_{it}, l_{it})$ represent a positive trapezoidal fuzzy number representing the estimated performance rating for an alternative A_i with respect to an objective attribute C_t, where $0 \le e_{it} \le g_{it} \le h_{it} \le l_{it}$ ($i = 1, 2, \cdots, m$; $t = s+1, s+2, \cdots, k$). Then the standardized performance rating $R_{it}=(o_{it}, p_{it}, q_{it}, r_{it})$ is also a trapezoidal fuzzy number, which is calculated by Equations *(12)* and *(13)* respectively, and $0 \le o_{it} \le p_{it} \le q_{it} \le r_{it} \le 1$,

$$R_{it} = (e_{it}/l_t^+, g_{it}/l_t^+, h_{it}/l_t^+, l_{it}/l_t^+), \text{ if } t \in B, \qquad (12)$$

$R_{it} = (e_t^-/e_{it}, e_t^-/g_{it}, e_t^-/h_{it}, e_t^-/l_{it})$, *if* $t \in C$, (13)

where B and C denote the sets of benefit and cost attributes, respectively, and $l_t^+ = \max_i l_{it}$, $e_t^- = \min_i e_{it}$.

Thus, the weighted rating can be calculated using Equation *(14)*:

$X_{it} = W_t \otimes R_{it} = (U_{it}, V_{it}, Y_{it}, Z_{it})$ *for* $i=1, 2, \cdots, m$, $t = s+1, s+2, \cdots, k$, (14)

where operator $\otimes$ denotes the fuzzy multiplication operator, and $U_{it} = a_t o_{it}$, $V_{it} = b_t p_{it}$, $Y_{it} = c_t q_{it}$, $Z_{it} = d_t r_{it}$. The fuzzy multiplication of trapezoidal fuzzy numbers is also a trapezoidal fuzzy number (Kaufmann and Gupta, 1991). Therefore, X_{it} is a trapezoidal fuzzy number defined by Equation *(14)*, as described by Karsak and Tolga (2001).

These fuzzy numbers can then be converted into a basic linguistic scale. Using Equation *(2),* the weighted rating X_{it} is converted into the basic linguistic scale V_1. Thus the fuzzy assessment vector on V_1, $F(X_{it})$ can be represented as follows:

$F(X_{it}) = (u(X_{it}, v_0), u(X_{it}, v_1), \cdots, u(X_{it}, v_{10}))$ *for* $i=1, 2, \cdots, m$, $t = s+1, s+2, \cdots, k$. (15)

4.3 Selection stage

This algorithm uses *MEOWA* operators to aggregate the parameter assessed by experts, and aggregates the results to yield the ranking order, and uses interactive decision analysis for selecting the appropriate AMT. The aggregation algorithm for a committee of experts is presented as follows:

(1) Aggregate $F(X_{it})$ to yield the fuzzy suitability vector $(F(X_{A(i)}))$. Using the concept of fuzzy majority over the attributes specified by a linguistic fuzzy quantifier Q_1, and using the *MEOWA* operator associated with W_1^*, yields the aggregated parameters for alternative A_i, as follows:

$X_{A(i)}(v_y) = \Phi_{Q1}(u(X_{i1}, v_y), u(X_{i2}, v_y), \cdots, u(X_{ik}, v_y))$ *for* $i=1,2,\cdots,m$, $y=0,1,\cdots,10$. (16)

Then, the fuzzy suitability vector on V_1 for A_i, $F(X_{A(i)})$ is defined as:

$F(X_{A(i)}) = (X_{A(i)}(v_1), X_{A(i)}(v_2), \cdots, X_{A(i)}(v_{10}))$ *for* $i = 1, 2, \cdots, m$. (17)

(2) Defuzzify $F(X_{A(i)})$ to yield the ranking value SA_i. To rank the alternatives involved in the problem, it is necessary to defuzzify all the fuzzy suitability vectors. In this research, Equation *(18)* defines the defuzzification employed by the centroid method. This method is use because it is intuitive and easy to implement.

$$\int_a^b x\,\mu(x)\,dx \Big/ \int_a^b \mu(x)\,dx, \qquad (18)$$

where *'a'* and *'b'* are the lower and upper limits of the integral, respectively. This work has its centroids $G(v_0)=0.0333$, $G(v_1)=0.1$, $G(v_2)=0.2$, $G(v_3)=0.3$, $G(v_4)=0.4$, $G(v_5)=0.5$, $G(v_6)=0.6$, $G(v_7)=0.7$, $G(v_8)=0.8$, $G(v_9)=0.9$, $G(v_{10})=0.9667$ as the center of mass of $v_0, v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9, v_{10}$, respectively. Using Equation *(19)*, the SA_i for alternative A_i is obtained as follows:

$$SA_i = \sum_{y=0}^{10} G(v_y) \times X_{A(i)}(v_y) / \sum_{y=0}^{10} G(v_y) \quad for\ i=1, 2, \cdots, m. \qquad (19)$$

Clearly, the SA_i can be considered as the suitability of alternative A_i. The ranking order and most suitable alternative(s) are determined based on ranking values.

