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ORIGINAL ARTICLE

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An intelligent estimation method for product design time

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Abstract The planning and control of product development is based on the pre-estimation of product design time (PDT). In order to optimize the product development process (PDP), it is necessary for managers and designers to evaluate design time/effort at the early stage of product development. However, in systemic analytical methods for PDT this is somewhat lacking. This paper explores an intelligent method to evaluate the PDT regarding this problem. At the early development stage, designers lack sufficient product information and have difficulty in determining PDT via subjective evaluation. Thus, a fuzzy measurable house of quality (FM-HOQ) model is proposed to provide measurable engineering information. Quality function deployment (QFD) is combined with a mapping pattern of "function→principle→structure" to extract product characteristics from customer demands. Then, a fuzzy neural network (FNN) model is built to fuse data and realize the estimation of PDT, which makes use of fuzzy comprehensive evaluation to simplify structure. In a word, the whole estimation method consists of four steps: time factors identification, product characteristics extraction by QFD and function mapping pattern, FNN learning, and PDT estimation. Finally, to illustrate the procedure of the estimation method, the case of injection mold design is studied. The results of experiments show that the intelligent estimation method is feasible and effective. This paper is developed to provide designers with PDT information to help them in optimizing PDP.

Keywords Product design · Time estimation · House of quality · Fuzzy measure · Fuzzy neural network

1 Introduction

As global competition increases and product life-cycle shortens, companies try to employ effective management to accelerate product development. However, product development projects are often laden with schedule overruns. In most cases, problems of overruns are due to poor estimations, which equates to the saying "you can't control what you do not measure" [1]. In the whole product development process (PDP), product design is an important phase. The control and decision of product development is based on the pre-estimation of product design time (PDT).

At present, along with many advanced development patterns and techniques (e.g. concurrent engineering, collaborative product design and integrated product development), a great deal of quantitative studies on planning and scheduling of PDP have been carried out. These quantitative studies usually assume the PDT firstly and then use this time to optimize the PDP. Nevertheless, PDP always means the brand-new or modified product design. Thus the cycle time of the design process cannot be measured directly. Much attention has been focused on reducing the time/cost in product design, but little systematic research has been conducted into the time estimation. Traditionally, approximate design time is determined empirically by designers in companies. With the increase of market competition and product complexity, companies require more accurate and creditable solutions.

Recently, a small number of studies have dealt with the estimation of design time and effort. These existing approaches all belong to the factor analytical method. Using traditional regression analysis, Bashir and Thomson [2] propose two types of parametric models: a single-variable model based on product complexity, and a multivariable model based on product complexity and severity of requirements. As other factors have not been considered in these two models, the practicability and accuracy are suspectable. Griffin [3, 4] relates the product development cycle time to factors of project, process and team structure with a statistical method, and *qantitatively* analyzes the impact of the project novelty and complexity on cycle time. Nevertheless, he does not present an effective method for estimating the design time. Jacome and Lapinskii [5] present a model for estimating effort for electronic design which takes into account three major factors: size, complexity and productivity. However, this model is applicable only for the estimation of effort for electronic design. Therefore, there is

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a demand for more systematic and general methods which can be applied to a wide range of engineering design projects.

For those nonlinear systems that have many uncertainties, there are no precise mathematic models. Fortunately, adopting intelligent technologies such as neural network and fuzzy logic, is sometimes a good choice. Jahan-Shahi et al. [6] use multivalued fuzzy sets to model the activity time/cost estimation in flat-plate processing. The model and methodology of fuzzy set are good for dealing with uncertain or qualitative information, but the fuzzy rules cannot be determined easily. Based on neural networks, Seo et al. [7] present an approximate method for providing the product life-cycle cost in conceptual design. However, the traditional neural networks used by Seo are limited in processing qualitative information.

It is to this end that this paper develops a time estimation method for the product remodeling design, which is based on fuzzy neural network (FNN) model. There is a kind of nonlinear mapping relationship between engineering factors and PDT. Neural network can perform this mapping well. Fuzzy inference theory is introduced for dealing with the fuzzy input variables. Product characteristics are important parts of engineering factors. As the product characteristics are not available before a product design project begins, this paper attempts to extract product characteristics from customer demands using quality function deployment (QFD) and function mapping methodology. Therefore, the whole estimation method includes three steps: characteristics extraction, network learning and time estimation.

The rest of this paper is organized as follows: in Section 2, PDT factors are identified firstly; Section 3 describes a new house of quality (HOQ) model and introduces a mapping methodology for extracting product characteristics; in Section 4, a parsimonious model of fuzzy neural network is presented for realizing the estimation of the PDT; Section 5 presents an example for illustrating the estimation method and Section 6 is the conclusion.

2 Time factors identification

The PDT estimation method requires a careful selection and identification of the design variables that are related to design time. Therefore, time factors should be confirmed before extracting product characteristics. In order to identify the PDT factors, all possible influencing elements incurred in the design process should be investigated and enumerated. Based on the models described for product development cycle time (Zirger and Hartley [8, 9]; Ittner and Larcker [10]; Tatikonda and Rosenthal [11]; Ali et al. [12]), this paper proposes a conceptual model for the relationships between product design time and different factors, as shown in Fig. 1.

In Fig. 1, the original factor set affects the PDT target indirectly via a transitional factor set. The transitional factor set is composed of some factors that are not obvious and difficult to be measured or evaluated. Therefore, only the original factor set is acquirable and will be taken into account in this paper. The original factor set can be sorted into

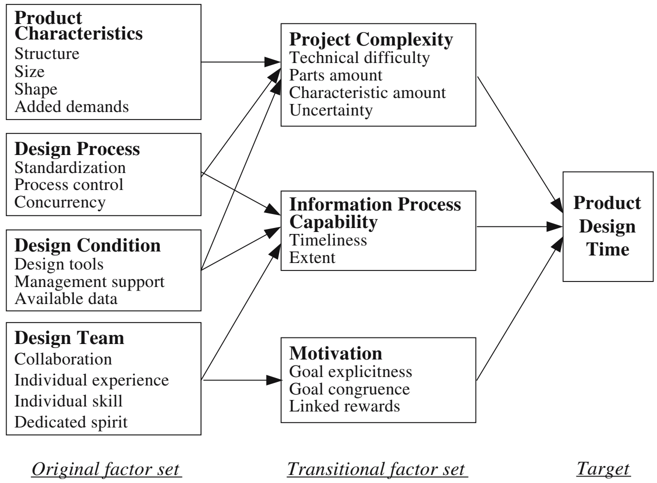

Fig. 1 Conceptual model of factors that influence design time

four main subsets: product characteristics, design process, design condition and design team. Here the nonlinear mapping relationship between the original factor set and PDT is realized by a fuzzy neural network, which will be proposed in the latter part of the paper.

In the original factor set, the factors of the latter three subsets can be evaluated directly, while product characteristics must be gained by transforming customer demands before a design process begins. Different types of products have distinct product characteristics. For a specific kind of product, a list of time factors with influencing weights can be determined by analyzing pre-existing design projects. Table 1 provides a sample of time factor set chosen for the design of a gear speed reducer.

3 Product characteristics extraction

QFD is a concept and mechanism for translating the voice of customers (WHATs) into quality characteristics (HOWs) through various stages of product planning, engineering and manufacturing [13, 14]. In the QFD process, a matrix called the house of quality (HOQ) is used to illustrate the complex relationships between WHATs and HOWs. During the QFD transformation, the HOQ is then developed to demonstrate how the quality characteristics satisfy the customer demands [15]. Initially, QFD is mainly used to improve the product quality and development process. Since the 1990s, QFD methodology has been extended and can be applied to many specific problems [16–18]. In this research, HOQ is employed to construct a framework that will help us to achieve the extraction of product characteristics in the conceptual design or preliminary design stage.

