Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 1709093, 10 pages
https://doi.org/10.1155/2022/1709093

Research Article

Research on the Importance of Intelligent Equipment Support Capability Indexes Based on the GQFD-BP Neural Network

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Received 9 March 2022; Revised 6 June 2022; Accepted 1 August 2022; Published 12 November 2022

Academic Editor: Jun Ye

The importance of the equipment support capability index is the premise and foundation of equipment support construction and is the logical starting point for carrying out related research. Determining the importance of equipment support capability indicators can guide and lead the improvement of support capability and promote the performance of equipment support. Aiming at the problems of high subjectivity and low reliability in the current method for determining the importance of the capability index, this paper proposes a gray relational quality function expansion method based on the GQFD-BP neural network. Through the process of determining the task index and the capability index, constructing an expert preference model, establishing the gray comprehensive correlation matrix, and building a house of quality, the importance of the intelligent equipment support capability index is determined, and a theoretical basis for the construction and application of intelligent equipment support capabilities is provided.

1. Introduction

The importance of the intelligent equipment support capability index is an important basis for determining the order of intelligent equipment support capability index, evaluating equipment support capabilities, and prioritizing equipment support construction. At present, the demonstration methods of the importance of capability index mainly include principal component analysis, analytic hierarchy process, combination weighting method, fuzzy comprehensive evaluation method, quality function expansion method—QFD (quality function deployment), and improved quality function expansion method—GQFD (gray quality function deployment) based on gray relational analysis [1–5]. However, these methods are greatly affected by subjective factors, lack objectivity, pertinence, and effectiveness and cannot meet the development needs of intelligent equipment support. It is necessary to introduce new methods to determine the importance of the intelligent equipment support capability index.

The neural network is a complex network system consisting of a large number of very simple processing units (or neurons) that are widely interconnected. It reflects the function of the human brain and many basic characteristics. It is a highly complex nonlinear dynamic system. The neural network has large-scale parallel distributed storage and processing, adaptive, and self-learning capabilities and is especially suitable for processing needs to consider many factors and conditional, imprecise, and ambiguous information processing problems. Reference [6] established a feature parameter prediction model by using the neural network to predict the characteristic parameters of special ice. Reference [7] proposed a projectile drop point prediction method based on the BP neural network and obtained the prediction method for the projectile drop point. The BP neural network model is simulated and tested. The simulation results show that the above method can predict the drop point of the projectile with high accuracy and is better than the numerical integration method in the solution time.

This paper uses the neural network algorithm to establish an intelligent index importance analysis method based on the GQFD-BP neural network and forms a dynamic importance evaluation mechanism, which can effectively solve the shortcomings of traditional analysis methods and make the results more objective, accurate, and reliable.

2. Determination of the Task Index and Capability Index of Intelligent Equipment Support

The intelligent combat is a new combat form after mechanized and informationized combat, featuring distributed deployment, networked links, unmanned confrontation, adaptive reconstruction, cross-domain collaboration, human-machine integration, and precise energy release [8, 9]. The establishment of intelligent equipment support capabilities that are compatible with intelligent operations is an inherent requirement of intelligent operations. It is necessary to analyze the intelligent combat process as a logical starting point and determine the intelligent equipment support capability index according to the method and steps of determining the task by the process and the capability by the task.

Intelligent combat is significantly different from the traditional mechanized combat process. It is generally implemented in accordance with the steps of "full-dimensional situational awareness-real-time information sharing-fast and accurate decision-making-self-organized coordination of actions-timely evaluation and feedback" [10–13]. This new combat process requires equipment support. By analyzing the connection and matching between the intelligent combat process and the equipment support process, the task index that needs to be completed for the energy and chemical equipment support can be defined as follows: real-time data collection, intelligent distribution information, accurate command and control, on-demand delivery materials, efficient repair equipment, and wide-area communication network. The indexes are numbered (to facilitate subsequent calculation) as shown in Table 1.

The acquisition process of intelligent equipment support capability is to realize the effective transformation of intelligent equipment support tasks to intelligent equipment support capabilities, that is, a corresponding conversion relationship is established between the task index and the capability index, which is embodied as a "one-to-one" or "one-to-many" mapping relationship. According to the above-determined intelligent equipment support task index, a mapping relationship between "intelligent equipment support tasks" and "intelligent equipment support capabilities" was established, as shown in Figure 1.

