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An Improved Model for Effectiveness Evaluation of Missile Electromagnetic Launch System

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ABSTRACT To solve the key problems of strong infrared radiation, poor continuous combat capability of the system, serious ablation of the launching device, and environmental pollution during missile launch, electromagnetic launch system (EMLS) has been studied for missile launching tasks. Since most of the current research is aimed at the key technologies and there is a lack of evaluation and balance of the entire system, the effectiveness of the missile electromagnetic launch system (MEMLS) needs to be evaluated. To solve the shortcomings of the existing effectiveness evaluation model, this paper establishes an improved model for effectiveness evaluation. The new model takes the availability-dependability-capability (ADC) model as the basic evaluation framework. The $L_{20}(2^{19})$ orthogonal table is constructed by using the orthogonal design idea without interaction. On the basis of quantifying and normalizing the indicators, different weighting methods are adopted according to the different characteristics of the two level indicators. The improved combination weighting model of game theory (ICWGT) is used to obtain the combined weights for indicators of each level. To coordinate the incompleteness, ambiguity, and randomness of the information, and at the same time meet the requirements of flexible numerical feature values, the asymmetric gray cloud model (AGCM) is used to determine the evaluation level and evaluation value of the inherent capability $\boldsymbol{C}$. On the basis of calculating the effectiveness evaluation value of each scheme by ADC model, the significance of each capability indicator of MEMLS was analyzed by variance analysis method. The conclusions obtained are consistent with the actual situation, which verifies the effectiveness of the model.

INDEX TERMS Missile electromagnetic launch system (MEMLS), effectiveness evaluation, availability-dependability-capability (ADC) model, orthogonal design, the improved combination weighting model of game theory (ICWGT), asymmetric gray cloud model (AGCM).

I. INTRODUCTION

Electromagnetic launch system (EMLS) is a launching technology that uses electromagnetic energy to convert it into payload kinetic energy [1]. EMLS can convert electrical energy into the kinetic energy required by the load in a short time, and push objects to reach a certain speed quickly [2]. EMLS has been widely used in military equipment such as artillery shells, carrier aircraft, etc. due to the advantages of low launch cost, safe handling, strong adaptability, easy energy control, and repeatable rapid launch. However, the application of electromagnetic launch (EML) technology to missiles is still in the demonstration stage and requires a common breakthrough in technology in multiple fields. Missile electromagnetic launch system (MEMLS) refers to changing the traditional cold launching and thermal launching methods, using EML technology to eject missiles from carriers such as launch cylinders, and then using propellants for initial acceleration. MEMLS can effectively solve the key problems of the traditional missile launch system, such as strong infrared radiation which is not conducive to concealment, poor continuous combat capability, serious ablation of the launcher, and environmental pollution.

At present, most of the research on MEMLS is still the research of core technologies such as pulsed energy storage power supply, pulsed power discharge, motor control, etc., and the evaluation of the entire system is relatively lacking. To make the demonstrated MEMLS more reasonable and reliable, the effectiveness of the system needs to be evaluated to determine the best demonstration plan. The methods for evaluating the effectiveness of weapon systems mainly include three categories: analytical calculation methods,

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index evaluation methods, and simulation methods. One of the most versatile and easy to expand and perfect methods is the availability-dependability-capability (ADC) model. The ADC model is an efficiency analysis model and method proposed by the US Industrial Weaponry System Effectiveness Advisory Committee. The system effectiveness evaluated by the ADC model is a measure of the degree to which the system meets the requirements of a specific set of operational functions and is a function of system availability, dependability, and inherent capability. In response to the improvement of the ADC model, Shao established the G-BDP-ADC model using the gray theory and weight distribution model, which solved the problem of evaluating the effectiveness of the LEO satellite communication system [3]; Pirzadeh studied the effectiveness of the hybrid ADC model on how to overcome the channel estimation error caused by coarse quantization [4]; Gui has established an effectiveness evaluation model of drone driving equipment based on the ADC method [5]. The above literature puts forward some ideas for the improvement of the ADC method, but the method for weighting the indicators at all levels is single, and there is no combination of objective and subjective factors. At the same time, the weighting methods for different levels of indicators are not different and targeted. In terms of weight combination, Niu calculated the combination of the two weighting methods by finding the difference coefficient [6]; Gao obtained the combination weight by using the objective data to modify the weighting method of the subjective data [7]; Zhai achieved the combined weight of the goal through an optimized planning method [8]. The above weight combination model is only suitable for the combination of two weighting methods and has a high dependence on one of the methods, which has certain limitations and cannot guarantee accuracy. In terms of gray fuzzy evaluation, Mi used gray clustering to effectively deal with the decision-making problem in the case of incomplete information [9]; Peng applied the gray cloud model to the whitening weight function and improved the method of determining the whitening weight of the gray evaluation method [10]. The above research discusses solutions to information ambiguity and subjective randomness in the evaluation, but the traditional normal gray cloud model (NGCM) limits the flexibility of the model's peak and boundary values, which affects the reliability of the evaluation results.

To solve the problem of effectiveness evaluation of MEMLS and improve the deficiencies of the above methods, this paper establishes a new effectiveness evaluation model. The main structure of this paper is as follows: Section I introduces the basic concepts and advantages of EMLS and MEMLS, and points out the current research status and deficiencies of the existing effectiveness evaluation methods, ADC model, combined weighting method and gray cloud model; Section II establishes a new system effectiveness evaluation model, specifically describing the ADC model, fuzzy analytic hierarchy process (FAHP), active loop method (ALM), entropy weight method (EWM), improved combination weighting model of game theory (ICWGT) and asymmetric gray cloud model (AGCM); In section III, the $L_{20}(2^{19})$ orthogonal table is constructed by using the orthogonal design idea without interaction. The effectiveness of MEMLS is evaluated by using the established model combined with specific sample data. And variance analysis is carried out on the effectiveness evaluation value of the schemes, and the results of significance comparison of capability indicators of MEMLS are obtained and analyzed; Section IV summarizes the main innovations and conclusions of this paper.

II. SYSTEM EFFECTIVENESS EVALUATION MODEL

This section mainly introduces a new effectiveness evaluation model for MEMLS established in this paper. The steps and methods of model establishment are shown in Fig. 1.

A. EFFECTIVENESS EVALUATION FRAMEWORK BASED ON ADC MODEL

First, establish the basic framework of the ADC model, the general model [11] is

$$\boldsymbol{E} = \boldsymbol{A} \cdot \boldsymbol{D} \cdot \boldsymbol{C} \tag{1}$$

In the formula: $\boldsymbol{E}$ is the effectiveness of the system; $\boldsymbol{A}$ is the availability vector of the system; $\boldsymbol{D}$ is the dependability matrix of the system; $\boldsymbol{C}$ is the inherent capability vector of the system.

Next, the availability vector, dependability matrix and inherent capability vector model of the system are analyzed and established.

1) AVAILABILITY VECTOR OF THE SYSTEM

The availability vector of the system can be expressed as

$$\boldsymbol{A} = [a_1, a_2, a_3, \ldots, a_i, \ldots, a_n] \tag{2}$$

In the formula: a_i is the probability that the state of the system is i at the initial moment; n is the number of possible states of the system at the initial moment.

The representation of the availability vector model for series and parallel systems [12], [13] is discussed below.

a: SERIES SYSTEM

Suppose a system is composed of m subsystems. Each subsystem has only two states: normal and fault. If any of the subsystems fails, the system is faulty. If all subsystems are normal, the system is normal. Such a system is a series system. It is easy to get that the system has only two states: normal and faulty. In this case, the system availability vector is

$$\boldsymbol{A} = [a_1, a_2] = \left[\prod_{i=1}^{m} \frac{MTBF_i}{MTBF_i + MTTR_i + MLDT_i}, \; 1 - \prod_{i=1}^{m} \frac{MTBF_i}{MTBF_i + MTTR_i + MLDT_i} \right] \tag{3}$$