3.1 Fuzzy measurable HOQ

Since there are many subjective and ambiguous evaluations in the QFD process, some researchers have begun to integrate fuzzy logic methods with QFD [14, 16]. However,

Table 1 PDT factors of a gear speed reducer

Time factor set		Unit	Expression	Weight
Factor subsets	Factors			
Product characteristics	Size (length, width, height)	mm	Numerical information	0.75
	Reduction ratio	Dimensionless	Numerical information	0.80
	Power	kW	Numerical information	0.80
	Transmission torque	N.m	Numerical information	0.75
	Transmission efficiency	%	Numerical information	0.50
	Transmission precision	°(Degree)	Numerical information	0.60
	Manufacturing precision	μm	Numerical information	0.60
	Airproof capability	Dimensionless	Linguistic information	0.55
	Lubrication type	Dimensionless	Linguistic information	0.50
	Reliability	Dimensionless	Linguistic information	0.60
	Modularity	Dimensionless	Linguistic information	0.35
	Disassemblability	Dimensionless	Linguistic information	0.25
Design process	Standardization	Dimensionless	Linguistic information	0.50
	Process control	Dimensionless	Linguistic information	0.75
	Concurrency	Dimensionless	Linguistic information	0.75
Design condition	Design tools	Dimensionless	Linguistic information	0.50
	Management support	Dimensionless	Linguistic information	0.60
	Available data	Dimensionless	Linguistic information	0.75
Design team	Collaboration	Dimensionless	Linguistic information	0.50
	Individual experience	Dimensionless	Linguistic information	0.90
	Individual skill	Dimensionless	Linguistic information	0.75
	Dedicated spirit	Dimensionless	Linguistic information	0.60

these existing works just partially apply fuzzy theory such as fuzzy logic-based requirements analysis [19], fuzzy multi-criteria models for QFD [20], fuzzy ranking procedure [21] and fuzzy models for deriving optimum targets [22]. Using traditional HOQs, we can only obtain qualitative information of product characteristics, while measurable values will be grateful and helpful in PDT estimation. Therefore, we add fuzzy measures and fuzzy measure relationships to traditional HOQs, and propose a fuzzy measurable house of quality (FM-HOQ) model, as shown in Fig. 2.

Definition 1 Let Q denote the demand domain, which is a collection of all customer demands for a certain product family. Let P denote the characteristic domain, which is a collection of all technical characteristics for a certain product family.

Definition 2 Let W^Q denote the demand weight domain. Let W^P denote the characteristic weight domain.

For a given design project, demand weight set $\widetilde{B}$ is a fuzzy subset of W^Q, and characteristic weight set $\widetilde{E}$, is a fuzzy subset of W^P. $\widetilde{B}$ and $\widetilde{E}$ can be expressed as: $\widetilde{B} = \{[\widetilde{q}, \mu_{\widetilde{B}}(\widetilde{q})], \widetilde{q} \in W^Q\}$, $\widetilde{E} = \{[\widetilde{p}, \mu_{\widetilde{E}}(\widetilde{p})], \widetilde{p} \in W^P\}$ where $\mu_{\widetilde{B}}(\widetilde{q})$ denotes the membership value of demand weight $\widetilde{q}$ in $\widetilde{B}$. $\mu_{\widetilde{E}}(\widetilde{p})$ denotes the membership value of characteristic weight $\widetilde{p}$ in $\widetilde{E}$.

The membership values of $\widetilde{B}$ and $\widetilde{E}$ are represented by fuzzy numbers defined in [0,1]. Since domains W^Q and W^P are finite, $\widetilde{B}$ and $\widetilde{E}$ can be represented respectively by such fuzzy membership matrices as $[\widetilde{B}]$ and $[\widetilde{E}]$,

$$[\widetilde{B}]_d = \mu_{\widetilde{B}}(\widetilde{q}_d), \quad d = 1, 2,..., m; \widetilde{q}_d \in W^Q \tag{1}$$

$$[\widetilde{E}]_i = \mu_{\widetilde{E}}(\widetilde{p}_i), \quad i = 1, 2,..., n'; \widetilde{p}_i \in W^P \tag{2}$$

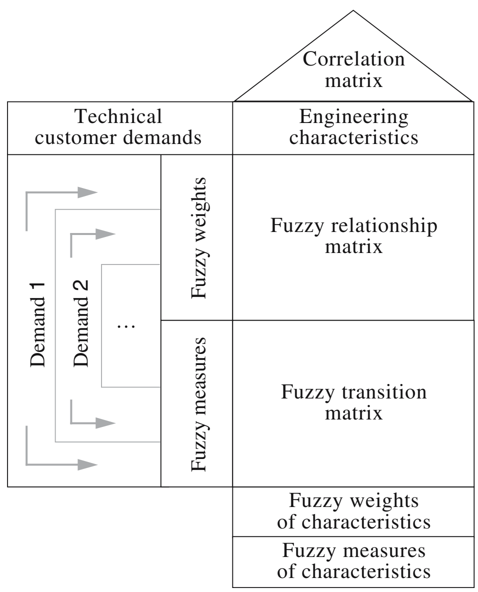

Fig. 2 The structure of FM-HOQ

where m is the number of demands and n' is the number of characteristics. $\mu_{\widetilde{B}}(\widetilde{q}_d)$ and $\mu_{\widetilde{E}}(\widetilde{p}_i)$ denote the grades of membership of demand weights and characteristic weights.

In $Q \times P$, the relationships between fuzzy demand weights and fuzzy characteristic weights can be defined by fuzzy relationship matrix $[R]$, as follows:

$$[R]_{di} = r_{di} = \mu_R(\widetilde{q}_d, \widetilde{p}_i), \quad d = 1, 2, ..., m; \; i = 1, 2, ..., n' \tag{3}$$

where $\widetilde{q}_d \in W^Q$ and $\widetilde{p}_i \in W^P$.

Any fuzzy set, e.g. $\widetilde{B}$, can be considered as a relationship of itself on its domain. According to the synthesis theory of fuzzy relationships [23], the characteristic weight set $\widetilde{E}$ can be formalized as a composition of $\widetilde{B}$ and R, i.e.: $\widetilde{E} = \widetilde{B} \circ R$. Then, we can have

$$\mu_{\widetilde{E}}(\widetilde{p}_i) = \mu_{\widetilde{B} \circ R}(\widetilde{p}_i) = \sup_{1 \le d \le m} \min[\mu_{\widetilde{B}}(\widetilde{q}_d), \mu_R(\widetilde{q}_d, \widetilde{p}_i)], \quad i = 1, 2, ...n'. \tag{4}$$

For those measurable demands and characteristics, there is a kind of mapping relationship between the demand measure sets and characteristic measure sets. Fuzzy relationship matrix $[R]$ just reflects the degree of correlativity between demands and characteristics, but does not reveal the mapping relationships of measures.

