

## Research Article

# Product Module Attribute Parameter Configuration Model considering Customer Requirements Preferences

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In the process of modular product configuration, it is necessary to transform customer requirements into product module attributes (PMA) parameters. However, previous research lacks consideration about customer requirement preference in the process of this transformation. First, we use a preference graph (PG) to obtain the customer preference weight vector for the requirement node. Second, on the basis of traditional Quality Function Deployment (QFD), the method of fuzzy correlation evaluation is introduced to get the correlation value between module attributes, and the combination programming model of PMA is further obtained by synthesizing the preference weight vector. Finally, the final configuration scheme is obtained by solving the model with the genetic algorithm. By integrating the weights of the above-mentioned nodes, the similarity of the product case is obtained, and a more satisfied case of the customer is obtained. Taking the automated guided vehicle car product as an example, the effectiveness and practicability of the proposed method are verified.

## 1. Introduction

With the increasing variety of product models, the customer's individual requirements continue to grow. In modern models of personalized manufacturing, rapid responses to the individual needs of customers and shorten product design cycles are the key to win the market competition. Therefore, it is a great challenge for enterprises to design a product that meets the customers' individual needs quickly. However, customers are not professional and could not fully understand the functions of products or services [1]. In order to obtain configuration schemes of products, designers need to use scientific analysis methods to transform customer requirements into product model parameters, because the requirements of products or services are not clear [2]. Meanwhile, this process is also the premise and basis of product design. However, traditional research lacks the consideration of customer requirement preference [3, 4].

Because modular design is the core idea of family construction of the product, the concept of modular product configuration is widely accepted [5]. Modular product

configuration is actually a combination of product module models and the related constraints for avoiding invalid configuration and improving product configuration efficiency [6]. Mohammad et al. [7] proposed a modular product platform configuration model which uses assembly and disassembly to configure product variants and coplanning of product platforms (MPCC) and their assembly lines. Victor et al. [8] proposed fourteen modular drivers based on available literature. In addition, Quality Function Deployment (QFD) is deployed to accomplish modular product design with two major phases. Y. Qin et al. [9] presented that the modular structure of product family is established with generic modules, and the module model denoted by attribute variate is established for each generic module, and customer requirements are translated into the value of module attributes. Yan et al. [10] put forward a mapping method of customer requirements by integrating QFD and rule-based reasoning method aiming at product configuration problem oriented to customer requirements analysis. In view of the dynamic change of customer requirements, Yang et al. [11] proposed a Bayesian Nash equilibrium

configuration model for product variant design driven by CRs. Shi et al. [12] calculated the similarity of primary modules by utilizing the closest similar strategy, and the similarity of middle modules was gotten by synthesizing the similarity of primary modules. Liu et al. [13] proposed a modular configuration design method using the fuzzy similarity priority ratio and gray correlation analysis algorithm. Wen et al. [14] put forward the concept of knowledge module, and the model of knowledge module was established by the object-oriented method. Han Yudong. et al. [15] proposed a method of modular product configuration considering both perceptual requirement and functional requirements to meet the customer perceptual requirement in product configuration.

The traditional product configuration process is usually completed by designers, so it is easy to cause the lack of requirements and mismatches. In this paper, the weight value of module attribute parameters is synthetically obtained by calculating the relationship between configuration parameters and the weight of requirement preference. Thus, it can make the configuration result possess higher customer satisfaction.

Requirement preferences refer to the degree of customers' preferences for product structure or attributes [16]. Analyzing customers' preferences could help to increase customer satisfaction and promote the development of enterprise products. The ultimate goal of product similarity case acquisition is to find the product that meets the needs and satisfaction of customers. Therefore, the analysis and consideration of customer requirement preferences are very important for the acquisition activities of cases. There are also many ways to obtain customer preferences, such as Kano model [17], joint analysis method [18], and Nahm et al. [19] which proposed a novel approach to prioritize CRs from the viewpoint of company's competitiveness and the key characteristic of the proposed approach is to present the customer's preference structure as the form of customer satisfaction function by combining the competitive benchmarking analysis and Kano's analysis. Yang et al. [20] proposed a similar case solution method considering customer requirement preference. Barnett et al. [3] presented an up-to-date survey of the state-of-the-art in consumer requirement modelling. Arguea et al. [21] explored the possibility of using market data to identify consumer preferences using 1969–86 data compiled from Consumer Reports and Ward's Automotive Yearbook. Jun-Jie et al. [22] presented design process modelling, concept information representation, design scheme generation, design scheme selection, and prototype system development based on analyzing the design concept and general process of conceptual design.

The above research focuses on the research methods of customer requirement preferences. In the process of product configuration, this paper introduces customer requirement preferences to realize the weight calculation of module parameters, then to establish the corresponding relationship between customer preferences and module attribute parameters.

Based on that, this paper proposes a parameters configuration of product module attributes driven by customer requirements preferences. In order to maximize customer requirement revenue and constrain the prices, PMA parameters configuration is constructed by utilizing product module attribute parameters obtained by the product service system. PMA configuration model is customer-centered and aims to provide the optimal product solution under the demand conditions.

