RESEARCH ON MULTI-ATTRIBUTE DECISION MAKING AND VERIFICATION METHODS FOR SYSTEMS CONFRONTATION

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Abstract

Multi-attribute decision making (MADM) serves as a crucial method for optimizing schemes during the conceptual design phase of aircraft. However, the lack of effective quantitative evaluation methods for the accuracy of decision results poses a challenge. To address this, a method for verifying and optimizing multi-attribute decision results of aircraft conceptual design schemes based on System-of-systems (SoS) confrontation simulation is proposed. Initially, the general process of MADM is delineated, forming the SAWC modeling framework. Utilizing this framework, a MADM model for aircraft tactical-level conceptual schemes is constructed. Subsequently, a method for establishing a systematic verification environment for aircraft is designed, utilizing system modeling language, component modeling, and task completion rate as key components. Finally, a model verification method leveraging the Pearson correlation coefficient as the indicator is developed. Additionally, a model optimization algorithm based on particle swarm optimization with mapping function and weight factor as optimization targets is explored. The proposed method is validated through a ground attack mission scenario involving a ground attack UAV. Systematic verification demonstrates an improvement in the accuracy of the MADM model from 0.6976 to 0.9154. These results highlight the effectiveness of the method in verifying decision results within the aircraft domain, as well as explaining and optimizing the decision model. Ultimately, this approach can contribute to the systematic demonstration stage of aircraft conceptual design.

Keywords: aircraft conceptual design, multi-attribute decision making, system-of-systems confrontation, model verification, particle swarm optimization

1. General Introduction

The aircraft concept design plays an important role in the overall design process as it begins and determines the entire design process [1]。

The main work content of this stage is to determine the design parameters according to the task requirements[2,3]. Due to the complexity of combat tasks and the aircraft itself, the design space corresponding to the design task is very large and contains a lot of design points[4]. How to select an appropriate design scheme from the design space for a specific task is a problem that needs to be solved[5,6]. Multi-attribute decision-making (MADM) is a decision-making analysis technology derived from operations research and economics[7–10]. The core idea of MADM is to use mathematical methods to model decision-making objects, processes and behaviors, and then complete the evaluation of various options.

In recent years, MADM method is widely used in the field of aircraft design. Bai[11] proposed a multi-objective solution optimization method that combines multi-objective solution evaluation methods and visual aids. This method can effectively screen out superior solutions from a large number of non-inferior solutions, providing a reference for designers to make decisions. Pu[12] used Game Theory to comprehensively integrate the empowerment method, AHP method, and TOPSIS method in the command post threat assessment of drone raids. They established a threat assessment index system from both attack and defense aspects, and obtained a more practical, adaptable and portable threat assessment methods. Besides, in view of the large number of decision-making activities in the aircraft assembly/manufacturing process, Md[13] proposed the concept of flexible industrial decision-making method, designed the MADM preference method, and integrated eight forward-looking MADM methods based on preference ranking and shows certain potential in solving practical engineering problems.

However, since the conceptual design is too early in the full life cycle of aircraft, it is difficult to verify the early decision-making results using real aircraft as design results. When applying these MADM methods to make aircraft design decisions, it is often only possible to rely on experts. Subjective methods such as experience evaluate decision-making results qualitatively and lack quantitative evaluation, making it difficult to guarantee the credibility of decision-making results. This also leads to the lack of sufficient basis when building a MADM model, making it difficult to improve and optimize the decision-making model.

System of Systems (SoS) confrontation simulation can use simulation methods to obtain the actual combat effects of the aircraft through scenario deduction without completing the specific design. Gao[14] used SoS confrontation simulation as an input and proposed an optimization method for the design of aircraft Mission Success Space based on Gaussian fitting and Genetic Algorithm. Using this method, the optimal design of the two indicators of speed and RCS area can be completed under system confrontation conditions.

Based on this idea, a verification and optimization method of MADM model for aircraft conceptual design scheme based on system confrontation simulation is proposed. Through this method, a decision-making model for aircraft conceptual design solutions with high credibility and reliability can be quickly constructed. In the meanwhile, the built MADM model can also be verified and optimized, and the impact of a specific type of aircraft can also be reversely be obtained.

The structure of this article is as follows: Section 2 gives the basic framework of the method; Sections 3 and 4 introduce the basic process of MADM modeling and SoS confrontation simulation for aircraft in this method, respectively. Section 5 explains Steps for model verification and optimization based on MADM results and SoS confrontation simulation results; finally, Section 6 gives a case for method verification.

2. Framework of the verification and optimization method

The core idea of this method is to use SoS verification method to simulate the actual operational effects of the conceptual design scheme and provide a verification and optimization standard for the MADM model. The basic framework of the method is shown in Figure 1, and the following are the specific steps:

Step 1 Classify the design parameters involved in the aircraft concept design stage and select a set of indicators suitable for the decision object of the MADM.

Step 2 Based on the characteristics of the evaluation object, the SWAC framework based on MADM is used to determine the evaluation indicator set (represented by EIS), and appropriate indicator assignment method, calculation method of indicator weight, and comprehensive evaluation method are selected to complete the preliminary evaluation based on MADM method.

Step 3 In a SoS verification environment, formal modeling languages are used to complete task scenario assumptions, component-based modeling methods are used to complete evaluation object modeling, quantitative task evaluation indicators are selected, simulation experiments are designed, and SoS verification of the design scheme is completed.

Step 4 Select correlation indicators such as Pearson correlation coefficient or Spearman coefficient, and use the SoS verification results as the standard to check and verify the decision results of the MADM model

Step 5 By using optimization algorithms such as particle swarm optimization and genetic algorithm, and taking correlation indicator as the adaptability function, appropriate optimization targets in the modeling framework of the MADM model can be selected, optimize the model, and a MADM model that meets the actual SoS confrontation effect can be obtained.

