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Research on Optimization Strategies for Functional Modules of Smart Home Products Based on Parameterization

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ABSTRACT

The article firstly outlines the concept of parametric design and modeling techniques and processes, then expresses the relationship between customer needs and functional design parameters of smart home products with discrete sensitivity matrix, and introduces the fuzzy pairwise comparison method to calculate the importance of customer needs. The correlations in the dataset are mined on the Rough Set (RS) tool. AGO and IAGO are used to predict the customer demand importance and design parameter importance in the future cycle, and the parametric product family optimization model is solved by combining the non-occupancy sorting genetic algorithm with congestion distance. In this paper, the optimization ranking and core parts of the functional modules of the smart flowerpot are obtained through the parametric smart home design method, and the functional rankings of the modules are automatic irrigation function, intelligent light replenishment function, monitoring function, and human-computer interaction function; the core parts include temperature and humidity sensors, light sensors, water tanks, and single-chip microcomputer parts, and so on. In the intelligent flowerpot product family design, this paper finds that the efficiency of this paper's optimization method increases significantly (4.23%-9.12%) and the weight of the product decreases significantly (0.1141kg-0.617kg), both in the known platform mode and in the unknown platform mode. The results of this paper are extremely important for the development and design of parametric product families based on platforms.

Keywords: Parametric design, Fuzzy pairwise comparison, Rough set (RS), Genetic algorithm, Parametric product family optimization model

1. Introduction

With the arrival of the big data era, mankind has entered the age of intelligence, artificial intelligence products instead of mass production workers on the production line or robots, behind the changes is the ubiquitous technological innovation, artificial intelligence has brought emerging technologies to

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society [1-2]. The state advocates the "development of intelligent industry, expanding intelligent life", traditional industrial products will be integrated into the design of intelligence, intelligence will be the theme of future design, traditional furniture design is certainly no exception [3-4].

Through the use of network communication technology, computer technology, automatic control technology and security technology and other key technologies, it will be closely connected with the facilities related to home life, and jointly build a highly efficient operation of the family affairs management system and residential facilities management system, which is called the smart home, and the main purpose of the smart home is to improve the convenience, comfort and safety of the home [5-6]. The above mentioned smart home technology is called the key technology of smart home, relying on China's management platform, to carry out scientific and integrated management of all aspects of home life, so that life becomes intelligent [7-8].

Smart home along with the improvement of material level and the continuous development of science and technology, residents for the safety and comfort of life put forward higher requirements, at the same time thanks to the development and maturity of high-speed Internet technology and the Internet of Things technology, to further promote the in-depth development of the smart home. The smart home control system was firstly chosen to be built by telephone or GSM network and realized remote control with the help of Internet technology [9-12]. The smart home embodies many characteristics of networking, remote and intelligent from the very beginning [13]. At this stage, there are still some problems in the field of smart home in China, mainly in the performance is not stable enough, the product function is not perfect, the industry standards and norms are not unified, and there are many brands of uneven quality. Most of the home consumers have many misunderstandings about the smart home, while hesitating in the purchase process [14-16]. Overall, the consumer market for the smart home requirements, it has a stable performance, reasonable price, easy to use, and at the same time can realize intelligent control [17].

Module in a broad sense can be understood as the composition of the upper layer of the system, can be combined, replaced, variant units. According to the hierarchy, it can be divided into the whole machine, components, parts, structural units and other modules, and according to the generality of the division, it can be divided into general-purpose modules, specialized modules [18-20]. Module in the narrow sense can be understood as a module, the broader definition of the basis, so that the module unit has independent functions and standard interface constraints requirements, the most important feature is to have independent functions. Modularity contains a basic unit concept, module family, refers to a group of modules with the same or similar shape and characteristics of the combination [21-23].

Smart home is not only a single furniture product, but a whole set of integrated problem solutions [24]. First of all, the smart home needs to have an intelligent processing center, according to the demand for integrated configuration of the functions of the modules, or through the Smartlink terminal system, remote login to the center for management. Security control electronic control government center and multimedia center, etc. are the basic functions of the modular design of the smart home [25-27].

Firstly, some researchers have studied and discussed the current status of smart home practice, functional characteristics, and advantages and disadvantages through literature review, questionnaire survey and other analytical and descriptive methods, which have deepened people's understanding of smart home. Literature [28] analyzed the advantages and risks of smart furniture technology (sht) in a multi-dimensional way based on a questionnaire survey to obtain users' perceptions of smart furniture, pointing out that policy makers can support the development of smart home by setting design and operation standards, conducting data and privacy guidelines, and promoting quality control and field research programs.

Literature [29] enumerates the benefits and risks associated with smart homes through smart home primary data collection, information acquisition from expert interviews, and a systematic review of smart home-related research literature, and targets seven policy recommendations in favor of the good development of smart homes. Meanwhile, some scholars focus on the integration of smart home and Internet of Things and security issues, and conduct in-depth research on the performance of smart home system framework. Literature [30] combines current research on IoT frameworks and different components, builds an overall framework to facilitate the integration of smart furniture and IoT, and conceptualizes a smart furniture management model based on it. Literature [31] provides an in-depth analysis of the core components as well as the functions of the smart home, into the high-resource devices that handle the communication, and numerically analyzes to corroborate the security performance of the proposed BC smart home framework.

Some researchers have also considered the compatibility of smart home management, convenience and user personalization and other demands, and conducted in-depth research on the modular design of smart home. Literature [32] explored the compatibility problem of smart home systems and proposed mass customization and modular design solutions to cope with the compatibility problem of smart home systems. Literature [33] analyzes the mobile terminal application management and WEB server intelligent management scheme in order to improve the convenient management of smart devices in smart home systems, and proposes a modular design scheme to realize the convenient and intelligent management of smart home devices. Literature [34] obtains users' needs for smart home through big data analysis and innovates with the application of modular design in smart home to meet the personalized needs of smart home users.

In this paper, the sensitivity analysis method is used to determine the sensitivity of customer demand to each design parameter, and it is used as an important basis for identifying the parameters of product functional modules. The sensitivity degree is obtained by utilizing the bias derivative or the ratio of the amount of change between the two according to the relationship between customer demand and design parameters. The fuzzy pairwise comparison method is used to calculate the importance of customer demand in the past cycle, and the importance of future customer demand is accurately predicted on the gray prediction model. After that, the parametric product family optimization design is classified, two different design ideas and methods of parametric product family are introduced, and the parametric product family integrated optimization model is proposed. And the non-occupancy sorting genetic algorithm based on congestion distance, including non-occupancy sorting, crossover and mutation of chromosomes, and the processing method of constraints, is elaborated to solve the optimization model. Finally, the application effect of the model is simulated and verified.