In order to deal with the different types of measures, a unified measurement scheme for demands and characteristics is established. A fuzzy measure set M consists of r subsets $M_u(u{=}1, 2, ..., r)$, associated with r description levels. Here we consider the two domains Q and P. The fuzzy subsets M_u^B of Q and fuzzy subsets M_u^E of P corresponding to demand measures and characteristic measures in M_u can be represented as

$$M_u^B = \left\{ \left[q^M, \mu_{M_u^B}(q^M) \right], \quad u = 1, 2, ..., r; q^M \in Q \right\} \tag{5}$$

$$M_u^E = \left\{ \left[p^M, \mu_{M_u^E}(p^M) \right], \quad u = 1, 2, ..., r; p^M \in P \right\} \tag{6}$$

where $\mu_{M_u^B}(q^M)$ and $\mu_{M_u^E}(p^M)$ denote the grades of membership of demand measures and characteristic measures.

The demand measure set and characteristic measure set can be represented respectively by fuzzy membership matrices $[M^B]$ and $[M^E]$ denoted as follows:

$$[M^B]_{ud} = \mu_{M_u^B}(q_d^M), \quad u = 1, 2, ..., r; \; d = 1, 2, ..., m'; q_d^M \in Q \tag{7}$$

$$[M^E]_{ui} = \mu_{M_u^E}(p_i^M), \quad u = 1, 2, ..., r; \; i = 1, 2, ..., n''; p_i^M \in P \tag{8}$$

where m' is the number of measurable demands, n' is the number of measurable characteristics, $m' \le m$ and $n'' \le n'$.

The mapping relationships between measurable demands and measurable characteristics can be denoted by fuzzy transition matrix $[A]$, expressed as

$$[A]_{di} = a_{di} = \mu_A(q_d^M, p_i^M), \quad d = 1, 2, ..., m'; \; i = 1, 2, ..., n''. \tag{9}$$

The characteristic measure set M^E can also be formalized as a composition of M^B and A, i.e. $M^E = M^B \circ A$. Thus we can have

$$\mu_{M_u^E}(p_i^M) = \mu_{M_u^B \circ A}(p_i^M) = \sup_{1 \le d \le m'} \min\left[\mu_{M_u^B}(q_d^M), \mu_A(q_d^M, p_i^M)\right], \quad i = 1, 2, ...n'' \tag{10}$$

The fuzzy characteristic weights of $\widetilde{E}$ can be used to obtain the degrees of importance by ranking. Each characteristic measure of M^E obtained by computing consists of r fuzzy subsets and should be defuzzified.

3.2 FM-HOQ-based product characteristic mapping

In order to find out product characteristics in the early stage of the product development, a systematic mapping method based on FM-HOQ is proposed. Customer demands are composed of functional ones and technical ones. FM-HOQs are applied to mapping and measuring characteristics for technical demands in the decomposing concept of QFD. This is an interactive process performed by a multi-functional team. Planning FM-HOQ, design FM-HOQ and operating FM-HOQ are constructed before the design for project begins.

For functional demands, a mapping pattern of "function→principle→structure" is adopted (refer to the design methodology [24] and axiomatic design (AD) theory [25]). The mapping process begins from the input of function expression and forms the process of function decomposition via three views such as principle ones, functional ones and structure ones. Each function corresponding to a functional demand can be decomposed into subfunctions, each of which can also be decomposed, and so on, to the basic function units. By studying the working principles of these function units, we can find the corresponding principle components. Principle components [24] are the carriers of relations between functions and structures. Geometrical and shape information of product parts are included in principle components. By combining these principle components, the functional tree is mapped into the structural tree. Then the product structure can be determined. For the design project of remodeling products, new functional demands are few and reference data are available. Thus the principle solving process is relatively easy.

The whole mapping processes of technical and functional demands form the framework of characteristic extraction as shown in Fig. 3. There are some connections between the process of functional decomposition and that of technical decomposition. The functional decomposition process is restricted by basic engineering characteristics, while the component and process characteristics need the structure information. From the mapping framework, we can obtain the product characteristics that are defined in the list of time factors.

4 Fuzzy neural network model

Fuzzy neural network (FNN) is an ingenious combination of fuzzy logic and neural network, and it draws on the advantages of these two kinds of intelligent technologies [26]. The characteristics gained by evaluation and mapping include crisp numerical values and fuzzy linguistic values. FNN can be adopted to realize the fusion of these two kinds of information.

For a multivariable FNN system, the increase in the number of variables means an exponential increase in the number of the fuzzy rules, which will result in the corresponding expansion in the size of the network. As a consequence, the configuration of the network becomes so complicated that learning and operations of the network will be very difficult for the multivariable system. The problem incurred here is also referred to as 'curse of dimensionality'. This paper makes use of fuzzy comprehensive evaluation to reduce the dimensionality and present a parsimonious FNN model.

4.1 The principle of parsimonious model

In the list of time factors, many characteristics are expressed by fuzzy linguistic information. If the influencing weights of these factors can be evaluated thoroughly and precisely, these factors can be integrated by fuzzy comprehensive evaluation. Let the input variables of a fuzzy neural network—shown in Fig. 4a—be denoted as $x = (x_1, x_2, \ldots, x_{n_1}, x_{n_1+1}, x_{n_1+2}, \ldots, x_n)$, where n is the number of variables. In view of the expression of variables, $n = n_1 + n_2$ holds, where n_1 and n_2 respectively denote the number of numerical variables and linguistic variables. Each input variable represents a kind of characteristic factor.

Take the factors of n_2 linguistic variables into consideration. Let $\overline{w_i}(i = n_1 + 1, n_1 + 2, \ldots, n)$ denote the influencing weight of factor i. The fuzzy set of each factor variable is divided into r fuzzy subsets and the corresponding membership functions are $\overline{\mu}^{j'}(x_i)(j' = 1,\ 2, \ldots, r;\ i = n_1 + 1, n_1 + 2, \ldots, n)$.

After fuzzy comprehensive evaluation, a new integrated fuzzy set can be obtained. The membership function of the jth subset of this new fuzzy set can be expressed as

$$\mu^j(z_{n_1+1}) = \mu^j\left(x_i\big|_{n_1+1}^{n}\right) = \frac{\sum\limits_{i=n_1+1}^{n} \overline{\mu}^{j'}(x_i)\overline{w}_i}{\sum\limits_{i=n_1+1}^{n} \overline{w}_i},\ j' = 1,\ 2, \ldots, r;\ j = j'. \tag{11}$$