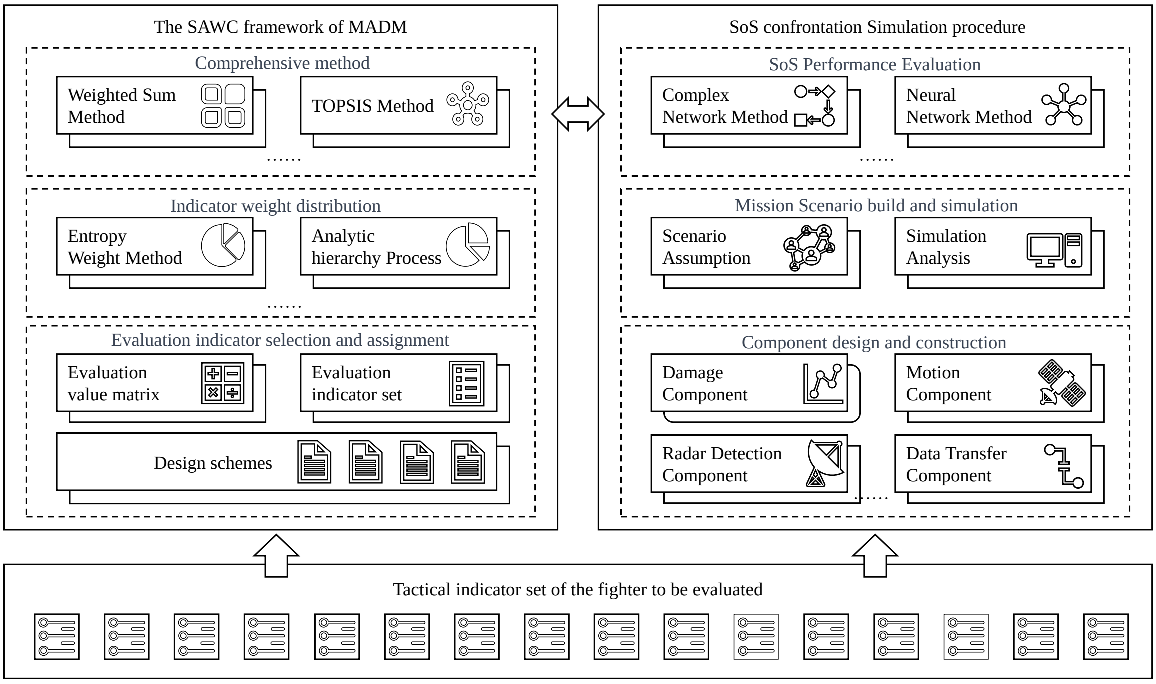

Figure 1-Evaluation and verification Framework

3. Aircraft MADM model based on SAWC framework

3.1 The SAWC framework of general MADM models

Over an extended period of development, MADM has yielded a series of well-established methods, such as the Analytic Hierarchy Process (AHP)[15], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)[16–18], and the *ÉLimination Et Choix Traduisant la REalité* (ÉLECTRE) methods[19]. As statistical methodologies have advanced, numerous scholars have embarked on exploring more intricate MADM issues, including group MADM, temporal MADM, and MADM under incomplete information. In response to these complexities, a range of new methods have been specifically developed, such as the ELECTRE III method[20], which is based on the theory of stochastic dominance, and the Stochastic Multi-criteria Acceptability Analysis (SMAA) method[21]. Despite the diverse backgrounds and research focuses of these MADM methods, they share common procedural steps, which primarily include the following aspects:

(1) Evaluation indicator selection: The first step involves identifying the various attributes or indicators to be considered in the decision-making process. These indicators should represent key factors essential for assessing and comparing different alternatives.

(2) Evaluation Indicator assignment: This step entails assigning values to each alternative based on their performance across the various attributes. The assignment process includes both qualitative and quantitative assessments, with quantitative assignments involving methods for standardizing indicators.

(3) Evaluation Indicator Weight distribution: The relative importance of each evaluation indicator is reflected through the distribution of weights. Methods for calculating these weight factors can be categorized into objective weighting and subjective weighting, depending on the underlying principle of calculation.

(4) Comprehensive evaluation: Utilizing the indicator values and their respective weights, a comprehensive evaluation of each alternative is performed. This process results in a final evaluation score and a corresponding ranking for each alternative.

Based on the four key steps of MADM—Selection, Assignment, Weighting, and Comprehensive evaluation—a framework named SAWC is proposed, as illustrated in Figure 2, and the MADM process for aircraft design schemes is modeled using the SAWC framework.

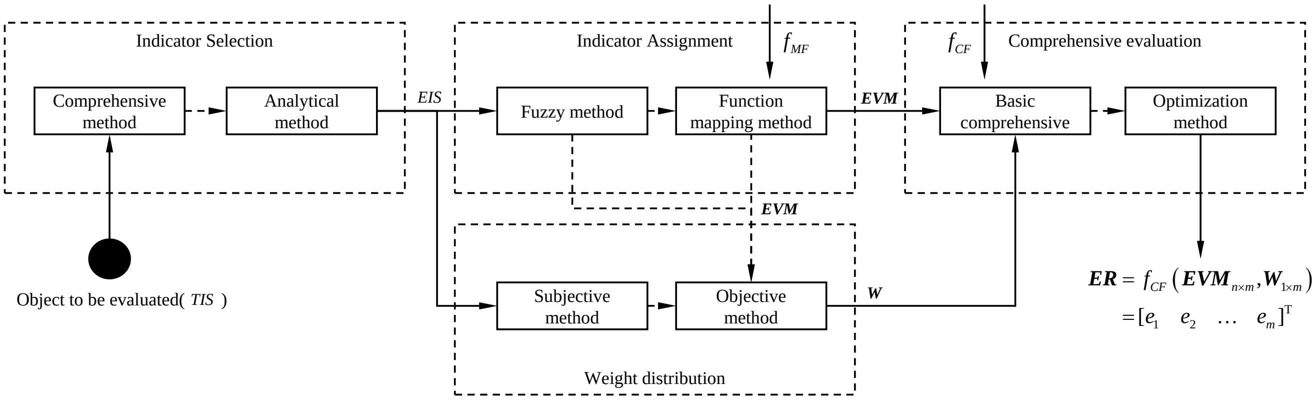

Figure 2-The SAWC framework of MADM modeling process

3.2 Evaluation indicator selection

One of the key tasks in aircraft design is to start from the mission requirements and systematically decompose these requirements layer by layer to form design indicators. These indicators are generally categorized into three types:

(1) Textual Description: This includes qualitative requirements such as high altitude, high speed, strong stealth capability, long range, and flight duration. These descriptions provide a qualitative understanding of the desired performance characteristics.

(2) Tactical Indicators: These are quantitative indicators directly related to the operational effectiveness of the aircraft, such as range, speed, climb rate, and maximum take-off weight. Tactical indicators are typically independent of one another, with minimal coupling effects.

(3) Technical Indicators: These indicators are necessary to achieve the desired tactical performance and include metrics such as thrust-to-weight ratio, wing loading, lift-to-drag ratio, and fuel consumption rate. Technical indicators often exhibit strong interdependencies and coupling relationships.

The SoS confrontation emphasizes the application effectiveness of aircraft in actual combat scenarios. Therefore, when validating the MADM results of a design scheme through system countermeasure simulations, tactical indicators should be selected as the primary evaluation criteria.

A literature review and analysis of typical aircraft cases identified 14 fighter tactical indicators, forming a Tactical Indicator Set (TIS). Based on TIS, an Evaluation Indicator Set (EIS) was constructed, detailing parameter names, units, and indicator types (J for benefit indicators and K for cost indicators) as shown in Table 1.

Table 1-Fighter tactical indicator set

Capacity	Parameter	Unit	Indicator type
Loading capacity (B_1)	Structure Weight (C_1)	kg	J
	Fuel Weight (C_2)	kg	J
	Weapon Weight (C_3)	kg	J
Flight performance (B_2)	Maximum Speed (C_4)	Ma	J
	Cruising Speed (C_5)	Ma	J
	Maximum Climb Rate (C_6)	m/s	J
	Range (C_7)	km	J
	Ceiling (C_8)	m	J
Environmental Adaptability (B_3)	Length (C_9)	m	K
	Height (C_{10})	m	K
	Wingspan (C_{11})	m	K
	Takeoff Run Distance (C_{12})	m	K
	Landing Roll Distance (C_{13})	m	K
	Radar Cross Section Area (C_{14})	m^2	K

3.3 Evaluation indicator assignment

Since the indicators in both the TIS and the EIS are quantitative, the evaluation indicator value can be directly calculated through a function mapping method (denoted as f_{MF}) based on the tactical indicator value. To simplify the model complexity, all indicators are initially mapped using linear functions. For an EIS containing m evaluation indicators, the f_{MF} of the evaluation indicator is represented by Eq (1):

$$\begin{cases} r_j = \dfrac{x_j - \min(range_j)}{\max(range_j) - \min(range_j)}, \boldsymbol{X}_j \in \boldsymbol{J}, j = 1, 2, \ldots, m \\ r_j = \dfrac{x_j - \min(range_j)}{\max(range_j) - \min(range_j)}, \boldsymbol{X}_j \in \boldsymbol{K}, j = 1, 2, \ldots, m \end{cases} \tag{1}$$

Where x_j is the element value of TIS, r_j the element value of EIS, $\min(range_j)$ and $\max(range_j)$ represent the minimum and maximum values of the reference range, respectively. $\boldsymbol{X}_j$ signifies a tactical indicator, where $\boldsymbol{J}$ represents the set of benefit indicators and $\boldsymbol{K}$ represents the set of cost indicators.