## 2. PMA Parameters Configuration Model Driven by Requirement

PMA configuration is customer-centered and aims to provide the best product solution under the demands of customer requirement conditions. However, as the change of market conditions, customer requirement tends to diversify. For customers in different industries, the expression and perspective of requirement are often different. How to quickly translate customer requirements into product models is the key to quickly respond to customer requirements. The framework of the product module parameters configuration model is shown in Figure 1.

Firstly, QFD is used as a tool to establish the relationship between requirement weights and PMA. In order to facilitate the expression of this relationship by experts, semantic evaluation is used to describe it. The exact weight of module attributes is obtained by the semantic triangular fuzzy transformation. Secondly, the module combination optimization model is established. In the product service system established by the enterprise, the module attribute parameters of the product and the corresponding product price are selected. According to the characteristics of module attributes, an optimization model is established. Finally, the genetic algorithm is used to solve the problem, and the parameters combination scheme of PMA parameters is obtained.

*2.1. Analysis of Customer Requirements Node Preferences.* Nahm et al. [22] proposed a graph-based representation technique to simulate incomplete or uncertain human preference structure, called PG (preference graph). With this technology, customers only need to build preferences for the requirement nodes they know, rather than for all existing nodes. As most customers do not know the product's professional knowledge, they usually express their preferences for some attributes of the product according to their own needs. PG allows customers to specify partial ranking of  $v_i$ , so this method is used to analyze the preferences of requirement nodes, which not only facilitates the expression of customers but also provides more realistic access to customer preferences.

Through the analysis of product information, enterprises can establish  $n$  requirement nodes which can be combined into two groups to provide customers. Customers choose the one they prefer by comparing the two nodes. PG can be made from the relative preference relationship among the nodes (in Figure 2).

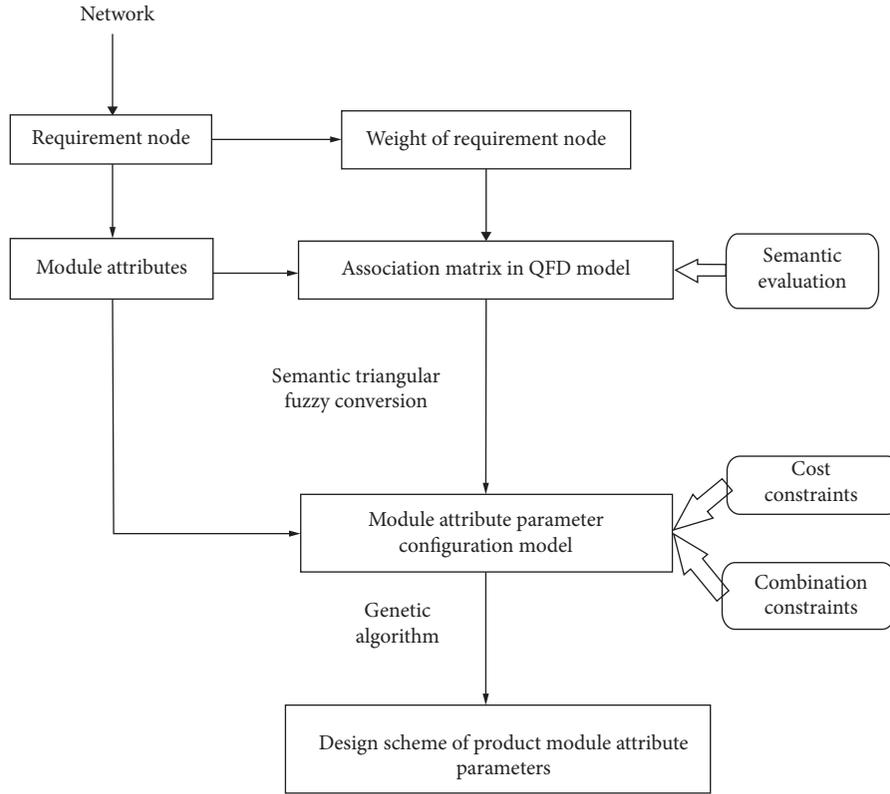


FIGURE 1: Product module parameters configuration model driven by requirements.

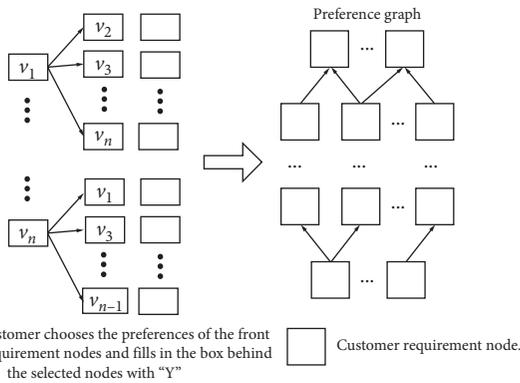


FIGURE 2: PG acquisition of customer requirement node attributes.

The adjacency matrix  $PG^M$  is constructed from PG as follows:  $pg_{ij}$  is the element of the adjacency matrix  $PG^M$ . Its value represents the  $M$ -order dominance of the requirement node  $i$  over the requirement node  $j$ .