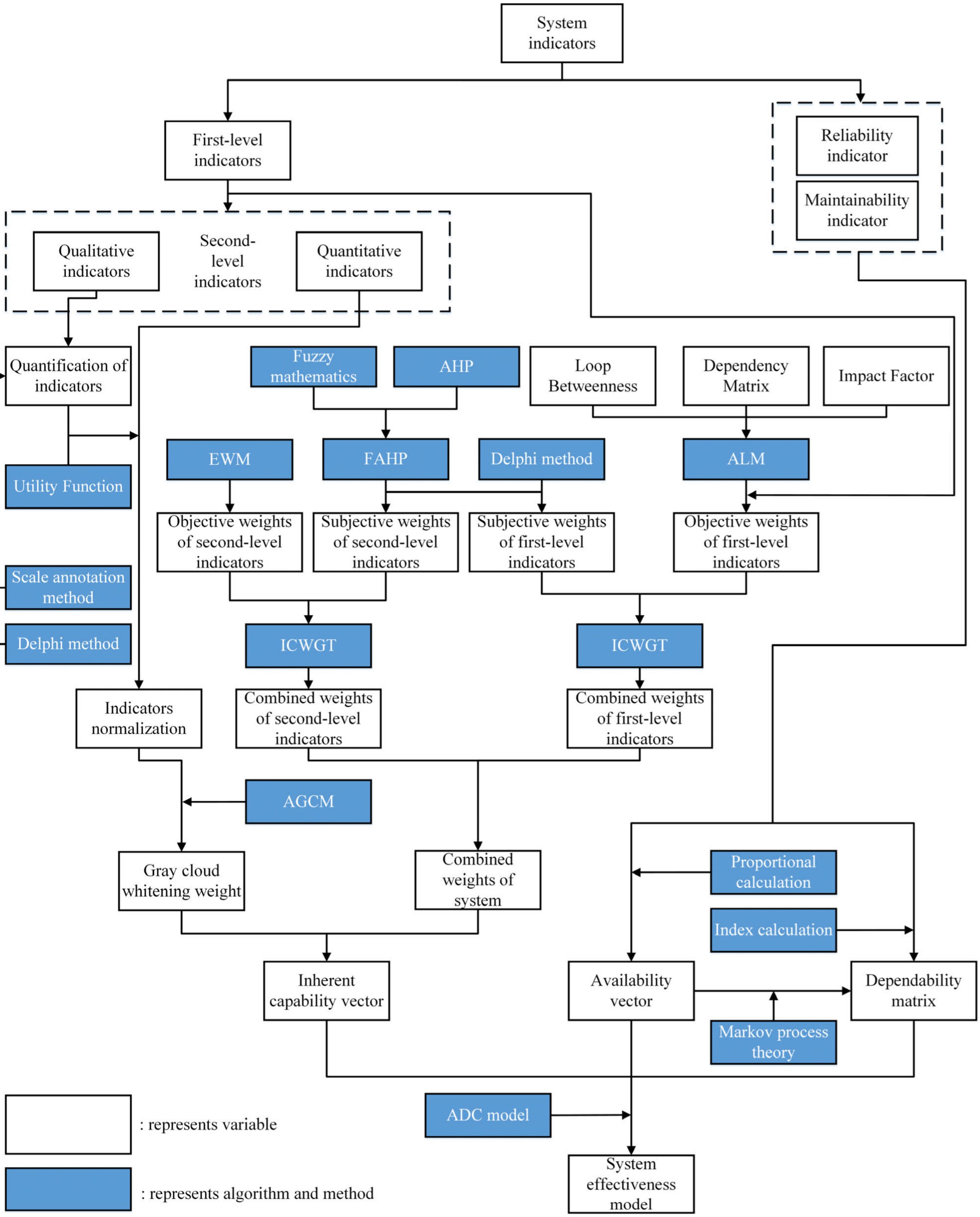

FIGURE 1. The establishment steps and methods of MEMLS effectiveness evaluation model.

In the formula: a_1 is the probability that the initial state of the system is normal; a_2 is the probability that the initial state of the system is fault; $MTBF_i$ is the average time between failures of the i-th subsystem; $MTTR_i$ is the average repair time of the i-th subsystem; $MLDT_i$ is the i-th The average delay time of each sub-system is guaranteed.

b: PARALLEL SYSTEM

Suppose a system consists of m subsystems connected in parallel. Each subsystem has only two states: normal and fault. If any of the subsystems is normal, the system is normal. Such a system is a parallel system. It is easy to get that the system has 2^m states. Note that a_{si} is the availability of the i-th subsystem and $\overline{a_{si}} = 1 - a_{si}$ is the unavailability of the i-th subsystem. Then the availability vector of the system is as follows.

$$\begin{aligned} \boldsymbol{A} &= [a_1, a_2, a_3, \ldots, a_m, a_{m+1}, a_{m+2}, \ldots, a_{2^m}] \\ &= \begin{bmatrix} a_1 \cdot a_2 \cdot a_3 \cdot \ldots \cdot a_{sm} \\ \overline{a_{s1}} \cdot a_2 \cdot a_3 \cdot \ldots \cdot a_{sm} \\ a_1 \cdot \overline{a_{s2}} \cdot a_3 \cdot \ldots \cdot a_{sm} \\ \vdots \\ a_1 \cdot a_2 \cdot a_3 \cdot \ldots \cdot \overline{a_{sm}} \\ \overline{a_{s1}} \cdot \overline{a_{s2}} \cdot a_3 \cdot \ldots \cdot a_{sm} \\ \vdots \\ \overline{a_{s1}} \cdot \overline{a_{s2}} \cdot \overline{a_{s3}} \cdot \ldots \cdot \overline{a_{sm}} \end{bmatrix} \end{aligned} \tag{4}$$

In the formula: a_i is the probability that the system is i at the initial moment; a_{si} is the availability of the i-th subsystem; $\overline{a_{si}} = 1 - a_{si}$ is the unavailability of the i-th subsystem.

2) DEPENDABILITY MATRIX OF THE SYSTEM

Suppose that the number of possible states of the system is n, these n states can be converted to each other. According to Markov process theory [14], the state transition matrix is

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{5}$$

In the formula: $\boldsymbol{P}$ is a transition state matrix; p_{ij} represents the probability that the state i becomes j after a transition.

Suppose that the number of possible states of the system is n, and if the system cannot be repaired during the mission, the dependability matrix of the system is expressed as

$$\boldsymbol{D} = \begin{bmatrix} d_{11}(t) & d_{12}(t) & \ldots & d_{1n}(t) \\ 0 & d_{22}(t) & \ldots & d_{2n}(t) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 1 \end{bmatrix} \tag{6}$$

In the formula: $d_{ij}(t)$ represents the probability of transitioning from the i state to the j state at time t when the system is working.

Each element in the matrix meets the following conditions.

$$\begin{cases} 0 \le d_{ij}(t) \le 1 & i, j = 1, 2, \cdots n \\ \sum_{j=1}^{n} d_{ij}(t) = 1 & i = 1, 2, \cdots n \end{cases} \tag{7}$$

The reliability of series and parallel systems is discussed below. When the system structure is different, the reliability expression of the system is also different. Suppose that m subsystems have independent failures and the reliability of each subsystem is R_i, then the reliability of series and parallel systems [15] can be expressed as

$$R_s(t) = \prod_{i=1}^{m} R_i(t) \tag{8}$$

$$R_s(t) = 1 - \prod_{i=1}^{m} (1 - R_i(t)) \tag{9}$$

Suppose that the Markov assumption is true, the steps to establish the dependability matrix calculation model are as follows:

a: DETERMINE THE SYSTEM STATUS

Combine the different states of the same ability in the process of the system into a state.

b: ESTABLISH A STATE TRANSITION PROBABILITY MATRIX *P*

Analyze and determine the value of each element in the system state transition matrix.

c: ESTABLISH THE SYSTEM STATE EQUATION

The probability that the system is in different states at time t is expressed as

$$\begin{cases} p_1(t) = \mathrm{P}\{\mathrm{S}(t) = \mathrm{S}_1\} \\ p_2(t) = \mathrm{P}\{\mathrm{S}(t) = \mathrm{S}_2\} \\ \vdots \\ p_n(t) = \mathrm{P}\{\mathrm{S}(t) = \mathrm{S}_n\} \end{cases} \tag{10}$$

In the formula: $\mathrm{S}(t) = \mathrm{S}_i$ represents the event that the system state is i at time t.

The probability that the system is in a certain state at time t can be expressed by the probability of another state and its state transition probability, that is, after Δt time, there is

$$\boldsymbol{P}_j(t) = p_i(t) p_{ij} \cdot \Delta t \tag{11}$$

When Δt tends to 0, a set of equations can be obtained.

$$\begin{cases} \dfrac{\mathrm{d}\boldsymbol{p}(t)}{\mathrm{d}t} = \boldsymbol{U}\boldsymbol{p}(t) \\ \boldsymbol{U} = [\boldsymbol{P}^{\mathrm{T}} - \boldsymbol{I}] = \begin{bmatrix} p_{11} - 1 & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} - 1 & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} - 1 \end{bmatrix} \\ \boldsymbol{p}(t) = [p_1(t), p_2(t), \cdots p_n(t)]^{\mathrm{T}} \end{cases} \tag{12}$$

d: SOLVE THE DEPENDABILITY MATRIX

From the n initial states of the system, n special solutions are calculated, and the dependability matrix of the system can be obtained as

$$\boldsymbol{D} = \begin{bmatrix} \boldsymbol{d}_1(t) & \boldsymbol{d}_2(t) & \cdots & \boldsymbol{d}_n(t) \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} d_{11}(t) & d_{12}(t) & \dots & d_{1n}(t) \\ d_{21}(t) & d_{22}(t) & \dots & d_{2n}(t) \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1}(t) & d_{n2}(t) & \dots & d_{nn}(t) \end{bmatrix} \tag{13}$$

3) INHERENT CAPABILITY VECTOR OF THE SYSTEM

The inherent capability vector C of the system can be expressed as

$$\boldsymbol{C} = [c_1, c_2, c_3, \dots, c_i, \dots, c_n] \tag{14}$$

In the formula: c_i is a measure of the ability of the system to complete the task when the state of the system is i during the execution of the task.

If the relevant assumptions hold, then the steps to solve the inherent capability vector of the system are as follows

a: SELECTION OF THE INHERENT CAPABILITY INDICATORS OF THE SYSTEM

The inherent capability indicators of the system refer to the index parameters that the system plays a certain role in the effectiveness of the task in the process of completion, generally including quantitative indicators and qualitative indicators. For more complex systems, first-level and second-level indicators can be set up for hierarchical solution.

b: QUANTIFICATION OF QUALITATIVE INDICATORS

For qualitative indicators, the scale annotation method or Delphi method can be used to score certain performance indicators.

c: NORMALIZATION OF INDICATORS AFTER QUANTIZATION

The utility function is used to normalize the dimension indicators. If the values of different schemes of the same performance indicators are normalized, there are

If the system effectiveness is positively correlated with x, then the maximum value is x', then

$$R(x) = \frac{x}{x'} \tag{15}$$

If the system effectiveness is negatively correlated with x, then the minimum value is x', then

$$R(x) = \frac{x'}{x} \tag{16}$$

B. WEIGHT CALCULATION

1) CALCULATION OF SUBJECTIVE WEIGHT BASED ON FAHP

AHP regards the problem of complex multiobjective decision-making as a system and decomposes the objective layer into objectives, criteria, and indicators. The AHP uses the expert scoring method to determine the relative importance, and the weight of the indicator is determined by solving the feature vector method [16]. However, the AHP has certain deficiencies, such as the difficulty of consistency testing, and the lack of a scientific basis for the criterion $CR < 0.1$, which is different from the consistency of human thinking. The FAHP introduces the idea of fuzzy mathematics [17] into the traditional AHP. FAHP originated in 1983. Van Loargoven of the Netherlands used the relevant ideas of fuzzy mathematics to fuzzyly expand Satty's ranking. Since then, the FAHP has been continuously applied to systemic evaluation and analysis, covering various fields such as risk assessment, analysis of complex environments, industrial production and sales, economic finance, and military technology [18]–[21].