Mapping the m tactical indicators of n design schemes through Eq (1) yields the evaluation value matrix (represented by $\boldsymbol{EVM}_{n\times m}$) as shown in Eq (2):

$$\boldsymbol{EVM}_{n\times m} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{2}$$

3.4 Evaluation indicator weight distribution

In the initial decision-making phase, the evaluation indicators' weights can be processed equally. However, to consider the influence of subjective tendencies and experience in design, facilitate comparison with system simulation results, and enhance subsequent model optimization efficiency, the AHP method is utilized for preliminary weight distribution.

The core concept of AHP involves obtaining a comparison matrix by pairwise comparison of all evaluation indicators. Subsequently, by calculating the normalized eigenvector corresponding to the maximum eigenvalue of the comparison matrix, the weight vector of the evaluation indicators can be derived. Upon completion of the calculation, consistency testing is generally conducted to ensure the reliability of the results.

When dealing with a large number of evaluation indicators, it is essential to categorize them and establish a hierarchical evaluation indicator model, such as the aircraft TIS in this scenario. In such cases, it becomes necessary to compute the weight vector separately for each layer as the relative weight. These relative weights of each layer are then combined to derive the absolute weight value of each indicator. The resulting weight distribution outcome, obtained through the aforementioned steps, is expressed as Eq (3):

$$\boldsymbol{W}_{1\times m} = [w_1 \quad w_2 \quad \dots \quad w_m] \tag{3}$$

3.5 Comprehensive Evaluation

After determining the $\boldsymbol{EVM}_{n\times m}$ and $\boldsymbol{W}_{1\times m}$, the evaluation result of each solution can be calculated through the comprehensive function (represented by f_{CF}), expressed as vector $\boldsymbol{ER}$:

$$\boldsymbol{ER} = f_{CF}\left(\boldsymbol{EVM}_{n\times m}, \boldsymbol{W}_{1\times m}\right) \tag{4}$$

To simplify the calculation, a linear weighting function f_{CF} is employed in this article. Consequently, Eq (4) can be expressed as Eq (5):

$$\boldsymbol{ER} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} \tag{5}$$

4. Evaluation of aircraft design schemes based on SoS confrontation simulation

Using SoS confrontation simulation software as a test platform to conduct aircraft systematic verification and evaluation is an important research method in the field of SoS research[22–24].

Following the general logic of “Modeling-Simulation-Evaluation”, a SoS verification and evaluation framework for aircraft is proposed, as illustrated in Figure 3. When utilizing system confrontation simulation to provide verification support for the multi-attribute decision-making model of aircraft tactical-layer design schemes, it is essential to concentrate on three key aspects: mission objectives, model composition, and performance indicators.

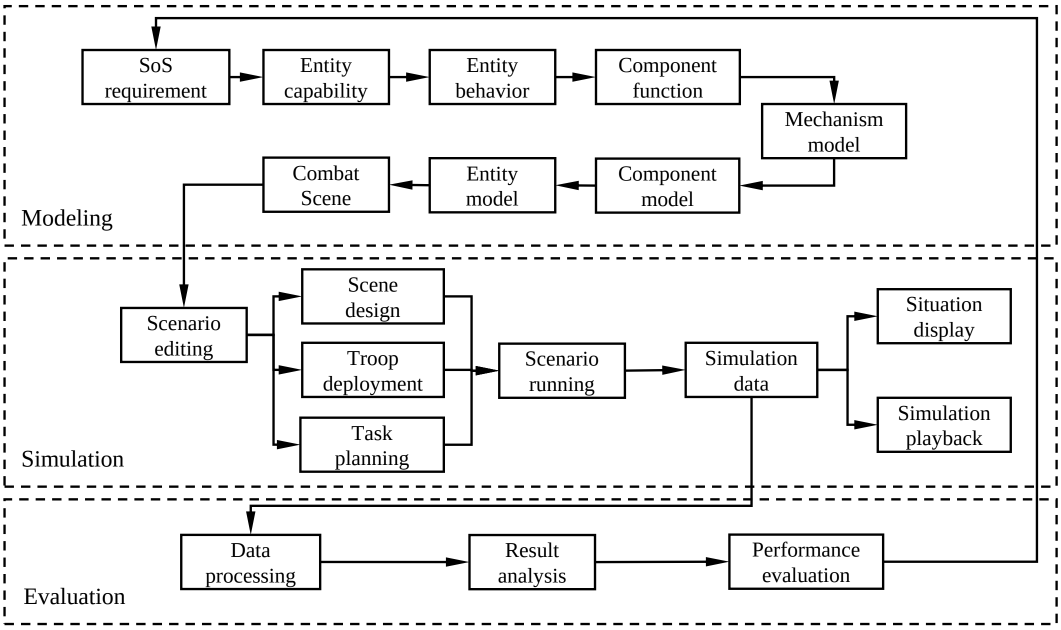

Figure 3-SoS verification and evaluation framework

4.1 Mission scenario construction based on formal modeling language

Constructing mission scenarios is fundamental for studying aircraft tactical-level indicators and system effectiveness. Describing a complex system, such as a combat system, using textual natural language is particularly challenging. Therefore, to clearly, accurately, and comprehensively describe the development process of a battle and define the capabilities and typical behaviors of aircraft, it is necessary to use formal modeling languages for modeling combat systems and combat tasks. Table 2 presents commonly used system modeling languages, modeling tools, and modeling methodologies.

Table 2- Modeling tools, languages and methodology

Nos.	Modeling Language	Modeling Methodology	Modeling Tools
1	MagicDraw	UML	OOSEM
2	MetaEdit+	SysML	Harmony-SE
3	IBM Rhapsody	UPDM	ARCADIA
4	Capella	AIRM	DoDAF

4.2 Combat Entity Construction Based on Component Modeling

Existing SoS simulation software predominantly employs component modeling to construct combat entities. The core idea behind component modeling is to abstract the internal structure and external behavior of the simulation object, forming a series of executable and reusable components. These components are built on a unified and extensible model framework and are assembled to create combat entities that simulate the behavior of weapons and equipment in real combat scenarios.

To address the requirements of aircraft tactical-level design simulation, a standard template for modeling aircraft components is developed, focusing on both the ontology and behavior of aircraft. This template is illustrated on the left side of Figure 4.