The adjacency matrix  $PG^M$  is expressed as

$$PG^M = \begin{bmatrix} pg_{11} & pg_{12} & \cdots & pg_{1n} \\ pg_{21} & pg_{22} & \cdots & pg_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ pg_{n1} & pg_{n2} & \cdots & pg_{nn} \end{bmatrix}. \quad (1)$$

The dominance matrix  $D$  is defined as the sum of the adjacency matrices  $PG^M$  of each order; that is,

$$D = PG^1 + PG^2 + \cdots + PG^M + \cdots + PG^{n-1}. \quad (2)$$

The sum of the  $N$ -line elements of the dominance matrix  $D$  is defined as  $d_N$ , which represents the preference value of the  $N$ th requirement node directly or indirectly relative to other requirement nodes. If  $d_N$  is 0, then the requirement node is suboptimal compared with other nodes. Since the customer has proposed this requirement node, then the customer is concerned about this requirement node and the preference value is 0, which is obviously unreasonable. At this point, the definition adds the value of  $d_N$  to 1 and calculates it accordingly. Then, the relative degree of preference (RDP) is calculated as follows:

$$r dp_N = \frac{(1 + d_N)}{\max_{N=1, \dots, n} (1 + d_N)}, \quad (3)$$

$$RDP = (r dp_1, r dp_2, \dots, r dp_N, \dots, r dp_n).$$

The RDP is normalized and the preference weight vector of the requirement node is obtained:

$$\delta = (\delta_1, \delta_2, \dots, \delta_i, \dots, \delta_n), \quad (4)$$

$$\delta_i = \frac{r dp_i}{\sum_{i=1}^n r dp_i}, \quad i = 1, 2, \dots, N, \dots, n.$$

2.2. Expression of Uncertain Semantic Information. Yoji Aki proposed QFD in the 1970s as a tool for quality development [23]. It is a very important technology to consider the needs of

stakeholders. QFD translates the quality requirements of stakeholders or customers of enterprises, suppliers, and employees into product quality characteristics (as shown in Figure 3).

Traditional QFD requires a group of experts to input a 1–5 or 1–9 scale system corresponding to each quality requirement standard [24] and to qualitatively evaluate the relationship between requirement and quality. So, evaluators must be very familiar with the corresponding content of the scale system in order to complete the evaluation, which is not an easy task. To address these shortcomings, expert uncertain semantics can be well applied to the evaluation system. This sector establishes a fuzzy association evaluation by introducing uncertain semantics. The specific process is as follows.

Firstly, the customer's  $m$  requirements are obtained. Secondly, the relationship between customer requirement nodes and module attribute parameters is evaluated by a group of experts in this field. The evaluation method uses the uncertain semantics proposed above, and different semantics represent different fuzzy trigonometric functions. Thirdly, the fuzzy correlation matrix  $\tilde{R}$  between customer requirement and PMA parameters is constructed by QFD as follows:

$$\tilde{R} = [\tilde{r}_{ij}] = \begin{matrix} & M_1 & \cdots & M_j & \cdots & M_n \\ \begin{matrix} C_1 \\ \vdots \\ C_i \\ \vdots \\ C_m \end{matrix} & \begin{bmatrix} \tilde{r}_{11} & \cdots & \tilde{r}_{1j} & \cdots & \tilde{r}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{r}_{i1} & \cdots & \tilde{r}_{ij} & \cdots & \tilde{r}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \end{matrix} \quad (5)$$

Among them,  $\tilde{r}_{ij}$  is the fuzzy trigonometric mean of the semantic evaluations of  $n$  experts on the relationship between customer needs and PMA parameters:

$$\tilde{r}_{ij} = \frac{1}{n} \times (\tilde{r}_{ij}^1 + \tilde{r}_{ij}^2 + \cdots + \tilde{r}_{ij}^n). \quad (6)$$

**2.3. Computing the Relative Importance of PMA Based on Relative Degree.** How to transform triangular fuzzy numbers into exact values needs to be analyzed by relative degree. *Up*. Operator can deal with this kind of relative relation. This operator is used for corresponding calculation.

Suppose there is a set of fuzzy triangles which are represented by  $\tilde{x}_1, \tilde{x}_2, \tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_a$ . For the expression of the fuzzy triangles as  $\tilde{x} = (x_{il}, x_{ih}, x_{iu})$ , the mean value of the set of fuzzy triangles is  $\bar{x}$ . The calculation of  $\bar{x}$  is as follows:

$$\bar{x} = \frac{1}{n} \times (\tilde{x}_1 + \tilde{x}_2 + \cdots + \tilde{x}_n) = (\bar{x}_l, \bar{x}_h, \bar{x}_u). \quad (7)$$

*Up*. Operator relative degree calculation of fuzzy trigonometric number is defined as

$$Up(\tilde{x}_i, \bar{x}_i) = \frac{1}{2} \times \left( \frac{(x_{il} - \bar{x}_u) + 2(x_{ih} - \bar{x}_h) + (x_{iu} - \bar{x}_l)}{2Ts} + 1 \right), \quad (8)$$