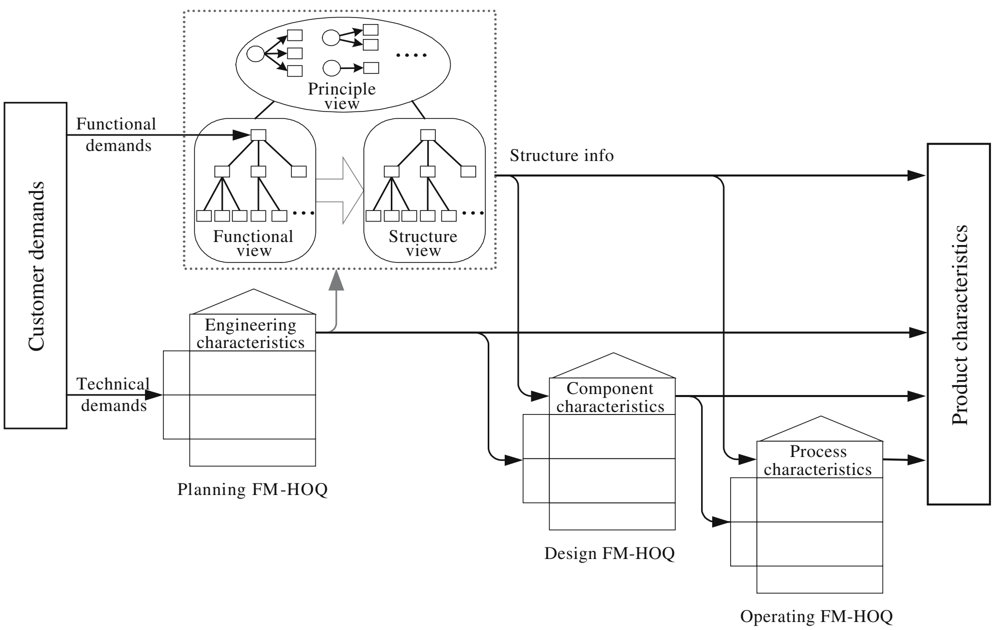

Fig. 3 Characteristic extraction framework based on QFD

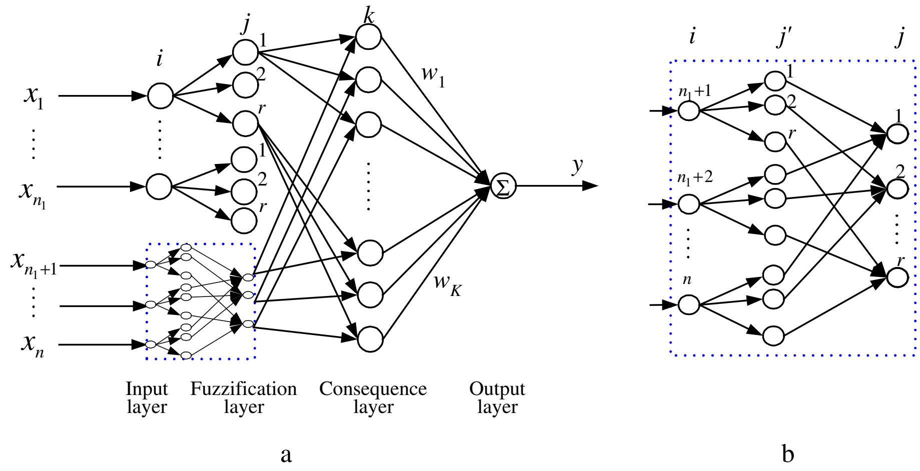

Fig. 4 The structure of parsimonious fuzzy neural network

where z_{n_1+1} denotes the result of fuzzy comprehensive evaluation for linguistic variables $x_i|_{n_1+1}^{n}$.

In the process of fuzzy comprehensive evaluation, compression of variables can accommodate to fuzzification operations as shown in Fig. 4b.

4.2 Parsimonious model of fuzzy neural network

The FNN is a multi-input-single-output (MISO) system and consists of four layers as shown in Fig. 4a. Figure 4b is a magnified part of the network and represents the process of fuzzy comprehensive evaluation.

The input layer concerns the linguistic variables, which are evaluated into five description levels, i.e. r=5. The numerical variables with different dimensions should be normalized. The following normalization is adopted:

$$\bar{x}_i^l = \frac{x_i^l - \min\left(x_i^l|_{l=1}^{L}\right)}{\max\left(x_i^l|_{l=1}^{L}\right) - \min\left(x_i^l|_{l=1}^{L}\right)}, \quad i = 1,\ 2,\ldots,n_1 \tag{12}$$

where L is the number of samples of numerical variable x_i.

The aim of the second layer, or fuzzification layer, is to fuse information and compress dimensionality while fuzzifying the input variables. The fuzzification performs a mapping from the crisp or vague inputs to uniform fuzzy sets, which are characterized by membership functions. Membership function is a key element in the fuzzy system. In this model, the fuzzy set of each input variable consists of five fuzzy subsets associated with five description levels, and is shown as follows:

$$A_i = \left\{A_i^1, A_i^2, A_i^3, A_i^4, A_i^5\right\} = \{\mathrm{VL, L, M, H, VH}\} \tag{13}$$

where VL, L, M, H, VH are abbreviations for very low, low, moderate, high and very high, respectively.

For the linguistic variables, if the description of $\bar{x}_i = (i = n_1 + 1, n_1 + 2,\ldots, n)$ accords with A_i^j, j=1, 2,..., 5, then $\mu_{A_i^j}(\bar{x}_i) = 0.9$, $\mu_{A_i^{j-1}}(\bar{x}_i) = \mu_{A_i^{j+1}}(\bar{x}_i) = 0.75$, $\mu_{A_i^{j-2}}(\bar{x}_i) = \mu_{A_i^{j+2}}(\bar{x}_i) = 0.25$, and others are 0.1.

The membership functions of the numerical variables are represented by the Gaussian distribution function which is understood as follows:

$$\mu_{A_i^j}(\bar{x}_i) = \exp\left[-\frac{1}{2}\left(\frac{\bar{x}_i - c_i^j}{\sigma_i^j}\right)^2\right], \quad i = 1,\ 2,\ldots, n_1;\ j = 1,\ 2,\ldots, 5 \tag{14}$$

where $\mu_{A_i^j}(\bar{x}_i)$ is the membership function of $\bar{x}_i$ in A_i^j. c_i^j 285
and σ_i^j (refer to algorithm 1 in Section 4.3 concerning their computation) are the center and the width of the function. For the fuzzy subsets of {very low} and {very high}, we set membership values as follows:

$$\begin{cases} \mu_{A_i^1}(\bar{x}_i) = 1, & \text{if } \bar{x}_i < c_i^1 \\ \mu_{A_i^5}(\bar{x}_i) = 1, & \text{if } \bar{x}_i > c_i^5. \end{cases} \tag{15}$$

According to the fuzzification and fuzzy comprehensive evaluation, the number of linguistic variables is compressed from n_2 to one, thus the number of neurons in this layer is $5(n_1+1)$.

In the third layer, or the consequence layer, the input variables are combined completely. Therefore, the number of neurons in this layer is $K = 5^{n_1+1}$. Each neuron represents a fuzzy inference rule of the Takagi–Sugeno (T–S) type [27], which has the following form:

Rule k: IF $\bar{x}_1$ is A_1^k, and $\bar{x}_2$ is A_2^k, and ..., and $\bar{x}_{n_1}$ is $A_{n_1}^k$, and z_{n_1+1} is $A_{n_1+1}^k$,

THEN y_k is $B_k(\boldsymbol{x})$, k=1, 2,..., K where y_k is the conclusion of the kth rule, and $B_k(\boldsymbol{x})$ is a fuzzy subset defined in the domain of conclusion. A_i^k is a certain fuzzy subset of A_i corresponding to the kth rule.