Through the established mapping relationship, the six intelligent equipment support capability indexes are determined as follows: situation real-time perception, data intelligent processing, intelligent command decision, materials precise support, intelligent detection and repair, and internet smart protection. The indexes are numbered (to facilitate subsequent calculation) as shown in Table 2.

3. Analysis Method of Capability Index Importance Based on the GQFD-BP Neural Network

The basic process of the capability index importance analysis method based on the GQFD-BP neural network are as follows: firstly, on the basis of determining the equipment support task index and equipment support capability index, an expert preference model is constructed to score the two, and the task index matrix and the capability index matrix are determined. Secondly, by using the mapping analysis method of GQFD, the task index matrix and the capability index matrix are processed by gray correlation, and the gray correlation matrix and the task index importance between the task index and the capability index are obtained. Finally, the gray relational matrix is used to replace the relative relational matrix in the traditional QFD method, the "task index-capability index" house of quality HOQ based on the gray relational matrix is constructed, the quality function is expanded according to the traditional QFD analysis method, and the importance weight of the capability index is determined. The specific analysis process is shown in Figure 2.

3.1. *Building an Expert Preference Model.*

In the expert scoring stage, the ambiguity and variability of experts' knowledge reserves, work experience, emotionality, and preference for capability index seriously affect the objectivity and fairness of scoring. On the basis of the expert's historical scoring information, the BP (back propagation) neural network algorithm is used to construct the expert preference model. The purpose is to automatically score the index importance by the machine instead of the expert so as to reduce the influence of subjective factors on the index importance [7, 14].

3.1.1. *Index Feature Attribute Matrix.*

Each index has its own attributes, such as location, role, and scope, and each expert must compare and select based on these characteristics when scoring an index. All index features are described by a set $h = [\, h_1 \;\; h_2 \;\; \cdots \;\; h_d \;\; \cdots \;\; h_v \,]$, where v is the number of all index features. An index can have multiple features, and the index is usually described by its own multiple index feature information, that is, an index T can be represented by a vector composed of index feature attributes as follows:

$$p_T = [\, p_1 \;\; p_2 \;\; \cdots \;\; p_d \;\; \cdots \;\; p_v \,]. \tag{1}$$

In the above vector, p_d is the characteristic attribute of the index, $1 \le d \le v$, and in

$$p_d = \begin{cases} 0, & \text{without } h_d, \\ (0,1], & \text{with } h_d. \end{cases} \tag{2}$$

3.1.2. *Expert Preference Model Analysis.*

The preference degree of experts to the index features is the premise of scoring the index. A preference function can be used to define the expert's preference for an index feature d:

Table 1: Intelligent equipment support task index.

Number	X_1	X_2	X_3	X_4	X_5	X_6
Task index	Real-time data collection	Intelligent distribution information	Accurate command and control	On-demand delivery materials	Efficient repair equipment	Wide-area communication network

