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Toward developing agility evaluation of mass customization systems using 2-tuple linguistic computing

Wen-Pai Wang *

Department of Industrial Engineering and Management, National Chin-Yi University of Technology, 35, Lane 215, Section 1, Chung-Shan Road, Taiping City, Taichung 411, Taiwan, ROC

Abstract

Mass customization (MC) relates to the ability to provide individually designed products and services to every customer through high process flexibility and integration. For responding to the mass customization trend it is necessary to develop an agility-based manufacturing system to catch on the traits involved in MC. An MC manufacturing agility evaluation approach based on concepts of TOPSIS is proposed through analyzing the agility of organization management, product design, processing manufacture, partnership formation capability and integration of information system. The 2-tuple fuzzy linguistic computing manner to transform the heterogeneous information assessed by multiple experts into an identical decision domain is inherent in the proposed method. It is expected to aggregate experts' heterogeneous information, and offer sufficient and conclusive information for evaluating the agile manufacturing alternatives. And then a suitable agile system for implementing MC can be established.

Keywords: Mass customization; Agile manufacturing; Heterogeneity; TOPSIS; 2-Tuple fuzzy linguistic computing

1. Introduction

Due to the globalization of competition in the manufacturing industry and the diversification of customers' demands, more requirements for enterprises have been put forth at present, such as more product variety, shorter time-to-market, lower product cost and higher quality. The enterprises respond to fierce competition and increasing consumer awareness with shorter product life cycles, quicker delivery of new products to the market, and decrease in operating costs at the same time. With product development times only one-third of their competitors and needing only a fraction of the resources, time-based manufacturing were capable to deliver new products much quicker to the market. This enabled quick response to changing market preferences, and the continuous introduction of innovative technology. Time-based manufacturers were able to continually introduce new products with more features, increasing the variety offered to customers. From the success of time-based competition emerged a new paradigm-mass customization (MC) (Alford, Sackett, & Nelder, 2000).

MC as a viable approach to competitive strategy is capturing the imagination of both managers and business academics. The growing interest in MC has led researchers to suggest that firms that shift from mass production to the emerging paradigm of MC will gain a competitive advantage (Kotha, 1996; Silveira, Borenstein, & Fogliatto, 2001; Wang, 2007). The term mass customization was coined by Davis (1989) who predicted that the more a company was able to deliver customized goods on a mass basis, relative to their competition, the greater would be their competitive advantage. Pine II (1993) stated that mass customizers develop, produce, market and distribute goods and services with such variety that nearly everyone finds exactly what they want at a price they can afford. Manufacturers must look beyond the provision of standard products at low cost, to better meet the needs and desires of

* Corresponding author. Tel.: +886 4 23924505x6018; fax: +886 4 23921742.
E-mail address: wangwp@ncut.edu.tw

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customers. With low cost, high quality and quick delivery simply qualifiers in the customer purchasing process, manufacturers must customize products or services to humor customer needs and stimulate market demand. Hart (1995) offered an operational definition that MC is the use of flexible processes and organizational structures to produce varied and often individually customized products and services at the price of standardized, mass produced alternatives. Consequently, MC as a competitive strategy requires that different production types be employed simultaneously. The concepts of flexibility, timeliness and variety are essential to the intention of mass customization. In recent years, the development efforts of MC have been mostly concentrated on agile manufacturing, but little has been focused on systematic perspective about the agility evaluation of manufacturing MC products.

Companies in either manufacturing or servicing have to be restructured or re-organized in order to overcome with challenges of the 21st century in which customers are not only satisfied but also delighted. To increase manufacturing responsiveness yet reduce costs incurred by frequent changeovers, many enterprises transform the factory into an agile manufacture facility. This agility copes with changes in customer requirements including price, quality, customization, and promised delivery dates. Agile manufacturing (AM), a relatively new operations concept that is intended to improve the competitiveness of firms, has been advocated as the 21st century manufacturing paradigm (Sanchez & Nagi, 2001). It is seen as the winning strategy to be adopted by manufacturers bracing themselves for dramatic performance enhancements to become national and international leaders in an increasingly competitive market of fast changing customer requirements. AM can be grouped under the following themes: (i) strategic planning, (ii) product design, (iii) virtual enterprise, and (iv) automation and information technology (Gunasekaran & Yusef, 2002). The goal of this paper makes a point of developing an evaluation approach for determining the most suitable agile manufacturing system for implementing MC strategies.

For achieving an appropriate strategy the business decision mechanism is usually composed of multiple experts who implement alternatives evaluation and decision analysis in the light of association rules and criteria. Experts devote to judge by their experiential cognition and subjective perception in decision-making process. However, there exist considerable extent of uncertainty, fuzziness and heterogeneity (Hwang & Yoon, 1981). Consequently, the heterogeneous information that includes crisp values, interval values and linguistic expression is likely to happen under different criterion. Effective aggregation for each kind of assessments generated by experts to implement substantial and correct decision – analysis is a critical managerial issue. Developing a heterogeneous information aggregation platform to evaluate and rank appropriate alternatives is an indispensable essential to a robust decision mechanism. Chen (2000) extended the TOPSIS to group decision making problems under fuzzy environment and applied a vertex method to calculate the distance between two triangular fuzzy numbers. According to the concept of the TOPSIS, a closeness coefficient is defined to determine the ranking order of all alternatives by calculating the distances to both the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS) simultaneously.