The steps to calculate the weights using FAHP are as follows:

a: ESTABLISH A HIERARCHICAL ANALYSIS STRUCTURE MODEL

The establishment of the hierarchical analysis structure model of the system indicators is based on the system identification, and the inherent capability indicators of the system are layered into several groups, and then different levels are formed according to the rules. In the hierarchical structure model, the following hierarchical analysis structure model is mainly established:

1) Objective layer: Indicate the objective of the solution required by AHP.
2) Criteria layer: Generally, choose the weight and normalized value of the solution target.
3) Factor layer: There are many general indicators of the system, so the factor layer often has multiple layers.

b: CONSTRUCT FUZZY COMPLEMENTARY JUDGMENT MATRIX

After establishing the hierarchical analysis structure model, the membership relationship between the upper and lower layers is determined accordingly. First, construct a fuzzy judgment matrix. In this paper, the comparison between the two levels of indicators adopts the quantitative expression of the importance of one indicator compared with the other. Generally, the nine-scale method in Table 1 is used to get the quantity scale between indexes and establish the fuzzy judgment matrix $\boldsymbol{F} = (f_{ij})_{q\times q}$. If $f_{ij} + f_{ji} = 1$, then $\boldsymbol{F}$ is the fuzzy complementary judgment matrix.

c: CALCULATE FUZZY CONSISTENCY JUDGMENT MATRIX AND WEIGHT VECTOR

Sum each row of the fuzzy complementary judgment matrix and make a mathematical transformation to obtain the fuzzy consistency judgment matrix $\boldsymbol{R} = (r_{ij})_{q\times q}$, as in formula (17).

$$\begin{cases} r_i = \sum_{j=1}^{q} f_{ij} & i = 1, 2, \cdots, q \\ r_{ij} = \dfrac{r_i - r_j}{2(q-1)} + \dfrac{1}{2} & i, j = 1, 2, \cdots, q \end{cases} \tag{17}$$

Perform row and normalization processing on the matrix $\boldsymbol{R}$ to obtain the indicator ranking vector, in which the weight

TABLE 1. Nine-scale method scale.

Scale value	Value condition
0.5	Indicator i is as important as indicator j
0.6	Indicator i is slightly more important than indicator j
0.7	Indicator i is obviously more important than indicator j
0.8	Indicator i is much more important than indicator j
0.9	Indicator i is extremely more important than indicator j
0.1, 0.2, 0.3, 0.4	Inverse comparison of the above indicators

vector satisfies

$$\omega_i' = \frac{\sum_{j=1}^{q} f_{ij} - 1 + \frac{q}{2}}{q(q-1)} \quad i = 1, 2, \cdots, q \tag{18}$$

d: CONSISTENCY TEST OF FUZZY COMPLEMENTARY JUDGMENT MATRIX

In this paper, when the consistency test is performed, the selection criterion is the compatibility indicator of the fuzzy judgment matrix and its characteristic matrix. Calculate the characteristic matrix of fuzzy judgment matrix.

$$\begin{cases} W_{ij} = \dfrac{\omega_i'}{\omega_i' + \omega_i'} & i, j = 1, 2, \cdots, q \\ \boldsymbol{W}^* = (W_{ij})_{n\times n} & i, j = 1, 2, \cdots, q \end{cases} \tag{19}$$

In the formula: $\boldsymbol{W}^*$ is the characteristic matrix of the fuzzy judgment matrix.

Construct compatibility indicator.

$$I(\boldsymbol{F}, \boldsymbol{W}^*) = \frac{\sum_{i=1}^{q}\sum_{j=1}^{q} \left| f_{ij} - W_{ij} \right|}{q^2} \tag{20}$$

In the formula: $I(\boldsymbol{F}, \boldsymbol{W}^*)$ is the compatibility indicator.

When the formula (21) is satisfied, the judgment matrix is considered to satisfy consistency. The weight obtained by formula (18) is the subjective weight based on FAHP.

$$I(\boldsymbol{F}, \boldsymbol{W}^*) \leq \alpha \tag{21}$$

In the formula: α represents the attitude of the decision maker. The smaller α, the higher the consistency requirement of the decision maker. α is generally 0.1.

2) CALCULATION OF OBJECTIVE WEIGHT BASED ON ALM

With the widespread application of complex network theory, network measurement methods are commonly used to evaluate system nodes in the field of combat systems, including quantitative analysis of the importance of system nodes using indicators such as intermediaries, compactness, and feature vectors. The reference [22] proposed a ring ranking metric based on closed path detection, but the evaluation result is not precise enough to judge the importance of similar nodes. To solve the related problems, this paper uses ALM to calculate the objective weight of the system that satisfies the loop model. The reference [23] has verified the effectiveness and accuracy of the method and will not repeat the proof here.

First, define the evaluation indicators.

a: LOOP BETWEENNESS lb_i

represents the ratio of the number of loops passing through this node in the network to the total number of network loops, the calculation formula is as follows.

$$lb_i = \frac{num_i}{sum(loop)} \tag{22}$$

In the formula: num_i represents the number of loops passing through node i; $sum(loop)$ represents the total number of network loops.

b: DEPENDENCY MATRIX DM

indicates the degree of dependence between nodes, d_{ij} is the shortest distance from node i to node j, $1/d_{ij}$ is the degree of dependence, and the degree of node dependence on itself is 1. The dependency matrix $\boldsymbol{DM}$ can be constructed according to the method.

c: IMPACT FACTOR k_i:

According to the study of distance by network science, the more the number of edges between two nodes, the more difficult it is to reach two points, and the greater the possibility that the loop passing through the two points will be destroyed. Therefore, the impact factor can be used to express the various uncertainties that affect the smooth completion of the loop. The calculation formula is as follows.

$$k_i = \frac{ave_i}{\max(loop)} \tag{23}$$

In the formula: ave_i represents the average size of the loop through node i; $\max(loop)$ represents the number of sides of the largest loop in the network.

Next, calculate the importance of nodes in the network relative to other nodes, which can be represented by $\boldsymbol{H}$.

$$\boldsymbol{H} = \boldsymbol{DM} \cdot \left[lb_1, lb_2, \cdots, lb_q\right]^{\mathrm{T}} \tag{24}$$

The importance set of nodes can be expressed as $\boldsymbol{IM}$.

$$\boldsymbol{IM} = \boldsymbol{H} \times \left[\frac{1}{k_1}, \frac{1}{k_2}, \cdots, \frac{1}{k_q}\right]^{\mathrm{T}} \tag{25}$$

Finally, the elements in the obtained $\boldsymbol{IM}$ are normalized and normalized to obtain the objective weight of the loop node.

3) CALCULATION OF OBJECTIVE WEIGHT BASED ON EWM

For indicators that have no network relationship and can be quantified as specific values, EWM can be used to calculate objective weights. The concept of entropy was first applied to the field of thermodynamics in physics. EWM originated in 1948. N. Wiener and C. E. Shannon founded information theory. At the same time, the uncertainty of the signal of the information source in the communication process is called information entropy. The proposal of this theory solves the problem of describing information. EWM is a mathematical method for weighting based on the objective information of the indicator. This method calculates the weight based on the comprehensive consideration of the amount of information provided by the indicator. As an objective weighting method, EWM has been widely used in the field of system evaluation.

The steps and methods of calculating the weight of each indicator by information entropy [24] are as follows:

(1) Construct a data matrix

The data set composed of p samples and q indicators is normalized to obtain a data set X_{ij} for evaluation.

$$\boldsymbol{X}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1q} \\ x_{21} & x_{22} & \cdots & x_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pq} \end{bmatrix} \tag{26}$$

In the formula: x_{ij} is the normalized value of the j-th index value in the i-th sample.

(2) Calculate the proportion of the i-th sample under the j-th indicator to all samples of the indicator.

$$t_{ij}=\frac{x_{ij}}{\sum_{i=1}^{p} x_{ij}} \quad (j=1,2,\cdots,q) \tag{27}$$

(3) Calculate the entropy of the j-th indicator.

$$e_j=\frac{\sum_{i=1}^{p} t_{ij}\ln(t_{ij})}{-\ln(p)} \quad (j=1,2,\cdots,q) \tag{28}$$

(4) Calculate the weight

The weight is determined by the difference coefficient of the indicator. The greater the difference value of the indicator, the greater the effect on the evaluation and the smaller the entropy value. The weight calculation formula based on EWM can be obtained.

$$\omega_j''=\frac{1-e_j}{\sum_{j=1}^{q}(1-e_j)} \quad (j=1,2,\cdots,q) \tag{29}$$

In the formula: ω_j'' is the EWM weight of the j-th indicator.

4) CALCULATION OF COMBINED WEIGHT BASED ON ICWGT

The weights obtained by FAHP reflect the experience of experts, but they are subjectively arbitrary and difficult to guarantee objectivity. The weights obtained by ALM are based on the loop and are objective, but they are greatly affected by loop analysis. And the weights obtained by EWM are based on the indicator value, which are objective, but unstable, and are greatly affected by data fluctuations. How to determine the combined weights under the conditions of taking into account both subjective decision-making and objective data is a process of mutual coordination and competition. The object of game theory research is competitive things, and it is a tool for balanced decision-making when analyzing the influence of multiple decision-making schemes. The assumption of game theory is that the decision-making schemes are all rational decisions, that is, the decision-making schemes are all positive decisions made to achieve the goals. Game theory seeks to maximize common interests in the decision-making process.

CWGT uses the idea of game theory to synthesize different weighting schemes. Since this game is a noncooperative game, the basic goal is to minimize the spread between the weighting schemes, that is, to achieve Nash balance.

However, the traditional CWGT is prone to the situation that the obtained combination coefficient is negative, which clearly does not meet the objective requirements. Therefore, this paper uses ICWGT.