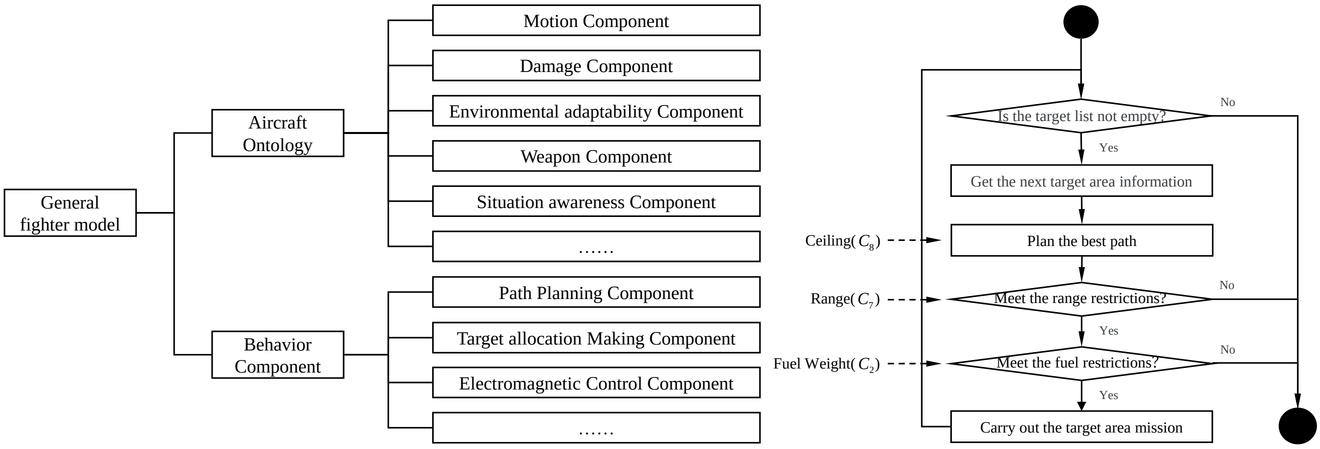

Figure 4-Fighter standard modeling template and Path Planning Component work flow

These components link the tactical indicators of the design scheme with the aircraft entity in the following ways:

(1) Motion Component

Controls the aircraft's maneuvering mode, including flight speed, flight direction, flight attitude, etc.; includes three indicators: maximum speed (C_4), cruising speed (C_5), and climb rate (C_6). The indicator values are directly used as input attribute values of the motion state.

(2) Survivability Component

Determines the probability of the aircraft being detected and hit by the enemy, as well as its availability after being attacked, including the Radar Cross Section (C_{14}) and the aircraft structure parameters (C_1).The working logic of this component is based on the following assumptions: RCS area is negatively correlated with the probability of being discovered and hit, and the weight of the aircraft structure is positively correlated with the availability after being hit.

(3) Environmental adaptability Component

This component mainly controls the deployment of aircraft, including parameters such as aircraft length (C_9), aircraft height (C_{10}), wingspan (C_{11}), takeoff run distance (C_{12}), and landing run distance (C_{13}). These five parameters determine the deployment capability between different airports on the battlefield.

(4) Weapon Component

The weapon component is used to determine the type of weapons that the aircraft can carry, including the weapon weight (C_3). The weapon weight is divided into multiple levels, and each level corresponds to a different loading scheme.

(5) Path planning Component

This component determines the behavior of the aircraft by controlling the path, controlling the mission execution and return conditions. It includes indicators such as ceiling (C_8), range (C_7), and fuel weight (C_2). The right side of Figure 4 shows how these three indicators participate in the path planning process.

4.3 Evaluation indicators of SoS confrontation simulation results

Upon completion of the SoS confrontation simulation, the mission completion rate (MCR) can be utilized to describe the actual application effectiveness of the combat system incorporating a particular design scheme. The MCR is defined as shown in Eq (6):

$$\varphi_{MCR} = \frac{1}{N_{ST}} \sum_{i=1}^{N_{ST}} \frac{n_{id}}{n_{it}} \tag{6}$$

Where φ_{MCR} is MCR, N_{ST} is the total simulation times of this mission, n_{id} is the number of destroyed target, n_{it} is the number of total targets.

After the test is completed, the MCR of all design schemes is represented by a vector shown as Eq (7):

$$\boldsymbol{SR} = \begin{bmatrix} \varphi_{MCR,1} & \varphi_{MCR,2} & \cdots & \varphi_{MCR,n} \end{bmatrix}^{\mathrm{T}} \tag{7}$$

5. Verification method and optimization procedure

Based on $\boldsymbol{ER}$ and $\boldsymbol{SR}$, the Pearson correlation coefficient can be calculated to verify the consistency between the two methods. Eq (8) shows the calculation method of the Pearson correlation coefficient:

$$\rho_{Pearson}(\boldsymbol{ER}, \boldsymbol{SR}) = \frac{\sum_{i=1}^{n} \left(e_i - \overline{\boldsymbol{ER}}\right)\left(\varphi_{MCR,i} - \overline{\boldsymbol{SR}}\right)}{\left\{\sum_{i=1}^{n} \left(e_i - \overline{\boldsymbol{ER}}\right)^2 \sum_{i=1}^{n} \left(\varphi_{MCR,i} - \overline{\boldsymbol{SR}}\right)^2\right\}^{1/2}} \tag{8}$$

Where $\rho_{Pearson}$ is Pearson correlation coefficient, $\overline{\boldsymbol{ER}}$ is the average value of vector $\boldsymbol{ER}$, $\overline{\boldsymbol{SR}}$ is the average value of vector $\boldsymbol{SR}$.

Using $\rho_{Pearson}$ as the fitness function and using the particle swarm optimization (PSO) algorithm, the MADM model can be optimized. The basic process of particle swarm optimization is shown in Figure 5. Based on the basic process in the SAWC framework, f_{MF} and $\boldsymbol{W}_{1\times m}$ can be selected as the optimization objective functions for optimization.

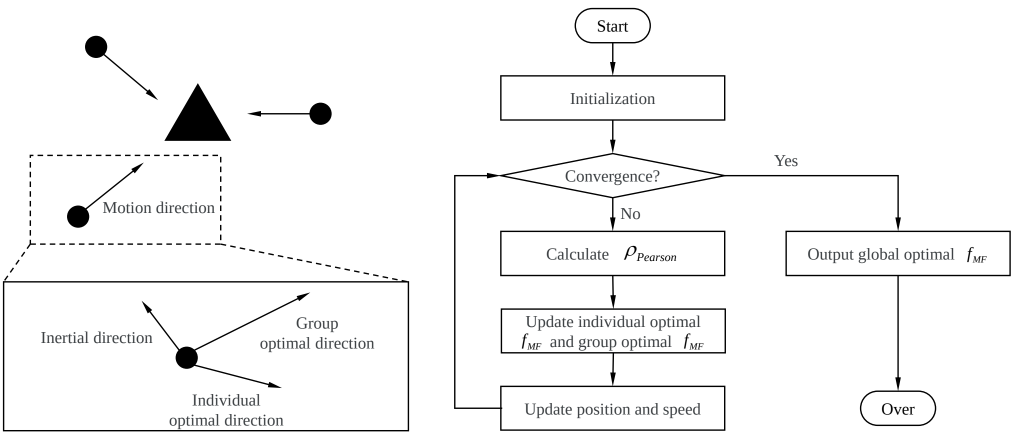

Figure 5-Optimization procedure of MADM model based on PSO algorithm

5.1 Weight vector as the optimization objective function

In the weight distribution step of SAWC, although the AHP method is used to initially weight each evaluation indicator, the results of AHP are still greatly affected by people's subjective experience. In order to make the MADM model have higher credibility, the weight vector $\boldsymbol{W}_{1\times m}$ is used as the optimization variable to perform PSO procedure. At this time, the position of each particle is a possible weight vector, and $\boldsymbol{ER}$ is calculated directly through f_{CF}.