Based on suchlike ideas this research therefore focuses on establishing an agility measurement approach for MC manufacturing system. We apply concepts of the TOPSIS manner which is based on values of the best and the worst fuzzy linguistic, and determines the alternative sequence of agile manufacturing systems on the strength of the distance computation of linguistic variables under fuzzy decision environments. The proposed method is to adequately come at connotation of every evaluated alternative and then to enhance the believability and the adoptability of analysis results, as well as to increase productivity for achieving the goal of MC.

The rest of this paper is organized as follows. Next Section discussed the dimensions of agility evaluation. Section 3 presented the basic definitions and notations of the fuzzy number and linguistic variable as well as three kinds of heterogeneous information transformation, respectively. In Section 4 we proposed a fuzzy linguistic agility evaluation model for the selection of MC systems. And then, the proposed method is illustrated with an example. Finally, some conclusions are pointed out in the end of this paper.

2. Dimensions of agility evaluation

To be agile in the global competitive environment, the enterprises conclude specific objectives for the production system to be more responsive to customer demands, be able to adjust schedules more frequently, anticipate and avoid production delays and detect quality problems before they became disruptive (Katayama & Bennett, 1999). Suchlike objectives generally include responsiveness, customization, competitive pricing, small lots, quick changeovers, minimum WIP, modern technology, skillful workers, efficient facilities, and so forth. The keys to conforming to these objectives are to thoroughly reduce the lot size and install an online, real-time communication system throughout the organization with special emphasis on the production floor. Agility and flexibility are consequently required to accommodate the dynamic workload imbalances inherent in generating distinct product styles.

To hold out agility in company's competitive environment, the production system must be proficient at responding to frequent adjustments to the schedule and hourly changeovers in the production lots. In accordance with the individual demands an agile manufacturing system is necessary to settle on for producing mass customization products. Consequently, the corresponding desirable agility evaluation method is worthy of development. Yang and Li (2002) concluded that the MC product processing manufacture agility evaluating index system established should take account of three major indices. They are the agility in relation to organization management, product design and processing manufacture, respectively. The main drivers of agility include; quality and speed to market; widening customer choice and expectation; competitive priorities of responsiveness, new product introduction, delivery, flexibility, concern for the environment and international competitiveness. Agility has four underlying components; delivering value to the customer; being ready for change; valuing human knowledge and skills; forming virtual partnerships (McCurry & McIvor, 2002). Yusuf, Sarhadi, and Gunasekaran (1999) pointed out that the core concepts of agile manufacturing are core competence management, virtual enterprise, knowledge-driven enterprises, capability for re-configuration, respectively. Agility has four underlying components; delivering value to the customer; being ready for change; valuing human knowledge and skills; forming virtual partnerships (Sanchez & Nagi, 2001).

We summarized the above-mentioned literature and concluded the main entries for evaluating the agility of MC product manufacturing as follows:

L_1: *Organization management agility*
It includes inter-organization cooperative extent, the speed of the team building, network connection extensiveness, the application degree of the VE, and so on.

L_2: *Product design agility*
It contains the design period, the proportion of design period in product periods, the seriating degree of products, the generalization degree of parts, the similar degree of products structure, and so on.

L_3: *Processing manufacture agility*
It comprehends the time organizational form of the production process, the space organizational form of the production process, displacement compatibility, re-configurable flexibility, supplement tool displacement, and so on.

L_4: *Partnership formation capability*
It involves the degree of cooperating with other enterprises, institutional framework agility, the form of institutional framework, the form of institutional framework, and so on.

L_5: *Integration of information system*
It contains information and network utilization rate, perfect degree of information system, customer demand information agile to get, he way of demand information got, the proportion of information processing time in product periods, and so on.

3. Transformation of heterogeneous information

Many aspects of different activities in the real world cannot be assessed in a quantitative form, but rather in a qualitative one, i.e., with vague or imprecise knowledge. Whereas characteristics of the fuzziness and vagueness are inherent in various decision-making problems, a proper decision-making approach should be capable of dealing with vagueness or ambiguity. In the following, we briefly review some basic definitions of fuzzy sets from Kaufmann and Gupta (1991) and Zimmermann (1991). These basic concepts and notations below will be used throughout the paper until otherwise stated.

3.1. Fuzzy number

A fuzzy number is a special fuzzy set $F = \{x \in R | \mu_F(x)\}$, where x takes its values on the real line R_1: $-\infty < x < +S\infty$ and $\mu_F(x)$ is a continuous mapping from R_1 to the close interval $[0, 1]$. A fuzzy number is a fuzzy subset in the universe of discourse X that is both convex and normal. Further, a fuzzy set $\widetilde{A}$ in a universe of discourse X is characterized by a membership function $\mu_{\widetilde{A}}(x)$ which associates with each element x in X a real number in the interval $[0, 1]$. The function value $\mu_{\widetilde{A}}(x)$ is termed the grade of membership of x in X. A larger $\mu_{\widetilde{A}}(x)$ means a stronger degree of belongingness for x in X. In short, a fuzzy number should possess the following three fundamentals in accordance with the definition by Dubois and Prade (1978).