(3) Interactive decision analysis. It analyzes that the evaluation results obtained in the before stages is accurate and reliable enough to make a consistent decision. According to this analysis, the process has to go back to the initial stages in order to gathering additional information of the problem, or has to accept the evaluation results in order to accomplish the decision-making process.

The proposed approach presented above includes the following steps:

Step 1. Form a committee of experts (or decision makers), and identify the alternatives available for consideration.

Step 2. Identify the selection attributes (subjective or objective) with types (cost or benefit) of them.

Step 3. Determine an appropriate linguistic scale chosen by experts using qualitative assessment versus subjective attributes, and identify the appropriate numerical scales using the quantitative evaluation versus objective attributes

Qualitative assessment stage (with respect to subjective attributes)：

Step 4. Collect expert opinions (performance rating and importance grade) for each alternative.

Step 5. Aggregate the performance rating and importance grade to obtain a linguistic weighted rating (X_{it}).

Step 6. Transform X_{it} into its corresponding fuzzy number by using an appropriate linguistic scale as determined in Step 3.

Step 7. Convert the corresponding fuzzy number of X_{it} to yield the fuzzy assessment vector $(F(X_{it}))$.

Quantitative evaluation stage (with respect to objective attributes)：

Step 8. Identify expert opinions (performance rating and importance grade) for each alternative.

Step 9. Standardize the performance ratings.

Step 10. Aggregate the standardized performance rating and importance grade to obtain the numerical weighted rating (X_{it}).

Step 11. Convert the corresponding fuzzy number of each X_{it} to obtain the fuzzy assessment vector $(F(X_{it}))$.

Selection stage：

Step 12. Aggregate $F(X_{it})$ to yield the fuzzy suitability vector $(F(X_{A(i)}))$ for alternative A_i.

Step 13. Defuzzify $F(X_{A(i)})$ to yield the ranking value (SA_i) for alternative A_i, and then rank the alternatives according to SA_i, and select the alternative with the maximum SA_i as the best.

Step 14. Interactive decision analysis. According to a group of experts analyze the evaluation results, the process has to go back the initial stages or has to accept the evaluation.

5. Case Study

In this section, the application of the proposed selection method to the case of a Taiwanese firm in the bicycle industry is discussed. For reasons of confidentiality, the name of the firm is not revealed. This case originated from a feasibility evaluation of Optional Operation System for the bicycle industry, and the data was taken from a study entitled *'Fuzzy multi- attribute decision-making for evaluating manufacturing flexibility'* (Chuu, 2005).

Since increasing customization, a few years ago the case firm decided that it needed a flexible manufacturing system *(FMS)* that would allow a customized bike, designed according to the requirements of the customer, to be delivered within a week. After performing task analysis, it was confirmed that the new system would produce customized mountain and road racing bikes. Each bike consists of 11 subsystems including a frame, suspension fork, derailleur shifters, brokers, hubs and rims, tires, pedals, handle bar, stem, saddle, and seat post. Furthermore, each subsystem includes several models among which customers can select. Following preliminary screening, three competing *FMS* alternatives, A_1, A_2 and A_3, are identified that are capable of

performing this production task. To evaluating the suitability of *FMS*, the alternatives considered in this case study are evaluated by a committee of experts regarding each attribute.

The effects of adopting a FMS include both quantitative and qualitative effects. Subjective attributes are used to assess the qualitative effects of *FMS*, while objective attributes are used to evaluate the quantitative effects of *FMS*. The prospective FMS buyer can offer to spend at most $1,700,000. Objective attributes have been identified including that desired capacity should be at least 15,000 units per day, required floor space should be at most 10,000 ft^2 and lead times should be 12 hours or less. In the industry considered, the subjective attributes identified are process flexibility, product quality, learning, and exposure to labor unrest. The selection decision is made based on four objective attributes and four subjective attributes. Table 2 lists the properties of these attributes, including attribute type and assessment type, which are critical to *FMS* function. This paper chooses a basic linguistic scale V_1 with 11 labels, as listed in Table 1. For convenience, with respect to the alternative A_1 and the proposed algorithm can be expressed as follows.