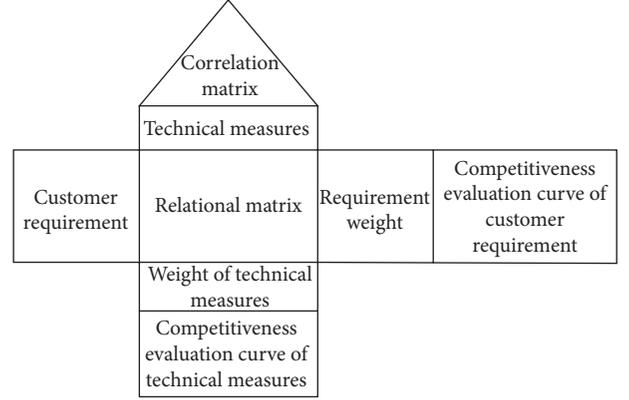


FIGURE 3: QFD framework.

where  $\|Ts\|$  is

$$\|Ts\| = \begin{cases} \frac{(g_{sl}^+ - g_{su}^-) + 2(g_{sh}^+ - g_{sh}^-) + (g_{sl}^+ - g_{sl}^-)}{2}, & g_{sl}^+ \geq g_{su}^-; \\ \frac{(g_{sl}^+ - g_{su}^-) + 2(g_{sh}^+ - g_{sh}^-) + (g_{sl}^+ - g_{sl}^-)}{2} + 2(g_{su}^- - g_{sl}^+), & g_{sl}^+ < g_{su}^- \end{cases} \quad (9)$$

In formula (9), the other variables are

$$\begin{aligned} g_{sl}^+ &= \max_i \{x_{il}\}, g_{sh}^+ = \max_i \{x_{ih}\}, g_{su}^+ = \max_i \{x_{iu}\}, \\ g_{sl}^- &= \min_i \{x_{il}\}, g_{sh}^- = \min_i \{x_{ih}\}, g_{su}^- = \min_i \{x_{iu}\}. \end{aligned} \quad (10)$$

The relative importance of the fuzzy triangle number can be obtained by the above calculation. According to the calculation of fuzzy semantics expression of the relationship between customer requirements and module attributes,  $Up(\tilde{r}_{ij}, \bar{r}_{ij})$  can be defined as the relative correlation degree between module attributes  $M_j$  and customer requirements  $CR_i$ .

Finally, by multiplying the customer requirement weight vector  $I$  with the relative correlation degree value, the weight vector  $J$  of module attribute parameters is obtained. That is to say,

$$\omega_j = \sum_{i=1}^m \eta_i \times Up(\tilde{r}_{ij}, \bar{r}_{ij}), \quad (11)$$

where  $\bar{r}_{ij}$  is the mean value of the fuzzy trigonometric function of the correlation relationship of PMA corresponding to customer requirement  $i$ .

### 3. Establishment and Solution of PMA Combination Model

According to the customer's requirements, how to establish the relationship with the product model to facilitate the design of products by technicians can be achieved through the combination of module attributes corresponding to the product service system. This method optimizes the design steps and quickly transforms the nonspecialized requirements

put forward by customers into the specialized requirements of products.

**3.1. Objective Function.** For mechanical and electrical products, the product modules can be divided into qualitative and quantitative methods according to their characteristics. The quantitative parameters can be standardized through the characteristic types of benefit and cost, and the process is as follows.

For the benefit-based quantitative product module parameters, the normalized return value of PMA is solved as follows:

$$x_j^p = \frac{V_j^p - \min_t V_j^p}{\max_t V_j^p - \min_t V_j^p}, 1 \leq j \leq n. \quad (12)$$

For the cost-based quantitative product module parameters, the normalized return value of PMA is solved as follows:

$$x_j^p = \frac{\max_t V_j^p - V_j^p}{\max_t V_j^p - \min_t V_j^p}, 1 \leq j \leq n. \quad (13)$$

In the equation,  $v_j^p$  is the first corresponding attribute parameters value of module attribute  $j$ .  $x_j^p$  is the corresponding income value of  $v_j^p$ , and  $t$  is the number of attribute parameters; that is,  $1 < p < t$ .

For the determination of the profit value of the qualitative product module parameters, the profit values of the different attribute parameters corresponding to the module can be obtained by means of the expert semantic judgement in Section 3.1.

The profit values of product module attribute parameters can be obtained by the above two methods respectively, which are exact values, and the parameters of the product model are composed of module attribute parameters. Thus, the fitness function  $f_s$  of the product module parameters combination model can be established by the idea of product configuration.

The fitness function  $f_s$  is constructed as follows:

$$\max f_s = \max \sum_{j=1}^n \sum_{p=1}^t \omega_j (x_j^p X_j^p). \quad (14)$$

In the equation, the value of  $X_j^p$  is whether the parameter  $x_j^p$  corresponding to the property of the  $j$ th module is selected.