2. Parameterization-based Optimization Method for Functional Modules of Smart Home Products

2.1. Parametric design

2.1.1. Parametric design concepts. The computational and parametric tools of parametric design can benefit architectural design in an increasingly urbanized and turbulent environment. A complete design system that includes the trinity of parametric design thinking, parametric modeling techniques, and rapid prototyping. Parametric design, or parametric design, employs a series of tools and algorithms to generate design solutions by adjusting computer parameters. Parametric design is the design of all aspects and stages of the work, through the mathematical model to control, in order to improve design efficiency. The core idea of parametric design is “parameter transfer”. Its essence is to free the designer from complicated calculations and data processing work, and put more energy into the control of the design process, i.e., to improve the design efficiency through parametric methods. In the design process, different design requirements and constraints are data into different parameters and associated together, thus constituting a kind of parametric model that can be described by computer, and the designer can quickly obtain a variety of product form solutions by adjusting each parameter. The use of computer-aided modeling for the parametric design of bionic forms can have strong logic and systematicity in the design process, which increases the flexibility of the appearance design of bionic products.

2.1.2. Parametric modeling techniques. Parametric modeling technique is a digital modeling technique defined as the use of data, numbers and algorithms to design complex geometries through computer programmable and/or algorithm-based tools. These tools are usually in the form of computer programs, software and software accessories and are considered parametric tools. Commonly used parametric modeling tools include Rhino, Catia, AutoCAD, Matlab and Maya. In contrast to traditional modeling systems, parametric modeling is an algorithm-based technique for designing and modeling geometries that can be altered, defined, or coded with parameters and variables. Parametric modeling allows for significant functional and typological versatility in design generation and modification by simply changing parameters without recoding or re-modeling.

2.1.3. Parametric Design Process. Parametric design utilizes the rules of each feature variable as the basis of parametric design. Each variable parameter represents a key characteristic, which may be quantity, structure, volume or some mathematical or physical qualities, and the interrelationships between the linkage structure of each feature of the design and the data are used to generate the base form of the design. In parametric design, the data of a variable represents the parameters of a feature. For example, a quantity in a design feature may be a physical or mathematical quantity. Parametric design represents the variable as a parameter of a certain base form, and the parameters and data interact with each other to influence the final form of a design feature. Parametric design mainly solves the correlation between different features while designing, so that different products can have common basic attributes, which makes the products have a better consistency. Parametric modeling method has the advantages of improving modeling speed, easy to modify the model, etc. It can greatly improve the efficiency of modeling work in geometric modeling and scheme modification.

The essence of parametric modeling is the modeling expression of the product under a set of constraints, in the parametric software, Rhino's Grasshopper modeling platform allows the designer to program through the visualization of the battery operation program, which greatly reduces the complexity of the program, so that more users can use the programming method to model the model, which gives the design solution to bring more Possibilities. Parametric design can give full play to its function in the bionic form of the product, and its design process is similar to the top-down design process of the product, which is to determine the target design requirements first, and then carry out the form design. In the parametric design process of product morphology, dynamic analysis is carried out by adjusting the parameters of the morphology, and finally the designer optimizes the product design to achieve the morphology design result that meets the design requirements. The parametric design process of product form is shown in Figure 1.

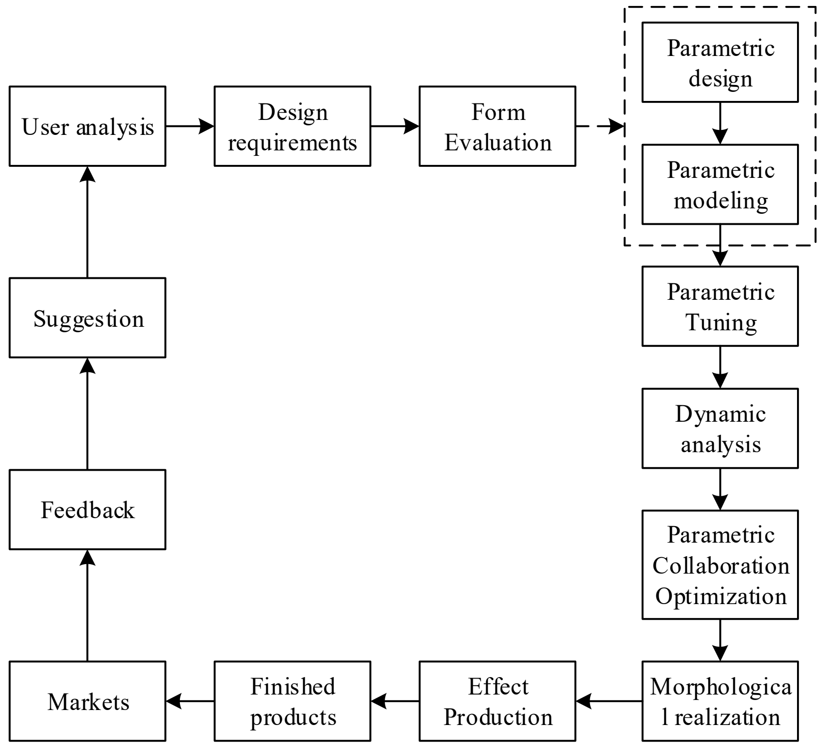

Fig. 1. The parameterized design process of product form

2.2. Functional parameter identification of smart home products based on improved QFD

2.2.1. Discrete sensitivity matrix construction. When the relationship between customer requirements and design parameters can be explicitly expressed as a mathematical function, the sensitivity matrix of the design parameters can be obtained through the partial derivation operation [35] as follows:

$$E = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_t} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_2}{\partial x_t} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \cdots & \frac{\partial f_n}{\partial x_t} \end{bmatrix} \tag{1}$$

When the relationship between customer demand and design parameters is difficult to be expressed directly by mathematical functions, it is necessary to first discretize the values of the design parameters to determine the value levels of the design parameters, and then calculate the sensitivities of the design parameters by using the approximate differentiation method $(\Delta f / \Delta x)$ instead of the partial differentiation method $(\partial f / \partial x)$. The discretized sensitivity matrix E° is as follows:

$$E^{\circ}=\begin{bmatrix}\dfrac{\Delta f_1}{\Delta x_1} & \dfrac{\Delta f_1}{\Delta x_2} & \cdots & \dfrac{\Delta f_1}{\Delta x_t}\\ \dfrac{\Delta f_2}{\Delta x_1} & \dfrac{\Delta f_2}{\Delta x_2} & \cdots & \dfrac{\Delta f_2}{\Delta x_t}\\ \vdots & \vdots & \ddots & \vdots\\ \dfrac{\Delta f_n}{\Delta x_1} & \dfrac{\Delta f_n}{\Delta x_2} & \cdots & \dfrac{\Delta f_n}{\Delta x_t}\end{bmatrix} \tag{2}$$

where: $\Delta f_j / \Delta x_i$ - sensitivity of design parameter x_i to customer demand f_j;

n - the number of customer demands;

t - the number of design parameters.

2.2.2. Calculation of design parameter sensitivity. In order to reasonably compare the sensitivity of the design parameters, the customer demand values were standardized:

$$f^{*}=\frac{f-f_{\min}}{f_{\max}-f_{\min}} \tag{3}$$

where, $f_{\max}$, $f_{\min}$, f, f^{*} - the maximum, minimum, current and standard values of customer demand.

