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A multi-enterprise quality function deployment paradigm with unstructured decision-making in linguistic contexts

PENG Jian'gang[1], XIA Guang[2,*], SUN Baoqun[2], and WANG Shaojie[2]

1. Intelligent Manufacturing Institute, Hefei University of Technology, Hefei 230009, China;
2. Institute of Automotive Engineering, Hefei University of Technology, Hefei 230009, China

Abstract: This paper presents an operational framework of unstructured decision-making approach involving quality function deployment (QFD) in an uncertain linguistic context. Firstly, QFD is extended to the multi-enterprise paradigm in a real-world manufacturing environment. Secondly, hesitant fuzzy linguistic term sets (HFLTSs), which facilitate the management and handling of information equivocality, are designed to construct a house of quality (HoQ) in the product planning process. The technique of computing with words is applied to bridge the gap between mechanisms of the human brain and machine processes with fuzzy linguistic term sets. Thirdly, a multi-enterprise QFD pattern is formulated as an unstructured decision-making problem for alternative infrastructure project selection in a manufacturing organization. The inter-relationships of cooperative partners are directly matched with a back propagation neural network (BPNN) to construct the multi-enterprise manufacturing network. The resilience of the manufacturing organization is considered by formulating an outranking method on the basis of HFLTSs to decide on infrastructure project alternatives. Finally, a real-world example, namely, the prototype manufacturing of an automatic transmission for a vehicle, is provided to illustrate the effectiveness of the proposed decision-making approach.

Keywords: decision-making, quality function deployment (QFD), uncertainty, fuzzy set.

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1. Introduction

Customer satisfaction, an overall concept that provides a means of translating customer requirements (CRs) into the appropriate technical requirements for each stage of product development and production, has attracted increasing attention in theoretical and practical domains [1−3]. Quality function deployment (QFD), which intrinsically integrates the "voice of the customer" into an appropriate "voice of enterprise requirements", is a key planning and problem-solving tool available to organizations for efficient product/service design and development [4−7]. QFD can help manufacturers introduce new or improved products/services faster and tackle the challenge of focusing on satisfying CRs in different fields [8−11]. Since the 1950s, QFD has been developed and successfully applied in a wide range of industries to improve customer satisfaction in areas such as industrial production [11−15], industrial economy [8,16−19], food [10], environment [2], and education [20].

As a core component of QFD, house of quality (HoQ) is utilized to transform the customer needs into four interlinked planning processes [9,16,21]. Decision-making is the key technology with regard to HoQ and encounters two challenges practically. One is the emerging production organization paradigm, and the other is the characteristic of uncertainty in the real-world context.

First, with the promotion of "mass entrepreneurship and innovation" strategy in China, the number of innovative and entrepreneurial companies has substantially increased. Regarding the Chinese economy, small- and medium-sized enterprises (SMEs) have contributed 80% of urban labor and employment and 90% of the number of enterprises [22]. Several SMEs have accumulated and mastered a single technology with core competitiveness in their specified domain. Synchronously, SMEs characterized by the sharing economy have created a strong desire for collaborative manufacturing fostered by Internet technology and new non-hierarchical organizations. Furthermore, CRs should be inevitably embedded in a new manufacturing ecosystem that extends beyond current manufacturing systems because of the keen global competition within sharing economy contexts [23]. The decision-making technology of the emerging production organization paradigm has also recently attracted the atten-

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*Corresponding author.
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tion of stakeholders in various fields [23−25].

A realistic organizational strategy extends beyond the old dogma of "one enterprise, one product" in conventional manufacturing paradigms. It is required a confrontation with market globalization and a competitive environment that meets the CRs, shares information and manufacturing capabilities, and consequently maximizes the return to each participant. Therefore, the cooperation among enterprises becomes inevitable. On the basis of the rapidly changing new market requirements and inability of a single enterprise to possess all the necessary skills and competencies to deal with CRs, Mikhailov [14] presented a new approach to select partners in the formation of the most recent organizational strategies in complex manufacturing organizations. From the problem-solving perspective, the multi-enterprise QFD (ME-QFD) involves a multi-expert multi-criteria decision-making problem practically. The ME-QFD attempts to allow a set of experts to select alternatives according to the experts' preferences in line with certain criteria [26,27]. Luo et al. [13] and Baidya et al. [17] investigated the group decision-making (GDM) approach to respond to CRs in QFD.

Next, the ME-QFD paradigm involves many decision-making processes that are essentially human cognitive problems. However, uncertainty juxtaposes human cognitive processes. The concept is hidden in data and information, manifesting as uncertainty in the human reasoning and concept formation processes [28]. Then, in the pursuit of maximum customer satisfaction, a well-designed product not only meets the basic functionality requirement, but also satisfies consumers' psychological demands (or feelings) [29]. As the demand consciousness that is stored in a customer's mind is implicit and tacit in nature, extracting this parameter with numerical values is difficult. Zadeh [30] argued that the theory of fuzzy information granulation was central in human reasoning processes. Thus, fuzzy theory and decision-making approaches that include group and multi-criteria technologies present an extraordinary contribution to QFD [8,11,16]. Additionally, research has corroborated that the fuzzy set theory is effectively employed to manage uncertain linguistic terms [13,18,31,32] and is widely applied to make decisions [11,12,16,31]. Kim et al. [12] combined fuzzy regression and fuzzy optimization theory to study QFD by applying multi-criteria value theory. Furthermore, hesitant fuzzy linguistic term sets (HFLTSs), as a means of dealing with imprecise and hesitant information fusion, have been widely applied to address cognitive information because of its advantage in representing vagueness and hesitation in real-world qualitative decision-making processes [33,34]. Luo et al. [35] developed a fuzzy interval linguistic technique for order preference by similarity to the ideal solution method to deal with multi-attribute GDM problems with HFLTSs.

Previous research has yielded fruitful achievements in decision-making, but some serious gaps exist by virtue of uncertainty in the multi-enterprise organization paradigm. On the one hand, the uncertain characterization of customer demand and expert preference is becoming more apparent. Fusing preference information comprehensively and selecting the optimal design effectively on the basis of assessments of the alternatives in an uncertain environment is extremely challenging. On the other hand, processes that enable decision-makers to face unstructured problems remain difficult and face the fundamental issue regarding a divergence between alternative formulations of the problem. Decision makers frequently face a value judgment which cannot be determined as true or false, only as good or bad. The conventional technical orientation of decision-making is unsuitable for those unstructured problems.

The motivation of our study is to focus on the independent development of an automatic transmission against technology blockade from foreign companies. The major practical contribution of this work is to realize the prototype trial production of a kind of automatic transmission. The main theoretical contribution is a unique problem-solving approach that is particularly useful for addressing an unstructured decision-making problem through extending QFD to a multi-enterprise paradigm. Furthermore, the manufacturing organization is constructed with a back propagation neural network (BPNN) and evaluated with resilience according to hesitant fuzzy linguistic term context.

The rest of this paper is organized as follows. Preliminary concepts of QFD, computing with words (CWW), and HFLTSs are reviewed in Section 2. In Section 3, an outranking method according to HFLTSs is defined, and then the ME-QFD based on HFLTS (ME-QFD-HFLTS) model is presented and described in detail to interpret the problem of the decision-making approach. Organizational resilience is defined legitimately to measure the performance of the ME-QFD-HFLTS model. Section 4 elaborates on the practicality and effectiveness of the proposed model by providing a real-world numerical example. Finally, concluding remarks are provided in Section 5.