**3.2. Constraint Condition.** In the process of configuration of the PMA composite model, there are constraints among module attributes, which affect the rationality of the product model, and the corresponding constraints are established. Specifically,

- (1) When configuring parameters attributes, a module attribute parameter combination, the corresponding

module attribute parameter has only one value taken in. It can be expressed as follows:

$$\begin{aligned} X_j^p &\in \{0, 1\}; \\ \sum_{p=1}^t X_j^p &= 1, \quad \text{for } \forall j. \end{aligned} \quad (15)$$

For the  $P$  parameters  $x_j^p$  corresponding to the  $j$  module attribute, when selected,  $X_j^p = 1$ ; otherwise,  $X_j^p = 0$ .

- (2) When determining the combination set of PMA parameters, the cost constraints of products should be considered. That is to say,

$$\sum_{j=1}^n \sum_{p=1}^t C_j^p X_j^p \leq C_{\Delta}, \quad (16)$$

where  $C_j^p$  is the manufacturing cost of the attribute parameters of the  $P$  module corresponding to the  $j$  module, and  $C_{\Delta}$  is the cost constraint set by the enterprise.

- (3) There are physical constraints, geometric constraints, and other constraints and associations among module attribute parameters, so compatibility constraints need to be considered. In module replacement, there are some module attribute parameters that cannot coexist and need to be constrained, which can be expressed by 0-1 matrix:

$$M = \begin{bmatrix} \phi_{1p_1,1p_1} & \cdots & \phi_{1p_1,jp_j} & \cdots & \phi_{1p_1,np_n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \phi_{jp_j,1p_1} & \cdots & \phi_{jp_j,jp_j} & \cdots & \phi_{jp_j,np_n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \phi_{np_n,1p_1} & \cdots & \phi_{np_n,jp_j} & \cdots & \phi_{np_n,np_n} \end{bmatrix}. \quad (17)$$

In this matrix, when  $\phi_{i p_i, j p_j} = 1$ , the parameter  $p_i$  of  $M_i$  in PMA is consistent with the parameter  $p_j$  of  $M_j$  in PMA; otherwise  $\phi_{i p_i, j p_j} = 0$ .

Since the combination of PMA parameters is feasible, the compatibility conditions must be satisfied, namely,

$$\phi_{i p_i, j p_j} = \begin{cases} 1 & X_i^{p_i} \times X_j^{p_j} = 1, \\ \{0, 1\} & X_i^{p_i} \times X_j^{p_j} \neq 1. \end{cases} \quad (18)$$

**3.3. Combination Programming Model.** Through the objective function and constraints of the product attribute parameters combination programming model, the final mathematical model is established as follows:

$$\left\{ \begin{array}{l} \max f_s = \max \sum_{j=1}^n \sum_{p=1}^t \omega_j(x_j^p X_j^p); \text{ s.t. } \sum_{p=1}^t X_j^p = 1, \text{ for } \forall j; \sum_{j=1}^n \sum_{p=1}^t C_j^p X_j^p \leq C_{\Delta}; \phi_{i p_i, j p_j} = \begin{cases} 1 & X_i^{p_i} \times X_j^{p_j} = 1, \\ \{0, 1\} & X_i^{p_i} \times X_j^{p_j} \neq 1, \end{cases} \end{array} \right. \quad (19)$$

#### 4. Solution of the Model

Because of the diversity of PMA parameters, there exists a problem of "combinatorial explosion" in the product attribute parameters combination programming model established above, which is difficult to implement by the exhaustive method. The genetic algorithm (GA) is a bio-simulation algorithm with high parallelism and adaptability [25, 26]. Compared with traditional optimization methods (enumeration, heuristics, etc.), the genetic algorithm has good convergence with biological evolution as the prototype and has the advantages of less computation time and high robustness when the calculation accuracy is required. Based on its characteristics, this paper uses the improved genetic algorithm to solve the problem. As shown in Figure 4, the specific flow of the algorithm is as follows:

*Step 1.* Parameters settings: Set the genetic algebra to  $M$ , population size  $P_0$ , crossover probability  $P_t$ , and mutation probability  $P_m$ .

*Step 2.* Coding: Binary coding is used to ensure the breadth of search, and a configuration scheme corresponds to a chromosome individual.

*Step 3.* Initialize and randomly generate the initial population  $G_0$ .

*Step 4.* Chromosome repair and fitness evaluation, for the generation of chromosomes that do not conform to the constraints in the iteration process of the algorithm adopts the strategy of repair and punishment.

*Step 5.* Selection: According to the competitive strategy, this paper uses roulette to selection.

*Step 6.* Crossover: Two individuals were randomly selected from the mating pool by uniform crossover, and the chromosome genes were partially exchanged to obtain new individuals. When the new individuals meet the constraints, they will be preserved as new individuals. Otherwise, they will be eliminated.

*Step 7:* mutation. Single locus mutation was used. Individuals are randomly selected, and the genes on their chromosomes are randomly changed. A new individual is obtained and returned to Step 4. If the conditions are not met, repeat the above steps; otherwise, move to Step 8.

*Step 8:* output the final solution.