During the experiment, the value of customer demand f_j is recorded as f^{j} when the design parameter value combination $x^{*}=\left\{x_1^{k_1}, x_2^{k_2}, \cdots, x_t^{k_t}\right\}$ is entered, where $1 \le k_i \le K_i$, $x_i^{k_i} \in \left\{x_i^{k_1}, x_i^{k_2}, \cdots, x_i^{K_i}\right\}$, $i=1,2,\cdots,t$, $j=1,2,\cdots,n$. Keeping the other design parameter values unchanged, the value of x_i is controlled so that it increases and decreases by $\Delta x_i^{k_r}$ at the value level $x_i^{k_r}$, respectively. Repeat the experiment and record the new values of customer demand f_j as f_{+}^{j} and f_{-}^{j}. Then the sensitivity of design parameter x_i to customer demand f_j at value level $x_i^{k_r}$ in that (h th) experiment is:

$$\left.\frac{\Delta f_j}{\Delta x_i}\right|_{x_i^{kr}}=\left|\frac{\left(f^{j*}-f_{+}^{j*}\right)+\left(f^{j*}-f_{-}^{j*}\right)}{2\Delta x_i^{k_r}}\right| \tag{4}$$

where $\Delta x_i^{k_r}$ - a very small positive number:

$f^{j*}, f_{+}^{j*}, f_{-}^{j*}$ - a standardized value of $f^{j}, f_{+}^{j}, f_{-}^{j}$.

Since the same level value of design parameter x_i occurs in several trials in the orthogonal test scheme, in order to improve the accuracy of the sensitivity calculation, the average of several sensitivities obtained at the same value level is defined as the sensitivity of x_i at that value level. Then the sensitivity of design parameter x_i at the taken level $x_i^{k_r}$ is:

$$\left.\frac{\Delta f_j}{\Delta x_i}\right|_{x_i^{k_r}}=\frac{\left.\dfrac{\Delta f_j}{\Delta x_i}\right|_{x_i^{k_r}}^{1}+\left.\dfrac{\Delta f_j}{\Delta x_i}\right|_{x_i^{k_r}}^{2}+\cdots+\left.\dfrac{\Delta f_j}{\Delta x_i}\right|_{x_i^{k_r}}^{m}}{m} \tag{5}$$

where, m - the number of times the value level $x_i^{k_r}$ is taken to occur in the test.

2.3. Forecast of Customer Demand Importance

2.3.1. Customer Segmentation:

1) Definition and expression of customer needs. In this paper, the fuzzy pairwise comparison method [36] is introduced to calculate the importance of customer needs in the past cycle. The relative importance between customer demand CR_i and customer demand CR_j is expressed by triangular fuzzy affiliation function $t_{ij} = \left(t_{ijl}, t_{ijg}, t_{iju}\right)$. The relative importance of the fuzzy affiliation function is graded as follows: extremely unimportant A = 0-3, unimportant B = 2-5, generally important C = 5-7, relatively important D = 7-9, and very important E = 9.

After two-by-two comparison of customer requirements to obtain relative importance, considering all customer requirements $CR_1, CR_2, \cdots CR_M$, the fuzzy pairwise comparison method results in a $M \times M$ relative importance matrix A as follows:

$$A = \begin{bmatrix} 1 & \left(t_{12l}, t_{12g}, t_{12u}\right) & \cdots & \left(t_{1Ml}, t_{1Mg}, t_{1Mu}\right) \\ \left(t_{21l}, t_{21g}, t_{21u}\right) & 1 & \cdots & \left(t_{2Ml}, t_{2Mg}, t_{2Mu}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(t_{M1l}, t_{M1g}, t_{M1u}\right) & \left(t_{M2l}, t_{M2g}, t_{M2u}\right) & \cdots & 1 \end{bmatrix} \tag{6}$$

where, when $i \neq j$, $\left(t_{jil}, t_{jig}, t_{jiu}\right) = \left(1/t_{ijl}, 1/t_{ijg}, 1/t_{iju}\right)$; when $i = j$, $\left(t_{jil}, t_{jig}, t_{jiu}\right) = (1,1,1)$.

In this paper, the fuzzy logarithmic least squares method is introduced to solve the optimization model to obtain the triangular fuzzy weight vector $\Omega = \left(\omega_1, \omega_2, \cdots \omega_M\right)$. The optimization model is as follows:

$$\begin{aligned} M\inf = \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} \Big(& \left(\ln \omega_{il} - \ln \omega_{ju} - \ln t_{ijl}\right)^2 + \left(\ln \omega_{ig} - \ln \omega_{jg} \right. \\ & \left. - \ln t_{ijg}\right)^2 + \left(\ln \omega_{iu} - \ln \omega_{jl} - \ln t_{iju}\right)^2 \Big) \end{aligned} \tag{7}$$

$$s.t. \begin{cases} \omega_{il} + \sum_{j=1, j\neq i}^{n} \omega_{ju} \geq 1 \\ \omega_{iu} + \sum_{j=1, j\neq i}^{n} \omega_{jl} \leq 1 \\ \sum_{i=1}^{n} \omega_{jg} = 1 \\ \sum_{i=1}^{n} \left(\omega_{jl} + \omega_{iu}\right) = 2 \\ 0 < \omega_{jl} \leq \omega_{jg} \leq \omega_{iu} < 1 \end{cases} \tag{8}$$

After solving the model, the triangular fuzzy number $\omega_i = \left(\omega_{il}, \omega_{ig}, \omega_{iu}\right)$ is the importance of each customer demand.

2) Calculation of relative importance and weight of customer needs. Using RCR_m to represent the importance of the m rd customer demand, using N_i to represent the number of customers with the same preference as customer C_i, and using the intermediate value of ω_{ig} to represent the importance of each customer demand, then the combined value of the importance of all customers in

the m th customer demand can objectively reflect the weight of the customer demand in all customer demands:

$$RCR_m = \sum_{i=1}^{T} N_i \omega_{ig} / \sum_{i=1}^{T} N_i \tag{9}$$

Therefore, the weighting formula for the m st customer requirement:

$$\varphi_m^C = RCR_m / \sum_{i=1}^{M} RCR_i \tag{10}$$

2.3.2. Classification of design parameters. Design parameters are a set of technical indicators describing the physical characteristics of a product, which is an external manifestation of the product design. Let $F_i = \left(f_{i1}, f_{i2}, \cdots, f_{iK}\right) | \forall i \in \left(1, 2, \cdots, T\right)$ be the mapping of the i nd customer transaction record on the design parameter space $Q = \left\{DP_k \mid \forall k = 1, 2, \cdots, K\right\}$, where f_{ik} represents the value of the k th design parameter in the i th customer transaction record, and T is the number of transaction records in the past cycle.