Suppose that there are q evaluation indicators and k weighting schemes, k basic weight sets can be obtained, and the linear combination of k basic weight sets can be expressed as

$$\omega=\sum_{i=1}^{k}\alpha_i\omega_i^{\mathrm{T}} \tag{30}$$

In the formula: ω is any combination of k basic weight sets; α_i represents the linear combination coefficient of the i-th weight set, $\alpha_i>0$; ω_i^{T} is the i-th weight set.

Based on the basic theory of CWGT [25], the optimized game model is

$$\min_{j=1,2,\cdots,k}\left\|\sum_{i=1}^{k}\alpha_i\omega_i^{\mathrm{T}}-\omega_j\right\|_2 \tag{31}$$

In the formula: ω_j is the weight set of the j-th weighting scheme.

According to the properties of matrix differential, to prevent the linear combination coefficient from being negative, the optimal condition of ICWGT is

$$\min_{\alpha_1,\alpha_2,\cdots,\alpha_k} f=\sum_{j=1}^{k}\left|\left(\sum_{i=1}^{k}\alpha_i\omega_j\omega_i^{\mathrm{T}}\right)-\omega_j\omega_j^{\mathrm{T}}\right| \tag{32}$$

Borrowing the constraints of the objective weighting method for maximizing dispersion, the linear combination coefficient can also satisfy the following conditions.

$$\begin{cases}\alpha_i>0 & i=1,2,\cdots,k \\ \sum_{i=1}^{k}\alpha_i^2=1 & \end{cases} \tag{33}$$

The Lagrange function is constructed as follows.

$$L(\alpha_i,\lambda)=\sum_{j=1}^{k}\left|\left(\sum_{i=1}^{k}\alpha_i\omega_j\omega_i^{\mathrm{T}}\right)-\omega_j\omega_j^{\mathrm{T}}\right|+\frac{\lambda}{2}\left(\sum_{i=1}^{k}\alpha_i^2-1\right) \tag{34}$$

Find the partial derivatives of α_i and λ respectively, combined with the constraints, and $\alpha_i > 0$, we can obtain

$$\alpha_i = \frac{\sum_{j=1}^{k} \omega_j \omega_i^{\mathrm{T}}}{\sqrt{\sum_{i=1}^{k}\left(\sum_{j=1}^{k} \omega_j \omega_i^{\mathrm{T}}\right)^2}} \tag{35}$$

Formula (35) is the only solution that satisfies the condition, and finally the α_i is normalized as follows.

$$\alpha_i^* = \frac{\sum_{j=1}^{k} \omega_j \omega_i^{\mathrm{T}}}{\sum_{i=1}^{k}\sum_{j=1}^{k} \omega_j \omega_i^{\mathrm{T}}} \tag{36}$$

The final combination weight is

$$\omega^* = \sum_{i=1}^{k} \alpha_i^* \omega_i^{\mathrm{T}} \quad i = 1, 2, \cdots, k \tag{37}$$

Different combination methods will get different combination weights, so it is essential to test the rationality of combination weighting. This paper uses the average degree of difference to test the rationality of the combination weights. The formula for calculating the average difference is as follows.

$$\overline{D(\omega^*)} = \frac{1}{k \times p} \sum_{l=1}^{k} \sum_{i=1}^{p} \sum_{j=1}^{q} \left| x_{ij}(\omega^*(j) - \omega_l(j)) \right| \tag{38}$$

In the formula: x_{ij} is the normalized value of the j-th indicator of the i-th sample; $\omega^*(j)$ is the weight of the j-th indicator of the combined weight; $\omega_l(j)$ is the weight of the j-th indicator of the l-th single weighting method; k is the total number of single weighting methods; p is the total number of samples; q is the total number of indicators.

The smaller the average difference is, the smaller the deviation between the combined weights and the weights obtained by other single weighting methods is, that is, the more reasonable the method of combined weighting.

C. AGCM DETERMINES THE EVALUATION VALUE

Due to the complexity of the evaluation system, the diversity of the indicators, and the uncertainty of the information, the system evaluation has strong ambiguity and grayness. To solve these problems, the gray cloud model is widely used in the field of system evaluation [26], [27]. According to the symmetry of the NGCM [28], the quantitative relationship between the peak value and the boundary value can be obtained, but at the same time it limits the flexibility of the model value and reduces the reliability of the evaluation results. Therefore, this paper uses AGCM to evaluate the system effectiveness [29], which can effectively solve the problem of information uncertainty and inflexibility of the model value in the evaluation process.

1) NGCM

The gray cloud model whose curve conforms to the normal distribution law is called the NGCM, which satisfies the following conditions.

$$\begin{aligned} Cx &= (Lx + Rx)/2 \\ En &= (Rx - Lx)/6 \\ He &= En/\gamma \end{aligned} \tag{39}$$

In the formula: Cx represents the peak value; Lx represents the left boundary value; Rx represents the right boundary value; En represents the entropy, that is, the measurement of the ambiguity of the left and right boundary values; He represents the superentropy, that is, the degree of dispersion of the cloud droplets; γ is given constant.

Suppose $T_1, T_2, \cdots, T_s$ is the gray class to which the clustering object belongs, and s is the total number of gray classes. Then the normalized gray cloud whitening weight function whose indicator j belongs to the gray class T_k satisfies the NGCM of moderate measurement, as shown in Fig. 2, the available formula is as follows.

$$f_j^k(x) = \begin{cases} \exp\left[-\dfrac{(x - Cx)^2}{2(En')^2}\right], & x \in [Lx, Rx] \\ 0, & x \notin [Lx, Rx] \end{cases} \tag{40}$$

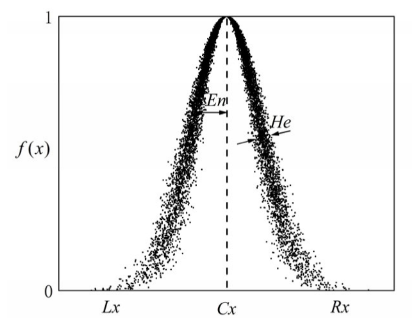

FIGURE 2. Moderately measured NGCM.

In the formula: En' is a normal random number with En as the expectation and He as the standard deviation.

The normalized gray cloud whitening weight function whose indicator j belongs to the gray class T_k satisfies the NGCM of lower limit measurement, as shown in Fig. 3,

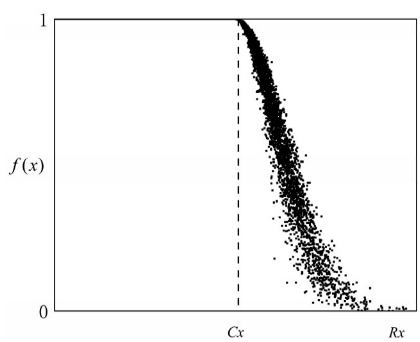

FIGURE 3. NGCM with lower limit measurement.

the available formula is as follows.

$$f_j^k(x) = \begin{cases} 1, & x \in [Lx, Cx] \\ \exp\left[-\dfrac{(x-Cx)^2}{2(En')^2}\right], & x \in [Cx, Rx] \\ 0, & x \notin [Lx, Rx] \end{cases} \tag{41}$$

The normalized gray cloud whitening weight function whose indicator j belongs to the gray class T_k satisfies the NGCM of upper limit measurement, as shown in Fig. 4, the available formula is as follows.

$$f_j^k(x) = \begin{cases} \exp\left[-\dfrac{(x-Cx)^2}{2(En')^2}\right], & x \in [Lx, Cx] \\ 1, & x \in [Cx, Rx] \\ 0 & x \notin [Lx, Rx] \end{cases} \tag{42}$$

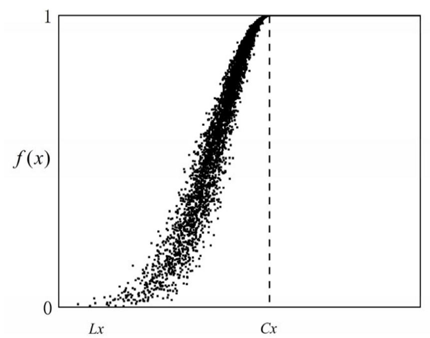

FIGURE 4. NGCM with upper limit measurement.

2) GRAY CLUSTER EVALUATION PROCESS BASED ON AGCM

In reality, the peak value of the system evaluation model is often not the middle value of the left and right boundary values, but any possible value within the range, so this paper establishes AGCM. AGCM is composed of two different half-curves of a moderately measured NGCM. Since it is taken from the NGCM, the half-edge curve of each AGCM retains the relevant properties of the normal curve. The gray clustering process of AGCM is as follows.

(1) Calculate the data set X_{ij} for evaluation, as in formula (30).

(2) Determine the evaluation level, determine and calculate various parameters of AGCM, and construct the model.

(3) Calculate the gray cloud whitening weight of each indicator. The gray cloud whitening weight indicates the degree of membership of a certain indicator data to the evaluation level. At the same time, since AGCM contains random variables, the whitening weight obtained each time is different. To solve this problem, this paper adopts the method of multiple operations and calculating the average value to reduce the uncertainty error. Finally, the whitening weights of different evaluation levels of the same indicator are summed and normalized. For example, the calculation formula for the j-th indicator of the i-th sample is as follows.

$$f^k(x_{ij}) = \left[f_1^k(x_{ij}) + f_2^k(x_{ij}) + \cdots + f_h^k(x_{ij})\right]/h \tag{43}$$

$$\mu^k(x_{ij}) = \frac{f^k(x_{ij})}{\sum\limits_{k=1}^{s} f^k(x_{ij})} \tag{44}$$

In the formula: $f^k(x_{ij})$ represents the average whitening weight of x_{ij} belonging to the gray class T_k; h represents the total number of operations of x_{ij}; $\mu^k(x_{ij})$ represents the normalized gray cloud whitening weight.