Product inference is chosen as the fuzzy reasoning mechanism. The firing length of the kth rule can be obtained by the product operation of the membership functions, as follows:

$$N_k(x) = \mu_{A^k_{n_1+1}}(z_{n_1+1})\prod_{i=1}^{n_1}\mu_{A^k_i}(\overline{x}_i),\quad k = 1,\ 2,\ldots,K. \tag{16}$$

The connection weights in the fourth layer, or output layer, are w_k(k=1, 2, ..., K). With a centroid defuzzifier, the overall output of the network can be expressed as the weighted average sum of each rule's output shown as:

$$y = \frac{\sum_{k=1}^{K} N_k(x)w_k}{\sum_{k=1}^{K} N_k(x)} = \frac{\sum_{k=1}^{K} w_k\left[\mu_{A^k_{n_1+1}}(z_{n_1+1})\prod_{i=1}^{n_1}\mu_{A^k_i}(\overline{x}_i)\right]}{\sum_{k=1}^{K}\left[\mu_{A^k_{n_1+1}}(z_{n_1+1})\prod_{i=1}^{n_1}\mu_{A^k_i}(\overline{x}_i)\right]} \tag{17}$$

4.3 Learning algorithm

The fuzzy C-Means (FCM) clustering algorithm [28] is applied to compute the parameters of Gaussian membership functions. FCM algorithm is an iterative optimization method that is widely used in the field of pattern recognition. The algorithm can be described as a minimization process of the following merit function:

$$\min J = \sum_{l=1}^{L}\sum_{j=1}^{C_i}\left[\gamma_j\left(\overline{x}^l_i\right)\right]^b\left\|\overline{x}^l_i - c^j_i\right\|^2 \tag{18}$$

where L is the amount of samples of numerical variable x_i(i=1, 2,..., n_1). c^j_i is the center of the jth class, and C_i is the clustering number, and C_I=5 in this paper. $\gamma_j\left(\overline{x}^l_i\right)$ is the membership function of lth sample $\overline{x}^l_i$ in the jth class. b is the weight index. Based on a large number of experiments, Howon and Jordan have proved that the optimal range of b is 1.5<b<2.5 [29].

Algorithm 1 Algorithm 1 is the clustering algorithm for the parameter evaluation of the membership function.

Step 1. Set weight index b and clustering number C_i, and assign initial values to the centers c^j_i.

Step 2. Use the following formulas to compute $\gamma_j\left(\overline{x}^l_i\right)$ and c^j_i:

$$\gamma_j\left(\overline{x}^l_i\right) = \frac{\left[1\big/\left\|\overline{x}^l_i - c^j_i\right\|^2\right]^{1/(b-1)}}{\sum_{k=1}^{c_i}\left[1\big/\left\|\overline{x}^l_i - c^k_i\right\|^2\right]^{1/(b-1)}},\quad l = 1,\ 2,\ldots,\ L;\ j = 1,\ 2,\ldots,C_i. \tag{19}$$

$$c^j_i = \frac{\sum_{l=1}^{L}\left[\gamma_j(\overline{x}^l_i)\right]^b\overline{x}^l_i}{\sum_{l=1}^{L}\left[\gamma_j(\overline{x}^l_i)\right]^b},\quad l = 1,\ 2,\ldots,\ L;\ j = 1,\ 2,\ldots,\ C_i. \tag{20}$$

Step 3. Update the merit function J. If the variation of J is less than a threshold error, then stop iteration and go to step 4; otherwise, go back to step 2.

Step 4. The clustering center c^j_i is just the center of the Gaussian function. $\gamma_j\left(\overline{x}^l_i\right)$ can be used to compute the width of the Gaussian function as follows:

$$\sigma^j_i = \frac{\sum_{l=1}^{L}\gamma_j\left(\overline{x}^l_i\right)\left\|\overline{x}^l_i - c^j_i\right\|}{\sum_{l=1}^{L}\gamma_j\left(\overline{x}^l_i\right)} \tag{21}$$

A gradient descent algorithm with momentum factor [30] is used to train the FNN. Define the error function as:

$$E = \sum_{l=1}^{L}E^l = \frac{1}{2}\sum_{l=1}^{L}\left(\widetilde{y}^{\,l} - y^l\right)^2,\quad l = 1,\ 2,\ldots,\ L \tag{22}$$

where $\widetilde{y}^{\,l}$ and y^l are the objective output and real output of the lth sample $\boldsymbol{x}^l$.

By adjusting the connection weights w_k, the error function will be minimized gradually with increasing iterations. For whole input data, the adjusting process can be formulated by:

$$\Delta w_k(t+1) = [1-\varepsilon(t)]\eta(t)\sum_{l=1}^{L}\left[\left(\widetilde{y}^{\,l} - y^l\right)\frac{N_k\left(x^l\right)}{\sum_{k=1}^{K}N_k\left(x^l\right)}\right] + \varepsilon(t)\Delta w_k(t) \tag{23}$$

where t is the iteration times, $\eta(t)$ is the parameter for self-adaptive adjustment of learning rate, and $\varepsilon(t)$ is an added momentum factor which can make the network avoid the local minimum. $\eta(t)$ and $\varepsilon(t)$ are defined as the following two equations:

$$\varepsilon(t+1) = \begin{cases} 0, & \text{if } E(t) > 1.04E(t-1) \\ 0.95, & \text{if } E(t) < E(t-1) \\ \varepsilon(t), & \text{otherwise} \end{cases} \tag{24}$$

$$\eta(t+1) = \begin{cases} 0.7\eta(t), & \text{if } E(t) > 1.04E(t-1) \\ 1.05\eta(t), & \text{if } \mathrm{E}(t) < E(t-1) \\ \eta(t), & \text{otherwise.} \end{cases} \tag{25}$$

The iterative training procedure of the FNN is summarized in the following algorithm.

Algorithm 2 The second algorithm is the FNN training algorithm.

Step 1. Give the training data $\boldsymbol{x}^l$ and the desired output values $\tilde{y}^l$, l=1, 2,..., L.

Step 2. Fuzzify the data of linguistic variables.

Step 3. Normalize the data of numerical variables and the desired output by by Eq. (12). Evaluate the parameters of the Gaussian membership functions with algorithm 1, and fuzzify the data of numerical variables.

Step 4. Set the initial values of connection weights w_k, learning rate η and momentum factor ε.

Step 5. Input the training input-output data.

Step 6. For each input datum, the real output y^l of the FNN is computed by Eqs. (16) and (17). The sum of squared errors is calculated by Eq. (22).

Step 7. If the sum of the squared errors is less than a threshold value, stop iteration; otherwise, use Eq. (23) to adjust the connection weights and go to step 5.

Algorithm 2 is different from the general learning algorithm for neural networks in that the fuzzification process (including algorithm 1 and fuzzy comprehensive evaluation) and consequence process are integrated with the gradient descent algorithm. Moreover, only the connection weights of output layer are adjusted in the learning process.

4.4 Estimating PDT by FNN

For the particular design team of a certain company, changes of design condition and design process are often infrequent. Therefore, only product characteristics are taken into account in this paper.

For an actual application, time factors should be identified firstly. Thus the architecture of the FNN can be confirmed. Enough samples are needed to train the FNN. The characteristics, extracted by the analyzing and mapping frame, can be taken as the training data. Having been trained, the FNN can be used to estimate the time for a given design project. The overall application procedure is shown in Fig. 5.

5 Case study

To illustrate this time-estimation method, the design of a plastic injection mold is studied. An injection mold is a kind of single-piece-designed product and the design process is usually driven by customer orders. Many product development projects involve the design process of injection mold and the pre-estimating time is meaningful for the planning, scheduling and optimization of the whole product development process.