The importance of design parameter DP_k is calculated as follows:

$$RDP_k = \sum_{m=1}^{M} \left(RCR_m \times a_{mk}\right)\left(k = 1, 2, \cdots, K\right) \tag{11}$$

Where, RDP_k - the importance of design parameter DP_k;

RCR_m - the importance of customer demand CR_m;

a_{mk} - the sensitivity of customer demand CR_m to design parameter DP_k.

After standardizing the values of $RDP_k (k = 1, 2, \cdots, K)$, the weights of all design parameters φ_k^D are obtained, which is calculated by the formula:

$$\varphi_k^D = RDP_k / \sum_{k=1}^{K} RDP_k \tag{12}$$

In order to reduce the influence of external factors, this paper uses the maximum-minimum normalization formula.

2.3.3. Consistency analysis. In this paper, consistency analysis is performed using rough sets (RS), which is an effective tool for revealing association relationships among attributes in a dataset. Transaction records on customer demand space P and design parameter space Q are classified into several classes, whose corresponding customer groups and design parameter classes are $\left(g_1, g_2, \cdots, g_s\right)$ and $\left(c_1, c_2, \cdots, c_t\right)$, respectively. X and Y are used to denote the non-empty subsets of finite domain U, and the parameter $inc(X,Y)$ denotes the degree of containment of set X to set Y, which is defined as follows:

$$inc\left(X, Y\right) = card\left(X \cap Y\right) / card\left(X\right) \tag{13}$$

where, $card$ - the number of elements in the set.

(1) Calculation of consistency of customer requirements on design parameters

For design parameters classes $c_i \in U^P / R^P (i = 1, 2, \cdots t)$, c_i about set U^C / R^C the γ - approximation set is calculated as:

$$A_\gamma\left(c_i\right) = \bigcup_{j=1}^{s}\left(g_j \in U^c / R^c : inc\left(g_j, c_i\right) \geq \gamma\right) \tag{14}$$

where $\gamma \in (0.5,1]$ - the inclusion threshold, which is predetermined in advance.

The degree of agreement of the set of customer requirements P to the set of design parameters Q is:

$$\alpha(P,Q,\gamma) = card\left(\bigcup_{i=1}^{t} A_\gamma\left(c_i\right)\right)/T \tag{15}$$

(2) Calculation of the consistency of the design parameters to the customer demand

For customer groups $g_j \in U^C / R^C (j=1,2,\cdots s)$, g_j about set U^P / R^P of γ' - approximation set calculation formula is:

$$A_{\gamma'}\left(g_j\right) = \bigcup_{i=1}^{t}\left(c_i \in U^P / R^P : inc\left(c_i, g_j\right) \geq \gamma'\right) \tag{16}$$

where $\gamma' \in \left(0.5,1\right]$ - the inclusion threshold, which is predetermined in advance.

The degree of agreement of the set of design parameters Q to the set of customer requirements P is:

$$\alpha'\left(P,Q,\gamma'\right) = card\left(\bigcup_{j=1}^{s} A_{\gamma'}\left(g_j\right)\right)\Big/T \tag{17}$$

Consistency $\alpha\left(P,Q,\gamma\right)$ and $\alpha'\left(P,Q,\gamma'\right)$ are indicative of the degree of association of customer needs with product design parameters and the strength of association of product design parameters with customer needs, respectively.

2.3.4. Forecast of Customer Demand Importance. In this paper, in order to reduce the impact of the disorder of customer demand importance in the past cycle on the future importance prediction results, AGO and IAGO are utilized to predict the customer demand importance and design parameter importance in the future cycle.

1) Time series equations. Firstly, the definitions of AGO and IAGO are introduced, assuming that $x^{(0)}$ is the original data series, i.e:

$$x^{(0)} = \left(x_1^{(0)}, x_2^{(0)}, \cdots, x_n^{(0)}\right) \tag{18}$$

where, $x_p^{(0)} (p=1,2,\cdots n)$ - the p rd element of the data sequence $x^{(0)}$;

n - the number of time points and $n \geq 2$.

Putting $x^{(0)}$ through the AGO conversion operation gives the AGO series $x^{(1)}$ of $x^{(0)}$ with the following expression:

$$x^{(1)} = \left(x_1^{(1)}, x_2^{(1)}, \cdots, x_n^{(1)}\right) \tag{19}$$

The transformation relation between $x^{(0)}$ and $x^{(1)}$ can be expressed as:

$$x_p^{(1)} = \sum_{i=1}^{p} x_i^{(0)} (p=1,2,\cdots,n) \tag{20}$$

Similarly, in turn, $x^{(0)}$ is known as the IAGO series of $x^{(1)}$.

The $GM\left(1,1\right)$ model is a first-order linear dynamic model with a single series and is the most widely used model in gray prediction theory. The composition of the model is shown below:

$$x_p^{(0)} + az_p^{(1)} = b(p=2,3,\cdots,n) \tag{21}$$

$$z_p^{(1)} = \alpha x_p^{(1)} + (1-\alpha) x_{p-1}^{(1)} (p = 2,3,\cdots,n) \tag{22}$$

where $z_p^{(1)}$ is its vernacular value, α is the adjustment factor, generally taken as 0.5, and a and b are the parameters to be determined.

2) Parameter estimation. In this paper, the above equations are solved using the least squares method to derive the estimated values of the parameters in the following matrix form:

$$x_p^{(0)} = \left(-z_p^{(1)}, 1\right)\begin{pmatrix} a \\ b \end{pmatrix}\left(p = 2,3,\cdots,n\right) \tag{23}$$

Applying the least squares method, vector $\begin{pmatrix} a \\ b \end{pmatrix}$ becomes:

$$\begin{pmatrix} a \\ b \end{pmatrix} = \left(Y^T Y\right)^{-1} Y^T X \tag{24}$$

where $Y = \begin{pmatrix} -z_2^{(1)} & 1 \\ -z_3^{(1)} & 1 \\ \vdots & \vdots \\ -z_n^{(1)} & 1 \end{pmatrix}$, $X = \begin{pmatrix} x_2^{(0)} \\ x_3^{(0)} \\ \vdots \\ x_n^{(0)} \end{pmatrix}$.

When $\rho \le 0.5$, the values of parameters a and b can be obtained by the following formula:

$$a = \frac{\sum_{p=2}^{n} z_p^{(1)} \sum_{p=2}^{n} x_p^{(0)} - (n-1)\sum_{p=2}^{n} z_p^{(1)} x_p^{(0)}}{(n-1)\sum_{p=2}^{n}\left(z_p^{(1)}\right)^2 - \left(\sum_{p=2}^{n} z_p^{(1)}\right)^2} \tag{25}$$

$$b = \frac{\sum_{p=2}^{n}\left(z_p^{(1)}\right)^2 \sum_{p=2}^{n} x_p^{(0)} - \sum_{p=2}^{n} z_p^{(1)} \sum_{p=2}^{n} z_p^{(1)} x_p^{(0)}}{(n-1)\sum_{p=2}^{n}\left(z_p^{(1)}\right)^2 - \left(\sum_{p=2}^{n} z_p^{(1)}\right)^2} \tag{26}$$

3) Reduced calculation. When the values of the pending parameters a and b are determined, equation (28) can be reduced to:

$$f_p^{(1)} = \left(x_1^{(0)} - \frac{b}{a}\right)e^{-a(p-1)} + \frac{b}{a}\left(p = 1,2,\cdots,n+1\right) \tag{27}$$

where, p - the order of gray prediction;

$f_p^{(1)}$ - the approximation scheme of the gray differential equation.