2. Preliminaries

2.1 ME-QFD

Relative to the concept of ME-QFD proposed in this study, the QFD implemented in a single enterprise is called traditional QFD and is an effective tool for product design and development that is available for organizations. Theoretically, a typical traditional QFD consists of four phases, namely, product planning, part deployment planning, process planning, and production planning [9,17]. In recent decades, traditional QFD is one of the fundamentally important customer-driven quality system tools that has typically been applied to improve customer satisfaction in a broad range of industries.

HoQ is of fundamental and strategic importance in ME-QFD as in traditional QFD. Given that CRs for the product/service are transformed into appropriate design requirements (DRs) through the four sequential stages mentioned above, cross-functional cooperation and communication are encouraged to achieve customer satisfaction [36,37] in the ME-QFD context. Therefore, the present ME-QFD primarily focuses on the HoQ integrated by fuzzy linguistic terms derived from customers to achieve vital information fusion between CR and design characteristics.

In terms of multi-enterprise attributes, transforming massive amounts of unstructured data into decision-support information is crucial for matching manufacturing demand-capabilities [25]. Furthermore, resilience is particularly important for multi-enterprise manufacturing systems involving conception, measurement, and management strategies [38−40].

2.2 CWW

CWW represents a methodology that bridges the gap between mechanisms of the human brain and machine processes to solve problems and provides computers with tools to address imprecision, uncertainty, and partial truth. CWW is also a computation method of words and propositions drawn from a natural language [41−44]. By allowing the modeling of perceptions and preferences in a human-like manner and providing computers some of the needed tools, CWW has been considered a very interesting methodology in recent years by many researchers in fuzzy optimization and in multi-source information-based decision systems [44,45].

2.3 HFLTSs

The fuzzy linguistic approach (FLA) [46−48], which interprets linguistic sets and their semantics, consists mainly of the ordered structure and the context-free grammar approaches. The former is a predefined assessment scale of the linguistic term distribution. For instance, a set ϑ of seven common linguistic terms for commodity quality is as follows:

$$\vartheta = \{s_{-3}: \text{Very\_poor}; s_{-2}: \text{Poor}; s_{-1}: \text{Slightly\_poor}; s_0: \text{Medium}; s_1: \text{Slightly\_good}; s_2: \text{Good}; s_3: \text{Very\_good}\}.$$

The latter generates linguistic terms such as words or sentences. A context-free grammar, denoted by G_H, is generally defined as a four-tuple as follows.

Definition 1 [49] Let $G_H = (\pi_N, \pi_T, \pi, R)$ be the revised context-free grammar, where π_N and π_T are the symbol sets of non-terminals and terminals, and π and R are the starting symbol and the production rules, respectively.

The transformation functions, denoted by $E_G(\cdot)$, which contain optional elements generated by Definition 2.1, are defined as follows:

$$E_G(s_i) = \{s_i : s_i \in \vartheta\},$$

$$E_G(\text{Ind}(s_i)) = \{s_j : s_j \in \vartheta \text{ and } s_j = \text{random}(s_{i+1}, s_i, s_{i-1})\},$$

$$E_G(\text{Non}(s_i)) = \{s_j : s_j \in \vartheta \text{ and } s_j < s_i\},$$

$$E_G(\text{Dom}(s_i)) = \{s_j : s_j \in \vartheta \text{ and } s_j \geqslant s_i \wedge \exists s_j > s_i\},$$

$$E_G(\text{Bet}(s_i, s_j)) = \{s_k : s_k \in \vartheta \text{ and } s_i < s_k < s_j\}.$$

Linguistic label sets and their operations: Given two arbitrary HFLTSs $s_\alpha, s_\beta \in S$, and φ, φ_1, $\varphi_2 \in [0,1]$, some operational rules [50,51] can be defined as follows:

$$\begin{cases} s_\alpha \oplus s_\beta = s_\beta \oplus s_\alpha = s_{\alpha+\beta} \\ \varphi s_\alpha = s_{\varphi\alpha} \\ (\varphi_1 + \varphi_2) s_\alpha = \varphi_1 s_\alpha \oplus \varphi_2 s_\alpha \\ \varphi(s_\alpha \oplus s_\beta) = \varphi s_\alpha \oplus \varphi s_\beta \end{cases}.$$

Hesitant fuzzy sets (HFSs), as an extension of fuzzy sets, are proposed to model uncertainty [52]. The motivation of HFSs is that determining the membership degree of an element to a set is sometimes difficult [53,54]. According to various membership degrees of an element, HFSs can efficiently interpret a human being's hesitancy or doubt, especially when multi-source of vagueness appears simultaneously [55]. Some basic concepts of HFSs are briefly reviewed.

Definition 2 [52] Suppose that X is a reference set. An HFS on X is a function ℓ that returns a subset of values in the interval [0,1]: $\ell: X \to \sigma([0,1])$.

Definition 3 [52] Suppose that $M = \{\mu_1, \mu_2, \cdots, \mu_n\}$ is a set of n membership functions. An HFS is defined by ℓ_M as follows:

$$\ell_M : X \to \sigma([0,1]),$$

$$\ell_M(x) = \cup_{i=1}^{n} \{\mu_i(x) | \mu_i \in M, x \in X\}.$$

Definition 4 [52] For a given HFS $\mathcal{L}$, its lower and upper boundaries are respectively defined as

$$\ell^{-}(x) = \min \ell(x) \ \ \ell^{+}(x) = \max \ell(x).$$

Linguistically assessed on the basis of HFSs: Linguistic terms allow a representation of uncertain information in a more direct and adequate form and have been utilized to express linguistic approximation with vagueness or inaccuracy. These terms have been derived from human beings according to human educational background and historical experience. In the real world, for instance, simple linguistic terms such as "tall" "very tall" "medium" "short" and "very short" may be used for evaluating a person's height instead of numerical values. Furthermore, linguistic assessments on the basis of comparative terms can be applied to estimate relative relationships, such as "between tall and short". With regard to particular alternatives, the relationship is based on the degree of preference defined with HFLTSs in light of the evaluation criteria, such as "inferior" "indifference" and "non-domination". Hesitation expresses uncertainty in human cognition and thought processes and can be mathematically represented by the membership degree to a given set with several possible values. Rodriguez et al. [49] modeled the uncertainty produced by human doubt when eliciting information with HFLTSs.

Definition 5 [33,49,56,57] Suppose that $S = \{s_0, s_1, \cdots, s_g\}$ is a linguistic term set, where s_i $(i = 1,2,\cdots, g)$ represents a possible value for a linguistic variable, and for which the following properties should exist:

(i) Order: $s_\alpha > s_\beta$, if $\alpha > \beta$;

(ii) Negation operator: Neg $(s_\alpha) = s_{g-\alpha}$;

(iii) $\max\{s_\alpha, s_\beta\} = s_\alpha$, and $\min\{s_\alpha, s_\beta\} = s_\beta$, if $s_\alpha \geqslant s_\beta$.

Definition 6 [33,49,56,57] Suppose that H_S is a set of all HFLTSs of the consecutive linguistic terms $S = \{s_0, s_1,\cdots, s_g\}$. The empty and full HFLTSs for a linguistic variable ϑ are defined as follows:

Empty: $H_S(\vartheta) = \varnothing$,

Full: $H_S(\vartheta) = S$.

Definition 7 [33,49,56,57] Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs on linguistic term set $S = \{s_0, s_1,\cdots, s_g\}$. The intersection and union operations are defined as follows:

Intersection operation: $H_S^1 \cap H_S^2 = \{s_i | s_i \in H_S^1 \text{ and } s_i \in H_S^2\}$;

Union operation: $H_S^1 \cap H_S^2 = \{s_i | s_i \in H_S^1 \text{ and } s_i \in H_S^2\}$.