(4) Calculate gray fixed weight clustering coefficient. The calculation formula of the i-th sample belonging to the gray class T_k is as follows.

$$\sigma_i^k = \sum_{j=1}^{q} \mu^k(x_{ij})\omega_j \tag{45}$$

In the formula: ω_j is the weight of indicator j in comprehensive clustering.

(5) Determine the evaluation level. The evaluation level of sample i is the gray class represented by k with the largest σ_i^k.

(6) Determine the evaluation value. If the k value of the grey class T_k is larger, the evaluation level is higher, then the calculation formula of the evaluation value is as follows.

$$G_i = \sum_{k=1}^{s} \sigma_i^k \cdot \frac{k}{s} \tag{46}$$

In the formula: s is the total number of gray classes.

III. EFFECTIVENESS EVALUATION OF MEMLS

This paper combines the ideas of ADC method, AHP method, and loop network to construct a MEMLS effectiveness evaluation hierarchical framework. From the analysis of all elements of the entire process of MEMLS operation, a hierarchical diagram of MEMLS effectiveness evaluation is obtained, as shown in Table 2.

According to table 2, the target layer is the effectiveness evaluation of MEMLS, and the criterion layer is the system availability, dependability, and inherent capability. Considering the whole combat process of MEMLS, including launch, enemy and foe confrontation after launch, equipment state loss after launch, and system further expansion and application ability, four first-level indicators are constructed, and the first-level indicators are subdivided, and a total of 18 second-level indicators are obtained. Next, the effectiveness of the system is evaluated according to the steps and methods in Fig. 1.

A. ANALYSIS OF SYSTEM AVAILABILITY AND DEPENDABILITY

The simple working process of MEMLS is that the energy storage of the pulse energy storage system, the discharge of the pulse power discharge system, and the pulse linear motor work together. Since the working process is a series system, and from the perspective of operational decision-making

TABLE 2. MEMLS effectiveness evaluation level table.

Target layer	Criteria layer	First-level indicator layer	Second-level indicator layer
Effectiveness evaluation of MEMLS	Availability $\boldsymbol{A}$		
	Dependability $\boldsymbol{D}$		
	Inherent capability $\boldsymbol{C}$	Launch capability U_1	Thrust control accuracy U_{11}
			Robustness during launch U_{12}
			Maximum thrust U_{13}
			Acceleration time U_{14}
			Initial ejection velocity U_{15}
		Confrontation capability U_2	Infrared radiation intensity U_{21}
			Electromagnetic anti-interference ability U_{22}
			Electromagnetic compatibility of own system U_{23}
			Initial anti-interception rate U_{24}
		State loss U_3	Energy utilization rate U_{31}
			Ablation degree of the launcher U_{32}
			Environmental pollution degree U_{33}
			Spare parts replacement rate U_{34}
		Expanding ability U_4	Ejection power unit weight U_{41}
			Launcher weight U_{42}
			Space-ratio performance U_{43}
			Continuous combat capability U_{44}
			Universality of launch system U_{45}

requirements, the division of more states of each subsystem at the initial time will make the system more complicated and not conducive to decision-making, so it is assumed that the MEMLS has only two states at the initial time, namely normal and fault. According to formula (3), the availability vector of MEMLS is

$$\boldsymbol{A} = [a_1, a_2] = \left[\frac{MTBF}{MTBF + MTTR + MLDT}, \; 1 - \frac{MTBF}{MTBF + MTTR + MLDT}\right] \tag{47}$$

In the formula: a_1 is the probability that the initial state of the system is normal; a_2 is the probability that the initial state of the system is fault; $MTBF$ is the average time between failures of the system; $MTTR$ is the average repair time of the system; $MLDT$ is the average guarantee delay time of the system.

Since the working process of MEMLS can be regarded as a Markov process satisfying ergodicity, according to the transition probability property of the Markov process, combined with formulas (13), the dependability matrix of the system can be obtained as

$$\boldsymbol{D} = \begin{bmatrix} e^{-\frac{t}{MTBF}} & 1 - e^{-\frac{t}{MTBF}} \\ 0 & 1 \end{bmatrix} \tag{48}$$

In the formula: t is the total duration of the task performed by MEMLS.

B. EXPLANATION OF SYSTEM INHERENT CAPABILITY INDICATORS AND ORTHOGONAL DESIGN

At the initial moment, MEMLS only has two states of normal and fault. At the same time, for the battlefield, the ability of the system to complete the task under the fault can be regarded as 0. Therefore, combining formula (14) and formula (47), the inherent capability vector of the system can be obtained as

$$\boldsymbol{C} = \begin{bmatrix} c \\ 0 \end{bmatrix} \tag{49}$$

In the formula: c is the inherent capability value of MEMLS under normal conditions.

1) SPECIFIC DESCRIPTION OF INDICATORS

The following is the description of the secondary indicators of inherent capability.

a: DIMENSIONAL INDICATORS

1) Maximum thrust U_{13} represents the maximum ejection force that MEMLS can exert on the missile, in kN.
2) Acceleration time U_{14} represents the time for the missile to accelerate to a predetermined speed via the guide rail, in ms.

3) Initial ejection velocity U_{15} indicates the speed at which the missile exits the barrel after being accelerated by the launcher, in m/s.
4) Infrared radiation intensity U_{21} is an important indicator to measure the missile's stealth performance during the launch process, in W/sr.
5) Ejection power unit weight U_{41} represents the total weight of the power unit directly used for ejection in the system, in kg.
6) Launcher weight U_{42} represents the total weight of all devices used for missile launching, in t.

b: CALCULATION OF QUANTITATIVE PROBABILITY AND RATIO INDICATORS

1) Initial anti-interception rate U_{24} is the probability of anti-interception during the initial phase after the missile is launched by the launch system.
2) Energy utilization rate U_{31} represents the ratio of the energy converted by the system for missile launch to the total energy consumed.

c: CALCULATION OF QUALITATIVE INDICATORS

The quantification of qualitative indicators is mainly evaluated by expert scoring method. The scoring range is 0 to 1. The higher the score, the better. The specific indicators are as follows.

1) Thrust control accuracy U_{11} indicates the closeness of the thrust of the launch system to the missile to the required value.
2) Robustness during launch U_{12} indicates the degree of stability of the system when the force changes suddenly.
3) Electromagnetic anti-interference ability U_{22} means our anti-interference ability in the face of enemy electromagnetic interference during the launch mission.
4) Electromagnetic compatibility of own system U_{23} indicates the electromagnetic compatibility capability of the transmitter's own system
5) Ablation degree of the launcher U_{32} indicates the degree of ablation damage of the launching system to our equipment such as launch vehicle and launch platform.
6) Environmental pollution degree U_{33} indicates the degree of pollution to the surrounding environment during the mission of the launching system.
7) Spare parts replacement rate U_{34} indicates the ability of the spare parts in the launcher to be temporarily replaced and repaired temporarily during the execution of the task.
8) Space-ratio performance U_{43} indicates that MEMLS occupies the space ratio of the entire missile combat system.
9) Continuous combat capability U_{44} means the ability of the launch system to perform multiple launch missions in a short period.
10) Universality of launch system U_{45} indicates the versatility of the launch system for launching other types of missiles.

2) ORTHOGONAL DESIGN WITHOUT INTERACTION AND NORMALIZATION

There are a total of 18 second-level indicators of MEMLS. To analyze the significant differences in the effectiveness of each indicator, it is assumed that each indicator has 2 selectable levels, and the indicators have no interaction. Therefore, according to the orthogonal design idea without interaction, the $L_{20}(2^{19})$ orthogonal table is selected, and a total of 20 sets of system design schemes are designed, as shown in Table 3. All the data samples used in this paper are derived from the demonstration plan of the research group and the laboratory on the MEMLS and the data of the active missiles using thermal and cold launch systems.

C. WEIGHT CALCULATION OF INHERENT CAPABILITY

The calculation of the weight of the indicator needs to select the appropriate weighting method according to the characteristics of the indicator. Because the first-level indicators of MEMLS are not specific values and cannot be directly quantified, but meet the characteristics of network loops, FAHP-ALM is used to calculate the subjective and objective weights respectively, and then the combined weights of the first-level indicators are calculated by ICWGT. The second-level indicators have been quantified and normalized in Table 3 and Table 4, so FAHP-EWM is used to calculate the subjective and objective weights, respectively, and then the combined weights are calculated by ICWGT. Finally, the weight of each secondary indicator relative to the total system is obtained through multiplication.

1) WEIGHT CALCULATION OF FIRST-LEVEL INDICATORS

The subjective weights based on FAHP method are calculated according to formulas (17)-(21). According to Table 1 and Delphi method, the fuzzy complementary judgment matrix of the first-level indicators can be obtained as

$$B_1 = \begin{bmatrix} 0.5 & 0.7 & 0.6 & 0.8 \\ 0.3 & 0.5 & 0.4 & 0.6 \\ 0.4 & 0.6 & 0.5 & 0.7 \\ 0.2 & 0.4 & 0.3 & 0.5 \end{bmatrix} \tag{50}$$

The fuzzy consistency judgment matrix is calculated as follows.

$$R_1 = \begin{bmatrix} 0.5000 & 0.6333 & 0.5667 & 0.7000 \\ 0.3667 & 0.5000 & 0.4333 & 0.5667 \\ 0.4333 & 0.5667 & 0.5000 & 0.6333 \\ 0.3000 & 0.4333 & 0.3667 & 0.5000 \end{bmatrix} \tag{51}$$

The weight vector of the first-level indicators based on the FAHP is calculated as follows.

$$\omega_1' = (0.3000, 0.2333, 0.2667, 0.2000) \tag{52}$$

TABLE 3. Orthogonal design table.