Finally, $f_p^{(1)}$ of $IAGO - f_p^{(0)}$ is:

$$f_{p+1}^{(0)} = f_{p+1}^{(1)} - f_p^{(1)}\left(p = 1,2,\cdots,n\right) \tag{28}$$

where, $f_p^{(0)}$ - the predicted value of the data series;

p - the order of gray prediction.

3. Parameterization of individual customer requirements

3.1. QFD-based Parameterization of Requirements

Requirements parameterization is an important method based on Quality Function Deployment (QFD) to correlate customer requirements with product characteristics in a quality house manner. It transforms customer needs into quantifiable design parameters and integrates them with product design to meet customer needs while optimizing product design, improving product quality and enhancing market competitiveness. The research in this paper focuses on the function of smart flower pots rather than the comparison with other brands, so the quality house established in this paper sheds the assessment of market competitiveness of the product, and mainly builds two quality houses to complete the transformation of customer demand - product parameters, i.e., the transformation of customer demand - product function and the transformation of product function - structure and function mapping, to get the product function corresponding to the customer demand, the product structure and its importance, and through the matrix form, the customer demand, the product structure and its importance will be correlated. Matrix form to visualize the relationship between customer demand, product function and structure, in order to better carry out the product design of intelligent flower pots.

1) Customer Requirements-Product Function Quality House To establish the customer requirements-product function quality house, firstly, we need to determine the customer requirements, identify the key requirements, determine the various functions possessed by the intelligent flowerpot product, and decompose the product functions, and decompose the customer requirements into specific product functions. Secondly, the customer needs and this product function are presented in the form of a matrix to establish the correlation matrix. Finally, the absolute importance and relative importance of the product function are calculated to complete the parameterization of customer demand-product function.

2) Product Function-Structure Function Quality House After determining the product function, the Product Function-Structure Function Quality House is established, which is used to visualize the relationship between the product function and its realized structural function, determine the corresponding product structure for the product function, and establish the Product Function-Structure Relationship Matrix to quantify the degree of association between them. Evaluate the product functions, calculate the degree of importance of the product structure, complete the transformation of product functions to product structure, and clarify how each product function is realized by the product structure.

3.2. Customer Requirements-Product Functional Quality Configuration Relationships

When constructing the QFD model, it is necessary to consider the independence between each function of the product to avoid conflicting functions and ensure the accurate expression of functions. The principle of independence in axiomatic design is applied to ensure that the functions of the intelligent flowerpot are independent of each other during the design process, and the main functions of the product are: A automatic irrigation function, B intelligent light supplementation function, C monitoring function, and D human-computer interaction function. Based on QFD to establish the quality house of customer demand-product function, the expert scoring method is used to determine the relationship between each function of the intelligent flowerpot and customer demand, in the relationship matrix, 0-9 is usually used to indicate the degree of correlation between parameters, the higher number indicates high correlation, while “0” indicates that there is no correlation between two parameters have no correlation with each other. The relationship between customer demand for smart planters and the quality configuration of product features is shown in Table 1.

Table 1. Customer demand - product function quality configuration

Customer demand	Demand weight	A	B	C	D
CR1	0.0838	6	4	9	2
CR2	0.0849	2	2	1	9
CR3	0.0836	9	2	0	0
CR4	0.0795	6	9	2	1
CR5	0.079	8	5	7	1
CR6	0.074	2	3	0	1
CR7	0.0735	5	6	0	4
CR8	0.0736	1	1	2	2
CR9	0.0726	2	1	0	0
CR10	0.0775	0	2	2	1
CR11	0.0663	2	2	3	1
CR12	0.0789	0	1	0	1
CR13	0.0722	1	1	1	2

The absolute importance of each function of the smart planter product is calculated according to the weight of customer demand, and the relative importance of the product is calculated through normalization, and the importance of the function of the smart planter product is shown in Table 2. From the table, it can be seen that the automatic irrigation function and the intelligent replenishment function of the intelligent flowerpot are more important, and the monitoring function and the human-computer interaction function are the second most important. Through the design and realization of the monitoring function and human-computer interaction function, the customer experience can be improved to better meet the needs of customers. Before constructing the product function-structure function quality house of the intelligent flowerpot, the four functions of the product are divided in detail to accurately grasp the various functional characteristics of the product.

Table 2. The function of intelligent flowerpot product is important

Importance	A	B	C	D
Absolute importance	3.0610	3.0134	2.0733	1.6887
Relative importance	0.3188	0.2959	0.2209	0.1644

The determination of the importance of the sub-functions corresponding to the four functional modules is based on the professional knowledge and experience of the designer of this product, and the importance of the sub-functions of the intelligent flowerpot is shown in Table 3. The smart planter mainly uses sensors to monitor various parameters in the plant growth environment, then analyzes and processes the data, compares the analysis results with the pre-set values, and finally regulates the plant growth environment by controlling the peripheral devices.

Table 3. The importance of intelligent flowerpot

Functional module	Subfunction	Functional importance
A:Automatic irrigation	A1:Time watering	0.4715
	A2:Water control	0.2964
B:Intelligent complementary light function	B1:Color temperature regulation	0.3084
	B2:Time control	0.2983
	B3:Intensity regulation	0.3288
C:Monitoring function	C1:Temperature monitoring	0.4465
	C2:Environmental light intensity monitoring	0.3895
	C3:Soil moisture monitoring	0.4057
D:Human-computer interaction	D1:Speech interaction	0.4951
	D2:Mobile app control	0.3745
	D3:Touch screen control	0.3065

The smart planter includes other additional functions in addition to its main function. Various sensors, control panels and water tanks constitute the corresponding structural components, and the detailed smart planter parts are shown in Table 4.

Table 4. Intelligent flowerpot parts

Serial number	Parts	Serial number	Parts
1	Water pump	9	Loudspeaker
2	Driving machine	10	Charging seat
3	Soil moisture sensor	11	Water injection port
4	Temperature sensor	12	Warning light
5	Light sensor	13	Lifting rod
6	Water tank	14	Breathable hole
7	Led lamp	15	Control circuit board
8	Control panel	16	Battery

According to the function and parts of the intelligent flowerpot to build intelligent flowerpot product function-structure-function quality configuration relationship. Intelligent flowerpot product function-structure-function quality configuration relationship is shown in Table 5.