Definition 8 [49] Suppose that H_S is arbitrary HFLTSs on linguistic term set $S = \{s_0, s_1, \cdots, s_g\}$. The upper and lower boundaries of H_S are denoted by

$$H_{S^+} = \max\{ s_i | s_i \in H_S \},$$

$$H_{S^-} = \min\{ s_i | s_i \in H_S \}.$$

3. ME-QFD-HFLTS architecture

3.1 Problem description

The decision-making situations in real life involve factual and value elements. Unstructured decision-making, which broadly exists in real life, is value-laden [58] and occurs in wicked-structured contexts [59,60]. The traditional decision support systems are unsuitable for wicked problems in asymmetrical criteria settings [61] because the analytical criteria only relate well to a subset of the alternative solutions in the decision-making process [58]. In addition, the uncertainty in decision-making situations further deteriorates the unstructured problem. As the design theory integrates reality into an alternative solution, decision-makers should choose kernel design technologies suitable for their particular settings to assist with decision-making.

The ME-QFD-HFLTS model used in this study that contains the construct of HoQ and includes product planning in multi-enterprise is formally described below. A focus group consists of k customers, denoted by $E = \{e_1, e_2,\cdots, e_k\}$. A finite discrete set of product feature alternatives is expressed by $X = \{x_1, x_2, \cdots, x_n\}$ $(n \geqslant 2)$ under the set of m criteria defined as $C = \{c_1, c_2 \cdots, c_m\}$ to determine the final priority ratings of DRs in HoQ. As HoQ is also fundamentally important in ME-QFD, the main focus of this study is the stage of prioritizing DRs from CRs. The other planning stages of QFD, namely, part deployment planning, process planning, and production planning, are not explored in this paper. First, infrastructure resource selection and optimization are formulated as a multi-criteria group decision-making problem in multi-enterprise settings. Then, an infrastructure project alternative is selected as an optimization problem.

3.2 Outranking method on the basis of HFLTSs

Motivated by the outranking relational system of HFLTSs [34], an outranking method on the basis of HFLTSs is formulated to evaluate alternatives of the following constructed architecture in the ME-QFD context in this subsection.

Definition 9 [34] Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S = \{s_0, s_1, \cdots, s_g\}$. The distance between H_S^1 and H_S^2 is defined as follows:

$$d(H_S^1, H_S^2) = \sqrt{(\text{lab}(H_{S^+}^1) - \text{lab}(H_{S^+}^2))^2 + (\text{lab}(H_{S^-}^1) - \text{lab}(H_{S^-}^2))^2}$$

where lab $(S) = i$, $(i = 0, 1, \cdots, g)$ represents the label of linguistic term $S \in \{s_0, s_1, \cdots, s_g\}$. H_{S^+} and H_{S^-}, as explained in Definition 8, are the upper and lower boundaries of H_S, respectively.

Property 1 [34] Suppose that H_S^1, H_S^2, and H_S^3 are three arbitrary HFLTSs in a linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. The following relationships are true:

$$d(H_S^1,H_S^2)=0 \Leftrightarrow H_S^1=H_S^2,$$

$$d(H_S^1,H_S^2)=d(H_S^2,H_S^1),$$

$$d(H_S^1,H_S^3)\leqslant d(H_S^1,H_S^2)+d(H_S^2,H_S^3).$$

Definition 10 [34] Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. The following binary relation P is defined:

$$P(H_S^1,H_S^2)=\begin{cases}1, & \text{lab}(H_S^1)>\text{lab}(H_S^2)\\ 0, & \text{otherwise}\end{cases}.$$

Definition 11 [34] Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. The outranking degree between H_S^1 and H_S^2 is defined as follows:

$$\delta(H_S^1,H_S^2)=\frac{1}{\sigma_1\cdot\sigma_2}\sum P(H_S^1,H_S^2)$$

where σ_1 and σ_2 are the total numbers of subscripts for H_S^1 and H_S^2, respectively.

Property 2 [34] Suppose that H_s^1 and H_s^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. The following relationship is true:

$$0\leqslant\delta(H_S^1,H_S^2)\leqslant 1.$$

If $\delta(H_S^1,H_S^2)\neq 1$ or $\delta(H_S^2,H_S^1)\neq 1$, then $\delta(H_S^1,H_S^2)+\delta(H_S^2,H_S^1)<1$, $\delta(H_S^1,H_S^2)\neq\delta(H_S^2,H_S^1)$.

Definition 12 [34] Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. The strong dominant relation between H_S^1 and H_S^2 is defined as follows: H_S^1 strongly dominates H_S^2, and H_S^2 is strongly dominated by H_S^1 (denoted by $H_S^1\succ_s H_S^2$ or $H_S^2\prec_s H_S^1$), if and only if $\delta(H_S^1,H_S^2)=1$.

Clearly, $H_s^1\succ_s H_s^2$ means that every element of H_S^1 is greater than that of H_S^2.

Definition 13 [34] Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. The weak dominant relation between H_S^1 and H_S^2 is defined as follows: H_S^1 weakly dominates H_S^2, or H_S^2 is weakly dominated by H_S^1 (denoted by $H_S^1\succ_W H_S^2$ or $H_S^2\prec_W H_S^1$), if and only if $0.5\leqslant\delta(H_S^1,H_S^2)<1$.

Evidently, $H_S^1\succ_W H_S^2$ means that the frequency at which lab $(H_S^1)>$ lab (H_S^2) occurs is greater than or equal to the frequency at which lab $(H_S^1)\leqslant$ lab (H_S^2) occurs.

Definition 14 Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1, \cdots, s_g\}$. σ_1 and σ_2 are the total numbers of subscripts for H_S^1 and H_S^2. The indifference relation between H_S^1 and H_S^2 is defined as follows: H_S^1 is indifferent to H_S^2 (denoted by $H_S^1\sim H_S^2$), if and only if $H_{S^-}^1=H_{S^-}^2$, $H_{S^+}^1=H_{S^+}^2$, and $\sigma_1=\sigma_2$.

Obviously, $H_S^1\sim H_S^2$ indicates that the total number of elements in H_S^1 is equal to the number of elements in H_S^2 and that the upper and lower boundaries of H_S^1 are correspondingly the same as the boundaries of H_S^2.

Definition 15 Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. σ_1 and σ_2 are the total numbers of subscripts for H_S^1 and H_S^2. The inclusiveness relation between H_S^1 and H_S^2 is defined as follows: H_S^1 is inclusive of H_S^2 (denoted by $H_S^1\supset H_S^2$ or $H_S^2\subset H_S^1$), if and only if $H_{S^-}^1=H_{S^-}^2$, $H_{S^+}^1=H_{S^+}^2$, and $\sigma_1>\sigma_2$.

Hence, $H_S^1\supset H_S^2$ means that all the elements of H_S^2 consist of H_S^1.

Definition 16 Suppose that H_S^1 and H_S^2 are two arbitrary HFLTSs in linguistic term set $S\in\{s_0, s_1,\cdots, s_g\}$. If none of the relations described in Definitions 12–15 exist between H_S^1 and H_S^2, then H_S^1 and H_S^2 are incomparable, as denoted by $H_S^1\triangleq H_S^2$.

Namely, $H_S^1\triangleq H_S^2$ implies that the relation between H_S^1 and H_S^2 is not a strong dominant, weak dominant, indifference, or inclusiveness relation.