Firstly, it is necessary to obtain PDT factor values of mold characteristics by FM-HOQs and Eqs. (4) and (10) in Section 3. Take the constructing process of the planning FM-HOQ for example. Let us consider a design order for a kind of injection mold. Suppose that the customer has given us the specification of the molding product. Thus we should analysis the customer demands and extract some useful mold characteristics. The technical customer demands are taken into consideration here. Originally, some

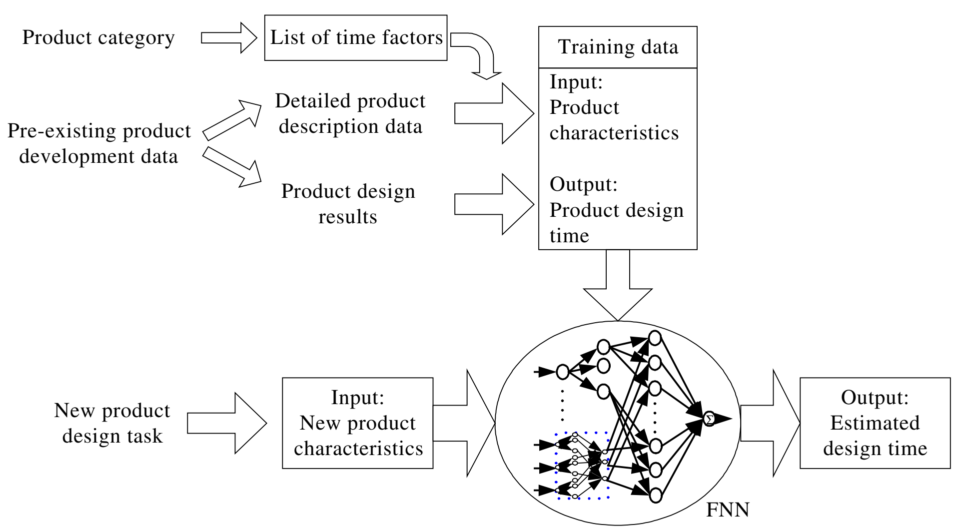

Fig. 5 The application procedure of the FNN model

Table 2 The technical customer demands for an injection mold

Customer demands q		Unit	Weight set $\widetilde{B}$	Measure set M^B
No.	Name			
1	Molding product size	mm	(0.5)	(0.25, 0.75, 0.9, 0.75, 0.25)
2	Molding product precision	μm	(0.8)	(0, 0.25, 0.75, 0.9, 0.75)
3	Molding product structure	Dimensionless	(0.3)	(0.75, 0.9, 0.75, 0.25, 0)
4	Molding product shape	Dimensionless	(0.6)	
5	Minimum thickness	mm	(0.9)	(0, 0.25, 0.75, 0.9, 0.75)
6	Underpropping surface dimension	mm^2	(0.3)	(0, 0.1, 0.5, 0.9, 0.5)
7	Molding batch	Dimensionless	(0.5)	(0.1, 0.5, 0.9, 0.5, 0.1)
8	Mold life	h	(0.9)	(0, 0, 0.25, 0.75, 0.9)
9	Plastic type	Dimensionless	(0.8)	

demands are expressed as quantitative information (e.g. the mold life is 3,000 h), while others are described as qualitative information (e.g. the molding product precision is high). We establish a unified fuzzy measurement scheme for all these demands, and five linguistic levels are used. The degrees of importance of these demands are also represented by fuzzy weight sets.

For the specific mold design, it is required that the designer should specify the grades of membership of demand weights and demand measures, i.e. $\mu_{\widetilde{B}}(\widetilde{q})$ and $\mu_{M^B}(q^M)$. The assignment of $\mu_{\widetilde{B}}(\widetilde{q})$ and $\mu_{M^B}(q^M)$ can be accomplished on the basis of the customer demands given on the design order, and on the designer's objective evaluation of the degrees of importance and scope of the demands. In this example, $\mu_{\widetilde{B}}(\widetilde{q})$ and $\mu_{M^B}(q^M)$ were assigned by several designers, as shown in Table 2. The value $\mu_{\widetilde{B}}(\widetilde{q}_8) = 0.9$ means that the designers view mold life as a very important demand, and the value $\mu_{M^B}\left(q_8^M\right) = (0,\ 0,\ 0.25,\ 0.75,\ 0.9)$ indicates that the measure of "mold life" (i.e. 3,000 h) is roughly between high and very high levels.

From Table 2, we have

$$\left[\widetilde{B}\right] = \begin{bmatrix} 0.5 & 0.8 & 0.3 & 0.6 & 0.9 & 0.3 & 0.5 & 0.9 & 0.8 \end{bmatrix}$$

$$[M^B] = \begin{array}{cc} \begin{bmatrix} 0.25 & 0 & 0.75 & 0 & 0 & 0.1 & 0 \\ 0.75 & 0.25 & 0.9 & 0.25 & 0.1 & 0.5 & 0 \\ 0.9 & 0.75 & 0.75 & 0.75 & 0.5 & 0.9 & 0.25 \\ 0.75 & 0.9 & 0.25 & 0.9 & 0.9 & 0.5 & 0.75 \\ 0.25 & 0.75 & 0 & 0.75 & 0.5 & 0.1 & 0.9 \end{bmatrix} & \begin{matrix} M_1 \\ M_2 \\ M_3 \\ M_4 \\ M_5 \end{matrix} \\ \begin{matrix} q_1 & q_2 & q_3 & q_5 & q_6 & q_7 & q_8 \end{matrix} & \end{array} \tag{26}$$

A survey-based methodology is employed to identify engineering characteristics and time factors. This work is performed via self-administered questionnaires in several mold companies in Nanjing (ESTUN Mould & Die, PANDA Mold, etc.). Then, we select nine kinds of engineering characteristics of injection mold design, i.e., (p1) mold structure, (p2) cavity number, (p3) form feature number, (p4) wainscot gauge variation, (p5) injection pressure, (p6) injection capacity, (p7) ejector type, (p8) runner shape and (p9) manufacturing precision. Then we can construct a planning FM-HOQ. According to the relative design handbooks and experience, the fuzzy relationship matrix and fuzzy transition matrix are given as follows:

$$[R] = \begin{array}{cc} \begin{bmatrix} 0.5 & 0.2 & 0.1 & 0 & 0.6 & 0.8 & 0.5 & 0 & 0.1 \\ 0 & 0 & 0 & 0.3 & 0.2 & 0 & 0.1 & 0.6 & 0.8 \\ 0.9 & 0.1 & 0.5 & 0.5 & 0.2 & 0.2 & 0.3 & 0.5 & 0.3 \\ 0.6 & 0.2 & 0.6 & 0.6 & 0.3 & 0.2 & 0.6 & 0.3 & 0 \\ 0.5 & 0 & 0 & 0.8 & 0.5 & 0 & 0 & 0.5 & 0.2 \\ 0.2 & 0.3 & 0 & 0.2 & 0.1 & 0.1 & 0.8 & 0 & 0 \\ 0.8 & 0.9 & 0.3 & 0 & 0.2 & 0.5 & 0.2 & 0.3 & 0.1 \\ 0.1 & 0 & 0 & 0.1 & 0.3 & 0 & 0.6 & 0.1 & 0.3 \\ 0 & 0.2 & 0 & 0.3 & 0.5 & 0.6 & 0.5 & 0.8 & 0.3 \end{bmatrix} & \begin{matrix} q_1 \\ q_2 \\ q_3 \\ q_4 \\ q_5 \\ q_6 \\ q_7 \\ q_8 \\ q_9 \end{matrix} \\ \begin{matrix} p_1 & p_2 & p_3 & p_4 & p_5 & p_6 & p_7 & p_8 & p_9 \end{matrix} & \end{array}$$

$$[A] = \begin{array}{cc} \begin{bmatrix} 0.6 & 0.3 & 0 & 0 & 0.8 & 0.9 & 0.3 \\ 0 & 0 & 0 & 0.4 & 0.5 & 0.1 & 0.9 \\ 0.6 & 0 & 0.2 & 0.1 & 0 & 0.2 & 0.5 \\ 0.8 & 0 & 0 & 0.9 & 0.1 & 0.2 & 0.3 \\ 0.5 & 0.4 & 0.1 & 0.3 & 0 & 0.3 & 0 \\ 0.6 & 0.9 & 0.9 & 0 & 0.4 & 0.8 & 0.2 \\ 0.5 & 0 & 0 & 0.2 & 0.3 & 0 & 0.5 \end{bmatrix} & \begin{matrix} q_1 \\ q_2 \\ q_3 \\ q_4 \\ q_5 \\ q_6 \\ q_7 \end{matrix} \\ \begin{matrix} p_1 & p_2 & p_3 & p_4 & p_5 & p_6 & p_9 \end{matrix} & \end{array} \tag{27}$$

