Intelligent Assessment method of Air-Defense & Anti-Missile Command Model Based on Genetic Algorithm Optimization

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Abstract. In order to solve the problems existing in the traditional assessment methods of Air-Defense and Anti-Missile command models, based on the requirements of the command model assessment, an intelligent Air-Defense and Anti-Missile command model intelligence assessment method based on genetic algorithm optimization was proposed. On the one hand, in order to meet the needs of the intelligent assessment, the evaluation knowledge bases is established based on the Air-Defense and Anti-Missile operational command process; on the other hand, basing on the historical data the objectivity of the assessment is improved by adjusting the index weights dynamically with the entropy weighting method and the intelligent optimization method. At the same time, the fuzzy relation matrix is obtained by real-time data processing of the command model and then using the multiple fuzzy comprehensive evaluation method to get the result. Finally, the feasibility of the method is verified by examples.

1. Introduction
Modeling and simulation is an effective method to study the Air-Defense and Anti-Missile command system. Whether or not the established model is true and reliable is the key to the success of the research, the evaluation of the model is an effective solution to the problem[1]. On the one hand, there is little research on the command model assessment in China, and the traditional assessment method has some disadvantages such as strong subjectivity, which cannot effectively solve the problem of the model assessment. To solve the problem of lack of objectivity due to excessive intervention of human factors, the literature[2] uses the intelligent means such as Expert System (ES) to realize the evaluation intelligence and improve the assessment results; on the other hand, the index is the key to assess the merits of the assessment method, and the importance of the indicator is differently, the relative weight of each indicator needs to be determined before the assessment[3]. In view of the shortcomings of AHP and other single-class methods in index weighting, combining with the characteristics of the model, a genetic algorithm is used to intelligently optimize the weights of the indexes.

2. Air-Defense and Anti-Missile operations command process and command model analysis
The Air-Defense and Anti-Missile warfare has changed the previous pattern of Air-Defense and Anti-Missile warfare relying solely on its own defense systems, and has turned into an integrated networked model for coordinated operations. The Air-Defense and Anti-Missile command system is the key node for carrying out integrated networked operations. The new-generation command system must have the ability to coordinate the control of two combat operations. Although the command process of Anti-Missile warfare calls for the accuracy of the command system is much higher than Air-Defense combat, both is based on the target data provided by the early-warning detection system to conduct a
series of command, control and decision-making. The specific Air-Defense and Anti-Missile warfare command process is shown in Figure 1.

![Figure 1. The operational command processes.](image)

The process includes eight sub-processes: target tracking selection, target identification, interception suitability analysis, threat assessment, interception sorting, goal allocation, launch decision and effect assessment. At the same time, on the one hand the command process of Air-Defense and Anti-Missile warfare involves the types of equipment, the interaction of information, the complex coordination of operations, the rules of battle, the rules of engagement and the optimal design of operational logic are non-unique. On the other hand, Air-Defense and Anti-Missile operations include various types of combat aircraft, cruise missiles, unmanned aerial vehicles, ballistic missiles and other weapons. The combat targets are unknown and dynamic, so it is difficult to predict the time, space, mode of operations and the intension. And the use of combat resources has the characteristics of nonlinearity, dynamic programming and multi-objective and multi-attribute decision-making[4]. These characteristics determine that the air defense and missile defense allegation model assessment is a difficult problem that is multi-scale, multi-parameter, qualitative and quantitative. Now the evaluation in China is basically based on the evaluation of the model's own software and the realization of functions. There are few studies on the scientific nature of the Air-Defense and Anti-Missile command model that are close to operational requirements.

3. Intelligent assessment framework design

3.1. Intelligent assessment process

The intelligent assessment mainly aims at constructing corresponding evaluation knowledge bases for evaluation objects[5]. The evaluation situation knowledge base is established according to the corresponding air conditions, and the evaluation task knowledge base is established basing on the different tasks faced during the command process at each stage. Then, an knowledge bases of evaluation rules is generated by combining specific air conditions and specific tasks in each phase to obtain evaluation rules. Each rule mainly corresponds to the data and parameters generated by the corresponding command sub-process in the case of specific air conditions, that is, the corresponding command model processing generates the data and parameters. During the entire process, the data and parameters that associated with each command model are recorded and detected through the evaluation platform, and compared with the corresponding evaluation rules to evaluate and acquire the assessment data, and the evaluation results are calculated through multiple fuzzy comprehensive evaluations[6]. In the index weights, using the entropy weight method and historical evaluation data
to dynamically adjust the weights and optimize the genetic algorithm. The framework is shown in Figure 2.