Table. 5. Product function-structural function quality configuration relationship

Subfunction	weight	1	2	3	4	5	6	7	8	9	10	11	12	13
A1	0.1431	9	8	8	1	3	10	1	1	1	0	7	1	0
A2	0.0858	8	3	0	0	2	5	2	1	1	1	3	2	1
B1	0.0915	1	1	2	0	7	3	5	0	1	0	1	2	1
B2	0.0735	2	1	0	1	3	1	8	1	0	3	1	3	1
B3	0.0971	0	1	1	5	10	1	0	0	0	0	1	2	1
C1	0.0991	1	0	0	11	1	1	2	0	4	-1	0	2	1
C2	0.0852	1	2	2	2	11	0	9	0	3	1	2	0	0
C3	0.0881	1	2	10	1	-2	0	1	1	4	1	1	3	0
D1	0.0886	1	0	1	1	1	2	2	0	4	1	1	0	1
D2	0.0816	4	2	0	0	0	3	0	6	0	1	0	0	1
D3	0.0664	2	1	0	0	0	5	0	9	0	3	2	0	0

The results of the importance of smart planter parts are shown in Table 6. As can be seen from the table, the core parts of the smart planter include temperature and humidity sensors, light sensors, water tanks and microcontroller parts, which are used to control the operational input and output of the product in order to provide the best conditions for plant growth. Therefore, in order to better meet customers' individual needs, these parameters of the smart planter should be focused on to optimize the product design.

Table 6. The important results of intelligent flowerpot components

Parts number	Absolute importance	Relative importance
1	2.2364	0.1059
2	1.569	0.084
3	1.807	0.0892
4	1.2681	0.0577
5	2.4159	0.1237
6	2.4811	0.1466
7	2.4127	0.1095
8	0.8098	0.0252
9	1.1676	0.0543
10	0.2794	0.0224
11	1.3989	0.0803
12	0.5678	0.0019
13	0.1469	0.0335
14	0.1971	0.0029
15	0.7219	0.0233
16	0.4164	0.0396

4. Parametric product family optimization design methods

4.1. Parametric product family optimization methods and models

The new product family design [37] process consists of designers segmenting the market and determining the product family design parameters based on the needs of the customer base. It is assumed that the number of product family diversity instances is m, each product design parameter is n, and x_{ij} is the j th design variable for the i th product instance. The multi-objective optimization model for product family optimization can be expressed as:

$$\max f_{CI}\left(x_{ij}\right), \max \sum_{k=1}^{s} \omega_k f_{performance\_k}\left(x_{ij}\right)$$
$$Subject\ to \begin{cases} g_e\left(x_{ij}\right) \le a_e & e=1,\ldots,p \\ h_f\left(x_{ij}\right) = b_f & f=1,\ldots,q \\ l_j \le x_{ij} \le u_j \end{cases} \tag{29}$$

where, $\max f_{CI}\left(x_{ij}\right)$ is the product family commonality index, the higher commonality will indicate the higher degree of parts sharing, thus reducing the diversified operation cost due to the diversity of customer needs. $\max \sum_{k=1}^{s} \omega_k f_{performance\_k}\left(x_{ij}\right)$ is the product family performance index, which has different performance indexes and is weighted to characterize the performance of the whole product family in the optimization model. x_{ij} is the design variable, g_e and h_f are the inequality and equation constraints respectively.

Product family development and design based on existing product examples

The formation and evolution of product families is a dynamic process in the actual operation of enterprises. In this paper, a parametric product family optimization solution method is proposed to reduce the difficulty of problem solving by decomposing the complex optimization problem into different sub-problems and sub-steps for solving.

Step 1: Determine the Pareto optimization solution for each product instance. Designers will design the product optimization for each customer demand with performance as the goal in the design process, it is a multi-objective optimization problem, the mathematical model is shown in the following equation:

$$\max f_{performance\_1}\left(x_j\right), \ldots, \max f_{performance\_s}\left(x_j\right)$$
$$Subject\ to \begin{cases} g_e\left(x_j\right) \le a_e & e=1,\ldots,p \\ h_f\left(x_j\right) = b_f & f=1,\ldots,q \\ l_j \le x_j \le u_j \end{cases} \tag{30}$$

where $\max f_{performance\_1}\left(x_j\right), \ldots, \max f_{performance\_s}\left(x_j\right)$ denotes the different objective functions of product design, x_j is the design variable, and g_e and h_f are the inequality and equation constraints, respectively.

Step 2: Determine the Pareto optimization solution of the product family theory based on the Pareto optimization solution of the product optimization example. Combining the optimization solutions of all product instances solved in the first step to take the product family performance as the optimization objective is essentially a combinatorial optimization problem with the objective function shown in the following equation:

$$\max\sum_{k=1}^{m} f_{performance\_1}^{k}\left(x_{ij}\right),\ldots,\max\sum_{k=1}^{m} f_{performance\_s}^{k}\left(x_{ij}\right)$$
$$Subject\ to\begin{cases} g_e\left(x_{ij}\right)\le a_e & e=1,\ldots,p \\ h_f\left(x_{ij}\right)=b_f & f=1,\ldots,q \\ l_j\le x_{ij}\le u_j \end{cases} \tag{31}$$

where $\max\sum_{k=1}^{m} f_{performance\_s}^{-1}\left(x_{ij}\right)$ denotes the sum of some objective function of the product family design, x_{ij} is the design variable, g_e and h_f are the inequality and equation constraints, respectively.

Step 3: Parametric product family integration optimization solution. In this paper, the parametric product family integrated optimization is modeled with product family generalization and product family performance as multi-objectives, instead of weighting the performance objectives, the integrated optimization model is shown in the following equation:

$$\max f_{CI}\left(x_{ij}\right),\max\sum_{k=1}^{m} f_{performance\_s}^{k}\left(x_{ij}\right),\cdots,\max\sum_{k=1}^{m} f_{performance\_s}^{k}\left(x_{ij}\right)$$
$$Subject\ to\begin{cases} g_e\left(x_{ij}\right)\le a_c & e=1,\ldots,p \\ h_f\left(x_{ij}\right)=b_f & f=1,\ldots,q \\ l_j\le x_{ij}\le u_j \end{cases} \tag{32}$$

where $\max f_{CI}\left(x_{ij}\right)$ is the generalizability index of the product family, $\max\sum_{k=1}^{m} f_{performance\_s}^{k}\left(x_{ij}\right)$ denotes the sum of some objective function of the product family design, x_{ij} is the design variable, and g_e and h_f are the inequality and equation constraints, respectively.

4.2. Genetic Algorithm for Non-Occupancy Ranking Based on Congestion Distance

In this paper, the optimization model is solved based on NSGAII algorithm.

4.2.1. Chromosome coding and population initialization. In genetic algorithms, coding is the expression of the solution of a problem in terms of genes by some rule so that the genetic algorithm can process it. After chromosome coding, population initialization is carried out to determine the initial value of the operation, which is usually generated in a random way with the following formula:

$$u(i,j)=\min\left(v_j\right)+\left(\max\left(v_j\right)-\min\left(v_j\right)\right)*rand\left(1\right)$$
$$i=1,2,\ldots M;\ j=1,2,\ldots N \tag{33}$$

$u(i,j)$ denotes the gene value of the j rd gene on chromosome i; M denotes the population size.