5.2 Mapping function as the optimization objective function

In the initial MADM model, when calculating the evaluation indicator valve r of $\boldsymbol{EVM}_{n\times m}$, all evaluation indicators are mapped from the tactical indicator values based on the linear f_{MF} shown in Eq (1), which is different from the actual situation. Therefore, the linear f_{MF} is changed to an S-shaped f_{MF} and the most suitable mapping function for each indicator is obtained by optimizing the coefficients. The initial function form is shown in Eq (9):

$$r_j = \frac{1}{1 + a_0 e^{-\frac{b_0}{\max(range_j) - \min(range_j)}\left(x_j - \frac{\max(range_j) + \min(range_j)}{2}\right)}} \tag{9}$$

In this case, the position of each particle in the PSO algorithm is represented by a 14×2 matrix, where each row corresponds to a possible coefficient set for f_{MF} of the evaluation indicator. The $\boldsymbol{EVM}_{n \times m}$ can be calculated using this matrix, after which subsequent optimization steps are performed.

6. Case Study

The case study will be based on a ground attack unmanned aerial vehicle (ga-UAV). The main mission scenario for a ga-UAV involves attacking enemy ground radars and air defenses in coordination with AWACS, jammers, and other allied forces.

6.1 MADM Model Construction

6.1.1 Indicator selection

Since the primary mission of the ga-UAV is ground attack, the tactical indicators it involves are similar to those considered for general fighter aircraft. Therefore, its EIS can be directly constructed by selecting the 14 evaluation indicators shown in Table 1.

6.1.2 Indicator assignment

In this study, the conceptual scheme of the ga-UAV participating in MADM was generated with the assistance of a large language model. This method has seen rapid development in recent years[25–27]. Specifically, the task requirements are input into the large language model (LLM) through textual descriptions, requesting the model to output the reference range of each tactical indicator. Subsequently, a total of 1,000 schemes are generated using the Monte Carlo sampling method.

Taking the first design scheme as an example, the 14 tactical indicator values and reference ranges are as shown in Table 3.

Table 3- Tactical indicators of the first design scheme

Nos.	Tactical indicator	Unit	Value	Reference range
1	Maximum Takeoff Weight	kg	2789.37	[3000,5000]
2	Fuel Weight	kg	1535.85	[600,1400]
3	Weapon Weight	kg	602.12	[200,600]
4	Maximum Speed	Ma	1.17	[0.8,1.4]
5	Cruising Speed	Ma	0.70	[0.6,0.8]
6	Maximum Climb Speed	m/s	42.21	[40,60]
7	Range	km	2169.63	[1500,2500]
8	Ceiling	m	11382.59	[9000,13000]
9	Length	m	10.11	[8,12]
10	Height	m	2.52	[2,4]
11	Wingspan	m	8.47	[6.10]
12	Takeoff Run Distance	m	439.75	[300,500]
13	Landing Roll Distance	m	676.12	[600,800]
14	Radar Cross Section	m^2	0.55	[0.01,1]

Use a linear f_{MF} represented by Eq (1) to map each indicator value to evaluation indicator value, then the $\boldsymbol{EVM}_1$ is calculated as Eq (10):

$$\boldsymbol{EVM}_1 = [0.21 \quad 0.54 \quad 0.51 \quad 0.42 \quad 0.51 \quad 0.61 \quad 0.67 \quad 0.60 \quad 0.47 \quad 0.74 \quad 0.38 \quad 0.30 \quad 0.62 \quad 0.50]^{\mathrm{T}} \tag{10}$$

Process all design schemes with the above method and we can get the $\boldsymbol{EVM}_{1000 \times 14}$.

6.1.3 Indicator weight distribution

For this ga-UAV application scenario, the AHP method is employed to distribute weight factors to the evaluation indicators. Taking the loading capacity (B_1) as an example to illustrate the calculation process, the comparison matrix A_{11} corresponding to the three tactical indicators is as Eq (11) shows:

$$A_{11} = \begin{bmatrix} & C_1 & C_2 & C_3 \\ C_1 & 1 & 1/3 & 1/6 \\ C_2 & 3 & 1 & 1/3 \\ C_3 & 6 & 3 & 1 \end{bmatrix} \tag{11}$$

Calculate the maximum eigenvalue of A_{11} as $\lambda_{\max} = 3.0183$, and normalize its corresponding eigenvector to obtain the relative weight of C_1, C_2, C_3 as:

$$\boldsymbol{W}_{11} = [0.0960 \quad 0.2510 \quad 0.6530] \tag{12}$$

Calculate the consistency index CI and consistency ratio CR respectively as:

$$CI = \frac{\lambda_{\max} - 3}{3-1} = 0.0091 \tag{13}$$

$$CR = \frac{CI}{RI} = \frac{0.0091}{0.58} = 0.0158 < 0.1 \tag{14}$$

Where RI is the random consistency index. When the number of indicators participating in the evaluation equals 3, $RI = 0.58$.

Calculate the relative weight vectors $\boldsymbol{W}_{12}$ and $\boldsymbol{W}_{13}$ of the evaluation indicators corresponding to flight performance(B_2) and environmental adaptability(B_3) in the same way, and then calculate the relative weight $\boldsymbol{W}_1$ of B_1, B_2 and B_3.Combining the above weight vectors, the total weight is shown in Eq (15)

$$\begin{aligned} \boldsymbol{W}_{1\times 14} &= \boldsymbol{W}_1 \times \begin{bmatrix} \boldsymbol{W}_{11} \\ \boldsymbol{W}_{12} \\ \boldsymbol{W}_{13} \end{bmatrix} \\ &= [0.0627 \quad 0.1639 \quad 0.4264 \quad 0.0258 \quad 0.1213 \quad 0.0258 \quad 0.0565 \\ &\quad\; 0.0216 \quad 0.0041 \quad 0.0027 \quad 0.0079 \quad 0.0159 \quad 0.0309 \quad 0.0344] \end{aligned} \tag{15}$$

Draw a weighted pie chart, as shown in Figure 6.

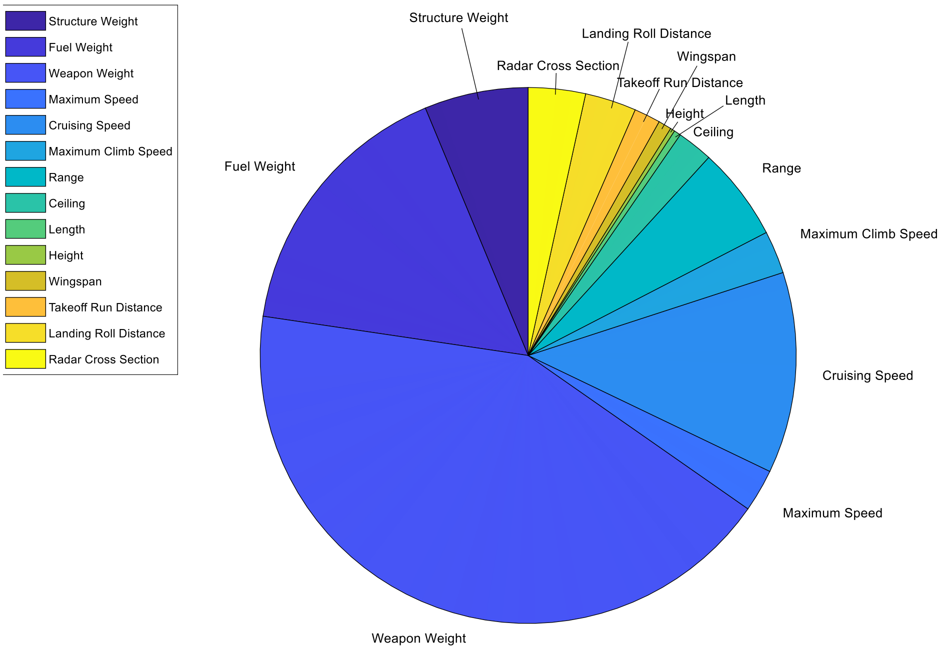

Figure 6-Initial weight distribution results

6.1.4 Comprehensive Evaluation

Based on the calculation results of $\boldsymbol{EVM}_{1\times14}$ and $\boldsymbol{W}_{1\times14}$, the linear weighted operator f_{MP} is used to calculate the evaluation results of each design scheme. The results of the top 100 schemes are shown in Figure 7.