No.	Indicators																		
	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{21}	U_{22}	U_{23}	U_{24}	U_{31}	U_{32}	U_{33}	U_{34}	U_{41}	U_{42}	U_{43}	U_{44}	U_{45}	Empty
1	0.5	0.5	150	10	40	10	0.7	0.8	0.6	0.8	0.8	0.8	0.3	300	8	0.5	0.4	0.7	2
2	0.5	0.5	150	20	35	20	0.5	0.5	0.7	0.8	0.8	0.4	0.3	500	8	0.5	0.8	0.2	2
3	0.5	0.5	150	20	35	20	0.7	0.8	0.6	0.5	0.8	0.4	0.7	300	3	0.4	0.8	0.7	1
4	0.5	0.5	200	10	35	20	0.5	0.8	0.6	0.5	0.4	0.8	0.7	500	8	0.5	0.4	0.2	1
5	0.5	0.5	200	10	40	10	0.5	0.8	0.7	0.8	0.4	0.4	0.7	500	3	0.4	0.8	0.7	2
6	0.5	0.9	150	20	40	10	0.5	0.8	0.7	0.5	0.4	0.8	0.3	300	3	0.5	0.8	0.2	1
7	0.5	0.9	150	20	40	10	0.7	0.5	0.6	0.8	0.4	0.4	0.7	500	8	0.4	0.4	0.2	1
8	0.5	0.9	200	10	35	20	0.7	0.5	0.7	0.8	0.4	0.4	0.3	300	3	0.5	0.4	0.7	1
9	0.5	0.9	200	10	40	20	0.7	0.5	0.6	0.5	0.8	0.8	0.3	500	3	0.4	0.8	0.2	2
10	0.5	0.9	200	20	35	10	0.5	0.5	0.7	0.5	0.8	0.8	0.7	300	8	0.4	0.4	0.7	2
11	0.9	0.5	150	10	35	10	0.7	0.5	0.7	0.5	0.4	0.8	0.3	500	8	0.4	0.8	0.7	1
12	0.9	0.5	150	10	40	20	0.5	0.5	0.7	0.8	0.8	0.8	0.7	300	3	0.4	0.4	0.2	1
13	0.9	0.5	200	20	35	10	0.7	0.5	0.6	0.8	0.4	0.8	0.7	300	3	0.5	0.8	0.2	2
14	0.9	0.5	200	20	40	10	0.5	0.5	0.6	0.5	0.8	0.4	0.3	500	3	0.5	0.4	0.7	1
15	0.9	0.5	200	20	40	20	0.7	0.8	0.7	0.5	0.4	0.4	0.3	300	8	0.4	0.4	0.2	2
16	0.9	0.9	150	10	35	10	0.7	0.8	0.7	0.5	0.8	0.4	0.7	500	3	0.5	0.4	0.2	2
17	0.9	0.9	150	10	40	20	0.5	0.5	0.6	0.5	0.4	0.4	0.7	300	8	0.5	0.8	0.7	2
18	0.9	0.9	150	20	35	20	0.5	0.8	0.6	0.8	0.4	0.8	0.3	500	3	0.4	0.4	0.7	2
19	0.9	0.9	200	10	35	10	0.5	0.8	0.6	0.8	0.8	0.4	0.3	300	8	0.4	0.8	0.2	1
20	0.9	0.9	200	20	40	20	0.7	0.8	0.7	0.8	0.8	0.8	0.7	500	8	0.5	0.8	0.7	1

Normalize the data in Table 3 to get Table 4.

Next, the consistency test of the fuzzy complementary judgment matrix is performed, and the characteristic matrix of the fuzzy judgment matrix of the first-level indicators is calculated as

$$W_1 = \begin{bmatrix} 0.5000 & 0.5625 & 0.5294 & 0.6000 \\ 0.4375 & 0.5000 & 0.4667 & 0.5385 \\ 0.4706 & 0.5333 & 0.5000 & 0.5714 \\ 0.4000 & 0.4615 & 0.4286 & 0.5000 \end{bmatrix} \tag{53}$$

The compatibility index is obtained as follows, satisfying the conditions.

$$I(B_1, W_1) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|B_{1ij} - W_{1ij}\right| = 0.0831 < 0.1 \tag{54}$$

The objective weights based on the first-level indicators of ALM are calculated below. First, analyze the network loop of the system to obtain Fig. 5.

According to formulas (22)-(25), the dependency matrix is calculated as in formula (55), and the loop betweenness, relative importance, impact factor, importance, and normalized importance are shown in Table 5.

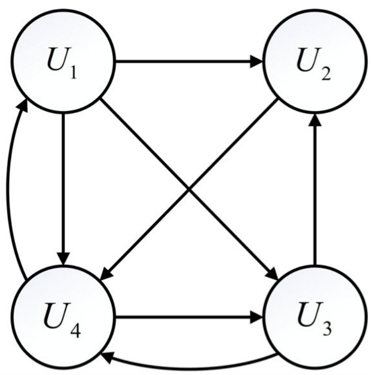

FIGURE 5. Network loop of first-level indicators.

$$\boldsymbol{DM} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0.5 & 1 & 0.5 & 1 \\ 0.5 & 1 & 1 & 1 \\ 1 & 0.5 & 1 & 1 \end{bmatrix} \tag{55}$$

From Table 5, the objective weight vector based on ALM is obtained, that is, $\omega_1'' = (0.2845, 0.1945, 0.2517, 0.2693)$.

TABLE 4. Indicators normalized value table.

No.	Indicators																	
	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{21}	U_{22}	U_{23}	U_{24}	U_{31}	U_{32}	U_{33}	U_{34}	U_{41}	U_{42}	U_{43}	U_{44}	U_{45}
1	0.5	0.5	0.75	1	1	1	0.7	0.8	0.6	0.8	0.8	0.8	0.3	1	0.375	0.5	0.4	0.7
2	0.5	0.5	0.75	0.5	0.875	0.5	0.5	0.5	0.7	0.8	0.8	0.4	0.3	0.6	0.375	0.5	0.8	0.2
3	0.5	0.5	0.75	0.5	0.875	0.5	0.7	0.8	0.6	0.5	0.8	0.4	0.7	1	1	0.4	0.8	0.7
4	0.5	0.5	1	1	0.875	0.5	0.5	0.8	0.6	0.5	0.4	0.8	0.7	0.6	0.375	0.5	0.4	0.2
5	0.5	0.5	1	1	1	1	0.5	0.8	0.7	0.8	0.4	0.4	0.7	0.6	1	0.4	0.8	0.7
6	0.5	0.9	0.75	0.5	1	1	0.5	0.8	0.7	0.5	0.4	0.8	0.3	1	1	0.5	0.8	0.2
7	0.5	0.9	0.75	0.5	1	1	0.7	0.5	0.6	0.8	0.4	0.4	0.7	0.6	0.375	0.4	0.4	0.2
8	0.5	0.9	1	1	0.875	0.5	0.7	0.5	0.7	0.8	0.4	0.4	0.3	1	1	0.5	0.4	0.7
9	0.5	0.9	1	1	1	0.5	0.7	0.5	0.6	0.5	0.8	0.8	0.3	0.6	1	0.4	0.8	0.2
10	0.5	0.9	1	0.5	0.875	1	0.5	0.5	0.7	0.5	0.8	0.8	0.7	1	0.375	0.4	0.4	0.7
11	0.9	0.5	0.75	1	0.875	1	0.7	0.5	0.7	0.5	0.4	0.8	0.3	0.6	0.375	0.4	0.8	0.7
12	0.9	0.5	0.75	1	1	0.5	0.5	0.5	0.7	0.8	0.8	0.8	0.7	1	1	0.4	0.4	0.2
13	0.9	0.5	1	0.5	0.875	1	0.7	0.5	0.6	0.8	0.4	0.8	0.7	1	1	0.5	0.8	0.2
14	0.9	0.5	1	0.5	1	1	0.5	0.5	0.6	0.5	0.8	0.4	0.3	0.6	1	0.5	0.4	0.7
15	0.9	0.5	1	0.5	1	0.5	0.7	0.8	0.7	0.5	0.4	0.4	0.3	1	0.375	0.4	0.4	0.2
16	0.9	0.9	0.75	1	0.875	1	0.7	0.8	0.7	0.5	0.8	0.4	0.7	0.6	1	0.5	0.4	0.2
17	0.9	0.9	0.75	1	1	0.5	0.5	0.5	0.6	0.5	0.4	0.4	0.7	1	0.375	0.5	0.8	0.7
18	0.9	0.9	0.75	0.5	0.875	0.5	0.5	0.8	0.6	0.8	0.4	0.8	0.3	0.6	1	0.4	0.4	0.7
19	0.9	0.9	1	1	0.875	1	0.5	0.8	0.6	0.8	0.8	0.4	0.3	1	0.375	0.4	0.8	0.2
20	0.9	0.9	1	0.5	1	0.5	0.7	0.8	0.7	0.8	0.8	0.8	0.7	0.6	0.375	0.5	0.8	0.7

TABLE 5. ALM calculation result table.

First-level indicators	U_1	U_2	U_3	U_4
Loop betweenness	0.6	0.4	0.6	1
Relative importance	2.6	2	2.3	2.4
Impact factor	0.8889	1	0.8889	0.8667
Importance	2.9250	2.0000	2.5875	2.7692
Normalized Weights	0.2845	0.1945	0.2517	0.2693

From formulas (30)-(37), the combined coefficients of subjective and objective weights obtained by ICWGT are 0.5004 and 0.4996, respectively, and the combined weights vector of the first-level indicator is calculated, that is, $\omega_1 = (0.2923, 0.2139, 0.2592, 0.2346)$.

Compare the combined weights and the weights of individual weighting methods, as shown in Fig. 6. It can be seen that the ICWGT method combines subjective and objective weights, effectively avoiding the problems of uncertainty and poor reliability caused by the single weighting method.

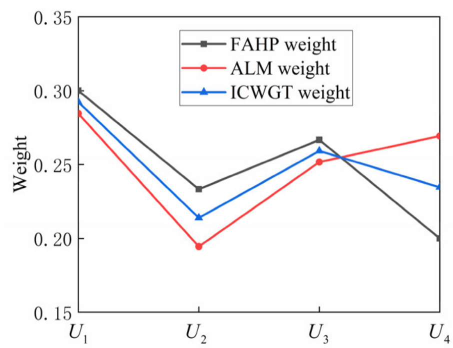

FIGURE 6. Weights of first-level indicators based on different weighting methods.