Table 2. The *FMS* selection attributes

Subjective attribute	Objective attribute
C_1：Process flexibility	C_5：Required floor space (ft^2×1,000)
C_2：Product quality	C_6：Capacity (unit×1,000)
C_3：Learning	C_7：Lead time (hr)
C_4：Exposure to labor unrest	C_8：Purchase cost ($×10,000)

Table 3. Linguistic variables of performance rating and importance grade

Seven ranks of performance rating and importance grade	Fuzzy number
s_0：Definitely low（*DL*）	（0,0,0.1,0.2）
s_1：Very Low（*VL*）	（0.1,0.2, 0.2,0.3）
s_2：Low（*L*）	（0.2,0.3,0.4,0.5）
s_3：Middle（M）	（0.4,0.5,0.5,0.6）
s_4：High（*H*）	（0.5,0.6,0.7,0.8）
s_5：Very High（*VH*）	（0.7,0.8,0.8,0.9）
s_6：Definitely high（*DH*）	（0.8,0.9,1.0,1.0）

5.1 Qualitative assessment stage calculations (Steps 4~7)

For each of the subjective attributes (C_1, C_2, C_3 and C_4), experts provide their opinions using the linguistic scale S_1, as shown in Table 3. Consequently, Table 4 lists expert linguistic assessments for each alternative.

Using Equations *(9)* and *(10)*, and letting $w_1=0.5$, the weighted ratings for each *FMS* versus subjective attributes can be obtained, as shown in Table 5. With respect to alternative

Table 4. The importance grades and performance ratings evaluated for three alternatives

Subjective attribute	Importance grade	Performance rating		
		A_1	A_2	A_3
C_1	DH	VL	H	VH
C_2	VH	L	M	DH
C_3	M	VL	M	DH
C_4	VL	DL	H	VH
Objective attribute	**Importance grade**	**Performance rating**		
		A_1	A_2	A_3
C_5	M	(5, 6, 6.5, 7)	(7.5, 8, 8, 9)	(7, 8.5, 9, 9.5)
C_6	M	(16, 18, 19, 20)	(24, 25, 25, 26)	(29, 31, 31, 32)
C_7	VH	(9.5, 10, 10, 11)	(4, 5, 5.5, 6.5)	(2.5, 3, 3.5, 4)
C_8	DH	(90, 100, 110, 120)	(130, 140, 140, 145)	(145, 150, 155, 160)

Table 5. Expert weighted ratings for three alternatives under each subjective attribute

Subjective attribute	A_1	A_2	A_3
C_1	H	VH	DH
C_2	H	H	DH
C_3	L	M	VH
C_4	VL	M	M

Table 6. The standardized performance ratings for three alternatives under each objective attribute

Objective attribute	A_1	A_2	A_3
C_5	(0.7143,0.7692,0.8333,1.0)	(0.5556,0.625,0.625,0.6667)	(0.5263,0.5556,0.5882,0.7143)
C_6	(0.5,0.5625,0.5938,0.625)	(0.75,0.7813,0.7813,0.8125)	(0.9063,0.9688,0.9688,1.0)
C_7	(0.2272,0.25,0.25,0.2632)	(0.3846,0.4545,0.5,0.625)	(0.625,0.7143,0.8333,1.0)
C_8	(0.75,0.8182,0.9,1.0)	(0.6207,0.6429,0.6429,0.6923)	(0.5625,0.5806,0.6,0.6207)

A_1, expert linguistic assessments for all the subjective attributes can be converted to trapezoidal fuzzy numbers using the linguistic scale S_1; for example *'VL'* can be represented by the trapezoidal fuzzy number (0.1, 0.2, 0.2, 0.3), and these fuzzy numbers are then transformed into fuzzy assessment vectors $(F(X_{it}))$ on the basic linguistic scale V_1 by Equations *(2)* and *(11)*, respectively. The results are obtained as follows:

$F(X_{11}) = (0, 0, 0, 0, 0, 0.5, 1, 1, 0.5, 0, 0)$, $F(X_{12}) = (0, 0, 0, 0, 0, 0.5, 1, 1, 0.5, 0, 0)$,

$F(X_{13}) = (0, 0, 0.5, 1, 1, 0.5, 0, 0, 0, 0, 0,)$, $F(X_{14}) = (0, 0.5, 1, 0.5, 0, 0, 0, 0, 0, 0, 0)$,

5.2 Quantitative evaluation stage calculations (Steps 8~11)

With respect to each of the objective attributes (C_5, C_6, C_7 and C_8), based on the evaluation information provided by management, the performance rating and important grade for each *FMS* are identified by a group of experts, as listed in Table 4. Using Equations *(12)* and *(13)*, the standardized performance ratings for each alternative versus the objective attributes are listed in Table 6. For example, for alternative A_1 with respect to C_5, the performance rating of *(5, 6, 6.5, 7)* can be transformed into the standardized performance rating of *(0.7143, 0.7692, 0.8333, 1.0)* using Equation *(13)*. Using Equation *(14)*, the numerical weighted rating X_{it} $(i=1,2,3,\ t= 5,6,7,8)$ can be

listed in Table 7. Also as for alternative A_1, using Equations *(2)* and *(15)* respectively, experts fuzzy assessments for all the objective attributes are converted into fuzzy assessment vectors $(F(X_{it}))$ on V_1. The following results thus are obtained:

$F(X_{15}) = (0, 0, 0.0719, 0.3425, 1, 0.7060, 0.353, 0, 0, 0, 0),$

$F(X_{16}) = (0, 0, 0.1031, 0.9826, 0.4211, 0, 0, 0, 0, 0, 0),$

$F(X_{17}) = (0, 0.2908, 1, 0.2695, 0, 0, 0, 0, 0, 0, 0),$

$F(X_{18}) = (0, 0, 0, 0, 0, 0, 0.423, 0.846, 1, 1, 0.5),$

Table 7. Experts' weighted ratings for three alternatives under each objective attribute

	A_1	A_2	A_3
C_5	(0.2857,0.3846,0.4167,0.6)	(0.2222,0.3125,0.3125,0.4)	(0.2105,0.2778,0.2941,0.4286)
C_6	(0.2,0.2813,0.2969,0.375)	(0.3,0.3907,0.3907,0.4875)	(0.3625,0.4844,0.4844,0.6)
C_7	(0.159,0.2,0.2,0.2369)	(0.2692,0.3636,0.4,0.5625)	(0.4375,0.5714,0.6667,0.9)
C_8	(0.6,0.7364,0.9,1.0)	(0.4966,0.5786,0.6429,0.6923)	(0.45,0.5225,0.6,0.6207)

5.3 Selection stage calculations (Steps 12~14)

In this stage, all the fuzzy assessment vectors for experts are aggregated for each attribute as follows:

(1) Aggregate $F(X_{it})$ to yield the fuzzy suitability vector $(F(X_{A(i)}))$. Using Equations *(16)* and *(17)* respectively, the MEOWA operator Φ_{Q1} guided by *'most'* with the pair *(0.3, 0.8)*, and the algorithm for calculating W_1^* yields $W_1 = [0, 0, 0.15, 0.25, 0.25, 0.25, 0.1, 0]$, $\alpha_1 = 0.4429$, and $W_1^* = [0.0941, 0.1016, 0.1097, 0.1185, 0.1279, 0.1381, 0.1491, 0.1610]$.

The fuzzy suitability vector for alternative A_1 thus is obtained as follows:

$F(X_{A(1)})=(0,.0766, 0.2720, 0.3239, 0.2419, 0.2313, 0.2840, 0.2886, 0.1998, 0.0941, 00471),$

(2) Defuzzify $F(X_{A(i)})$ to yield the ranking value SA_i. Using Equation *(19)*, the ranking value SA_1 of alternative A_1 can be obtained:

$SA_1 = 0.1880.$

Similarly, $SA_2=0.1676$ and $SA_3=0.2317$. For a committee of experts, based on ranking

value, the ranking order of three alternatives is given as $A_3 \succ A_1 \succ A_2$.

With respect to the detailed analysis of evaluation results such as competing FMS alternatives, effects of FMS, properties of attributes, computational process and so on, the decision-making process will be completed if experts accept the evaluation results. Otherwise, experts can modify their opinions step by step through the collection of additional information, or modify the linguistic fuzzy quantifier until a consistent decision is obtained. After the detailed decision analysis of this case study, a committee of experts accepts that the best alternative is A_3, while $A_1$and A_2 are ranked second and third, respectively.

6. Conclusion

AMT selection is important to improving manufacturing system competitiveness. This study first identified two groups of attributes, and then classified them as either subjective or objective. A fuzzy multiple attributes decision-making scenario was modeled to solve the AMT evaluation problem. The proposed method applied in the decision-making is more suitable for solving manufacturing technology evaluation problems involving subjective and imprecise information. In the proposed method, we also present a new fusion approach of fuzzy information. According to decision-makers' attitude, a linguistic fuzzy quantifier chosen by the manager of the decision problem is used in *MEOWA* operators. The proposed method enables the decision-makers to incorporate and aggregate fuzzy information provided for multiple attributes. A case study of *FMS* selection has been conducted to exemplify the feasibility of the proposed method.

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