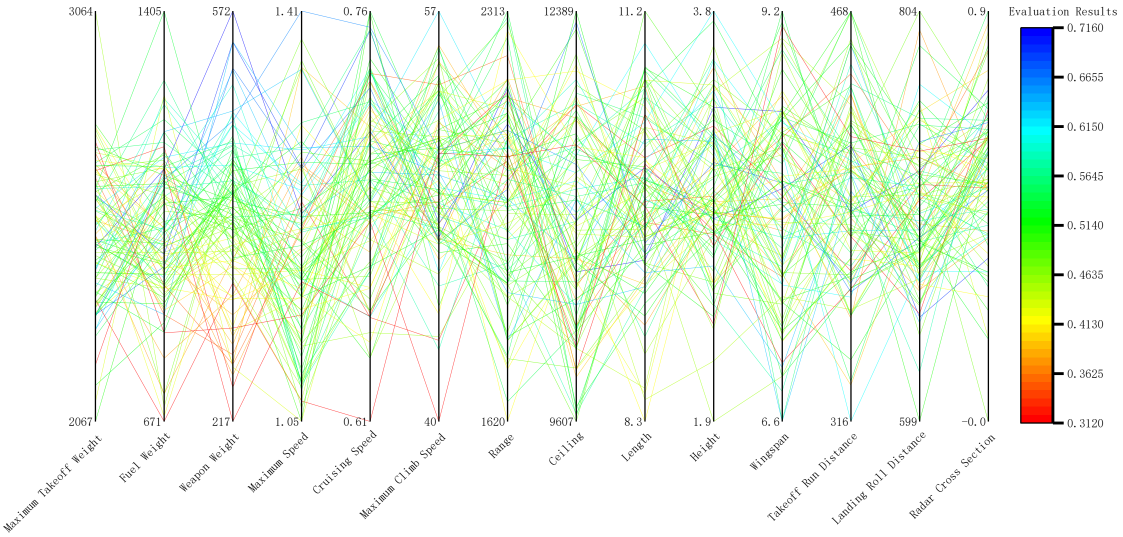

Figure 7-MADM evaluation results of 100 design schemes

The tactical indicator set of the best design scheme are shown in Table 4.

Table 4-The best design scheme tactical indicators

Tactical indicator	unit	Value	Tactical indicator	unit	Value
Structure Weight	kg	2490.26	Ceiling	m	10619.76
Fuel Weight	kg	1122.34	Length	m	9.46
Weapon Weight	kg	572.23	Height	m	3.39
Maximum Speed	Ma	1.23	Wingspan	m	8.60
Cruising Speed	Ma	0.71	Takeoff Run Distance	m	393.54
Maximum Climb Speed	m/s	47.87	Landing Roll Distance	m	724.03
Range	km	2183.49	Radar Cross Section	m^2	0.73

6.2 SoS confrontation simulation

Utilizing the Department of Defense Architecture Framework (DoDAF) and Unified Profile for DoDAF and MoDAF (UPDM) modeling language, the fundamental tasks of the ga-UAV were refined, and a combat system architecture model incorporating AV-1, OV-1, OV5a, and OV5-b was constructed, as depicted in Figure 8.

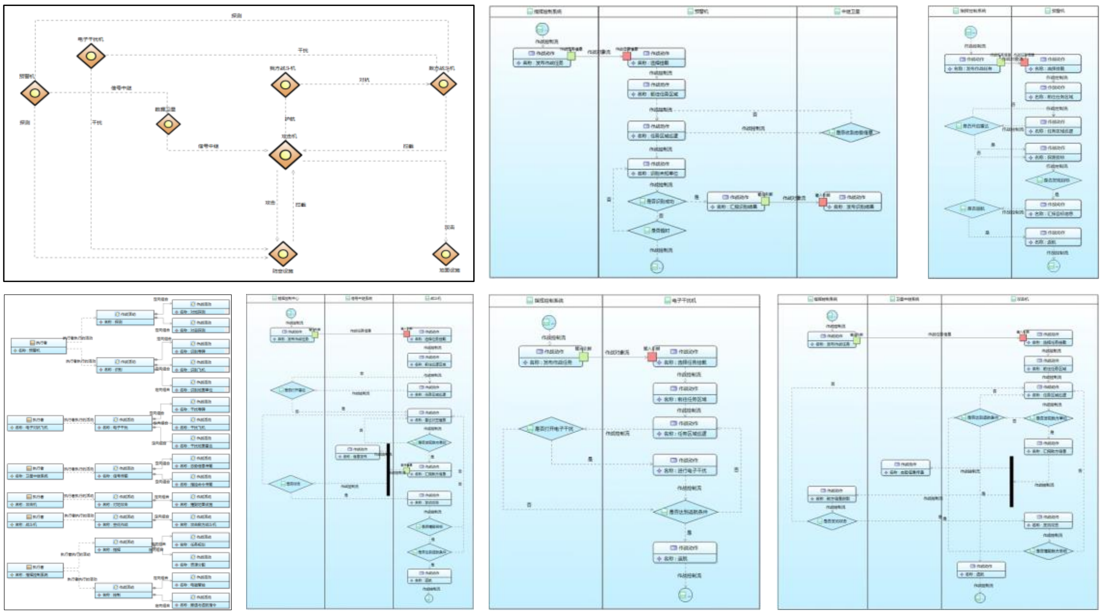

Figure 8-The combat SoS model of ga-UAV

Utilizing the constructed combat SoS architecture model, a mission scenario is developed. The primary mission scenario of the ga-UAV involves ground attack operations. The red side comprises 6 ga-UAVs, 1 early warning aircraft, and 1 electronic jammer. The blue side includes various land-based air defense systems and a series of significant military targets. The troop deployment situation of the mission scenario is depicted in Figure 9.