Definition 17 [34] The following sets reflect the relationship between the alternatives a_i and a_k with respect to assessment criterion j (j=1,2, $\cdots$, m) have several definitions:

$$C_S(a_i,a_k)=\{j|1\leqslant j\leqslant m, a_{ij}\succ_S a_{ik}\},$$

$$C_W(a_i,a_k)=\{j|1\leqslant j\leqslant m, a_{ij}\succ_W a_{ik}\},$$

$$D_S(a_i,a_k)=\{j|1\leqslant j\leqslant m, a_{ij}\prec_S a_{ik}\},$$

$$D_W(a_i,a_k)=\{j|1\leqslant j\leqslant m, a_{ij}\prec_W a_{ik}\}.$$

Definition 18 [34] The concordance index CI_{ik} between a_i and a_k is defined as follows:

$$\text{CI}_{ik}=\sum_{j\in C_S(a_i,a_k)}\omega_j+\sum_{j\in C_W(a_i,a_k)}\omega_j\delta(a_{ij},a_{kj})$$

where ω_j represents the weight of the jth criterion that is computed by using the method described by Peng et al. [62].

Remark 1 The concordance index CI_{ik} consists of the sum of the weights of the criteria if $a_{ij} \succ_S a_{kj}$ and the sum of the weighted outranking degrees when $a_{ij} \succ_W a_{ik}$.

Definition 19 [34] The discordance index DI_{ik} between a_i and a_k is defined as follows:

$$\mathrm{DI}_{ik} = \frac{\max\limits_{j \in D_S(a_i,a_k) \cup D_W(a_i,a_k)} \omega_j d(a_{ij},a_{kj})}{\max \omega_j d(a_{ij},a_{kj})}$$

where j is the set of subscripts for all criteria. $d(a_{ij},a_{kj})$ is calculated with the equation presented in Definition 9.

Remark 2 The discordance index DI_{ik} reflects the degree to which a_i is inferior to a_k. The larger the value of DI_{ik}, the greater the possibility that a_i is inferior to a_k. From the computing perspective, the maximal weighted distance is chosen as $a_{ij} \prec_s a_{kj}$ and $a_{ij} \prec_w a_{kj}$. Then, the value is divided by the maximum of all weighted distances $d(a_{ij},a_{kj})$.

Definition 20 The net dominance index according to the matching probability of the alternative a_k, CI_k, is defined as follows:

$$\mathrm{CI}_k = \eta_k \left(\sum_{l=1,l \neq k}^{m} \mathrm{CI}_{kl} - \sum_{l=1,l \neq k}^{m} \mathrm{CI}_{lk} \right).$$

Definition 21 The net disadvantage index matching probability of the alternative a_k, DI_k, is defined as follows:

$$\mathrm{DI}_k = \eta_k \left(\sum_{l=1,l \neq k}^{m} \mathrm{DI}_{kl} - \sum_{l=1,l \neq k}^{m} \mathrm{DI}_{lk} \right)$$

where η_k is the matching probability of the kth potential cooperative enterprise. A ranking rule of alternatives is obtained by calculating the net dominance and disadvantage indices in the present study. The relative proximity is used to obtain a total order in accordance with net dominance and the disadvantage indices for the alternatives. Therefore, when CI_k is substantial and DI_k is small, the dominance degree of alternative a_k is higher among all alternatives.

3.3 Architecture of ME-QFD-HFLTS

In this subsection, a new architecture is constructed through synthesizing CWW and BPNN techniques to manage and handle the uncertainty of linguistic terms in a multi-enterprise organization paradigm. The architecture of the ME-QFD-HFLTS, which ultimately generates a robust production network, consists of two components. One component is production planning, which is derived from CRs. The other component is an infrastructure scheme that responds to the existing production planning in social manufacturing settings. Fig. 1 shows the architecture of ME-QFD-HFLTS.

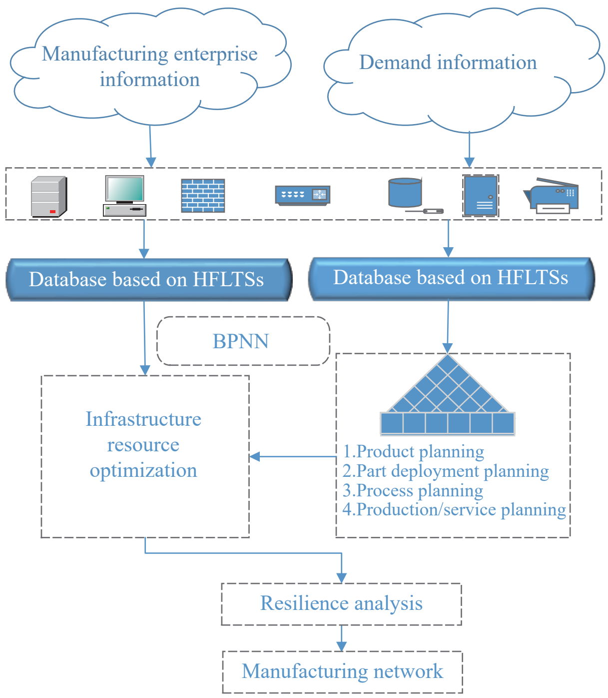


Fig. 1 Architecture of the ME-QFD-HFLTS

3.4 Construction of HoQ

HoQ, which is the core of ME-QFD, is a classic and foundational tool used to determine the relationship between CRs and the performance of corresponding products or services. Generally, the ultimate goal of HoQ is the final priority rating of DRs obtained by determining the relationship between CR and DR. Product planning is the main focus of this study. The entropy for fuzzy set is practically employed to measure the degree of uncertainty of a set in deciding whether an element belongs to that set or not. Therefore, the entropy on the basis of generalized distance [33], as denoted by En, is introduced to determine the final priority ratings of DRs. The entropy of i vectors En_i is defined as follows:

$$\mathrm{En}_i = \frac{1 - D_{gd}^i}{m - \sum\limits_{i=1}^{m} D_{gd}^i}$$

where m is the number of DRs, and D_{gd} is the generalized distance that evaluates DRs.

D_{gd} is defined as follows:

$$D_{gd}(H_\vartheta) = 1 - \frac{2}{n} \sum_{j=1}^{n} \gamma_j E$$

where

$$E = \left[\left(\frac{1}{L} \sum_{l=1}^{L} \left(\frac{\xi_l}{\tau} \right)^{\lambda} \right)^{\frac{1}{\lambda}} \right].$$

n, L denote the numbers of CRs and linguistic terms in

H_ϑ, respectively, τ represents the cardinality value of linguistic labels in ϑ, and λ represents the constant value that describes the different categories of distance concepts. Furthermore, ξ_l denotes the subscript of the linguistic terms in H_ϑ. The final importance rating of CRs, γ_j, is introduced to formulate the generalized distance associated with DRs.

3.5 Infrastructure resource optimization

A database according to HFLTSs is extracted from various entities in the multi-enterprise manufacturing paradigm. Theoretically, the database, which is characterized by enormous, comprehensive, and unstructured properties, contains numerous manufacturing/outsourcing relationships and extensive decision support information for multi-enterprise manufacturing demand-capability matchmaking. The ability to capture these relationships which contain considerable noise and irrelevant information remains a substantial challenge. A BPNN is employed for the relationship extraction task among various named entities instead of exploiting man-made features that are carefully optimized. Furthermore, an analysis of organizational resilience is implemented to select the most desirable manufacturing/outsourcing scheme corresponding to production planning derived from customer demands.