2) CALCULATION OF SECOND-LEVEL INDICATORS WEIGHTS AND COMPREHENSIVE WEIGHTS

Similarly, the fuzzy complementary judgment matrices of the second-level indicators of each first-level indicator are as follows.

$$B_{21} = \begin{bmatrix} 0.5 & 0.4 & 0.3 & 0.4 & 0.2 \\ 0.6 & 0.5 & 0.4 & 0.5 & 0.3 \\ 0.7 & 0.6 & 0.5 & 0.6 & 0.4 \\ 0.6 & 0.5 & 0.4 & 0.5 & 0.3 \\ 0.8 & 0.7 & 0.6 & 0.7 & 0.5 \end{bmatrix} \quad (56)$$

$$B_{22} = \begin{bmatrix} 0.5 & 0.6 & 0.7 & 0.6 \\ 0.4 & 0.5 & 0.6 & 0.5 \\ 0.3 & 0.4 & 0.5 & 0.4 \\ 0.4 & 0.5 & 0.6 & 0.5 \end{bmatrix} \tag{57}$$

$$B_{23} = \begin{bmatrix} 0.5 & 0.3 & 0.4 & 0.6 \\ 0.7 & 0.5 & 0.6 & 0.8 \\ 0.6 & 0.4 & 0.5 & 0.7 \\ 0.4 & 0.2 & 0.3 & 0.5 \end{bmatrix} \tag{58}$$

$$B_{24} = \begin{bmatrix} 0.5 & 0.6 & 0.5 & 0.4 & 0.7 \\ 0.4 & 0.5 & 0.4 & 0.3 & 0.6 \\ 0.5 & 0.6 & 0.5 & 0.4 & 0.7 \\ 0.6 & 0.7 & 0.6 & 0.5 & 0.8 \\ 0.3 & 0.4 & 0.3 & 0.2 & 0.5 \end{bmatrix} \tag{59}$$

Similarly, he weight vectors are calculated as follows.

$$\omega'_{21} = (0.1650, 0.1900, 0.2150, 0.1900, 0.2400) \tag{60}$$
$$\omega'_{22} = (0.2833, 0.2500, 0.2167, 0.2500) \tag{61}$$
$$\omega'_{23} = (0.2333, 0.3000, 0.2667, 0.2000) \tag{62}$$

Similarly, the compatibility index is obtained as follows, satisfying the conditions.

$$I(B_{21}, W_{21}) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|B_{21ij} - W_{21ij}\right| = 0.0773 < 0.1 \tag{63}$$

$$I(B_{22}, W_{22}) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|B_{22ij} - W_{22ij}\right| = 0.0499 < 0.1 \tag{64}$$

$$I(B_{23}, W_{23}) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|B_{23ij} - W_{23ij}\right| = 0.0831 < 0.1 \tag{65}$$

$$I(B_{24}, W_{24}) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|B_{24ij} - W_{24ij}\right| = 0.0764 < 0.1 \tag{66}$$

The objective weights based on EWM are calculated below. From Table 4 and formulas (26)-(29), the e_j and ω''_{2j} corresponding to the second-level indicators of each first-level indicator can be obtained, as shown in Table 6.

Similarly, ICWGT is used to obtain the combination coefficient and combination weights of subjective and objective weights, as shown in Table 7.

Compare the combined weights and the weights of individual weighting methods, as shown in Fig. 7. It can be seen that the ICWGT method combines subjective and objective weights, effectively avoiding the problems of uncertainty and poor reliability caused by the single weighting method.

To further verify the rationality of the combined weighting based on ICWGT, the formula (38) is used to calculate the degree of difference and compared with other methods, as shown in Table 8.

TABLE 6. EWM calculation result table.

First-level indicators	Second-level indicators	e_j	ω''_{2j}
	U_{11}	0.9862	0.2725
	U_{12}	0.9862	0.2725
U_1	U_{13}	0.9966	0.0674
	U_{14}	0.9811	0.3729
	U_{15}	0.9993	0.0146
	U_{21}	0.9811	0.5640
U_2	U_{22}	0.9953	0.1390
	U_{23}	0.9910	0.2676
	U_{24}	0.9990	0.0295
	U_{31}	0.9910	0.1208
U_3	U_{32}	0.9811	0.2546
	U_{33}	0.9811	0.2546
	U_{34}	0.9725	0.3699
	U_{41}	0.9895	0.0865
	U_{42}	0.9642	0.2937
U_4	U_{43}	0.9979	0.0169
	U_{44}	0.9811	0.1551
	U_{45}	0.9454	0.4477

TABLE 7. Combination weights table of second-level Indicators.

First-level indicators	Second-level indicators	FAHP coefficient	EWM coefficient	ω_{2j}
	U_{11}			0.2243
	U_{12}			0.2355
U_1	U_{13}	0.4486	0.5514	0.1336
	U_{14}			0.2908
	U_{15}			0.1157
	U_{21}			0.4424
U_2	U_{22}	0.4333	0.5667	0.1871
	U_{23}			0.2455
	U_{24}			0.1250
	U_{31}			0.1757
U_3	U_{32}	0.4876	0.5124	0.2767
	U_{33}			0.2605
	U_{34}			0.2871
	U_{41}			0.1403
	U_{42}			0.2464
U_4	U_{43}	0.4352	0.5648	0.1009
	U_{44}			0.1899
	U_{45}			0.3225

According to Table 8, compared with other methods, the ICWGT adopted in this paper has the smallest degree of difference, which verifies the rationality and superiority of the combined weighting method.

TABLE 8. Calculation table of difference degree based on different combined weighting methods.

Methods	Optimal planning [8]	Product normalization method	CWGT [25]	ICWGT
Combined weight of secondary indicators of U_1	0.8640	0.3165	0.3053	0.3053
Combined weight of secondary indicators of U_2	0.9158	0.2688	0.2679	0.2268
Combined weight of secondary indicators of U_3	0.0963	0.1117	0.0963	0.0963
Combined weight of secondary indicators of U_4	1.1530	0.1551	0.1542	0.1542

TABLE 9. Weight table of each second level indicator relative to the system.

First level indicators	Second level indicators	ω
U_1	U_{11}	0.0656
	U_{12}	0.0688
	U_{13}	0.0391
	U_{14}	0.0850
	U_{15}	0.0338
U_2	U_{21}	0.0946
	U_{22}	0.0400
	U_{23}	0.0525
	U_{24}	0.0267
U_3	U_{31}	0.0455
	U_{32}	0.0717
	U_{33}	0.0675
	U_{34}	0.0744
U_4	U_{41}	0.0329
	U_{42}	0.0578
	U_{43}	0.0237
	U_{44}	0.0446
	U_{45}	0.0757

Finally, through multiplication, the weights of the second level indicators relative to the system are calculated as shown in Table 9, and the line chart of weights is made as shown in Fig. 8.

D. CALCULATION OF INHERENT CAPABILITY EVALUATION LEVEL AND EVALUATION VALUE

1) AGCM ESTABLISHMENT

In this paper, the Delphi method is used to uniformly divide the evaluation levels of indicators.

That is, the indicators are divided into four gray categories I, II, III, and IV, which represent poor, medium, good, and excellent. The left and right boundary values and peak values of the four gray categories are given, and take $\gamma = 8$ to calculate entropy and superentropy, as shown in Table 10.

According to Table 10, make an AGCM chart for inherent capability evaluation, as shown in Fig. 9.

TABLE 10. AGCM gray classification and digital characteristics table.

Evaluat-ion level	Boundary value	Peak value	Entropy		Super-entropy	
			Left model entropy	Right model entropy	Left model superen-tropy	Right model superen-tropy
I	[0,0.5]	0.3		0.2/3		0.1/12
II	[0.3,0.7]	0.5	0.2/3	0.2/3	0.1/12	0.1/12
III	[0.5,0.8]	0.7	0.2/3	0.1/3	0.1/12	0.1/24
IV	[0.7,1]	0.8	0.1/3		0.1/24	

2) EVALUATION VALUE CALCULATION

In the calculation of whitening weights, the number of operations $h = 1000$. According to the formula (50) - (53), the comprehensive clustering coefficient, evaluation grade, and evaluation value of inherent capability of each scheme are calculated, as shown in Table 11.

E. EFFECTIVENESS EVALUATION AND ANALYSIS OF VARIANCE

The value of inherent capability has been calculated in section 3.4, and the system performance evaluation value can be obtained according to the ADC model. Since MEMLS is still demonstrating research, there is no accurate data on *MTBF*, *MTTR*, and *MLDT*. To further study the effectiveness of the missile EML in the research stage, it is assumed that the reliability and maintainability indicators of the EMLS and the active launch system are the same, taking $MTBF = 1000$h, $MTTR = 50$h, $MLDT = 20$h, $t = 1$h. Find $a_1 \cdot d_{11} = 0.9336$. The system effectiveness evaluation value can be obtained, as shown in Table 10.

The significance of each indicator is analyzed in conjunction with Table 3, as shown in Table 12.

Combined with the indicators of the demonstration scheme and variance analysis of MEMLS, this paper further analyzes the effectiveness evaluation results, and obtains the following three points.