1. $\mu_{\widetilde{A}}(x)$ is a continuous mapping from R to a closed interval $[0, 1]$;
2. $\mu_{\widetilde{A}}(x)$ is a convex fuzzy subset;
3. $\mu_{\widetilde{A}}(x)$ is the normality of a fuzzy subset. That is, there exists a number x_0 that makes $\mu_{\widetilde{A}}(x_0) = 1$.

Two very familiar types of fuzzy numbers are trapezoid and triangle, respectively. The former can be shown in Fig. 1 and denoted as $\widetilde{A} = (l, a, b, u)$ with the membership function $\mu_{\widetilde{A}}(x)$ formulated below

$$\mu_{\widetilde{A}}(x) = \begin{cases} (x-l)/(a-l), & l \leqslant x \leqslant a \\ 1, & a \leqslant x \leqslant b \\ (x-u)/(b-u), & b \leqslant x \leqslant u \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $-\infty < l \leqslant a \leqslant b \leqslant u < +\infty$. The interval $[a, b]$ offers the maximum grade of $\mu_{\widetilde{A}}(x)$, i.e. $\mu_{\widetilde{A}}(x) = 1$, $x \in [a, b]$. It signifies the most possible value of the evaluation data. On the other hand, l and u are the lower and upper bounds of the available area of the evaluation data, and they reflect the fuzziness of the evaluation data. The less the interval of $[a, b]$ narrows down, the lower the fuzziness of the evaluation data signifies.

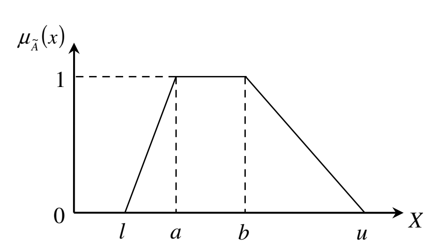

Fig. 1. A trapezoid fuzzy number $\widetilde{A}$.

The latter is a special case of a trapezoidal fuzzy number that a equals to b. Triangular fuzzy numbers appear as useful means of quantifying the uncertainty in decision making due to their intuitive appeal and computational-efficient representation (Kalargeros & Gao, 1998; Karsak & Tolga, 2001; Perego & Rangone, 1998). A triangular fuzzy number $\widetilde{A}$ can be defined by a triplet (a,b,c) illustrated in Fig. 2. The corresponding membership function is defined as

$$\mu_{\widetilde{A}}(x) = \begin{cases} (x-a)/(b-a), & a \leqslant x \leqslant b \\ (x-c)/(b-c), & b \leqslant x \leqslant c \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $a \leqslant b \leqslant c$ and a and c represent the lower and upper value of the support of $\widetilde{A}$, respectively, and b is the strongest grade of membership of $\widetilde{A}$. When $a = b = c$ it is a non-fuzzy number by convention.

According to the extension principle of Zadeh (1965), as is well-known, the main algebraic calculation of triangular fuzzy numbers includes fuzzy number addition $\oplus$, fuzzy number multiplication $\otimes$, fuzzy number subtraction $\ominus$, and fuzzy number division $\emptyset$, multiplication of a fuzzy number to any real number k. The main operational laws for two triangular fuzzy numbers $\widetilde{A}_1$ and $\widetilde{A}_2$ are as follows (Kaufmann & Gupta, 1991):

$$\widetilde{A}_1 + \widetilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$$
$$\widetilde{A}_1 \otimes \widetilde{A}_2 = (a_1 a_2, b_1 b_2, c_1 c_2)$$
$$\lambda \otimes \widetilde{A}_1 = (\lambda a_1, \lambda b_1, \lambda c_1) \quad \lambda > 0, \quad \lambda \in R$$
$$\widetilde{A}_1^{-1} \approx (1/a_1, 1/b_1, 1/c_1)$$

The vertex method is defined to calculate the distance between them as

$$d(\widetilde{A}_1, \widetilde{A}_2) = \sqrt{1/3[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2} \tag{3}$$

3.2. Linguistic variable

The fuzzy linguistic approach represents qualitative aspects as linguistic values by means of linguistic variables (Zadeh, 1975). The concept of linguistic variable is very useful in dealing with situations which are too complex or too ill-defined to be reasonably described in conventional quantitative expressions. At present, many aggregation operators have been developed to aggregate information. Herrera and Martinez (2000a, 2000b) and Herrera, Herrera-Viedma, and Martinez (2000) proposed a 2-tuple fuzzy linguistic representation Model. The main advantage of this representation is to be continuous in its domain. Therefore, it can express any counting of information in the universe of the discourse. They developed a computational technique for computing with words without any loss of information. The linguistic information with a pair of values is called 2-tuple that composed by a linguistic term and a number. It can be denoted by a symbol $L = (s, \alpha)$ where s represents the linguistic label of the information, and α is a numerical value representing the symbolic translation. For example, a set of five terms S could be given as follows: Figs. 3–5

$$S = \{s_0 : VL,\ s_1 : L,\ s_2 : F,\ s_3 : H,\ s_4 : VH\}$$

Suppose $L_1 = (s_1, \alpha_1)$ and $L_2 = (s_2, \alpha_2)$ are two linguistic variables represented by 2-tuples. The main algebraic operations are shown as follows (Herrera and Martinez, 2000a):

$$L_1 \oplus L_2 = (s_1, \alpha_1) \oplus (s_2, \alpha_2) = (s_1 + s_2, \alpha_1 + \alpha_2)$$
$$L_1 \otimes L_2 = (s_1, \alpha_1) \otimes (s_2, \alpha_2) = (s_1 s_2, \alpha_1 \alpha_2)$$

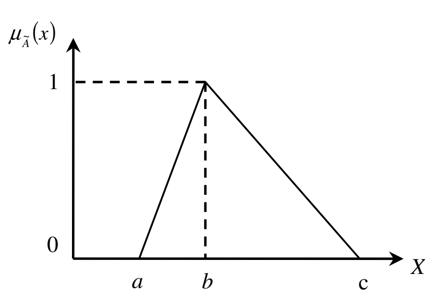

Fig. 2. A triangular fuzzy number $\widetilde{A}$.