3.6 Organizational resilience of ME-QFD

Resilience is the ability of an organization to continue to function at a desired level when it suffers from partial damage [38−40]. As an important decision indicator, the organizational resilience of ME-QFD is the adaptive capability of cooperative enterprises to prepare for emergencies, respond to disruptions, and recover from them by maintaining the robustness of manufacturing networks at the desired level of connectedness and control over structures and functions. The organizational resilience of ME-QFD, particularly regarding the assessment of infrastructure sources of risk across enterprises and the development of strategies to address these risks, focuses on the ability of the system to recover from partial damage to the system through better connectivity, interoperability, and sharing of resources among enterprises. The partners in a complex networked system of ME-QFD that critically relies on the timely and sustainable delivery of information are interdependent, and thus have a higher potential of cascading failures than non-networked systems [38]. Consequently, from the perspective of the infrastructure structure, organizational resilience is characterized by four attributes, namely, vulnerability (V), flexibility (F), adaptability (D), and synergism (S), which are identified with another key property of coordination and lay a foundation for assessing the constructed architecture in the ME-QFD model. Synergism reveals the nature of coordination among partners in the life cycle of ME-QFD. Without loss of generality, the organizational resilience of ME-QFD is defined as follows:

$$\mathrm{Re}_{\text{ME-QFD}} = f(V,F,D,S).$$

4. Case study

An independent research and development project named dual-clutch transmission with parallel planetary gear trains (DCT-PPGT) combines the characteristics of a hydraulic mechanical automatic transmission and dual-clutch automatic transmission. The DCT-PPGT fulfils the selective output of engine power through the different combinations of the clutch, brake, synchronizer, and planetary gear train. Consequently, DCT-PPGT effectively solves the problems involving the large size and complex structure of an automatic transmission axial bearing and currently contains more than six gears. Synchronously, the DCT-PPGT structure adopts the control methods of a static fuel supply to the clutch cylinder, thereby avoiding the technical difficulty caused by supplying oil to the rotary cylinder, and the working stability and reliability of the transmission shift mechanism are improved.

The trial production of a DCT-PPGT prototype involves many fuzzy decision components in a multi-enterprise manufacturing paradigm. A systematic description of the implementation process of the ME-QFD-HFLTS model is recommended.

4.1 HoQ of DCT-PPGT

Four CRs for the DCT-PPGT project are extracted linguistically according to customers. The CRs are as follows: CR_1 (shifting smoothness), CR_2 (dynamic characteristics), CR_3 (fuel economy), and CR_4 (maintenance cost). On the basis of the experience and expert knowledge of the research and design engineers, eight DRs that correspond to the four CRs are identified. These DRs include DR_1 (axial length of the transmission case), DR_2 (maintainability), DR_3 (gear parameter), DR_4 (gear number), DR_5 (control strategy), DR_6 (fault diagnosability), DR_7 (lubrication system), and DR_8 (hydraulic system).

The HoQ of the DCT-PPGT project is constructed using a decision-making QFD (DMQFD)-HFLTS approach originated from [62] as follows.

Step 1 Establishing fuzzy evaluation for the relative importance of CRs with the same linguistic variable. The relative importance of CRs is evaluated with the following linguistic variable:

$$\vartheta_1 = \{s_1: \text{Absolutely low (al)}, s_2: \text{Remarkably low (rl)}, s_3: \text{Slightly low (sl)}, s_4: \text{Medium (me)}, s_5: \text{Slightly high (sh)}, s_6: \text{Remarkably high (rh)}, s_7: \text{Absolutely high (ah)}\}.$$

Table 1 gives customer comparison assessments. The transformation functions of Definition 1 are used to convert customer requirements. A maximum of two linguistic variables are adopted in this study. The evaluations of customers' original voice expressed by HFLTSs are obtained and shown in Table 2. To simplify, the evaluation linguistic terms about relative relationships are listed as follows: "between" is abbreviated as "Bet", "inferior" is abbreviated as "Inf", "indifference" is abbreviated as "Ind", "domination" is abbreviated as "Dom", and "non-domination" is abbreviated as "Non", respectively.

Table 1 CRs matrix

Assessment	CR_1	CR_2	CR_3	CR_4
e_1	Bet(sh, ah)	Dom(sh)	Ind(me)	Ind(sh)
e_2	Dom(rh)	Ind(sh)	Non(rh)	Ind(rl)

Table 2 CRs matrix expressed by HFLTSs

Assessment	CR_1	CR_2	CR_3	CR_4
e_1	$\{s_6\}$	$\{s_5, s_6\}$	$\{s_3\}$	$\{s_4\}$
e_2	$\{s_6,s_7\}$	$\{s_6\}$	$\{s_4,s_5\}$	$\{s_3\}$

Step 2 Determining the final importance grades of CRs linguistically.

The final importance ratings of CRs are determined linguistically. The values of v and γ according to [62] are listed in Table 3 and Table 4.

From Table 3, the final importance grades of CR_j are generated as follows:

$$CR_1 > CR_2 > CR_3 > CR_4.$$

Step 3 Constructing the functional relationships between DRs and CRs.

Table 3 Values of v and γ

CR	v	γ
CR_1	0.3248	0.4172
CR_2	0.2906	0.3265
CR_3	0.2051	0.1482
CR_4	0.1795	0.1081

Aggregate a collective matrix of individual linguistic relationships between CRs and DRs. The development team examines the extent to which each DR can be measured by each CR with technical analysis and empirical judgment employing the following linguistic variables:

$$\begin{aligned}\vartheta_2 = \{&s_1: \text{Absolutely unimportant (au)},\\ &s_2: \text{Remarkably unimportant (ru)},\\ &s_3: \text{Slightly unimportant (su)},\\ &s_4: \text{Medium (me)},\\ &s_5: \text{Slightly important (si)},\\ &s_6: \text{Remarkably important (ri)},\\ &s_7: \text{Absolutely important (ai)}\}.\end{aligned}$$

Table 4 presents the evaluation matrix derived from the research and development team. The collective matrix of the linguistic relationships between CRs and DRs are converted into HFLTSs, as shown in Table 5.

Table 4 Relationships matrix between CRs and DRs

CR	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8
CR_1	Bet(me,ai)	Bet(ru,ri)	Non(ru)	Bet(ru,si)	Bet(me,ai)	Non(su)	Non(su)	Non(me)
CR_2	Non(su)	Non(su)	Bet(su,ai)	Bet(su,ri)	Bet(ru,ri)	Non(su)	Non(su)	Bet(su,ri)
CR_3	Bet(au,me)	Non(su)	Bet(ru,ri)	Bet(su,ri)	Bet(me,ai)	Bet(me,ai)	Bet(su,ri)	Bet(me,ai)
CR_4	Ind(su)	Bet(au,si)	Bet(ru,si)	Bet(su,ri)	Ind(au)	Non(ru)	Non(ru)	Bet(ru,ri)

Table 5 Collective matrix of linguistic relationships between CRs and DRs

CR	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8
CR_1	$\{s_5,s_6\}$	$\{s_3,s_4,s_5\}$	$\{s_1\}$	$\{s_3,s_4\}$	$\{s_5,s_6\}$	$\{s_1,s_2\}$	$\{s_1,s_2\}$	$\{s_1,s_2,s_3\}$
CR_2	$\{s_1,s_2\}$	$\{s_1,s_2\}$	$\{s_4,s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_3,s_4,s_5\}$	$\{s_1,s_2\}$	$\{s_1,s_2\}$	$\{s_4,s_5\}$
CR_3	$\{s_2,s_3\}$	$\{s_1,s_2\}$	$\{s_3,s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$
CR_4	$\{s_2\}$	$\{s_2,s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_2\}$	$\{s_1\}$	$\{s_1\}$	$\{s_3,s_4,s_5\}$

Step 4 Establishing the final priority grades of DRs.

The values of E and $D_{gd}(H_\vartheta)$ when $\lambda = 0.5, 1, 2, 3, 4, 5, 6$, and 10 are computed and listed in Table 6 and Table 7, respectively.