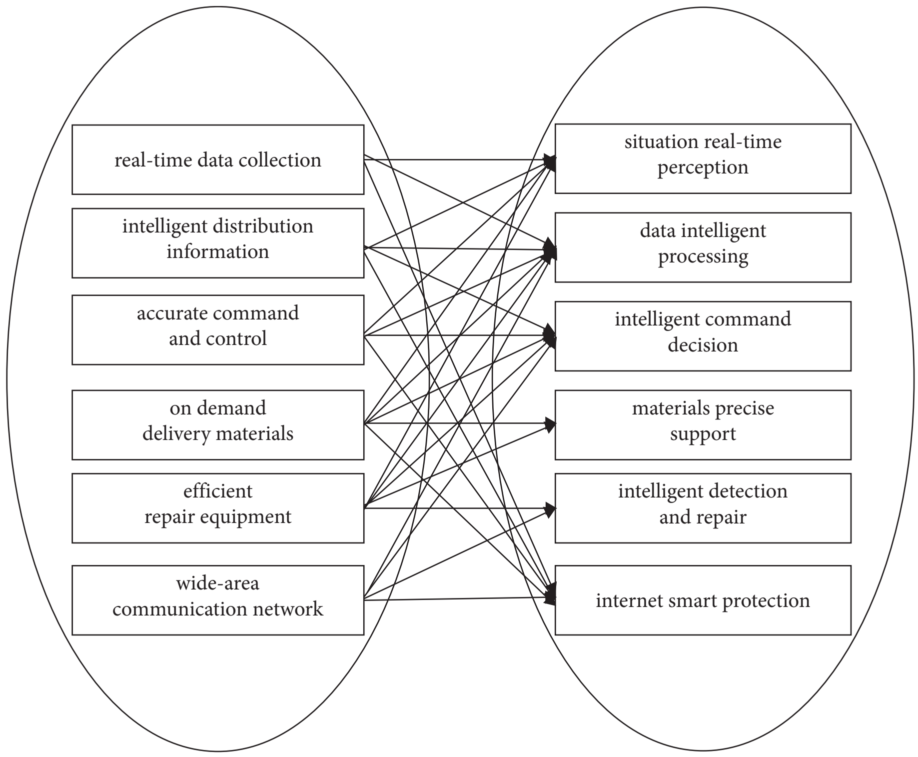

Figure 1: Mapping of intelligent equipment support tasks to intelligent equipment support capabilities.

$$c_d = f(h_d), \quad (3)$$

c_d is the expert's preference for the index feature h_d, which is defined as a continuous function on $[0, 1]$. 1 is the most liked, and 0 is the least liked.

The expert's score for a certain index T is the result of the combined effect of the experts' preference for each feature of the index. The definition for $y_T = c_d * p_T$; then, the joint action can be expressed as $d = g(y_1, y_2, \ldots, y_v)$.

From $c_d = f(h_d)$ and $d = g(y_1, y_2, \ldots, y_v)$ and their relationship $y_T = c_d * p_T$, the expert preference model expression is obtained as

$$d = l(p_1, p_2, \ldots, p_v). \quad (4)$$

It can be seen from the above formula that the importance attached by experts to the index is closely related to the characteristics contained in the index themselves. Determining the relationship between experts' emphasis on index and index characteristics is the key to constructing expert preference models. This paper adopts the machine learning method based on the BP neural network algorithm and establishes the expert preference model by simulating the complex and nonlinear mapping relationship between the two.

3.1.3. The Structure of the BP Neural Network. The construction of the expert preference model needs to be completed in two steps: the first step is the expert's preference for a certain index feature, that is, the construction of the formula $c_d = f(h_d)$ function, and the second step is to complete the construction of the formula $d = g(y_1, y_2, \ldots, y_v)$ function. The structure of the BP neural network is constructed as follows: the first layer is the input layer, which is used to input the index feature data, and the number of neurons is consistent with the number of index feature vectors; the second layer is the hidden layer, which represents the expert's preference for a certain index feature, and the number of neurons in this layer is the same as that in the input layer; the third layer is the output layer, which is used to output the capability index score and has only one neuron. The connection between the input layer and the hidden layer can be regarded as the first step function model to be constructed, and the connection between the hidden layer and the output layer can be regarded as the second step function model to be constructed. Its network structure is shown in Figure 3.

3.1.4. Sample Inputs and Outputs of Preference Models. BP neural network is a multilayer feedforward neural network, which has the characteristics of strong parallel computing

Table 2: Intelligent equipment support capability index.

Number	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
Capability index	Situation real-time perception	Data intelligent processing	Intelligent command decision	Materials precise support	Intelligent detection and repair	Internet smart protection

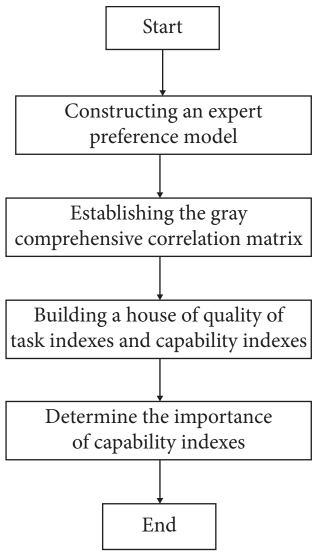

Figure 2: Analysis flow chart based on the GQFD-BP neural network method.

capability, good robustness, and outstanding nonlinear mapping capability. Its structure has input layer, hidden layer, and output layer, which is suitable for solving inaccurate or ambiguous nonlinear system problems [15, 16].