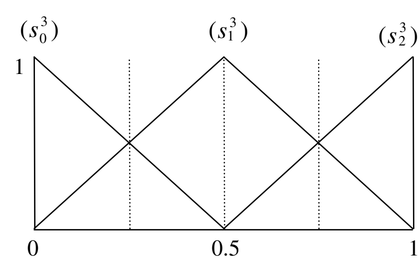

Fig. 3. Linguistic term set of three labels with its semantics.

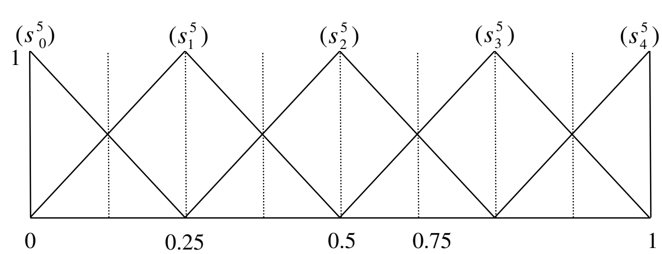

Fig. 4. Linguistic term set of five labels with its semantics.

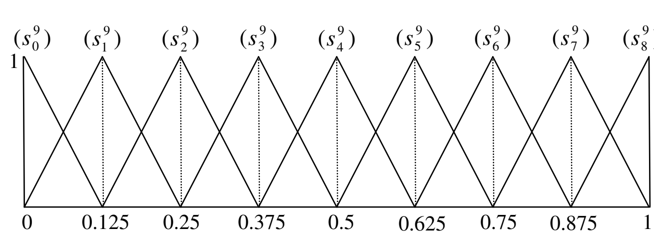

Fig. 5. Linguistic term set of nine labels with its semantics.

where $\oplus$ and $\otimes$ symbolize the addition and multiplication operations of parameters, respectively. s_i denotes the central value of the ith linguistic variable. α_i indicates the distance to the central value of the ith linguistic variable. The comparison of linguistic information represented by 2-tuples is carried out according to an ordinary lexicographic order. Let (s_i, α_i) and (s_j, α_j) be two 2-tuples, with each one representing a counting of information as follows:

- if $s_i > s_j$ then $(s_i, \alpha_i) > (s_j, \alpha_j)$;
- if $s_i = s_j$ and $\alpha_i = \alpha_j$ then $(s_i, \alpha_i) = (s_j, \alpha_j)$. This indicates the same information;
- if $s_i = s_j$ and $\alpha_i > \alpha_j$ then $(s_i, \alpha_i) > (s_j, \alpha_j)$;
- if $s_i = s_j$ and $\alpha_i < \alpha_j$ then $(s_i, \alpha_i) < (s_j, \alpha_j)$.

Three kinds of information transformation are classified according to the attributes of information. They are briefly expressed in the following.

3.2.1. Transformation between crisp value and 2-tuple linguistic variables

Suppose a linguistic term set, $S = \{s_0, s_1, s_2, \ldots, s_g\}$ and $s_0 = 0, s_1 = 1$, the crisp value $\beta(\beta \in [0,1])$ can be transformed into the 2-tuple linguistic variable by the following formula (Chen & Tai, 2005).

$$\Delta(\beta) = (s_i, \alpha) \text{ with } \begin{cases} s_i, & i = \text{round}(\beta \cdot g) \\ \alpha = \beta - \frac{i}{g}, & \alpha \in (-\frac{1}{2g}, \frac{1}{2g}) \end{cases} \tag{4}$$

where Δ denotes the symbol for transforming β into the 2-tuple linguistic variable.

On the contrary, the 2-tuple linguistic variable can be converted into the crisp value $\beta(\beta \in [0,1])$ by the following formula:

$$\Delta^{-1}(s_i, \alpha) = \beta = \frac{i}{g} + \alpha \tag{5}$$

where Δ^{-1} signifies the symbol for converting the 2-tuple linguistic variable into β.

3.2.2. Transformation among different 2-tuple linguistic variables

Herrera and Martinez (2001) dealt with multigranular linguistic information, i.e., linguistic preferences, focusing on those problems whose aspects are assessed by multiple sources of information. Such method permitted multiple experts to select diverse amount and domain of linguistic variables in accordance with their own needs for executing evaluation. Afterward the way transformed all evaluation values of decision makers into an identical definition of linguistic variables for preference aggregation.