Table 6 Value of *E* with the minimum distance

λ	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8
λ=0.5	0.234 8	0.169 3	0.042 8	0.149 0	0.234 8	0.042 8	0.042 8	0.081 7
	0.052 2	0.035 8	0.177 8	0.160 6	0.141 7	0.035 8	0.035 8	0.160 6
	0.110 0	0.064 8	0.175 9	0.199 4	0.243 9	0.243 9	0.199 4	0.243 9
	0.039 7	0.058 4	0.069 0	0.089 0	0.039 7	0.019 8	0.019 8	0.078 5
λ=1	0.235 3	0.171 1	0.042 8	0.149 7	0.235 3	0.042 8	0.042 8	0.085 6
	0.053 7	0.035 8	0.179 0	0.161 1	0.143 2	0.035 8	0.035 8	0.161 1
	0.111 1	0.066 7	0.177 8	0.200 0	0.244 4	0.244 4	0.200 0	0.244 4
	0.039 7	0.059 5	0.069 4	0.089 2	0.039 7	0.019 8	0.019 8	0.079 3
λ=2	0.236 3	0.174 6	0.042 8	0.151 2	0.236 3	0.042 8	0.042 8	0.092 4
	0.056 6	0.035 8	0.181 4	0.162 1	0.146 2	0.035 8	0.035 8	0.162 1
	0.113 3	0.070 3	0.181 4	0.201 2	0.245 4	0.245 4	0.201 2	0.245 4
	0.039 7	0.061 7	0.070 1	0.089 8	0.039 7	0.019 8	0.019 8	0.081 0
λ=3	0.237 2	0.178 0	0.042 8	0.152 7	0.237 2	0.042 8	0.042 8	0.097 9
	0.059 1	0.035 8	0.183 7	0.163 1	0.149 0	0.035 8	0.035 8	0.163 1
	0.115 4	0.073 4	0.184 9	0.202 4	0.246 4	0.246 4	0.202 4	0.246 4
	0.039 7	0.063 6	0.070 8	0.090 3	0.039 7	0.019 8	0.019 8	0.082 5
λ=4	0.238 2	0.181 0	0.042 8	0.154 1	0.238 2	0.042 8	0.042 8	0.102 3
	0.061 1	0.035 8	0.185 8	0.164 0	0.151 5	0.035 8	0.035 8	0.164 0
	0.117 3	0.075 9	0.188 1	0.203 6	0.247 4	0.247 4	0.203 6	0.247 4
	0.039 7	0.065 3	0.071 4	0.090 8	0.039 7	0.019 8	0.019 8	0.083 9
λ=5	0.239 1	0.183 8	0.042 8	0.155 4	0.239 1	0.042 8	0.042 8	0.105 7
	0.062 7	0.035 8	0.187 9	0.164 9	0.153 8	0.035 8	0.035 8	0.164 9
	0.119 0	0.077 9	0.190 9	0.204 7	0.248 4	0.248 4	0.204 7	0.248 4
	0.039 7	0.066 8	0.072 1	0.091 3	0.039 7	0.019 8	0.019 8	0.085 2
λ=6	0.240 0	0.186 3	0.042 8	0.156 7	0.240 0	0.042 8	0.042 8	0.108 4
	0.064 0	0.035 8	0.189 7	0.165 8	0.155 9	0.035 8	0.035 8	0.165 8
	0.120 5	0.079 4	0.193 5	0.205 8	0.249 3	0.249 3	0.205 8	0.249 3
	0.039 7	0.068 0	0.072 6	0.091 8	0.039 7	0.019 8	0.019 8	0.086 3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
λ=10	0.243 1	0.193 7	0.042 8	0.160 5	0.243 1	0.042 8	0.042 8	0.115 2
	0.066 8	0.035 8	0.195 7	0.168 8	0.162 1	0.035 8	0.035 8	0.168 8
	0.124 6	0.082 9	0.201 2	0.209 5	0.252 6	0.252 6	0.209 5	0.252 6
	0.039 7	0.071 5	0.074 4	0.093 5	0.039 7	0.019 8	0.019 8	0.089 8

Table 7 Value of generalized distance with the minimum distance

λ	D_{1gd}	D_{2gd}	D_{3gd}	D_{4gd}	D_{5gd}	D_{6gd}	D_{7gd}	D_{8gd}
λ=0.5	0.781 7	0.835 9	0.767 2	0.701 0	0.670 0	0.828 8	0.851 1	0.717 6
λ=1	0.780 1	0.833 5	0.765 5	0.700 0	0.668 7	0.828 6	0.850 8	0.714 8
λ=2	0.777 1	0.828 8	0.762 1	0.697 8	0.666 2	0.828 1	0.850 2	0.709 5
λ=3	0.774 3	0.824 6	0.758 9	0.695 7	0.663 9	0.827 6	0.849 6	0.705 0
λ=4	0.771 9	0.821 0	0.755 9	0.693 7	0.661 6	0.827 1	0.849 0	0.701 2
λ=5	0.769 8	0.817 9	0.753 2	0.691 8	0.659 5	0.826 6	0.848 4	0.697 9
λ=6	0.768 0	0.815 2	0.750 7	0.689 9	0.657 6	0.826 2	0.847 9	0.695 1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
λ=10	0.762 9	0.808 0	0.742 9	0.683 9	0.651 3	0.824 5	0.846 1	0.686 9

The entropies on the basis of generalized distances [62] are ascertained and shown in Table 8. The final priority ratings according to the entropies of DRs are listed in Table 9. The results in Table 10 indicate that when λ = 0.5, 1, and 2, the final priority ratings of DRs are generated according to En as follows:

$$DR_5 > DR_4 > DR_8 > DR_3 > DR_1 > DR_6 > DR_2 > DR_7.$$

Table 8 Entropy based on generalized distance

λ	En_1	En_2	En_3	En_4	En_5	En_6	En_7	En_8
$\lambda = 0.5$	0.1182	0.0889	0.1260	0.1619	0.1787	0.0927	0.0806	0.1529
$\lambda = 1$	0.1183	0.0896	0.1262	0.1615	0.1783	0.0923	0.0803	0.1535
$\lambda = 2$	0.1186	0.0911	0.1265	0.1607	0.1775	0.0914	0.0797	0.1545
$\lambda = 3$	0.1188	0.0923	0.1269	0.1601	0.1769	0.0907	0.0792	0.1552
$\lambda = 4$	0.1189	0.0933	0.1272	0.1596	0.1764	0.0901	0.0787	0.1557
$\lambda = 5$	0.1190	0.0941	0.1276	0.1593	0.1760	0.0896	0.0783	0.1561
$\lambda = 6$	0.1190	0.0948	0.1279	0.1590	0.1756	0.0892	0.0780	0.1564
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\lambda = 10$	0.1189	0.0963	0.1289	0.1586	0.1749	0.0880	0.0772	0.1571

Table 9 Final priority ratings based on entropy of DRs

λ	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8
$\lambda = 0.5$	5	7	4	2	1	6	8	3
$\lambda = 1$	5	7	4	2	1	6	8	3
$\lambda = 2$	5	7	4	2	1	6	8	3
$\lambda = 3$	5	6	4	2	1	7	8	3
$\lambda = 4$	5	6	4	2	1	7	8	3
$\lambda = 5$	5	6	4	2	1	7	8	3
$\lambda = 6$	5	6	4	2	1	7	8	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\lambda = 10$	5	6	4	2	1	7	8	3

Table 10 Evaluating potential cooperative enterprises

Enterprise	Scale	Delivery date	Quality	Research/design capability	Advanced equipment	η
a_1	3	5	4	3	4	0.9728
a_2	4	3	4	4	5	1.0000
a_3	3	3	4	3	4	0.9559