#### 5. Case Study

As a typical mechanical and electrical product, AGV is equipped with optical or electromagnetic automatic guidance devices, which can travel along a predetermined trajectory. At the same time, it is also a kind of transport vehicle

which is widely used in warehousing industry and manufacturing industry with safety protection and various transfer functions. This paper takes AGV as an example (as shown in Figure 5) to solve the transformation of customer requirements.

Customer requirements for enterprises include strong power ( $CR_1$ ), stability and reliability ( $CR_2$ ), strong carrying capacity ( $CR_3$ ), flexible action ( $CR_4$ ), fast service response ( $CR_5$ ), and moderate price ( $CR_6$ ).

Enterprise basic module attributes correspond to vehicle width ( $M_1$ ), load ( $M_2$ ), guidance mode ( $M_3$ ), parking accuracy ( $M_4$ ), walking speed ( $M_5$ ), turning radius ( $M_6$ ), safety factor ( $M_7$ ), and service maintenance strategy ( $M_8$ ). Fifteen experts in related fields use the semantic evaluation and triangular fuzzy number in Table 1 to transform the semantic evaluation of requirement and module attributes into a fuzzy triangular number and then use formulas (8) and (9) to transform into fuzzy importance.

Fifteen experts evaluated the relationship between customer requirements and module parameters. After statistics, tables were drawn, as shown in Table 2.

From the above table, we can get the relational matrix between  $CR_i$  and  $M_j$  and get the relative definite value of the relational relationship by formulas (6) and (7), as shown in Table 3.

The preference weight vector of customer requirement nodes can be obtained as  $\eta = (0.218, 0.170, 0.189, 0.173, 0.250)$  by using PG method, And the preference weights vector of customer requirement nodes are obtained as  $\delta = (0.475, 0.515, 0.455, 0.541, 0.505, 0.388, 0.503, 0.620)$ .

After normalization, the results are as follows:

$$\omega = (0.119, 0.129, 0.114, 0.135, 0.126, 0.097, 0.126, 0.155).$$

The values of attribute parameters and the corresponding cost values of the AGV module obtained by the product service platform are shown in Table 4. The guided mode ( $M_3$ ) and service maintenance strategy ( $M_8$ ) belong to qualitative parameters expression, which needs to be transformed into quantitative parameters expression. In this paper it can be referred to the previous description and the relative relationship can be calculated using expert evaluation to achieve the transformation from qualitative to quantitative.

The relative importance expression of qualitative parameters of the guided mode ( $M_3$ ) in AGV module attributes is shown in Table 5.

The relative importance of service maintenance policy ( $M_8$ ) in AGV module attributes is shown in Table 6.

According to market survey, the moderate  $CR_5$  is 180,000–200,000. Enterprises can divide it into three price scales: 180000, 190000, and 200000. The price indexing is

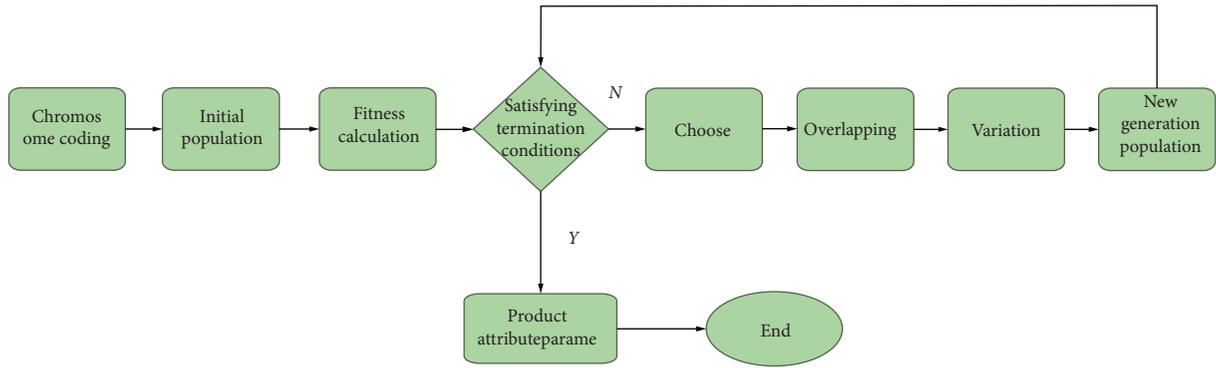


FIGURE 4: Genetic algorithms flow diagram.