Let $\text{LH} = U_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{s_0^{n(t)}, \ldots, s_{n(t)-1}^{n(t)}\}$. The transformation function from a linguistic label in level (or type) t to a label in level (or type) $t+1$, satisfying the linguistic hierarchy basic rules, is defined as

$$\text{TF}_{t+1}^{t} : l(t, n(t)) \rightarrow l(t+1, n(t+1))$$

$$\text{TF}_{t+1}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta\left(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}) \cdot (n(t+1) - 1)}{n(t) - 1}\right) \tag{6}$$

The transformation function from a linguistic label in level t to a label in level $t-1$, satisfying the linguistic hierarchy basic rules, is computed as

$$\text{TF}_{t-1}^{t} : l(t, n(t)) \rightarrow l(t-1, n(t-1))$$

$$\text{TF}_{t-1}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta\left(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}) \cdot (n(t-1) - 1)}{n(t) - 1}\right) \tag{7}$$

where t is a number that indicates the level of the hierarchy;

$n(t)$ is the granularity of the linguistic term set of the level;

$(s_i^{n(t)}, \alpha^{n(t)})$ denotes the ith 2-tuple linguistic variable at level t.

Eqs. (6) and (7) generalize these transformation functions to convert linguistic terms between any linguistic levels in the linguistic hierarchy. However, the transformation mode is incapable of translating in the initial domain because the linguistic variable domain enlarges when the number of linguistic variables increases. A modificatory way is proposed in this paper for extending the transformation in interval $[0,1]$. The ith 2-tuple linguistic variable and the crisp value $\beta(\beta \in [0,1])$ at level t can be mutually translated as

$$\Delta_t(\beta) = (s_i^{n(t)}, \alpha^{n(t)}) \text{ with } \begin{cases} s_i^{n(t)}, & i = \text{round}(\beta \cdot g_t) \\ & \alpha^{n(t)} = \beta - \frac{i}{g_t} \end{cases} \tag{8}$$

$$\beta = \Delta_t^{-1}(S_i^{n(t)}, \alpha^{n(t)}) = \frac{i}{g_t} + \alpha^{n(t)} \tag{9}$$

and $g_t = n(t) - 1, \alpha^{n(t)} \in (-\frac{1}{2g_t}, \frac{1}{2g_t})$.

Consequently, the way transformed $(S_i^{n(t)}, \alpha^{n(t)})$ into $(S_k^{n(t+1)}, \alpha^{n(t+1)})$ in domain $[0,1]$ can be defined as

$$\begin{aligned} \text{TF}_{t+1}^{t}(S_i^{n(t)}, \alpha^{n(t)}) &= \Delta_{t+1}(\Delta_t^{-1}(S_i^{n(t)}, \alpha^{n(t)})) \\ &= (S_k^{n(t+1)}, \alpha^{n(t+1)}) \end{aligned} \tag{10}$$

where $g_{t+1} = n(t+1) - 1, \alpha^{n(t+1)} \in (-\frac{1}{2g_{t+1}}, \frac{1}{2g_{t+1}})$.

3.2.3. Transformation between interval and 2-tuple linguistic variables

Suppose interval $I = [a, b]$, its membership function is denoted as

$$\mu_I(x) = \begin{cases} 1, & a \leqslant x \leqslant b \\ 0, & \textit{otherwise} \end{cases} \tag{11}$$

Calculations of the intersection of the interval and every linguistic variable inside the predefined standard linguistic term sets $S = \{s_0, s_1, s_2, \ldots, s_g\}$ can be obtained by the following (Herrera, Martinez, & Sanchez, 2005):

$$r_k = \max_x \min\{\mu_I(x), \mu_{S_k}(x)\}, \quad k \in \{0, 1, 2, \ldots, g\} \tag{12}$$

The crisp value can be computed as

$$I_\beta = \frac{\sum_{j=0}^{g} j \cdot r_j}{\sum_{j=0}^{g} r_j} \tag{13}$$

Afterward we use "(8)" to transform I_β into the 2-tuple linguistic variable.

4. Fuzzy linguistic agility evaluation model

The major contents of the proposed evaluation model contain the following segments.

1. Founding the decision-making squad for evaluating MC systems, picking out appropriate alternatives, confirming required evaluation criteria, defining selective linguistic category of terms for decision makers. According to distinct situations this paper defines three different types of linguistic variables (Table 1) for decision makers to select appropriate linguistic variables so as to analyze. Here, we must point out that in this paper we deal with linguistic terms whose membership functions are triangular-shaped, symmetrical and uniformly distributed in $[0, 1]$. In addition, the linguistic term sets have an odd value of granularity representing the central label the value of indifference.
2. Defining evaluation scale of agility level for the proposed model.
3. Defining standard 2-tuple fuzzy linguistic variables in interval $[0, 1]$.
4. Transforming heterogeneous information (values of crisp, interval and linguistic expression) generated from decision makers.
5. Aggregating standard 2-tuple fuzzy linguistic variables of multiple experts.
6. Based on the operations of 2-tuple linguistic variables, computing and evaluating the agility with relation to the agile manufacturing alternatives, afterward determining the priority of all feasible alternatives.