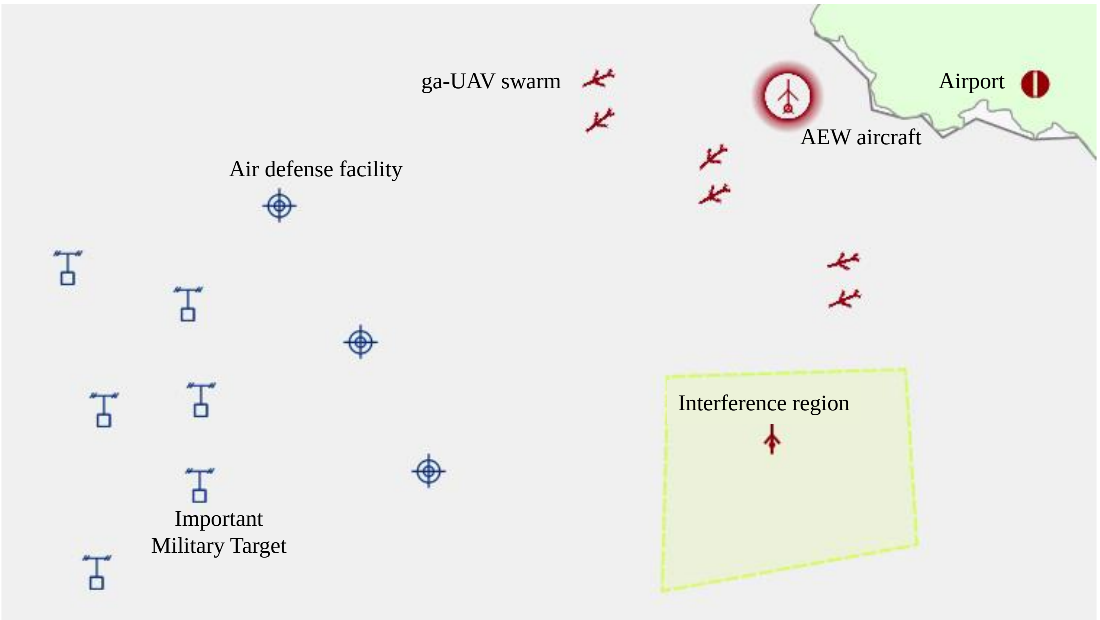

Figure 9-ground attack simulation scenario mission

6.2.1 Modeling ga-UAV

The red team's combat system comprises an airport, 6 ga-UAVs, 1 early warning aircraft, and 1 electronic jammer. Among these, the ga-UAV entity utilizes common components derived from 8 types of fighter jets for modeling, as depicted on the left side of Figure 10. These 8 types of components encompass 14 tactical indicators, and the design scheme can be instantiated by adjusting the values of the indicators within the components. For instance, within the motion component, adjustments can be made to indicators such as maximum flight speed, cruise speed, and maximum climb rate. Notably, the air-to-ground missiles carried by ga-UAVs also necessitate separate modeling, as illustrated on the right side of Figure 10.

The early warning aircraft and electronic jammers fulfill auxiliary roles in the middle and rear areas of the battlefield, and can be simulated using generic models.

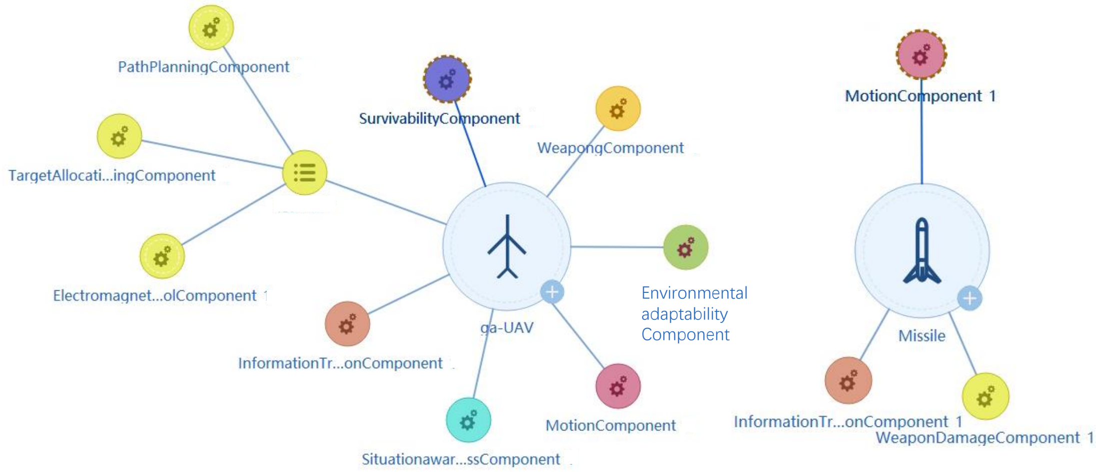

Figure 10-Topology diagram of ga-UAV model and missile model

Before engaging in battle, the early warning aircraft utilizes high-performance radar to approximate the enemy's location, while the electronic jammer flies to a secure area to conduct electronic interference, disrupting the detection and strike capabilities of the enemy's air defense facilities. The 6 ga-UAVs are organized into groups of two, maintaining an even distribution both longitudinally and laterally, as they fly towards the target combat area at cruising speed.

Upon detecting an enemy target via onboard radar, the ga-UAVs transition into combat mode, accelerating to maximum speed to penetrate enemy defenses. If under attack by enemy air defense facilities, they maneuver and climb to evade detection. Once within range, ga-UAVs in the same formation launch missiles to engage the target. If the target is destroyed, they proceed to search for the next target. If not, they hand over the task to the next formation for supplementary attack. If it is the final formation and missiles remain, they engage in another round of combat circling and follow-up firing. The aircraft returns to base under three conditions: complete destruction of enemy targets, depletion of weapons, or reaching maximum range.

6.2.2 Design of simulation experiment

The input data for this simulation experiment consists of the tactical indicator values of 1000 design schemes, with each design scheme serving as a test point. For each test point, Monte Carlo simulation randomly generates 6-9 targets. Subsequently, 10 simulation tests are conducted, and the test results are statistically analyzed to calculate φ_{MCR} .

Table 5-10 times simulation results of the first design scheme

No.	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
n_d	6	5	5	4	3	6	5	3	4	4
n_t	6	6	7	8	7	6	8	9	7	6

Taking the first test point as an example, the results of ten simulation tests are shown in Table 5, and based on the results of 10 simulation tests, we get:

$$\varphi_{MCR,1} = \frac{1}{10}\sum_{i=1}^{10}\frac{n_{id}}{n_{it}} = 0.6673 \tag{16}$$

By analogy, the simulation results corresponding to the 1000 design schemes are calculated, and the total simulation results is represented as:

$$\boldsymbol{SR} = \begin{bmatrix} 0.6673 & 0.4867 & \dots & 0.5683 \end{bmatrix}^{\mathrm{T}} \tag{17}$$

6.3 MADM Model verification and optimization

Based on the calculation results of $\boldsymbol{ER}$ and $\boldsymbol{SR}$, a scatter plot is drawn, as shown in Figure 11. The Pearson correlation coefficient of the two sets of results calculated through Eq (8) is:

$$\rho_{Pearson}\left(\boldsymbol{ER},\boldsymbol{SR}\right) = 0.6976 \tag{18}$$

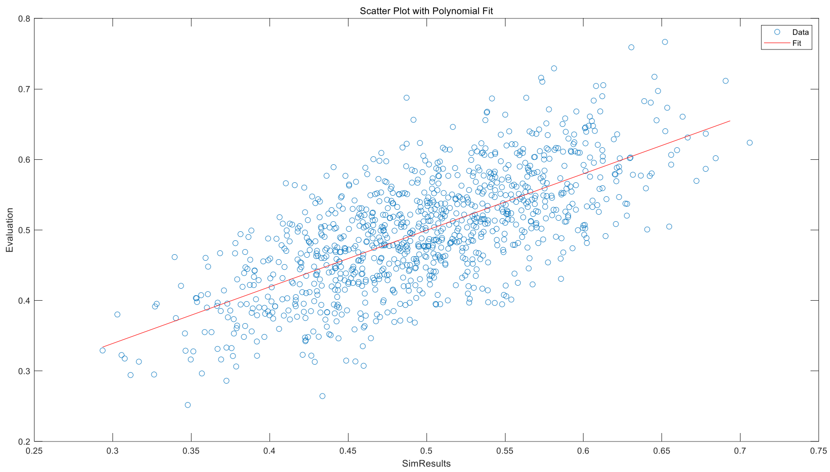

Figure 11-Scatter plot of design scheme evaluation results and simulation results

The calculation results reveal a low correlation between the outcomes of MADM and the results of simulation calculations, indicating that the MADM model is ineffective in predicting the effectiveness of the program system's confrontation application. To address this, the PSO method is employed to optimize the model. The optimization parameters are detailed in Table 6.