Moreover, when λ >2, the final priority ratings are as follows:

$$DR_5 > DR_4 > DR_8 > DR_3 > DR_1 > DR_2 > DR_6 > DR_7.$$

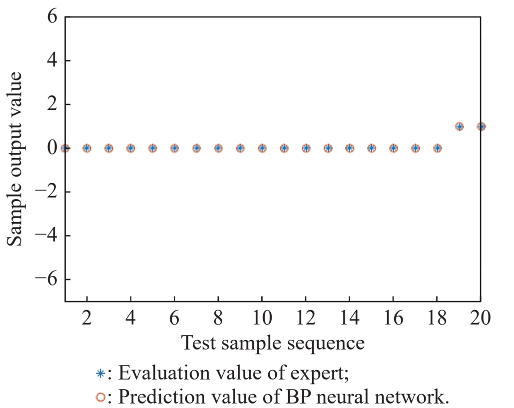
Obviously, the ranking results are relatively robust except DR_2 and DR_6. In particular, the outcomes of the first five relatively important DRs are completely consistent. Specifically, the control strategy is the most important, and the gear number and hydraulic system are the second and third most important among the eight design requirements, respectively. The ranking result of design requirements plays a crucial role in our design of transmission.

4.2 Infrastructure resource optimization based on BPNN

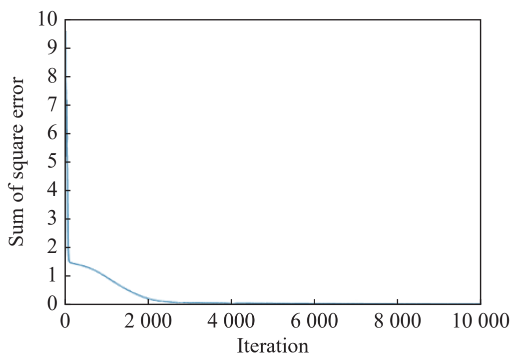
As mentioned, a DCT-PPGT contains multiple components, such as gears, planetary gear systems, axles, boxes, clutch discs, and standard parts. The part production of the gearshift mechanism during the prototype trial production, which is evidently a characteristic of personalized customization, is essential to achieve the entire function of the transmission mechanism.

For the illustration of the practicability of multi-enterprise customization, the matching of production capacity for gears is fulfilled with a BPNN in this study. The following parameters are established: network training sample number $N_{\text{train}} = 40$; network test sample number $N_{\text{test}} = 20$; number of hidden layer neurons $N_h = 10$; number of neurons in the input layer $N_i = 5$; number of neurons in the output layer $N_o = 1$; learning rate $R = 0.01$; maximum iterations $T = 10\ 000$; mean square error threshold $E_{\text{mse0}} = 0.01$. When the number of iterations reaches T or $E_{\text{mse}} = 0.01$, the network is stopped.

Initially, five experts are invited to assess manufacturing enterprises (a sample set) according to five criteria: scale, delivery date, quality, research and design capability, and advanced equipment. Thereafter, a BPNN is designed to obtain the experts' scoring rules, which are stored in the form of mathematical network weights for subsequent reasoning and prediction. Finally, the weights of BPNN with minimum error among five experts (in Fig. 2) are designated to implement production capacity matching with the potential cooperative enterprises.



(a) Comparison values of expert and prediction



(b) Iteration curve

Fig. 2 Performance of the BPNN

Three specialized potential cooperative enterprises, denoted separately by a_1, a_2, and a_3, are chosen to match the gear production network for DCT-PPG and scored with a five-point Likert scale, as shown in Table 10. Ultimately, the matching probability η of the three potential cooperative enterprises is solved separately and listed in Table 10.

As shown in Table 10, the priority value for potential cooperative enterprises is defined as follows:

$$a_2 > a_1 > a_3.$$

4.3 Manufacturing scheme decision-making according to organizational resilience

The relative importance of enterprises is evaluated by using the following linguistic variables:

$$\vartheta_1 = \{s_{-3} : \text{Absolutely low (al)}, s_{-2} : \text{Remarkably low (rl)}, s_{-1} : \text{Slightly low (sl)}, s_0 : \text{Medium (me)}, s_1 : \text{Slightly high (sh)}, s_2 : \text{Remarkably high (rh)}, s_3 : \text{Absolutely high (ah)}\}.$$

Two experts are invited to assess organizational resilience among three potential cooperative enterprises according to four criteria defined in Subsection 3.5 and illustrated in Table 11 and Table 12.

Table 11 Linguistic decision-making matrix of Expert 1

Attribute	a_1	a_2	a_3
V	Dom(me)	Bet(su,si)	Ind(ai)
F	Bet(me,ri)	Ind(su)	Bet(me,ri)
D	Ind(si)	Non(ai)	Dom(me)
S	Bet(si,ai)	Dom(me)	Non(su)

Table 12 Linguistic decision-making matrix of Expert 2

Attribute	a_1	a_2	a_3
V	Ind(ri)	Ind(me)	Non(ai)
F	Dom(ri)	Bet(si,ai)	Non(si)
D	Dom(si)	Ind(si)	Dom(ru)
S	Bet(si,ai)	Dom(me)	Ind(su)

After conversion using the transformation function E_G defined in Definition 1, the linguistic decision-making matrices for cooperative enterprises are transformed into HFLTSs, as shown in Table 13 and Table 14, respectively. The aggregation matrix of the decision-making for cooperative enterprises is illustrated in Table 15.

Table 13 Decision-making matrix of HFLTSs for Expert 1

Attribute	a_1	a_2	a_3
V	$\{s_4,s_5\}$	$\{s_4\}$	$\{s_6\}$
F	$\{s_5\}$	$\{s_4\}$	$\{s_5\}$
D	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$
S	$\{s_6\}$	$\{s_4,s_5\}$	$\{s_2,s_3\}$

Table 14 Decision-making matrix of HFLTSs for Expert 2

Attribute	a_1	a_2	a_3
V	$\{s_5\}$	$\{s_5\}$	$\{s_5,s_6\}$
F	$\{s_6,s_7\}$	$\{s_6\}$	$\{s_3,s_4\}$
D	$\{s_5,s_6\}$	$\{s_6\}$	$\{s_2,s_3\}$
S	$\{s_6\}$	$\{s_4,s_5\}$	$\{s_4\}$

Table 15 Aggregation of linguistic decision-making matrix

Attribute	a_1	a_2	a_3
V	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$
F	$\{s_5,s_6,s_7\}$	$\{s_4,s_6\}$	$\{s_3,s_4,s_5\}$
D	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_2,s_3,s_4,s_5\}$
S	$\{s_6\}$	$\{s_4,s_5\}$	$\{s_2,s_3,s_4\}$

Four criteria weights of organizational resilience are determined with the entropy measure approach according to generalized distance [62]. When λ =1, the values of E and $E_{gd}(H_\vartheta)$ are computed and are shown in Table 16.