For practical implementation, the above summarized segments for analyzing and evaluating the agility degree of alternate MC systems need to be processed. To this end a heuristic of the fuzzy linguistic agility evaluation model is proposed to be done as follows:

Step 1. Aggregate linguistic rating values of all experts for each alternative and then the fuzzy linguistic rating matrix can be represented as:

$$\widetilde{D} = [\tilde{x}_{ij}]_{m\times n}, \tilde{x}_{ij} = (S_{ij}, \alpha_{ij}), \quad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n.$$

The weighted fuzzy linguistic decision matrix can be formed as:

$$\widetilde{R} = [\tilde{r}_{ij}]_{m\times n}, \quad \tilde{r}_{ij} = \tilde{x}_{ij}(\cdot)\tilde{w}_j = \Delta(\Delta^{-1}(S_{ij}, \alpha_{ij}) * \Delta^{-1}(S_j^w, \alpha_j^w)) = (S_{ij}^r, \alpha_{ij}^r).$$

Step 2. Define the best and the worst fuzzy linguistic rating values ($\widetilde{P}^*$, $\widetilde{P}^-$), respectively, that is,

$$\widetilde{P}^* = (\tilde{r}_1^*, \tilde{r}_2^*, \ldots, \tilde{r}_n^*), \quad \widetilde{P}^- = (\tilde{r}_1^-, \tilde{r}_2^-, \ldots, \tilde{r}_n^-),$$
$$\tilde{r}_j^* = \max_i\left\{(S_{ij}^r, \alpha_{ij}^r)\right\}, \quad \tilde{r}_j^- = \min_i\left\{(S_{ij}^r, \alpha_{ij}^r)\right\}.$$

The linguistic rating values of every criterion for alternative A_i can be represented as $\widetilde{P}_i = (\tilde{r}_{i1}, \tilde{r}_{i2}, \ldots, \tilde{r}_{in})$. The nearer the distance between $\widetilde{P}_i$ and $\widetilde{P}^*$, the better the alternative A_i. If $\widetilde{P}_i = \widetilde{P}^*$, then alternative A_i is the best option. On the contrary, If $\widetilde{P}_i = \widetilde{P}^-$, then alternative A_i is the worst one.

Step 3. Define and compute the distance from $\widetilde{P}^*$ and $\widetilde{P}^-$ to $\widetilde{P}_i$ as

$$d_i^* = d(\widetilde{P}_i, \widetilde{P}^*) = \sum_{j=1}^{n} d(\tilde{r}_{ij}, \tilde{r}_j^*) \tag{14}$$

where d_i^* denotes the distance between $\widetilde{P}_i$ and $\widetilde{P}^*, 0 \leqslant d_i^* \leqslant 1$, and

$$d(\tilde{r}_{ij}, \tilde{r}_j^*) = \Delta^{-1}(\max_i\{(S_{ij}^r, \alpha_{ij}^r)\}) - \Delta^{-1}(S_{ij}^r, \alpha_{ij}^r);$$

$$d_i^- = d(\widetilde{P}_i, \widetilde{P}^-) = \sum_{j=1}^{n} d(\tilde{r}_{ij}, \tilde{r}_j^-) \tag{15}$$

where d_i^- denotes the distance between $\widetilde{P}_i$ and $\widetilde{P}^-$, $0 \leqslant d_i^- \leqslant 1$, and

$$d(\tilde{r}_{ij}, \tilde{r}_j^-) = \Delta^{-1}(S_{ij}^r, \alpha_{ij}^r) - \Delta^{-1}(\min_i\{(S_{ij}^r, \alpha_{ij}^r)\}) \tag{16}$$

Step 4. According to the values of d_i^*727 and d_i^-, define the ranking index of A_i as

$$\mathrm{RI}_i = \frac{d_i^-}{d_i^- + d_i^*}, \quad i = 1, 2, \ldots, m, \quad 0 \leqslant \mathrm{RI}_i \leqslant 1 \tag{17}$$

Table 1
Selective linguistic category of terms for decision makers

Type	Number of linguistic	Linguistic variable	Illustration
A	3	Poor(s_0^3), average(s_1^3), good(s_2^3)	Shown in Fig. 3
B	5	Very poor(s_0^5), poor(s_1^5), average(s_2^5), good(s_3^5), very good(s_4^5)	Shown in Fig. 4
C	9	Extremely poor(s_0^9), very poor(s_1^9), poor(s_2^9), fair(s_3^9), average(s_4^9), good(s_5^9), very good(s_6^9), extremely good(s_7^9), excellent(s_8^9)	Shown in Fig. 5

Step 5. Evaluate and rank the alternatives by RI_i, i.e. for alternatives A_i and A_j, if $\mathrm{RI}_i > \mathrm{RI}_j$, then A_i is better than A_j. On the contrary, if $\mathrm{RI}_i < \mathrm{RI}_j$, then A_i is worse than A_j.

Step 6. Transform RI_i of every feasible alternative into the standard 2-tuple linguistic variable in the end, i.e. $\Delta(\mathrm{RI}_i) = (S_i^{\mathrm{RI}}, \alpha_i^{\mathrm{RI}})$.

The proposed approach not only proceeds alternatives ranking effectively, but also investigates alternatives priority by linguistic terms. The believability and acceptance of analysis results can be enhanced.