(1) It can be obtained from Table 11 that among the 20 schemes using EMLS with different battle targets, 14 of the schemes have an inherent capability evaluation level of IV, and the overall system effectiveness

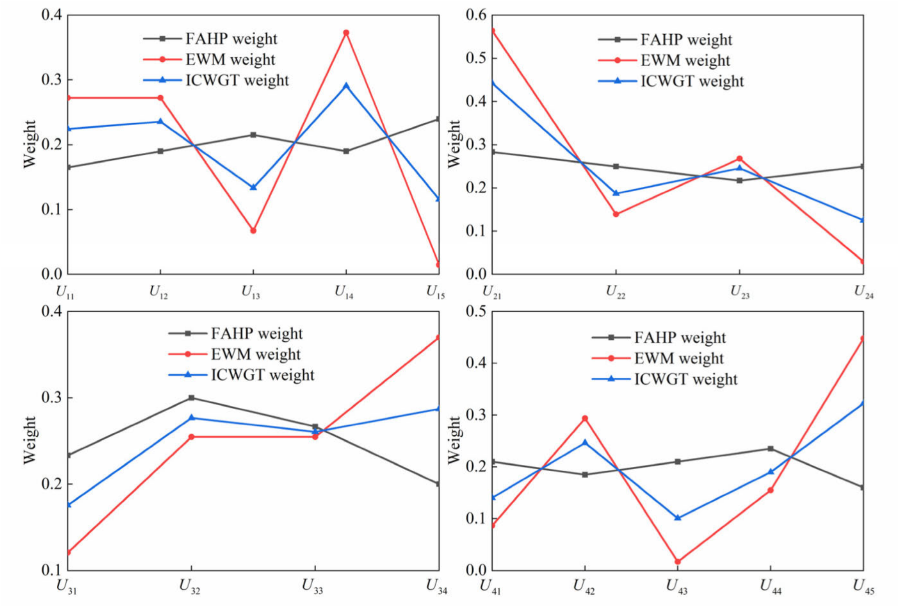

FIGURE 7. Weights of second-level indicators based on different weighting methods.

TABLE 11. Comprehensive clustering coefficients and evaluation results.

Group number	Comprehensive clustering coefficient				Evaluation level	Inherent capability value	Effectiveness evaluation
	I	II	III	IV			
1	0.1410	0.2068	0.1512	0.5009	IV	0.7530	0.7030
2	0.2329	0.4830	0.0711	0.2130	II	0.5660	0.5284
3	0.0506	0.4108	0.2251	0.3133	II	0.7002	0.6537
4	0.1822	0.4313	0.1093	0.2771	II	0.6203	0.5791
5	0.0842	0.2696	0.1927	0.4535	IV	0.7538	0.7038
6	0.1887	0.2894	0.0519	0.4699	IV	0.7007	0.6542
7	0.2258	0.3470	0.1639	0.2632	II	0.6161	0.5752
8	0.1684	0.3248	0.1423	0.3644	IV	0.6756	0.6308
9	0.1648	0.2938	0.0752	0.4660	IV	0.7106	0.6634
10	0.0817	0.3314	0.1778	0.4090	IV	0.7285	0.6801
11	0.1668	0.2436	0.1785	0.4110	IV	0.7084	0.6613
12	0.1139	0.2837	0.1242	0.4781	IV	0.7416	0.6923
13	0.1149	0.2741	0.1302	0.4807	IV	0.7441	0.6947
14	0.1342	0.3941	0.1090	0.3626	II	0.6749	0.6301
15	0.3007	0.4051	0.0700	0.2241	II	0.5543	0.5175
16	0.1330	0.1413	0.1761	0.5496	IV	0.7855	0.7333
17	0.1171	0.3480	0.1830	0.3518	IV	0.6923	0.6463
18	0.1471	0.3146	0.1284	0.4098	IV	0.7002	0.6537
19	0.2387	0.1132	0.0172	0.6309	IV	0.7600	0.7095
20	0.0466	0.2310	0.2341	0.4881	IV	0.7909	0.7384

is relatively high. This proves that from the perspective of effectiveness, it is necessary to change the traditional launch mode and study MEMLS.

(2) It can be seen from Table 12 that the effectiveness has not been greatly improved when the initial ejection velocity is increased. This is because the original

TABLE 12. ANOVA Table.

Source of variance	Sum of square	Degree of freedom	Mean square error	F value	P value
U_{11}	0.02331729	1	0.02331729	582932.25	0.001
U_{12}	0.02576025	1	0.02576025	644006.25	0.001
U_{13}	0.000529	1	0.000529	13225	0.006
U_{14}	0.03936256	1	0.03936256	984064	0.001
U_{15}	4.00E-08	1	4E-08	1	0.5
U_{21}	0.04875264	1	0.04875264	1218816	0.001
U_{22}	0.00219961	1	0.00219961	54990.25	0.003
U_{23}	0.01483524	1	0.01483524	370881	0.001
U_{24}	0.00024649	1	0.00024649	6162.25	0.008
U_{31}	0.01110916	1	0.01110916	277729	0.001
U_{32}	0.04318084	1	0.04318084	1079521	0.001
U_{33}	0.03833764	1	0.03833764	958441	0.001
U_{34}	0.02975625	1	0.02975625	743906.25	0.001
U_{41}	0.00332929	1	0.00332929	83232.25	0.002
U_{42}	0.03444736	1	0.03444736	861184	0.001
U_{43}	0.00019321	1	0.00019321	4830.25	0.009
U_{44}	0.01671849	1	0.01671849	417962.25	0.001
U_{45}	0.03125824	1	0.03125824	781456	0.001
Error	4.00E-08	1	4E-08		
Sum	0.36333364	19			

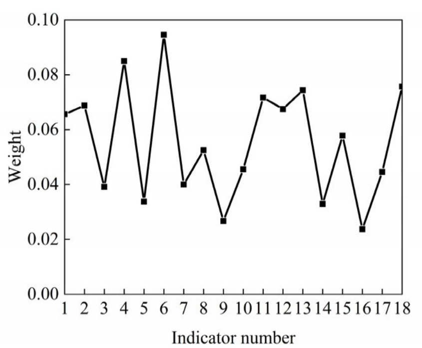

FIGURE 8. Line chart of weight of each second level indicator relative to the system.

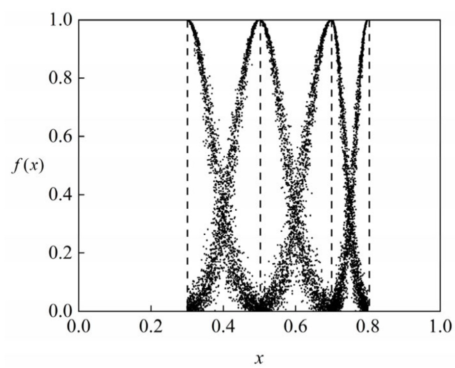

FIGURE 9. AGCM chart.

launch system can already meet the initial ejection velocity requirements of the missile. If the focus of the EMLS is on the improvement of the initial ejection velocity, there is no greater value and significance.

(3) Ranking the significance of the 18 indicators, the first six indicators with better significance were U_{21}, U_{32}, U_{14}, U_{33}, U_{42}, and U_{41}. It can be concluded that the main breakthrough points and advantages of MEMLS compared to traditional emission methods are to reduce the intensity of infrared radiation, reduce the ablation degree of the launcher, shorten the acceleration time and reduce the degree of environmental pollution. Further optimization of these indicators can significantly improve the effectiveness of EMLS, which is also the important goal of missile EML technology. At the same time, it can be found that the weight reduction of the launching device and the ejection power unit is also very significant. This is because, as a new launching system, in addition to the qualified technical indicators, it also needs to be suitable for the battlefield environment and missile weapon equipment to ensure the availability of the system on the battlefield. Therefore, it is also a key research direction.

According to the previous research of the research group [30], the field of motor control in MEMLS has been studied, aiming to strengthen the robustness of control and shorten the acceleration time during the launch process.

This is consistent with the results of this paper, which proves the reliability of the results and the contribution of research. It can be seen from the above results that the next step of the research is to further analyze and optimize the infrared radiation intensity and ablation degree of the system, which is also the work being carried out in the author's laboratory.

IV. CONCLUSION

The main contributions of this paper are as follows.

(1) It eliminates that most of the research only focuses on the key technical points of the MEMLS, and ignores the deficiencies of the evaluation and balance of the entire system.

(2) From the perspective of effectiveness, this paper demonstrates the necessity of using EMLS on missiles, and provides prerequisite support for the research of related key technologies. From the effectiveness evaluation results and variance analysis, several key indicators that have a greater impact on system effectiveness have been obtained, which provides direction and guidance for system development and optimization.

To solve the problem of the effectiveness evaluation of MEMLS, an improved effectiveness evaluation model is established in this paper. The innovative points of the method adopted in this paper are as follows.

(1) To solve the problem of exponential increase in evaluation samples caused by the large number of second-level indicators, an orthogonal design experiment method is adopted, which greatly reduces the number of samples.

(2) To solve the problem that the same methods are used for the primary and secondary indicators in the traditional weighting process, resulting in a lack of pertinence and unreliable evaluation. This paper adopts different weighting methods for the objective weights of first-level and second-level indicators to make the weight value obtained is more reliable and credible.

(3) To solve the problem that the traditional weight combination method has a strong dependence on a certain weighting method and the traditional CWGT may have a negative combination coefficient, this paper proposes IWCGT to solve the above problems.

(4) To solve the problem that traditional NGCM restricts the flexibility of the peak value and boundary value of the model, this paper proposes AGCM to perform gray clustering.

The proposed method has good scalability, mainly as follows.

(1) The model proposed in this paper is suitable for any indicator-based system effectiveness evaluation process, and in the later stage of weapon system demonstration and development, the method of function fitting can be used to quickly obtain the system effectiveness value.

(2) The orthogonal design method can be applied to the design of multi-indicator evaluation schemes, and the more indicators, the more simplified the number of schemes.

(3) The ALM proposed in this paper can be applied to the objective weighting problem of any indicator system that satisfies the characteristics of the loop, and EWM can be applied to the objective weighting problem of any quantifiable indicator system. ICWGT can be used to combine two or more weight sets.

(4) The AGCM proposed in this paper can flexibly adjust the peak value and boundary value of the model according to different systems and evaluation standards, and has good scalability.

DATA AVAILABILITY

The data used to support the findings of this study are included within the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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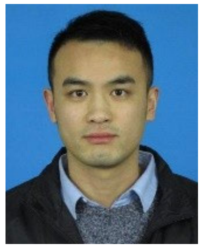

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