Table 3 PDT factors of mold characteristics

Mold characteristics	Unit	Expression	Weight
Structure complexity (SC)	Dimensionless	Linguistic information	0.90
Model difficulty (MD)	Dimensionless	Linguistic information	0.70
Wainscot gauge variation (WGV)	Dimensionless	Linguistic information	0.70
Cavity number (CN)	Dimensionless	Numerical information	0.80
Mold size (height/diameter) (MS)	Dimensionless	Numerical information	0.55
Form feature number (FFN)	Dimensionless	Numerical information	0.55

Table 4 Learning and testing patterns for the FNN

Molds		Input data						Desired PDT (h)
No.	Name	SC	MD	WGV	CN	MS	FFN	
1	Global handle	L	L	L	4	3.10	3	23.0
2	Water bottle lid	H	L	H	4	0.56	7	45.5
3	Medicine lid	H	M	VL	4	1.50	6	37.0
4	Footbath basin	VL	VL	VL	1	0.50	3	10.0
5	Litter basket	L	M	H	1	2.10	12	42.5
6	Plastic silk flower	L	M	M	1	7.10	4	29.5
7	Dining chair	M	H	L	1	0.50	15	48.0
8	Spindling bushing	H	VL	L	2	8.07	2	30.0
9	Three-way pipe	H	L	L	1	0.45	5	24.5
10	Hydrant shell	VH	H	M	1	0.30	7	49.0
...	...	...	...	...	...	...	...	...
71	Paper-lead pulley	L	M	H	8	6.10	6	55.0
72	Winding tray	M	M	VH	1	2.18	7	41.5

The values r_{71}=0.8 and r_{72}=0.9 in matrix $[R]$ imply that "mold structure" and "cavity number" are very important for meeting the demand "molding batch", while the value r_{27}=0.1 means that the engineering characteristic "ejector type" has little relation with the demand "molding product precision". In matrix $[A]$, each row indicates the impact of a demand measure on different characteristic measures, while each column indicates the effects of different demand measures on a characteristic measure. For example, the measure of molding batch demand has a very high influence on characteristic measures of cavity number and "form feature number" (a_{72}=a_{73}=0.9), and has no influence on the measure of "wainscot gauge variation" (a_{74}=0).

It is remarkable that two kinds of demands (i.e. "molding product shape" and "plastic type") and two kinds of characteristics (i.e. "ejector type" and "runner shape") are immeasurable. Thus they are excluded from the fuzzy transition matrix, and the fuzzy weights and measures of the mold characteristics are then computed by Eqs. (4) and (10) as follows.

$$
\begin{aligned}
\left[\widetilde{E}\right] &= \left[\widetilde{B}\right] \circ [R] \\
&= [\,0.6 \quad 0.3 \quad 0.6 \quad 0.6 \quad 0.5 \quad 0.6 \quad 0.5 \quad 0.6 \quad 0.8\,] \\
\left[M^E\right] &= \left[M^B\right] \circ [A] \\
&= \begin{array}{cc}
\left[\begin{array}{ccccccc}
0.6 & 0.25 & 0.2 & 0.1 & 0.25 & 0.25 & 0.5 \\
0.6 & 0.5 & 0.5 & 0.25 & 0.75 & 0.75 & 0.5 \\
0.75 & 0.9 & 0.9 & 0.75 & 0.8 & 0.9 & 0.75 \\
0.8 & 0.5 & 0.5 & 0.9 & 0.75 & 0.75 & 0.9 \\
0.75 & 0.1 & 0.1 & 0.75 & 0.5 & 0.3 & 0.75
\end{array}\right] & \begin{array}{c} M_1 \\ M_2 \\ M_3 \\ M_4 \\ M_5 \end{array} \\
\begin{array}{ccccccc} p_1 & p_2 & p_3 & p_4 & p_5 & p_6 & p_9 \end{array} &
\end{array}
\end{aligned}
$$

The constructing process of the design FM-HOQ is similar to that of the planning FM-HOQ. Therefore, some characteristic information of the corresponding compo-

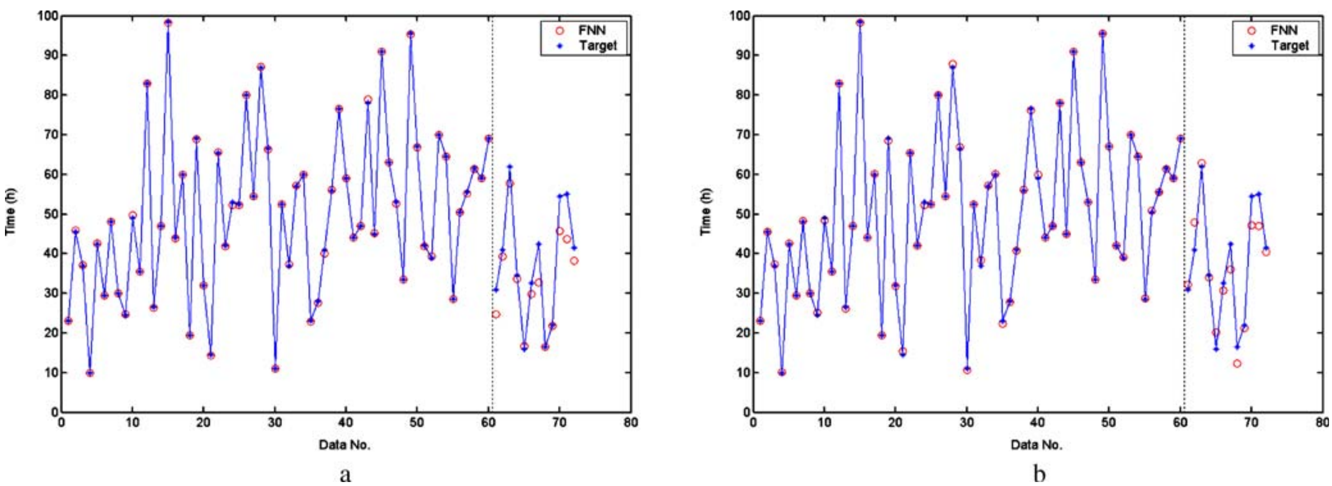

Fig. 6 Training and testing results on the FNNs of normal model (**a**), and parsimonious model (**b**)