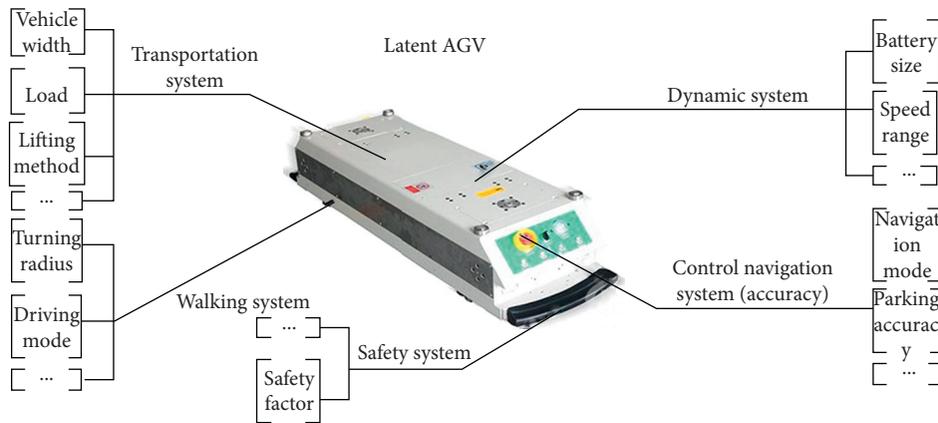


FIGURE 5: AGV structure and attribute description diagram.

TABLE 1: Conversion between semantic evaluation and triangular fuzzy numbers.

Semantic evaluation	VL	L	M	H	VH
Triangular fuzzy number	(0, 0, 0.3)	(0, 0.3, 0.5)	(0.3, 0.5, 0.7)	(0.5, 0.7, 0.9)	(0.7, 1, 1)

TABLE 2: Semantic evaluation of the relationship between customer requirements and module attributes.

	Semantic evaluation variables					Fuzzy relevance relation
	VL	L	M	H	VH	
$r_{11}$	0	0	2	5	8	(0.58, 0.83, 0.93)
$r_{12}$	1	9	2	2	1	(0.15, 0.41, 0.6)
$r_{13}$	3	10	2	0	0	(0.04, 0.27, 0.49)
$r_{14}$	3	11	1	0	0	(0.02, 0.25, 0.47)
...						
$r_{45}$	0	3	3	7	2	(0.39, 0.62, 0.79)
$r_{46}$	0	0	3	10	2	(0.49, 0.70, 0.87)
$r_{47}$	0	2	10	2	1	(0.31, 0.53, 0.72)
...						
$r_{56}$	9	4	2	0	0	(0.04, 0.15, 0.41)
$r_{57}$	4	8	3	0	0	(0.06, 0.26, 0.49)
$r_{58}$	0	0	1	4	10	(0.62, 0.89, 0.95)

TABLE 3: Precise values of the relationship between customer requirements and module attribute parameters.

Relation	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$	$M_7$	$M_8$
CR <sub>1</sub>	0.79	0.44	0.33	0.31	0.78	0.29	0.51	0.56
CR <sub>2</sub>	0.35	0.51	0.33	0.79	0.29	0.41	0.79	0.53
CR <sub>3</sub>	0.38	0.83	0.61	0.42	0.41	0.33	0.46	0.58
CR <sub>4</sub>	0.44	0.41	0.53	0.55	0.51	0.62	0.41	0.51
CR <sub>5</sub>	0.38	0.42	0.48	0.66	0.48	0.34	0.40	0.84

TABLE 4: AGV module properties and costs.

Modular	Module attributes		Parameters/cost (RMB)
Transportation system	$M_1$	Vehicle width	0.6 m/5000, 0.8 m/8000 1.0 m/10000, 1.2 m/15000
	$M_2$	Load	300 kg/2000, 500 kg/3000 800 kg/6000, 1000 kg/8000
Control system	$M_3$	Guidance mode	Magnetic strip/20000, electromagnetic type/35000, laser type/50000
	$M_4$	Parking accuracy	15 mm/30000, 20 mm/17500, 25 mm/12500
Dynamic system	$M_5$	Speed	0–45 m/min/15000, 0–60 m/min/25000 0–72 m/min/40000
Walking system	$M_6$	Turning radius	500 mm/55000, 600 mm/45000 800 mm/40000
Safety system	$M_7$	Safety factor	0.6/15000, 0.8/25000, 1.0/50000
Service support	$M_8$	Service maintenance strategy	Strategy 1/8500, strategy 2/11500, strategy 3/15000

TABLE 5: Relative importance of qualitative parameters of guidance mode ( $M_3$ ).

$M_3$	Semantic evaluation					Fuzzy importance	Relative importance
	VL	L	M	H	VH		
Magnetic strip	3	10	2	0	0	(0.04, 0.27, 0.49)	0.32
Electromagnetic type	0	2	11	2	0	(0.29, 0.50, 0.70)	0.49
Laser type	0	0	2	8	5	(0.54, 0.77, 0.91)	0.75

TABLE 6: Relative importance of qualitative parameters of service maintenance strategy ( $M_8$ ).

$M_8$	Semantic evaluation					Fuzzy importance	Relative importance
	VL	L	M	H	VH		
Strategy 1	2	10	3	0	0	(0.06, 0.30, 0.51)	0.25
Strategy 2	0	1	9	5	0	(0.35, 0.55, 0.75)	0.51
Strategy 3	0	0	2	6	7	(0.57, 0.81, 0.92)	0.74

used as the constraint  $C_\Delta$  and substituted into the product attribute parameters configuration model. At the same time, for the constraints, the laser safety factor 0.6 corresponding to  $M_3$  and  $M_7$  cannot be satisfied simultaneously.