On the premise of determining the input, output, and training samples of the preference model, the preference model is trained, and the connection weight of the neural network is continuously improved to better reflect the expert's preference for the index. The expert's scoring information on the past index is used as a training sample for the model. For each index t that has been scored, there is a mapping relationship, that is, the input factor of the preference model: index feature vector $p_T = [\, p_1(T) \;\; p_2(T) \;\; \cdots \;\; p_v(T) \,]$ and the output factor of the preference model: the expert's rating for this index $q(T)$. The two constitute a sample $yb(T) = (p_T, q(T))$ of the preference model, and the scoring information of all indexes evaluated by experts constitutes the sample set. For the index that have not yet been scored, the index features are used as input factors, the trained expert preference model is input, and the expert's preference (score) for the index is output.

In order to improve the learning efficiency of the network, the maximum and minimum method is used to normalize the data:

$$p_k(T) = \frac{p_k(T) - p_{\min}(T)}{p_{\max}(T) - p_{\min}(T)}. \tag{5}$$

In the formula, $p_{\max}(T)$ is the maximum number of data series, and $p_{\min}(T)$ is the minimum number of data series.

Then, the normalized data is input into the hidden layer for calculation. Calculate the hidden layer output H_t according to the input variable $p(T)$, the connection weight ω_{rt} between the input layer and the hidden layer, and the hidden layer threshold a:

$$H_t = f\left(\sum_{r=1}^{v} \omega_{rt} p_r(T) - a_t\right), \quad t = 1, 2, \ldots, v. \tag{6}$$

In the formula, since the number of neurons in the input layer and the hidden layer are equal, v is the number of hidden layer nodes, and f is the hidden layer activation function, this function uses the S-type function:

$$f(x) = \frac{1}{1 + e^{-ex}}. \tag{7}$$

According to the hidden layer output H_t, and the connection weight ω_{tk} and threshold b between the hidden layer and the output layer, since the output layer has only one neuron, so $k = 1, \omega_{tk} = \omega_t$; calculate the predicted output O of the neural network as

$$O = \sum_{t=1}^{v} H_t \omega_t - b. \tag{8}$$

Calculate the network prediction error e based on the network predicted output O and the actual output E as

$$e = O - E. \tag{9}$$

According to the network prediction error e, update the network connection weight ω_{rt} and ω_t as

$$\begin{aligned} \omega_{rt} &= \omega_t + \eta H_t (1 - H_t) * p_r(T) * \omega_t e, \\ \omega_t &= \omega_t + \eta H_t e. \end{aligned} \tag{10}$$

In the formula, $r = 1, 2, \ldots, v, t = 1, 2, \ldots, v$, and η is the learning efficiency.

Then, according to the network prediction error e, update the network connection weights a and b as

$$a_{rt} = a_t + \eta H_t (1 - H_t) * \omega_t e, \tag{11}$$

$$b = b + e. \tag{12}$$

3.1.5. Network Online Training Algorithm. In the operation of the actual scoring system, the expert preference changes dynamically. We use the preference model to score the index and get the score information of the preference model for the new index and use the new score data to improve the expert preference model. According to the specific situation, when the number of newly generated samples reaches N, the model update procedure is started. The specific online training steps are as follows:

(1) Update the training sample set. Replace the earliest N samples generated in the current neural network model $\mathrm{Net}(T)$ with the newly generated N samples to obtain a new training sample set of the neural network model $\mathrm{Net}(T + 1)$.

(2) Set the initial weights and thresholds of the network $\mathrm{Net}(T + 1)$. Make the initial weights and thresholds of the network $\mathrm{Net}(T + 1)$ equal to the weights and thresholds of the network $\mathrm{Net}(T)$.

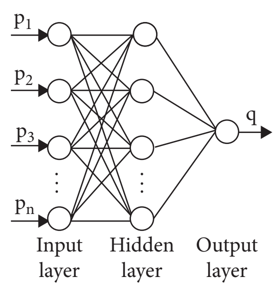

Figure 3: Structure diagram of the BP neural network.

(3) *Model Training*. Sample training for the network Net$(T+1)$.

(4) *Judgment*. If the accuracy converges to the minimum value, go to (6); otherwise, go to (5).

(5) *Judgment*. If the number of iterations is greater than the set number, go to (6); otherwise, go to (3).

(6) The algorithm terminates.

(7) *Model Verification*.