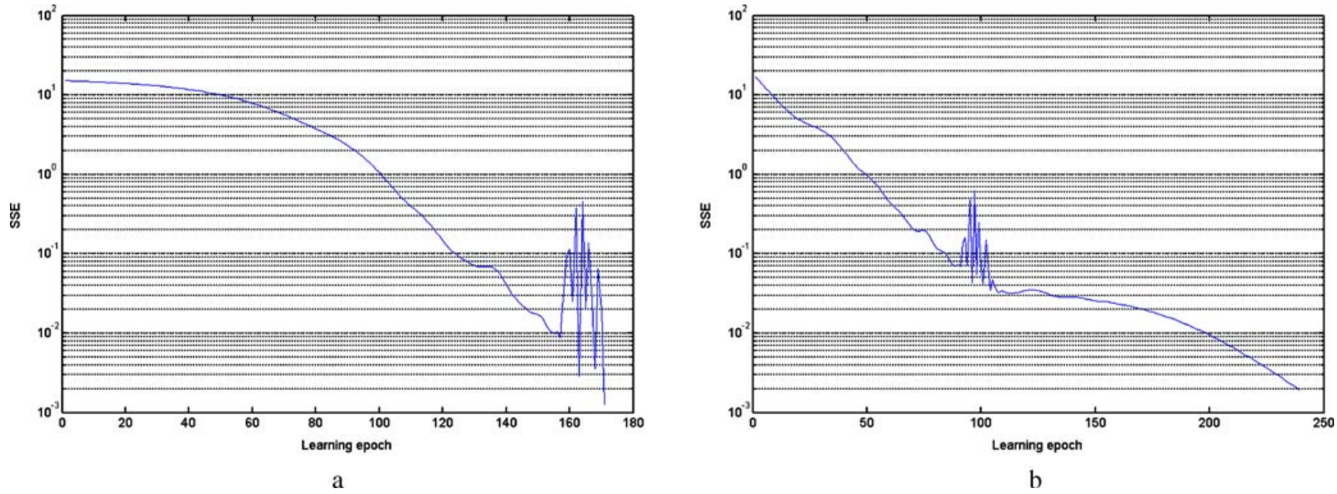

Fig. 7 The curve of SSE with respect to successive learning epochs on the FNNs of the normal model (**a**), and the parsimonious model (**b**)

nents and parts (e.g. cores, slides, mold base, cavity, gate, and so on) can be obtained. These acquired fuzzy measures of characteristics can be defuzzified into comprehensible forms (definite estimate values or linguistic descriptions).

In the following text, we construct an FNN to estimate the mold design time. We place emphasis on the mold characteristics associated with the design time. Some characteristics with large influencing weights are gathered to develop a time factor list as shown in Table 3. Here, the influencing weights that indicate the degree of influence on PDT are different from the indexes of importance in FM-HOQs.

In our experiments, 72 sets of molds with corresponding design times are selected from the past projects of a typical company. The detailed characteristic data and design time of these molds compose the corresponding patterns as shown in Table 4. We train the FNN with 60 patterns, and the others are used for testing.

MATLAB 6.1 is used to implement the PDT estimation method. The experiments are made on a 2.4 GHz Pentium IV personal computer (PC) with 512 MB memory under Microsoft Windows 2000. Some indexes such as sum of square error (SSE), mean square error (MSE), mean absolute percentage error (MAPE), maximal absolute error (MAXE) and minimal absolute error (MINE), are adopted to evaluate the performance of the FNN. The object training error of the network is 1.0e-3. Initial parameters are $\eta(0)=0.2$ and $\varepsilon(0)=0$.

We implement the intelligent estimation of the PDT with two modes. One is based on the normal FNN model, while the other is on the parsimonious FNN model. In the first mode, the dimensionality has not been compressed and each variable has five fuzzy subsets. Thus the number of fuzzy rules is 5^6. In the second mode, fuzzy comprehensive evaluation is used to reduce the input dimensionality. As shown in Fig. 4, the three linguistic variables (structure complexity, model difficulty and wainscot gauge variation) are fuzzified and synthesized into a new integrated fuzzy set by the influencing weights of Table 3. Thus, the number of fuzzy rules in this mode is 5^4.

In different initial connection weights, a good many experiments are performed for each mode. The results of network training and testing in a certain moment are shown in Fig. 6. The corresponding training processes can be represented by the error curves as shown in Fig. 7.

Table 5 Performances of the FNNs of two models

FNN		Performance indexes						
Model type	No.	SSE	MSE	MAPE (%)	MAXE	MINE	Duration (s)	Iteration number
Normal model	1	0.05673	0.00473	12.061	0.13352	0.00081	27.25	172
	2	0.05128	0.00427	11.582	0.14650	0.00517	27.36	171
	3	0.05978	0.00498	12.254	0.15099	0.00067	27.24	172
	4	0.04798	0.00400	11.193	0.12683	0.00077	27.28	172
	5	0.05266	0.00439	11.448	0.14427	0.00968	27.30	172
	6	0.05338	0.00445	11.892	0.13824	0.00137	26.91	171
Parsimonious model	1	0.03132	0.00261	10.085	0.10488	0.00314	0.734	260
	2	0.02516	0.00210	9.623	0.08837	0.00318	0.688	225
	3	0.03073	0.00256	9.499	0.11857	0.00367	0.733	258
	4	0.03030	0.00253	10.250	0.09340	0.00083	0.812	291
	5	0.03615	0.00301	10.751	0.10247	0.01409	0.704	239
	6	0.01794	0.00149	9.094	0.09587	0.00031	0.703	233

In Fig. 7, we can see that there are some local minimums appearing in the training processes, and these valleys are gotten over one by one. This advantage should be owed to the added momentum factor. During the experiments, we also find that over-fitting may occur when the objective training error is excessively small.

To compare the performances of both models, we select the results of several experiments and provide the corresponding data in Table 5. As shown in Table 5, both models have reasonable accuracy. The SSE, MSE and MAPE of the parsimonious model are somewhat smaller than those of the normal model. The parsimonious model needs more iteration numbers to reach the identical objective training error. However, the duration of training on the parsimonious model is extremely short. This is unquestionable because the computational complexity accords with the number of fuzzy rules. If the number of input variables is much more and the adjusting process of some initial parameters is considered, the computational workload of the normal model will be formidable. Thus, the conclusion can be reached that the parsimonious model is rather suitable for practical applications.

6 Conclusions

The control and decision of product development is based on the pre-estimation of PDT. However, this PDT estimation problem is always overlooked because of the insufficiency of quantitative methods. This research attempts to develop an intelligent estimation method. In order to find out product characteristics at the early stage of product development, a fuzzy measurable house of quality (FM-HOQ) model is established. This model is applied to measure and map characteristics from customer's technical demands, with the decomposition idea of QFD. For customer's functional demands, a mapping pattern of "functions→principle→structure" is taken on. With the data of product characteristics having been obtained, a new FNN model is presented for fusing data and realizing the estimation of design time. This model makes use of fuzzy comprehensive evaluation to simplify structure. The application of the FM-HOQ model and FNN-based intelligent estimation method to the design of injection molds indicates that the model and method are feasible.

This estimation method can be used for the remodeling products at the early stages of development. The known characteristics of existing products are used to train the FNN. Thus, this trained FNN can be approximated to the design time for a new product. For a certain kind of product, the accuracy of this method will be enhanced while more samples are added to the training set.

On the other hand, there are some limitations to this estimation method. For the brand-new products, this PDT estimation method will be inapplicable. The influencing weights of linguistic variables obtained by experience or experiment are important for the parsimonious FNN model. If all influencing weights of linguistic and numerical variables are used as the connection weights between the input layer and fuzzification layer, and optimized by the network learning, then the FNN model will be more reliable and these influencing weights will have further applicable value. This is a problem for future research.

In conclusion, the main contributions of this research can be shown as follows:

1. Develop a time estimation method that is helpful for product development
2. Propose a kind of fuzzy measurable HOQ for mapping and analysis of product characteristics
3. Provide a parsimonious FNN model for the MISO system with high-dimensionality and mixed-type inputs

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