According to the PMA combinatorial model proposed in this paper, the iteration curves of attribute parameters of AGV module with  $C_\Delta$  of 180000, 190000, and 200000 price indexing are obtained by genetic algorithm, respectively. Figure 6 shows the iteration curves of attribute parameters of AGV module with  $C_\Delta$  of 180000, 190000, and 200000 price indexing.

From the result of the genetic algorithm, we can get the optimal selection scheme and fitness function at different prices. The final result is shown in Table 7.

According to the configuration scheme of module parameters under different prices, we can get the change image of product module parameters as shown in Figure 7.

Figure 7 shows that there is variation in the configuration of the product parameter attributes under different price constraints, mainly due to the benefits of fitness function corresponding to different options of product attribute parameters. Under cost constraints of 190,000 RMB and 200,000 RMB, the parameters options corresponding to  $M_8$  in PMA have changed.  $M_83$  has improved relative to  $M_82$  product service maintenance strategy, and relative to the whole product revenue value has also increased. From the result of the whole PMA configuration scheme, compared with the PMA parameters of the market price in this

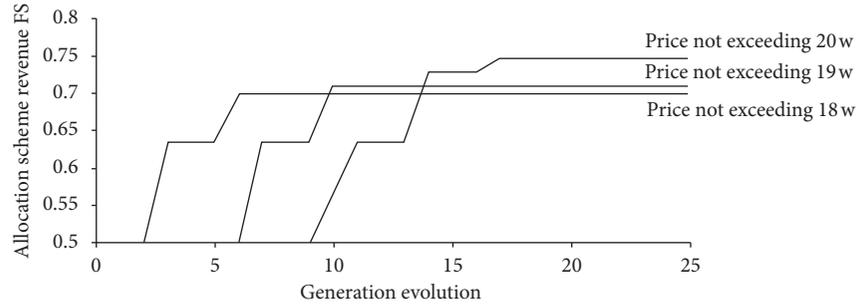


FIGURE 6: Calculation of PMA parametric allocation income at different prices.

TABLE 7: Optimal options at different prices.

$C_{\Delta}$	$f_s$	Module parameters configuration scheme
180000	0.696	$M_{14}, M_{24}, M_{31}, M_{41}, M_{52}, M_{62}, M_{72}, M_{82}$
190000	0.712	$M_{13}, M_{24}, M_{31}, M_{41}, M_{53}, M_{62}, M_{72}, M_{82}$
200000	0.749	$M_{13}, M_{24}, M_{31}, M_{41}, M_{53}, M_{62}, M_{72}, M_{83}$

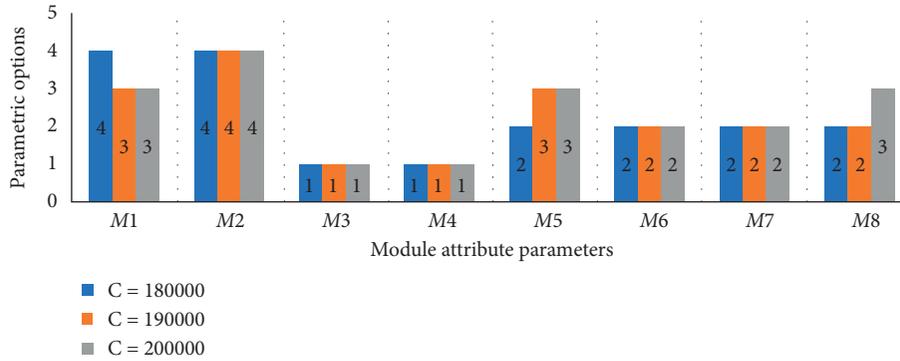


FIGURE 7: Module attribute parameters configuration at different price levels.

area, there are also some improvements. Therefore, this model can obtain the optimal configuration of product attribute parameters under different cost constraints. Enterprises can feed back the appropriate price level or price range to customers, and the customers can determine the required price. Then, the final PMA parameters configuration scheme is determined by price, which lays the foundation for the subsequent scheme design.

### 6. Conclusion

In order to make personalized customized products more satisfy the requirements of customers, the factors of customer requirement preference should be fully considered in the process of product configuration. In this paper, PG is used to get the adjustment vector from customer requirement preference and further complete the configuration of module attribute parameters.

The main contributions of this paper are as follows:

- (1) Using QFD as a tool, the relationship between customer requirement nodes and product model attributes is established through semantic evaluation, which facilitates the expression of experts and

overcomes the shortcomings of traditional fractal expression.

- (2) It establishes the revenue function, realizes the transformation from customer requirement to product parameters, and provides the optimal PMA combination parameters to meet customer requirements at different costs.
- (3) It takes customer requirement preference into consideration in this study and uses the requirement preference vector obtained by preference graph to adjust the weight vector of module attribute parameters.

In view of the shortcomings of the research on customer satisfaction of product configuration results in this paper, we are going to continue to explore the establishment of an effective feedback evaluation system in future research.

### Data Availability

The data in this paper were used for the production of AGVs at Gen-Song Technology, some of which are not readily available due to the company’s knowledge protection.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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