5. Exemplification

For adapting to this competitive environment, companies settle on objectives for their production systems to be more responsive to customer demands, be able to adjust schedules more frequently, anticipate and avoid production delays and detect quality problems before they became disruptive. A knack to meeting such objectives was to drastically increase agility throughout the organization. Therefore, a firm desires to shift from mass production to the emerging paradigm of MC for gaining a competitive advantage. After preliminary screening, three feasible agile systems A_1, A_2 and A_3 remain for further evaluation. An expert committee of three decision- makers, D_1, D_2 and D_3 has been formed to conduct the evaluation and to select the most suitable agile manufacturing system for the company. Five systematic agile criteria in accordance with characteristics of MC are considered:

(1) Organization management agility (L_1).
(2) Product design agility (L_2).
(3) Processing manufacture agility (L_3).
(4) Partnership formation capability (L_4).
(5) Integration of information system (L_5).

According to the abovementioned algorithm, the proposed method is currently applied to solve this problem and the computational procedure is summarized as follows:

Step 1: Aggregating linguistic rating values of all experts for each alternative.

The decision-makers select appropriate semantic types for linguistic variables in accordance with Table 2 to assess the importance of the criteria. The initial semantic weightings of decision makers under the concerned criteria are shown in Table 3. Afterward we transform the values into type II of the linguistic variable, as Table 4, and then initial performance ratings for decision makers under concerned criteria are displayed in Table 5 which can be transformed into 2-tuple linguistic ratings shown in Table 6. We aggregate semantic weightings of decision makers, as Table 7, and subsequently their 2-tuple linguistic ratings can be aggregated, as Table 8. Finally the weighted 2-tuple linguistic ratings can be obtained and shown in Table 9.

Step 2: Defining the best and the worst fuzzy linguistic rating values as in Table 10.

Step 3: Computing the distance between the best system and each alternative as Table 11 and the distance between the worst system and each alternative as

Table 2
Alternate semantic types for decision makers

Code of AM alternatives	Decision maker		
	D_1	D_2	D_3
A_1	Type I	Type II	Type III
A_2	Type I	Type II	Type III
A_3	Type I	Type II	Type III

Table 3
Initial semantic weightings of decision makers under the concerned criteria

Decision maker	Concerned criteria				
	C_1	C_2	C_3	C_4	C_5
D_1	$(s_2^3, 0)$	$(s_2^3, 0)$	$(s_1^3, 0)$	$(s_1^3, 0)$	$(s_2^3, 0)$
D_2	$(s_3^5, 0)$	$(s_2^5, 0)$	$(s_2^5, 0)$	$(s_3^5, 0)$	$(s_3^5, 0)$
D_3	$(s_8^9, 0)$	$(s_6^9, 0)$	$(s_6^9, 0)$	$(s_7^9, 0)$	$(s_6^9, 0)$

Table 4
Semantic weightings after transformation

Decision maker	Concerned criteria				
	C_1	C_2	C_3	C_4	C_5
D_1	$(s_4^5, 0)$	$(s_4^5, 0)$	$(s_2^5, 0)$	$(s_4^5, 0)$	$(s_4^5, 0)$
D_2	$(s_3^5, 0)$	$(s_2^5, 0)$	$(s_2^5, 0)$	$(s_3^5, 0)$	$(s_3^5, 0)$
D_3	$(s_4^5, 0)$	$(s_3^5, 0)$	$(s_3^5, 0)$	$(s_4^5, -0.125)$	$(s_3^5, 0)$

Table 5
Initial performance ratings

Code of AM alternatives	Concerned criteria	D_1	D_2	D_3
A_1	C_1	Good	Good	Good
	C_2	Good	Very good	Extremely good
	C_3	Average	Average	Good
	C_4	Average	Good	Very good
	C_5	Good	Very good	Very good
A_2	C_1	Good	Very good	Extremely good
	C_2	Good	Good	Very good
	C_3	Good	Average	Average
	C_4	Average	Good	Very good
	C_5	Average	Good	Very good
A_3	C_1	Average	Good	Average
	C_2	Average	Very poor	Good
	C_3	Good	Very good	Extremely good
	C_4	Poor	Average	Average
	C_5	Average	Very good	Good

Table 6
2-tuple linguistic performance ratings after transformation

Code of AM alternatives	Concerned criteria	D_1	D_2	D_3
A_1	C_1	$(s_4^5, 0)$	$(s_3^5, 0)$	$(s_3^5, -0.125)$
	C_2	$(s_4^5, 0)$	$(s_4^5, 0)$	$(s_4^5, -0.125)$
	C_3	$(s_2^5, 0)$	$(s_2^5, 0)$	$(s_3^5, -0.125)$
	C_4	$(s_2^5, 0)$	$(s_3^5, 0)$	$(s_3^5, 0)$
	C_5	$(s_4^5, 0)$	$(s_4^5, 0)$	$(s_3^5, 0)$
A_2	C_1	$(s_4^5, 0)$	$(s_4^5, 0)$	$(s_4^5, -0.125)$
	C_2	$(s_4^5, 0)$	$(s_3^5, 0)$	$(s_3^5, 0)$
	C_3	$(s_4^5, 0)$	$(s_2^5, 0)$	$(s_2^5, 0)$
	C_4	$(s_2^5, 0)$	$(s_3^5, 0)$	$(s_3^5, 0)$
	C_5	$(s_2^5, 0)$	$(s_3^5, 0)$	$(s_3^5, 0)$
A_3	C_1	$(s_2^5, 0)$	$(s_3^5, 0)$	$(s_2^5, 0)$
	C_2	$(s_2^5, 0)$	$(s_0^5, 0)$	$(s_3^5, -0.125)$
	C_3	$(s_4^5, 0)$	$(s_4^5, 0)$	$(s_4^5, -0.125)$
	C_4	$(s_0^5, 0)$	$(s_2^5, 0)$	$(s_2^5, 0)$
	C_5	$(s_2^5, 0)$	$(s_0^5, 0)$	$(s_3^5, -0.125)$