The validity and robustness of the expert preference model are verified with the help of the MovieLens database. The database uses integers between to represent experts' preference for products from low to high. This paper selects products with 2313 rating records as the validation dataset. The training samples are selected from the first 2000 data, and the test samples are selected from the last 313 data. Since the number of feature attributes of the product is 18, the number of neurons in the input layer and the hidden layer of the neural network model should also be 18, and the number of neurons in the output layer should be 1. The test error mean and test error variance are selected as the verification index, and the initial weights and thresholds of the network are randomly generated. Using the training sample set, the network scale is set to 20, and the model is independently trained 10 times to obtain 10 BP neural network models, the model's test error mean, training variance (model training accuracy), and test variance, as shown in Figure 4(a). It can be seen from the figure that the gap between the test error variance and the training variance is small, and the mean value of the test error fluctuates slightly around 0, indicating that the neural network model has good effectiveness, as shown in Figure 4(b). The robustness of the model is verified by the test sample set, and the error output of the 10 neural network models is basically stable, indicating that the neural network model has good robustness.

3.2. The Establishment of the Gray Relational Matrix. The calculation process of the GQFD method is based on the classical QFD method by constructing a gray relational matrix to sort the importance of the capability index. The specific calculation steps are as follows [17, 18].

Let $X_i = (x_i(1), x_i(2), \ldots, x_i(n))$ $(i = 1, 2, \ldots, s)$ be the task index sequence; $Y_j = (y_j(1), y_j(2), \ldots, y_j(n))$, $j = 1, 2, \ldots, m$, is the capability index sequence, n is the number of expert preference models, ε_{ij} is the gray absolute correlation between X_i and Y_j, r_{ij} is the gray relative correlation between X_i and Y_j, and ρ_{ij} is the gray comprehensive correlation between X_i and Y_j.

3.2.1. Calculating the Gray Absolute Correlation Degree ε_{ij}

$$\left|X_{si}\right| = \left|\sum_{k=2}^{n-1} x_i^0(k) + \frac{1}{2}x_i^0(n)\right|, \tag{13}$$

$$\left|Y_{sj}\right| = \left|\sum_{k=2}^{n-1} y_j^0(k) + \frac{1}{2}y_j^0(n)\right|, \tag{14}$$

$$\left|Y_{sj} - X_{si}\right| = \left|\sum_{k=2}^{n-1}\left(y_j^0(k) - x_i^0(k)\right) + \frac{1}{2}\left(y_j^0(n) - x_i^0(n)\right)\right|. \tag{15}$$

In formulas (13)–(15), the superscript "0" indicates that the data has undergone zero-point processing (zero-point zeroing: the number of each row minus the first number). The gray absolute correlation between X_i and Y_j is

$$\varepsilon_{ij} = \frac{1 + \left|X_{si}\right| + \left|Y_{sj}\right|}{1 + \left|X_{si}\right| + \left|Y_{sj}\right| + \left|Y_{sj} - X_{si}\right|}. \tag{16}$$

3.2.2. Calculating the Gray Relative Correlation Degree r_{ij}

$$\left|X_{si}'\right| = \left|\sum_{k=2}^{n-1} x_i^{0'}(k) + \frac{1}{2}x_i^{0'}(n)\right|, \tag{17}$$

$$\left|Y_{sj}'\right| = \left|\sum_{k=2}^{n-1} y_j^{0'}(k) + \frac{1}{2}y_j^{0'}(n)\right|, \tag{18}$$

$$\left|Y_{sj}' - X_{si}'\right| = \left|\sum_{k=2}^{n-1}\left(y_j^{0'}(k) - x_i^{0'}(k)\right) + \frac{1}{2}\left(y_j^{0'}(n) - x_i^{0'}(n)\right)\right|. \tag{19}$$

In formulas (17)–(19), the superscript "0" indicates that the data is initialized and then zeroed at the starting point (initialization: the number of each row is divided by the first number). The gray relative correlation between X_i and Y_j is

$$r_{ij} = \frac{1 + \left|X_{si}'\right| + \left|Y_{sj}'\right|}{1 + \left|X_{si}'\right| + \left|Y_{sj}'\right| + \left|Y_{sj}' - X_{si}'\right|}. \tag{20}$$

3.2.3. Calculating the Gray Comprehensive Correlation Matrix Ψ. The gray comprehensive correlation between X_i and Y_j is $\rho_{ij} = \theta\varepsilon_{ij} + (1-\theta)r_{ij}$, usually takes 0.5. After the above calculation, the gray comprehensive correlation matrix Ψ can be obtained as