4.2.2. Non-Preferential Ranking and Selection. The methodology for non-dominance ranking is as follows:

In the first step, the non-dominated rank of each individual is determined. A two-by-two comparison of all individuals is performed, first comparing the number of constraints satisfied.

In the second step, in the case where two individuals have the same nonprevailing rank, a comparison of the crowding distances is performed, and the individual with the larger crowding distance is ranked first.

4.2.3. Crossover and variation. Chromosome crossovers are usually computed using the analog binary crossover operator (SBX), which is calculated as follows:

$$c_{1,k} = \frac{1}{2}\left[(1-\beta_k)\,p_{1,k} + (1+\beta_k)\,p_{2,k}\right]$$
$$c_{2,k} = \frac{1}{2}\left[(1+\beta_k)\,p_{1,k} + (1-\beta_k)\,p_{2,k}\right] \tag{34}$$

$c_{i,k}$ indicates the k rd gene of the i nd child. $p_{i,k}$ denotes the k th gene of the i th parent individual. $\beta_k(\geq 0)$ is a random number that obeys the probability distribution of the following equation.

$$p(\beta) = \frac{1}{2}(\eta_c+1)\beta^{\eta_c} if\, 0 \leq \beta \leq 1$$
$$p(\beta) = \frac{1}{2}(\eta_c+1)\frac{1}{\beta^{\eta_c+2}} if\, \beta > 1 \tag{35}$$

η_c is the distribution index of the cross operator. Among them:

$$\beta(u) = (2u)^{\frac{1}{(\eta_c+1)}} u \leq 0.5$$
$$\beta(u) = \frac{1}{[2(1-u)]^{\frac{1}{(\eta_c+1)}}} u > 0.5 \tag{36}$$

where u is a random number uniformly distributed in the interval $[0,1]$.

The purpose of chromosome mutation is to increase the diversity of the population and to expand the search range of genetic operations. The variation operator uses the polynomial variation method for chromosome variation, which is shown below:

$$c_{i,j} = p_{i,j} + \left(p_{i,j}^u - p_{i,j}^l\right)\delta_j$$
$$\delta_j = \begin{cases} (2r_j)^{\frac{1}{\eta_m+1}} - 1 & if r_j < 0.5 \\ 1-\left[2(1-r_j)\right]^{\frac{1}{\eta_m+1}} & if r_j \geq 0.5 \end{cases} \tag{37}$$

$c_{i,j}$ represents the variable corresponding to the locus in the child individual. $p_{i,j}$ represents the variable corresponding to the gene in the parent individual. $p_{i,j}^u$ represents the upper limit of the variable in the parent chromosome. $p_{i,j}^t$ represents the lower limit of the variable in the parent chromosome. r_j is a random number uniformly distributed in the interval $[0,1]$. η_m is the variance distribution index.

4.2.4. Handling of constraints. For multi-constraint multi-objective optimization problems, the constraints need to be handled.

A method that combines constraint violations with the objective function. This is mainly the penalty function method. The following formula is usually used when adjusting the individual fitness:

$$F(x) = \begin{cases} F(x) \\ F(x) - P(x) \end{cases} \tag{38}$$

where $F(x)$ is the initial fitness; $F'(x)$ is the changed fitness; and $P(x)$ is the penalty function.

Binary tournament selection. In the case of containing constraints, the two solutions can be ranked non-optimally based on the total number of constraint violations and the value of the objective function, and the rule of ranking is:

1) $(\phi(x_1)=0 \wedge \phi(x_2)=0) \wedge (f(x_1)<f(x_2)) \Rightarrow x_1 \prec x_2, \prec$ indicates dominance; i.e., when both solutions satisfy the constraint, the smaller objective function value is dominant;

2) $(\phi(x_1)=0 \wedge \phi(x_2)>0) \Rightarrow x_1 \prec x_2$, i.e., when one satisfies the constraint and the other solution does not, the solution that satisfies the constraint prevails;

3) $(\phi(x_1)>0 \wedge \phi(x_2)>0) \wedge (\phi(x_1)<\phi(x_2)) \Rightarrow x_1 \prec x_2$, i.e., when both solutions do not satisfy the constraints, the one with small constraint violations prevails.

5. Example simulation and comparative analysis

5.1. Optimization of Multiplatform Product Families with Known Platform Patterns

The design variables N_c, N_s, A_{wf}, t, L are platform variables, and the number of common values are: 2, 2, 1, 1, 3. After optimization, the optimization results of the generic smart planter product family are shown in Fig. 2, and the optimal product family design scheme and related performance are shown in Table 7. The comparison between the algorithm of this paper and the traditional algorithm solving results is shown in Table 8. The difference between the j rd performance of the i nd product in the design scheme solved in this paper and the performance index of the traditional method scheme d_{ij} is calculated as:

$$d_{ij} = \frac{p_{ij}^2 - p_{ij}^1}{p_{ij}^1} \times 100\% \tag{39}$$

where: p_{ij}^2 is the value of the j rd performance of the i nd product in the design solution obtained in this paper; p_{ij}^1 is the value of the j th performance of the i th product in the design solution obtained in the traditional method.

The average weight of the smart flowerpot in the product family design solution determined by the best compromise solution using the traditional algorithm is 0.6829 kg; in this paper's algorithm, the mass of the flowerpot is 0.5688 kg, which is a significant reduction of the weight of the flowerpot by 0.1141 kg. In addition, the average efficiencies of this paper's method and the traditional method are 73.48% and 69.25%, which is 4.23% more than the traditional algorithm, i.e., the efficiencies are significantly less than the traditional algorithm. 4.23%, i.e., a significant increase in efficiency. Since both the increase in efficiency and the improvement in weight are greater than the traditional algorithm, it is considered that the algorithm proposed in this paper for solving the product family optimization of generic smart flower pots with known platform model has significant improvement over the traditional method.

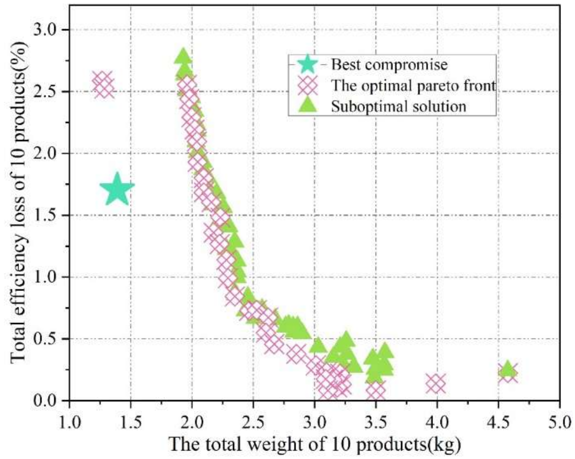

Fig. 2. Optimization results of universal intelligent flowerpot products

Table 7. Best product family design and correlation

Intelligent flowerpot number	1	2	3	4	5	6	7	8	9	10
N_c	1050	1050	1050	1050	1050	1050	1050	1050	1150	1150
N_s	70	70	70	70	70	65	65	65	65	65
A_{wa}	0.26	0.26	0.24	0.27	0.26	0.23	0.22	0.26	0.25	0.26
A_{wf}	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
r	3.3	1.3	3.3	3.3	1.3	3.3	1.3	1.3	3.3	4.3
t	9.6	7.6	8.6	7.6	7.6	8.6	8.6	8.6	8.6	8.6
I	4.75	3.77	4.99	4.6	2.82	1.87	1	5.62	4.42	2.71
L	2.57	2.37	2.3	2.33	2.59	2.35	2.44	2.21	2.38	2.56
T	0.18	0.2	0.16	0.15	0.18	0.18	0.18	0.19	0.15	0.19
P	250	250	250	250	250	250	250	250	250	250
n	88.45	85.44	88.25	76.94	82.08	68	67.77	65.61	58.22	54.02
M	0.362	0.411	0.457	0.479	0.545	0.574	0.651	0.693	0.719	0.797