3.2. Evaluation knowledge bases construction
According to the analysis of the process, the model assessment knowledge bases is constructed, which is divided into the assessment situation knowledge bases, the assessment task knowledge bases and the evaluation rule knowledge bases. The content of the situation knowledge bases are classified on the basis of the air-raid weapons, which contain aerodynamic targets, ballistic missile targets and the situation combining aerodynamic targets with ballistic missile targets. According to the specific conditions, they can be divided into large-scale air strikes, medium-scale air strikes, small-scale air strikes and other specific situations. The evaluation task knowledge bases are mainly divided into sub-processes such as target identification, threat assessment, interception sorting and target allocation according to the various stages of the process. The evaluation rule knowledge bases is constructed according to the corresponding air conditions and tasks in each stage. The evaluation rules are the basis for assessment, including the data and parameter changes in the sub-processes. The model verification and evaluation platform analyzes the rationality of the model by performing real-time dynamic observation and data collection of the corresponding sub-processes and comparing them with the evaluation rules.

3.3. Multiple fuzzy comprehensive evaluation
The basic principle of multi-fuzzy comprehensive evaluation is to quantify indicators with fuzziness using fuzzy transformation in fuzzy mathematics. The literature [7] pointed out that the evaluation considers each index related to the object being evaluated, uses the principle of fuzzy linear transformation and the principle of maximum membership degree to quantify the index, and then carries out comprehensive evaluation to realize the quantitative and qualitative analysis of the evaluation object. The main steps of this method are as follows:

- build an evaluation index system: the evaluation index system $U$ is determined by each model and evaluation rules, which is composed of $k$ indicators, $U=(u_1, u_2, \cdots, u_k)$. For more complex tasks, it can be re-decomposed to form the simple and independent evaluation sub-processes.

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**Figure 2.** The intelligent assessment framework.
Each sub-process corresponds to a subset of evaluation factors $u_p, (p = 1,2,\ldots, k)$, consisting of $q$ factors, $u_p = (u_{p1}, u_{p2}, \ldots, u_{pq})$.

- establish evaluation result set: setting up the evaluation result set $V = (v_1, v_2, \ldots, v_l)$ according to the evaluation rules, $l$ is the number of comments, and the specific evaluation result is determined by the percentage system or the level according to the specific circumstances.

- determining the fuzzy relationship matrix: it is to determine the fuzzy relationship matrix from the lowest evaluation indicator set $u_p$ to the evaluation result set $R_p = (r_{ij})_{pq}$. The elements in the matrix are all in the $[0,1]$ interval, indicating the degree of membership $u_{pi}$ to $v_j$. First, determine the single factor evaluation value $r_{ij}$ of the factor $u_{pi}$ for the comment $v_j$. When the membership degree is judged, $c_{ij}$ shows the number of votes for the item $i$ to obtain the comment $j$ is multiplied by the scale value corresponding to the quantitative membership of the indicator[8], that is:

$$r_{ij} = \frac{c_{ij}}{\sum_{k=1}^{l} c_{ik}}$$

- determining the index weight: the index weight is an important factor of the evaluation. According to the relative importance of the elements in the evaluation index set $U$ and the evaluation result data, the weight of each evaluation index is calculated layer by layer, and intelligent optimization is performed to obtain the weight set $W = (w_1, w_2, \ldots, w_k)$, and $w_p = (w_{p1}, w_{p2}, \ldots, w_{pq})$.

- single-level fuzzy comprehensive evaluation: the weighted average method, that is, the matrix multiplication, is used as a fuzzy synthesis operation model to calculate the underlying fuzzy evaluation results $B_p = w_p \times R_p$. If the result of the evaluation is represented by a quantitative percentile score, the underlying fuzzy evaluation result is $B_p = 100w_p \times R_p$.

- multiple fuzzy comprehensive evaluation: the weighted average method is used to weight and summarize multiple evaluation results layer by layer to obtain the final evaluation result $S = W \times B^T$, where $B = (B_1, B_2, \ldots, B_k)$.