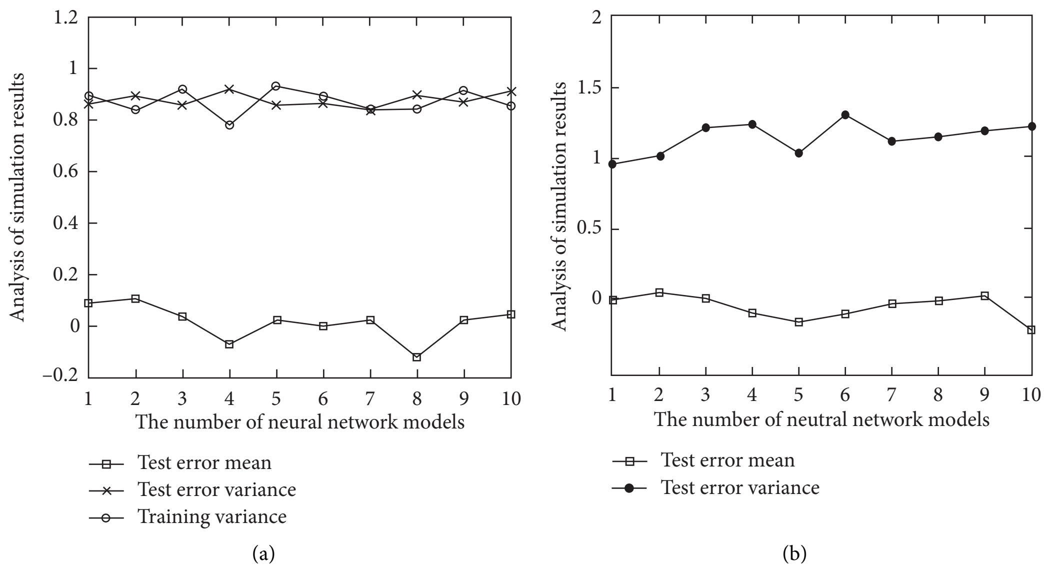

FIGURE 4: Effectiveness and robustness of the network training model. (a) Validity verification. (b) Robustness verification.

$$\psi = \rho_{ij_{s\times m}} = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1m} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{s1} & \rho_{s2} & \cdots & \rho_{sm} \end{bmatrix}. \tag{21}$$

3.2.4. Calculating the Importance Weight λ of the Task Index. If $\exists\ k, t \in \{1, 2, \ldots, s\}$ can make $\rho_{kj} \geq \rho_{tj}$, $j = 1, 2, \ldots, m$, it means that the index X_k is better than the index X_t, and it is said that $X_k > X_t$.

If $\exists k, t \in \{1, 2, \ldots, s\}$ can make $\sum_{i=1}^{m} \rho_{kj} \geq \sum_{i=1}^{m} \rho_{tj}$, $j = 1, 2, \ldots, m$, it means that the index X_k is quasibetter than the index X_t, and it is said that $X_k \geq X_t$.

According to the above task index priority comparison results, the importance order (order relationship) of the task index X_i can be obtained as $X_a \circ X_b \circ X_c \circ X_d \cdots$, $\circ \in \{>, \geq\}$, where $a, b, c, d \cdots$ belongs to a certain item in (1, 2, 3, ..., s) and then find its importance degree weight.

In the order of importance of task index from large to small, if the task index in position l is better than the task index in position $l + 1$, that is, $X_{i_l} > X_{i_{(l+1)}}$, the importance weight of the task index is

$$\lambda_{i_l} = s - l + 1. \tag{22}$$

If the task index in position l is quasibetter than the task index in position $l + 1$, that is, $X_{i_l} > X_{i_{(l+1)}}$, the importance weight of the task index is

$$\lambda_{i_l} = s - l + \mu, \tag{23}$$

where μ is the task index importance discrimination factor, and the general value range is $0 \leq \mu \leq 1$. The larger the μ, the larger the importance weight and the more important the task index. Usually, $\mu = 0.5$ is preferable.

3.3. Determination of the Importance of the Capability Index. After determining the gray relational matrix and the task index importance weights, the traditional QFD analysis method is used to establish a "task index-capability index" house of quality (HOQ) model, as shown in Figure 5. The left wall of the quality house is the intelligent equipment support task index matrix, the right wall is the intelligent equipment support task index importance, the ceiling is the intelligent equipment support capability index matrix, the roof is the intelligent equipment support capability index correlation matrix, the room is the gray correlation matrix of the intelligent equipment support task index and the support capability index, and the floor is the importance of the intelligent equipment support capability index.