Table 16 Values of E

Attribute	a_1	a_2	a_3	$E_{gd}(H_\vartheta)$
V	0.083 3	0.083 3	0.250 0	0.791 7
F	0.333 3	0.166 7	0.111 1	0.694 5
D	0.250 0	0.250 0	0.166 7	0.666 7
S	0.333 3	0.083 3	0.166 7	0.708 4

Four criteria weights of organizational resilience are computed according to [62]. The final priority ratings of criteria weights are obtained as

$$\omega = (0.182\,9, 0.268\,3, 0.292\,7, 0.256\,1).$$

The concordance and discordance indices are calculated according to Definitions 9–19 as follows:

Primarily, based on the relationships among the alternatives, the corresponding sets of subscripts are obtained as follows:

$$C_S(\alpha_1,\alpha_2) = \{4\}, \quad C_W(\alpha_1,\alpha_2) = \{2\},$$

$$D_S(\alpha_1,\alpha_2) = \varnothing, \quad D_W(\alpha_1,\alpha_2) = \varnothing,$$

$$C_S(\alpha_2,\alpha_3) = \varnothing, \quad C_W(\alpha_2,\alpha_3) = \{2,3,4\},$$

$$D_S(\alpha_2,\alpha_3) = \varnothing, \quad D_W(\alpha_2,\alpha_3) = \{1\},$$

$$C_S(\alpha_1,\alpha_3) = \{4\}, \quad C_W(\alpha_1,\alpha_3) = \{2,3\},$$

$$D_S(\alpha_1,\alpha_3) = \varnothing, \quad D_W(\alpha_1,\alpha_3) = \{1\}.$$

Thereafter, the concordance and discordance matrices are constructed according to Definition 18 and Definition 19, respectively:

$$\mathbf{CI} = \begin{bmatrix} - & 0.435\,0 & 0.750\,7 \\ 0 & - & 0.648\,4 \\ 0.137\,2 & 0.137\,2 & - \end{bmatrix},$$

$$\mathbf{DI} = \begin{bmatrix} - & 0 & 0.225\,9 \\ 1 & - & 0.279\,5 \\ 1 & 1 & - \end{bmatrix}.$$

Finally, the net dominance and disadvantage indices according to the matching probability are computed according to Definition 20 and Definition 21, respectively:

$$\mathrm{CI}_1 = 1.020\,0, \mathrm{CI}_2 = 0.076\,2, \mathrm{CI}_3 = -1.075\,1,$$

$$\mathrm{DI}_1 = -1.725\,8, \mathrm{DI}_2 = 0.279\,5, \mathrm{DI}_3 = 1.428\,7.$$

Ultimately, using the outranking method according to HFLTSs for alternatives described in Subsection 2.3, the prioritization results of the potential cooperative enterprises are ranked in accordance with CI_i and DI_i (i =1, 2, 3) as follows:

$$a_1 > a_2 > a_3.$$

In summary, the decision-making result of the manufacturing scheme according to the evaluation of organizational resilience indicates that the first enterprise, a_1, is the desired cooperative enterprise in terms of a gear manufacturing project. Recurring with the matching result of the gear production capacity, the second enterprise, a_2, displays the maximum matching probability. However, the first enterprise is evidently superior to the second in the organizational resilience attributes of flexibility and synergism. From the perspective of the synergy of social manufacturing, the first enterprise is more competitive than the second.

In reality, the first enterprise completes the manufacturing of all gears within the delivery time. The prototype is also successfully assembled according to the project schedule, and the bench test is performed (see Fig. 3).

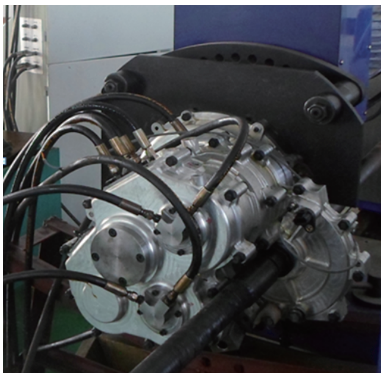


Fig. 3 Bench experiment of the prototype

5. Conclusions

An operational framework of an unstructured decision-making approach based on ME-QFD under uncertain linguistic term conditions is investigated in this study. First, from the perspective of practice, the proposed approach is successfully applied to establish a cooperative manufacturing network of an automatic transmission with proprietary intellectual rights. The construction of a manufacturing network considers the production capacity of cooperative enterprises and assesses the organizational resilience of the collaborative manufacturing network. The validity and relevance of the proposed ME-QFD-HFLTS model are verified with an authentic example. The breakthrough from conceptual design to product trial/ manufacturing is achieved for a real-life case.

Second, from an academic perspective, the technologies of fuzzy mathematics are employed to address uncertain information fusion in multi-enterprise manufacturing contexts. Fuzzy logic, which provides the machinery for fuzzy information granulation, has long played a major role in the applications of expressing and addressing uncertainty [30]. The outranking relation of fuzzy multi-criteria group decision-making methodology is systematically designed to allow the rendering of decisions about multi-enterprise collaborative schemes. Moreover, the outranking degree among arbitrary HFLTSs is defined according to the distance and a comparison of results of label values, thereby contributing both to theory and practice through restricting the same number of elements of HFLTSs in indifference relation compared to those in previous literature.

Third, from the perspective of technology, the architecture of ME-QFD-HFLTS characterized by diverse uncertainties is formulated with an asymmetrical criteria decision-making problem through multi-stage information fusion. Multiple kernel technologies, including HFLTS, CWW, BPNN, and decision-making, are integrated to achieve the proposed model architecture. As linguistic terms are more closely related to human cognitive processes, the HFLTS approach is qualitative rather than quantitative. That is, the variable values expressed by words or sentences instead of numbers and human judgments are more reliable and informative for decision-making. The CWW methodology, which enables the modeling of perceptions and preferences in a human-like manner and provides computers some of the needed tools, is introduced to bridge the gap between the mechanisms of the human brain and machine processes with HFLTSs in the decision-making field. Moreover, human cognition is a learned trait and the strategies used by the brain to perceive the world are constantly modified by experience, and perceptual learning can be quantitatively assessed using a computer model of well-defined neuronal networks [63]. The BPNN, a mentor-learning algorithm of gradient descent, is particularly suitable for predicting complex nonlinear systems [64]. Once trained, a five-criteria value network regarding organizational resilience, involving delivery date, quality, research and design capability and advanced equipment, is used to evaluate the potential cooperative manufacture networks.

Fourth, in the process of prototype design and trial production with completely independent intellectual property rights, we simultaneously consider both domestication of materials and nationalization of equipment, which are important factors restricting the independent research and development of automatic transmissions.

Finally, this study has two major limitations. First, the sample size of the dataset for production capacity matching used in the neural network is small for the use in the trial and production process of the prototype. The ability to match production capacity with big data is thus a promising direction in the future. Second, the expression and operation of uncertainty in the decision-making process presents an area for improvement. The application of advanced mathematical theory is expected to improve the level of uncertain information fusion by balancing the relationship between accuracy and fuzziness in the real world. Furthermore, exploring multi-granular information fusion accommodating uncertainties and hesitations in multi-criteria group decision-making regarding real-world complex systems should be encouraged in future investigations.

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Biographies

PENG Jian'gang was born in 1970. He received his Ph.D. degree in industrial engineering at the School of Mechanical and Automotive Engineering in 2016, Hefei University of Technology, China. He is currently an associate research fellow. His main research interests include production planning and scheduling, uncertain linguistic terms, and fuzzy decision-making.

E-mail: peng_jiangang@sina.com

XIA Guang was born in 1983. He received his Ph.D. degree in vehicle engineering from Hefei University of Technology. He is an associate research fellow in Hefei University of Technology. His research interest is vehicle dynamics control.

E-mail: xiaguang008@hfut.edu.cn.

SUN Baoqun was born in 1956. He received his B.S. degree from Hefei University of Technology. He is a researcher in Hefei University of Technology. His research interest is vehicle automatic transmission control.

E-mail: sbq1956@sina.com.

WANG Shaojie was born in 1973. He received his B.S. degree from Hefei University of Technology. He is a researcher in Hefei University of Technology. His research interest is vehicle automatic transmission control.

E-mail: wsj73@aliyun.con