4. Intelligent optimization of evaluating indicator weights

4.1. Weight calculation based on entropy weight method

Entropy is an effective method for evaluating the attributes and importance of indicators and mainly used in information theory, which can be used to measure the size of information. The greater the entropy value is, the smaller the amount of information that the corresponding evaluation index can provide, and the smaller the influence of the index on the evaluation decision. Therefore, the calculation of the entropy weight in this paper is mainly based on the real-time and historical correlation evaluation data of the command model evaluation index, and the appropriate adjustment according to the data changes[9]. There are $n$ evaluation objects, each evaluation object contains $m$ evaluation indexes, and the matrix $Y = (y_{ij})_{n \times m}$ is obtained by dimensionless processing of the evaluation data. The steps are as follows:

- normalization process:

$$z_{ij} = \frac{y_{ij}}{\sum_{j=1}^{m} y_{ij}}, \quad j = 1,2,\ldots,m \tag{2}$$
the calculation of the evaluation index entropy is as follows (in the formula: k is the adjustment coefficient, \( k = 1/\ln n \), so \( k = 0.2569 \):

\[
H(x_j) = -k \sum_{i=1}^{n} z_q \ln z_q, \quad j = 1, 2, \ldots, m
\]

4.2. Weight optimization based on genetic algorithm

The genetic algorithm is derived from the survival of the fittest, and mainly through the simulation of this evolutionary principle to achieve the best solution in the search domain[10], according to the characteristics of the real-time command model assessment, in its evaluation the weights are dynamically adjusted and intelligently optimized at the same time. The specific steps are as follows:

- determining the subjective weights \( W_s = (w_{s1}, w_{s2}, \ldots, w_{sm}) \)
- determining the objective weights \( W_o = (w_{o1}, w_{o2}, \ldots, w_{om}) \)
- using genetic algorithm to optimize indicator weights: Assume that the subjective weight ratio is \( X = (x_1, x_2, \ldots, x_m) \), and the objective weight ratio is \( X' = (x_1', x_2', \ldots, x_m') \), where \( x_i + x_i = 1, (i = 1, 2, \ldots, m) \). Then, the vector \( W \) is obtained by synthesizing the subjective and objective weights with the optimized parameter vector \( X \).

The Air-Defense and Anti-Missile warfare command process involves many types of equipment and complex air conditions, such as diversification of air strike weapons and complex operational coordination relationships. Therefore, when assessing command models, it is necessary to thoroughly consider the impact of objective factors on the assessment results. On the other hand, it is the complexity of the combat command process that makes it difficult to predict the target of operations, time and the strength. In many cases, the commander needs to make decisions based on experience, which has a great influence on the subjective evaluation of the command model assessment, and how to coordinate the subjective and objective aspects of the command model assessment is particularly important. Therefore, in order to ensure the minimum deviation of the evaluation results, a non-linear optimization is performed using a genetic algorithm, the degree of dispersion is represented by the discrimination degree of the evaluation data, and the weight for obtaining the least dispersion is calculated. By minimizing the deviation between the subjective and objective weights, the credibility of the assessment results can be improved to a greater extent. The specific function is as follows:

\[
F = \min \sum_{j=1}^{m} \sum_{d=1}^{n} \left[ y_{j} \times w_{dj} \times x_{j} - y_{j} \times w_{dj} \times x_{j} \right]^2
\]

s.t.
\[
\begin{align*}
x_j + x_j' &= 1 \\
0 \leq x_j &\leq 1 \\
0 \leq x_j' &\leq 1
\end{align*}
\]

5. Example verification and analysis

Take the threat assessment model of Air-Defense and Anti-Missile operations under specific conditions as an example, which mainly includes analysis of threat factors, such as air strike target type and capability estimation, importance analysis of covered objects, analysis of target flight time, target altitude, and comparing analysis of target route shortcuts and so on. And other processing processes such as threat calculation, each processing process also includes related logic processing and
operations. In this paper, the assessment objects are seven different types of threat assessment models and basing on the corresponding sub-processes and the acquisition and comparison of relevant data parameters producing by the seven types of threat assessment models, an evaluation index system $U$ is constructed, which consists of eight evaluation index subsets, $U = (u_1, u_2, \ldots, u_8)$. Each assessment index includes a number of single-factor indicators that form a multi-level assessment index system, and uses the percentage system to represent the evaluation results. The evaluation results of the seven models are calculated by single-level fuzzy comprehensive evaluation are shown in table 1.