Table 8. The algorithm is compared with the traditional algorithm

Intelligent flowerpot number	Traditional method		The method of this article		Performance difference	
	n(%)	M(kg)	n(%)	M(kg)	N(%)	M(kg)
1	84.516	0.2372	88.45	0.362	3.934	0.1248
2	84.5842	0.6806	85.44	0.411	0.8558	-0.2696
3	80.3286	0.6462	88.25	0.457	7.9214	-0.1892
4	72.7815	0.5972	76.94	0.479	4.1585	-0.1182
5	76.4524	0.6136	82.08	0.545	5.6276	-0.0686
6	68.1961	0.5604	68	0.574	-0.1961	0.0136
7	66.7723	0.7363	67.77	0.651	0.9977	-0.0853
8	52.6312	0.8145	65.61	0.693	12.9788	-0.1215
9	55.617	0.7309	58.22	0.719	2.603	-0.0119
10	50.6637	1.2125	54.02	0.797	3.3563	-0.4155

5.2. Multi-platform product family optimization with unknown platform model

In order to analyze the effectiveness of this paper's algorithm for solving the multi-platform product family problem and the reliability of the optimization results, the optimization search results are compared with the optimization result scheme of the single-platform product family in the traditional method. The optimization results of the design variables under the optimal platform mode for the generic smart flowerpot product family are shown in Figure 3.

In the traditional method Simpson used PPCEM method, on the selection of r, t as a single platform variable, the other six design variables of the universal intelligent planter product family optimization, to get the optimization scheme 1. The difference evaluation index value of this platform model $PFDI_2 = 0.55$, to get the comparison between the results of this paper's algorithm to solve the multi-platform product family problem and the optimization of the single-platform product family results as shown in Table 9. It can be seen by comparison: the multi-platform product family design scheme of universal smart flowerpot obtained by the algorithm of this paper has improved the efficiency of smart flowerpot by 9.12% on average compared with that of the scheme in the traditional method, while the weight has been reduced by 0.617kg on average.

A comprehensive comparison of the results shows that the co-optimization of the platform model and design scheme using the algorithm of this paper makes the variability within the product family reduce the versatility increase on the one hand, and on the other hand, the two performance indexes of the product, namely, the efficiency and the weight, have been improved. Due to the increase in versatility, it is conducive to reducing the time for equipment replacement and debugging in the production line during the product manufacturing process, which reduces waste and facilitates the goal of meeting diversified individual needs through large-scale production. The simulation experiments also illustrate the effectiveness of the algorithm to solve the multi-platform product family optimization problem.

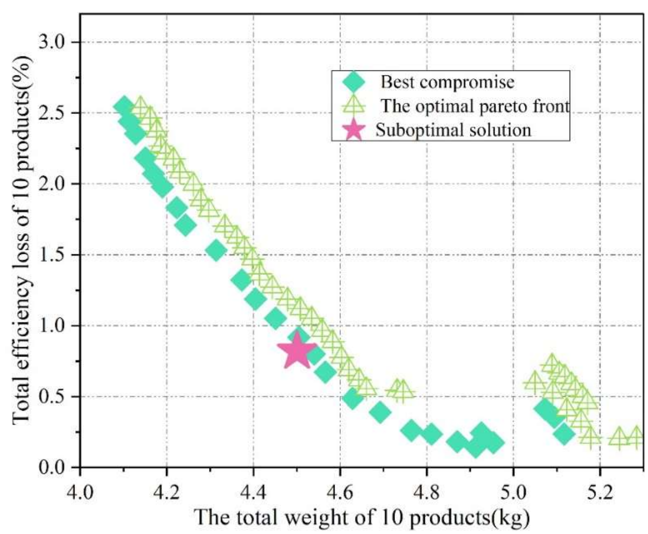

Fig. 3. Optimization of design variables for intelligent flowerpot products

Table 9. The results of the two methods to optimize the product family

Intelligent flowerpot number	Traditional method		The method of this article		Performance difference	
	n(%)	M(kg)	n(%)	M(kg)	N(%)	M(kg)
1	80.3485	0.7946	88.45	0.362	8.1015	-0.4326
2	79.9214	1.3023	85.44	0.411	5.5186	-0.8913
3	74.1243	1.081	88.25	0.457	14.1257	-0.624
4	71.0687	1.0215	76.94	0.479	5.8713	-0.5425
5	73.0817	0.9566	82.08	0.545	8.9983	-0.4116
6	62.203	1.0528	68	0.574	5.797	-0.4788
7	56.6524	1.4891	67.77	0.651	11.1176	-0.8381
8	48.4259	1.2504	65.61	0.693	17.1841	-0.5574
9	52.2832	1.1997	58.22	0.719	5.9368	-0.4807
10	45.4854	1.7121	54.02	0.797	8.5346	-0.9151

6. Conclusion

Aiming at the shortcomings of the existing platform parameter identification and product design parameter value methods, this paper proposes a parametric product family design method for smart home based on improved QFD and genetic algorithm, and proves the validity of the method proposed in this paper by taking the universal smart flowerpot as an example.

1) This paper proposes a product modularization design method based on improved QFD algorithm. A comprehensive discretization sensitivity matrix is constructed based on the functional, geometric, and physical relationships of the parts of the smart flowerpot, which comprehensively describes the dependency relationships of the parts of the smart flowerpot. Considering that the QFD algorithm is sensitive to the error value when dealing with small sample data and other problems, this paper applies the NSGAII algorithm to improve the QFD algorithm, and successfully realizes the parametric product family optimization design. And the core functions and parts of the smart flowerpot are determined by taking the smart flowerpot as an example.

2) Applying this paper's algorithm to the generalized intelligent flowerpot product family design problem, comparing it with the design scheme obtained by the traditional method, the efficiency of this paper's method increases by an average of 4.23% and 9.12% under the conditions of known and unknown platform modes, and the weight decreases by an average of 0.1141kg and 0.617kg. It can be seen that the design solution obtained by the algorithm proposed in this paper has a better solution performance for intra-product family optimization.

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