Table 7
Aggregation of semantic weightings for each criterion

	C_1	C_2	C_3	C_4	C_5
Semantic weighting	$(s_4^5, -0.08)$	$(s_3^5, 0)$	$(s_2^5, 0.08)$	$(s_3^5, -0.04)$	$(s_3^5, 0)$

Table 8
Aggregation 2-tuple linguistic ratings for each alternative

	C_1	C_2	C_3	C_4	C_5
A_1	$(s_3^5, 0.04)$	$(s_4^5, -0.04)$	$(s_3^5, 0.04)$	$(s_3^5, -0.08)$	$(s_4^5, -0.04)$
A_2	$(s_4^5, -0.04)$	$(s_3^5, 0.08)$	$(s_3^5, -0.08)$	$(s_3^5, -0.08)$	$(s_3^5, 0.08)$
A_3	$(s_2^5, 0.08)$	$(s_2^5, -0.12)$	$(s_4^5, -0.04)$	$(s_1^5, 0.08)$	$(s_2^5, -0.12)$

Table 9
Weighted 2-tuple linguistic ratings for each alternative

	C_1	C_2	C_3	C_4	C_5
A_1	$(s_3^5, -0.02)$	$(s_3^5, -0.03)$	$(s_2^5, -0.04)$	$(s_2^5, -0.02)$	$(s_3^5, -0.03)$
A_2	$(s_4^5, -0.12)$	$(s_2^5, 0.12)$	$(s_2^5, -0.11)$	$(s_2^5, -0.02)$	$(s_2^5, 0.12)$
A_3	$(s_2^5, 0.03)$	$(s_1^5, 0.04)$	$(s_2^5, 0.06)$	$(s_1^5, -0.02)$	$(s_1^5, 0.04)$

Table 10
The best and the worst fuzzy linguistic ratings

	C_1	C_2	C_3	C_4	C_5
A^*	$(s_4^5, -0.12)$	$(s_3^5, -0.03)$	$(s_2^5, 0.06)$	$(s_2^5, -0.02)$	$(s_3^5, -0.03)$
A^-	$(s_2^5, 0.03)$	$(s_1^5, 0.04)$	$(s_2^5, -0.11)$	$(s_1^5, -0.02)$	$(s_1^5, 0.04)$

Table 11
Distance between the best system and each alternative

	C_1	C_2	C_3	C_4	C_5
A_1	0.16	0	0.09	0	0
A_2	0	0.11	0.15	0	0.12
A_3	0.33	0.42	0	0.26	0.41

Table 12. Afterward we compute the distances from A_i to A^* and A^- as in Table 13.

Table 12
Distance between the worst system and each alternative

	C_1	C_2	C_3	C_4	C_5
A_1	0.18	0.44	0.06	0.24	0.43
A_2	0.36	0.33	0	0.26	0.33
A_3	0	0	0.16	0	0

Table 13
Distances from A_i to A^* and A^-

	A^*	A^-
A_1	0.24	0.92
A_2	0.26	0.89
A_3	1.08	0.19

Step 4: Computing the ranking index for each alternative as $\mathrm{RI}_1 = 0.82$, $\mathrm{RI}_2 = 0.79$ and $\mathrm{RI}_3 = 0.23$, respectively.

Step 5: Evaluating and ranking the alternatives by RI_i, that is $RI_1 > RI_2 > RI_3$.

Step 6: Transforming RI_i of every feasible alternative into the standard 2-tuple linguistic variable in the end, i.e.

It is evident that the agility level of the selective manufacturing systems A_1 and A_2 all belong to "good grade" on account of $\Delta(\mathrm{RI}_1) = (S_3^5, 0.03)$ and $\Delta(\mathrm{RI}_2) = (S_3^5, 0.03)$. They lie in identical agility grade, but even then A_1 is superior to A_2 as $\mathrm{RI}_1 > \mathrm{RI}_2$. Furthermore, manufacturing systems A_3 belongs to "poor grade" owing to $\Delta(\mathrm{RI}_3) = (S_1^5, -0.10)$. The overall ranking order of the three alternatives is $\{A_1\} > \{A_2\} > \{A_3\}$. We can see that the proposed method not only allows all experts (decision makers) to determine linguistic rating values of all alternatives but also can indicate explicitly the ranking index for each alternative. Therefore, it is more suitable and effective in dealing with heterogeneous information surrounding in an imprecise environment.

6. Conclusions

This paper presents a 2-tuple fuzzy linguistic evaluation model for selecting appropriate agile manufacturing system in relation to MC production. Based on concepts of the TOPSIS we proceeds feasible alternatives ranking, and utilizes the linguistic terms to represent the precedence of alternatives and then enhances the believability and acceptance of analysis results. The proposed method advantages managers to deal with heterogeneous information, and offers adequate and convincing argument for analyzing and evaluating the agile manufacturing alternatives. It is capable of providing the comprehension of agile manufacturing features for MC companies through the proposed agility index and related dimensions of management and technology. In addition it offers the reference of further regulating the market strategies for competitiveness through the proposed critical factors.

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