**Table 1. Single-level fuzzy comprehensive evaluation results.**

| Models | $u_1$ | $u_2$ | $u_3$ | $u_4$ | $u_5$ | $u_6$ | $u_7$ | $u_8$ |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1      | 86    | 89    | 81    | 75    | 78    | 80    | 92    | 79    |
| 2      | 70    | 88    | 79    | 86    | 69    | 74    | 70    | 78    |
| 3      | 74    | 45    | 69    | 67    | 44    | 57    | 53    | 70    |
| 4      | 82    | 47    | 70    | 83    | 89    | 83    | 85    | 86    |
| 5      | 60    | 77    | 51    | 56    | 65    | 42    | 67    | 45    |
| 6      | 79    | 91    | 81    | 77    | 78    | 79    | 92    | 75    |
| 7      | 63    | 73    | 76    | 86    | 91    | 82    | 91    | 67    |

Firstly, the subjective and objective weights of the evaluation indicators are determined by the Analytic Hierarchy Process (AHP) and the entropy method respectively, and then the subjective and objective biases are minimized and optimized by the genetic algorithm to obtain the combined weights. The population size is chosen 150, the crossover probability is 0.007, and the mutation probability is 0.003. After the evolution of 600 generations, the optimized weight ratio is obtained, and then the weights optimized by the genetic algorithm are obtained [11]. The weights of the indexes basing on the method are as follows:

$$ W_s = (0.0609, 0.2500, 0.0652, 0.1800, 0.1851, 0.1108, 0.0710, 0.0770) $$
$$ W_o = (0.1506, 0.1109, 0.1110, 0.1280, 0.1209, 0.1257, 0.1420, 0.1109) $$
$$ W = (0.0619, 0.1750, 0.0970, 0.1731, 0.1605, 0.1229, 0.0995, 0.1100) $$

Based on the index weights obtained above, the evaluation results obtained from multiple fuzzy comprehensive evaluations are shown in Table 2. At the same time, the average of the evaluation results obtained by multiple fuzzy comprehensive evaluations under different index weights is taken as the ideal value, and the error of the evaluation results of various methods are obtained and is shown in Table 3.

**Table 2. Multiple fuzzy comprehensive evaluation results.**

| Model | AHP   | Entropy Weight Method | Objective and Subjective Bias Minimization |
|-------|-------|-----------------------|------------------------------------------|
| 1     | 82.185| 82.724                | 81.957                                   |
| 2     | 78.841| 76.312                | 78.020                                   |
| 3     | 55.928| 60.143                | 57.808                                   |
| 4     | 87.075| 84.301                | 85.632                                   |
| 5     | 61.216| 58.047                | 59.056                                   |
| 6     | 82.200| 81.578                | 81.657                                   |
| 7     | 80.376| 79.442                | 80.373                                   |

**Table 3. Errors between assessment results.**

| Errors | AHP   | Entropy Weight Method | Objective and Subjective Bias Minimization |
|--------|-------|-----------------------|------------------------------------------|
| MAE    | 1.019 | 1.092                 | 0.238                                    |
| MRE    | 1.508 | 1.586                 | 0.331                                    |
| MSE    | 1.538 | 1.600                 | 0.070                                    |
6. Conclusion
Based on the current development and application of artificial intelligence in various fields, this paper proposes and designs a corresponding intelligent assessment method based on the characteristics of the command model assessment to improve the subjectivity of the experts. The treatment uses genetic algorithms for intelligent optimization. The feasibility of the method is verified by examples and the data obtained is analyzed. According to the results of data analysis, it can be intuitively understood that the intelligent assessment method is more reasonable and the error of the evaluation result is the smallest. However, the research is in the initial stage and there are still some problems existing. For example, the design of the current assessment knowledge bases or the lack of support for actual combat data; and there needs more in-depth study for the specific command model to ensure that the establishment of the evaluation index system is more reasonable and so on, so there are some study should be made in the follow-up.

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