Using the determined parameter information, according to the calculation method of the HOQ model, the importance weight ω_j of each intelligent equipment support capability is determined, and the importance of the intelligent equipment support capability index is sorted, as shown in formula (12).

$$\omega_j = \sum_{i=1}^{n} \rho_{ij} \lambda_i. \tag{24}$$

4. Determination of the Importance of the Intelligent Equipment Support Capability Index

In recent years, experts usually take an integer between 10 and 9 to represent the expert's preference for task index and capability index. Taking relevant sample sets, according to the above model construction method, construct the expert preference model and store it in the model library. Randomly select 15 well-trained expert preference models and score the importance of the intelligent equipment support task index $X_i = (X_i(1), X_i(2), \ldots, X_i(15), i = 1, 2, \ldots, 6)$ in Table 1 and the intelligent equipment support capability

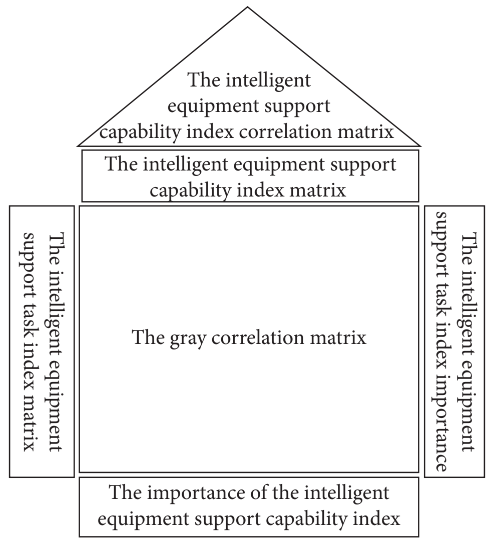

Figure 5: "Intelligent equipment support task index-intelligent equipment support capability index" HOQ model.

index $Y_j = (Y_j(1), Y_j(2), \ldots, Y_j(15), j = 1, 2, \ldots, 6)$ in Table 2 (see Table 3), respectively, $n = 15, s = 6$, and $m = 6$.

According to formula (21), the gray comprehensive correlation matrix ψ of intelligent equipment support task index X_i and intelligent equipment support capability index Y_j can be obtained by using the MATLAB tool:

$$\psi = \begin{bmatrix} 0.6266 & 0.8549 & 0.9508 & 0.6205 & 0.5634 & 0.6351 \\ 0.7654 & 0.8299 & 0.7606 & 0.7540 & 0.6293 & 0.7813 \\ 0.6844 & 0.9488 & 0.8821 & 0.6750 & 0.5938 & 0.6975 \\ 0.6367 & 0.9063 & 0.8457 & 0.6315 & 0.5649 & 0.6440 \\ 0.6168 & 0.8322 & 0.9250 & 0.6114 & 0.5578 & 0.6242 \\ 0.7837 & 0.6032 & 0.5839 & 0.7969 & 0.9148 & 0.7682 \end{bmatrix}. \quad (25)$$

Since the gray comprehensive correlation matrix satisfies

$$\sum_{j=1}^{6} \rho_{2j} > \sum_{j=1}^{6} \rho_{3j} > \sum_{j=1}^{6} \rho_{6j} > \sum_{j=1}^{6} \rho_{1j} > \sum_{j=1}^{6} \rho_{4j} > \sum_{j=1}^{6} \rho_{5j}, \quad (26)$$

the order relationship between the index of intelligent equipment support tasks can be obtained, $X_2 \geq X_3 \geq X_6 \geq X_1 \geq X_4 \geq X_5$. According to formula (23), take $\mu = 0.5$ and obtain the importance λ_i of the intelligent equipment support task index X_i:

$$(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6) = (2.5, 5.5, 4.5, 1.5, 0.5, 3.5). \quad (27)$$

Fill the gray comprehensive correlation matrix ψ and the absolute weight $(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6)$ of the intelligent equipment support task index X_i into the HOQ model, from formula (24). The importance ω_j of the intelligent equipment support capability index Y_j can be obtained, and the quality (Table 4) can be obtained.

$$(\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6) = (12.8624, 14.8581, 14.3045, 12.7779, 11.8698, 12.9905). \quad (28)$$

It can be seen from Table 4 that $Y_2 > Y_3 > Y_6 > Y_1 > Y_4 > Y_5$; the intelligent equipment support capability index Y_2 is the most critical, followed by Y_3; and Y_5 is the weakest. That is to say, among the six indexes of intelligent equipment support capability, intelligent data processing capability is the most critical, followed by intelligent command and decision-making capability.

Table 3: Expert preference model scoring table.

Index types	Expert preference model number														
	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*N*	*O*
X_1	7	6	6	5	7	4	6	5	7	7	5	4	6	3	6
X_2	6	7	4	6	6	7	5	6	4	3	6	7	4	5	6
X_3	9	8	8	9	8	8	7	8	8	9	7	8	7	7	8
X_4	4	7	4	5	6	5	3	5	4	6	4	6	5	5	6
X_5	6	6	5	3	5	4	5	6	5	4	3	3	4	5	5
X_6	8	9	7	8	8	7	8	7	9	8	8	7	8	8	9
Y_1	5	7	6	6	5	4	3	6	7	7	6	5	6	7	5
Y_2	7	7	8	5	6	7	5	5	6	7	4	5	7	6	5
Y_3	9	7	8	6	7	8	9	6	8	8	7	9	7	7	7
Y_4	7	8	6	7	8	7	7	6	8	7	9	6	7	8	8
Y_5	8	8	7	7	9	9	8	9	7	8	8	9	7	7	8
Y_6	5	4	5	6	5	4	5	5	6	4	5	6	6	7	6

Table 4: Intelligent equipment support "task index-capability index" quality table.

Intelligent equipment assurance mission indexes	Intelligent equipment support capability indexes						Importance of task index
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	
X_1	0.6266	0.8549	0.9508	0.6205	0.5634	0.6351	2.5
X_2	0.7654	0.8299	0.7606	0.7540	0.6293	0.7813	5.5
X_3	0.6844	0.9488	0.8821	0.6750	0.5938	0.6975	4.5
X_4	0.6367	0.9063	0.8457	0.6315	0.5649	0.6440	1.5
X_5	0.6168	0.8322	0.9250	0.6114	0.5578	0.6242	0.5
X_6	0.7837	0.6032	0.5839	0.7969	0.9148	0.7682	3.5
Equipment support capability index ω_j	12.8624	14.8581	14.3045	12.7779	11.8698	12.9905	
Sort	4	1	2	5	6	3	

5. Conclusion

5.1. Analysis of Results. The winning mechanism of intelligent equipment guarantee is "win by ingenuity" [19, 20]. Capturing the "right to control intellectual power" relies on the intelligent processing of data and information and focuses on computing power and algorithms. Therefore, among the six indexes of intelligent equipment support capability, intelligent data processing capability is the most important; intelligent command and decision-making is the starting point of all intelligent equipment support operations. Compared with other index capabilities, it is in a position to guide the direction of action; network intelligent protection is the basis of real-time situational awareness, and the two are the key capability index for obtaining assurance data and transmitting assurance information; precise material support is a prerequisite for intelligent detection and repair, and they all belong to specific equipment support activities, which need to be supported by the first few capability index. To sum up, the analysis results conform to the internal logic of the intelligent equipment support capability index, indicating the validity and scientificity of the analysis method, and this method is suitable for determining the importance of other capability indexes.

5.2. Method Innovation. The difference between the analysis method based on the GQFD-BP neural network and the traditional QFD analysis method is mainly reflected in the index scoring method and the process of determining the association matrix. The traditional QFD method is to select different experts to score the equipment support task requirement index and determine the importance of the equipment support task requirement index through the analytic hierarchy process. Delphi expert investigation method or weighted average method then directly scores the correlation degree between the equipment support task requirement index and the equipment support capability requirement index and determines the correlation matrix of "equipment support task-equipment support capability". The improved GQFD method is to score the equipment support task requirement index and the equipment support capability requirement index independently by constructing the expert preference model, and through a series of gray correlation analysis and processing, the gray correlation matrix and the important weights of equipment support task requirements are obtained.

The effectiveness and scientific nature of the method used in this paper have been fully verified above, and this method can overcome the shortcomings of the traditional QFD analysis methods, such as strong subjectivity and low effectiveness, form a dynamic importance evaluation mechanism, and make the results more objective, accurate, and reliable. This method has good generalization ability, that is to say, this method is also suitable for determining the importance of other indicators and can be widely used.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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