Table 6-PSO method parameters

Parameter	**Value**	**Parameter**	**Value**
Optimization object	$\boldsymbol{W}_{1\times 14} / f_{MF}$	Fitness function	$\rho_{Pearson}\left(\boldsymbol{ER},\boldsymbol{SR}\right)$
Number of Particles	1000	Cognitive Acceleration Coefficient	1.5
Position Range	[0,1]	Social Acceleration Coefficient	1.5
Velocity Range	[0.1,0.3]	Maximum Iterations	100000
Inertia Weight	0.8	Stop value	0.9

After completing 100,000 generations of search, the global optimal result was attained. Based on this optimized model, 1000 new design schemes were generated for evaluation to validate the accuracy of the model. The evaluation results and target destruction rate were obtained, as illustrated in Figure 12.

The correlation coefficient between $\boldsymbol{ER}$ and $\boldsymbol{SR}$ is $\rho_{Pearson} = 0.9154$, indicating that the optimized model has good prediction ability.

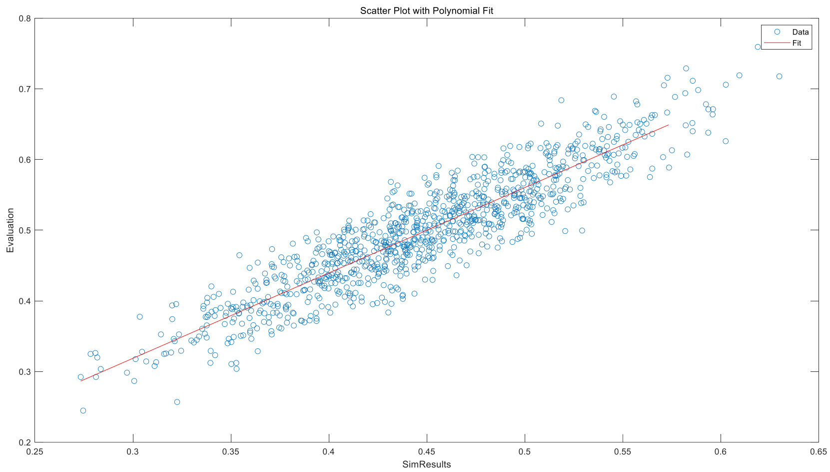

Figure 12-the evaluation results of optimized MADM model

7. Discussion

To address the challenge of verifying decision-making results during the aircraft concept scheme selection process, a method leveraging SoS confrontation simulation for verifying and optimizing MADM model is proposed. Firstly, for the conceptual design stage of the aircraft, the SAWC modeling framework of the MADM method is delineated, and the model is initially constructed based on the characteristics of aircraft conceptual design. Secondly, the process of SoS simulation of aircraft using architecture modeling tools, SoS confrontation simulation tools, and effectiveness evaluation methods is outlined. Finally, model optimization is achieved using the Pearson correlation coefficient as the model accuracy evaluation indicator and the weight vector as the optimization target.

Through this method, tactical indicator decision-making models can be constructed for different types of aircraft. The interpretable MADM model can offer valuable insights for aircraft conceptual design and enhance the consideration of system application effects in the early design stages.

However, while this method demonstrates good interpretability when the tactical indicator set is small, it may exhibit limitations when dealing with a large number of tactical indicators, potentially resulting in weight factors that tend to be average, thereby reducing its explanatory power.

In future research, we aim to consider the mapping function of each indicator as the optimization target. By leveraging SoS confrontation simulation results, we plan to derive independent mapping functions for each evaluation indicator, thereby enhancing the model's interpretability and performance.

8. Copyright Statement

9. References

[1] Raymer, D., *“Aircraft Design: A Conceptual Approach, Fifth Edition,”* American Institute of Aeronautics and Astronautics, Inc., Washington, DC, 2012.

[2] Liu, H., Luo, M., Sun, K., *“Aircraft Conceptual Design, 2nd edition,”* Beihang University Press, 2019

[3] Luo, M., Liu, H., and Wu, Z. Prototype System Research on Open Conceptual Aircraft Design. *Acta aeronautica et astronautica sinica*, Vol.29, No.4, pp. 954–959.

[4] Champasak, P., Panagant, N., Pholdee, N., Vio, G. A., Bureerat, S., Yildiz, B. S., and Yıldız, A. R., “Aircraft Conceptual Design Using Metaheuristic-Based Reliability Optimisation,” *Aerospace Science and Technology*, Vol. 129, 2022, p. 107803.

[5] Buonanno, M., and Mavris, D., “Small Supersonic Transport Concept Exploration Using Interactive

Evolutionary Algorithms," presented at the AIAA 4th Aviation Technology, Integration and Operations (ATIO) Forum, Chicago, Illinois, 2004.

[6] Sareni, B., Krahenbuhl, L., and Nicolas, A., "Niching Genetic Algorithms for Optimization in Electromagnetics. I. Fundamentals," *IEEE Transactions on Magnetics*, Vol. 34, No. 5, 1998, pp. 2984–2987.

[7] Chen, S.-J., and Hwang, C.-L., "Fuzzy Multiple Attribute Decision Making Methods," *Fuzzy Multiple Attribute Decision Making: Methods and Applications*, edited by S.-J. Chen and C.-L. Hwang, Springer, Berlin, Heidelberg, 1992, pp. 289–486.

[8] Hwang, C.-L., and Yoon, K., "Methods for Multiple Attribute Decision Making," *Multiple Attribute Decision Making: Methods and Applications A State-of-the-Art Survey*, edited by C.-L. Hwang and K. Yoon, Springer, Berlin, Heidelberg, 1981, pp. 58–191.

[9] Zanakis, S. H., Solomon, A., Wishart, N., and Dublish, S., "Multi-Attribute Decision Making: A Simulation Comparison of Select Methods," *European Journal of Operational Research*, Vol. 107, No. 3, 1998, pp. 507–529.

[10] Tzeng, G.-H., and Huang, J.-J., *"Multiple Attribute Decision Making: Methods and Applications,"* CRC Press, 2011.

[11] Bai, Z., Liu, H., Xu, M., and Wu, Z., "Preferred Selection Method for Multiobjective Concepts in Aircraft Conceptual Design Optimization," *Acta Aeronautica et astronautica sinica*, Vol. 30, No. 8, 2009, pp. 1447–1453.

[12] Pu, H,. Wang, F., and Zheng, Z., "TOPSIS Method of Command Post Threat Assessment Based on UAV Raid," *Command Control & Simulation*, Vol.44, No.6, 2022, pp. 29-34.

[13] Md Helal Miah, Jianhua Zhang, and Gurmail Singh Malhi, "Tacit Knowledge Service on Industrial Robot Selection for Efficient Aircraft Production Based on the Flexible MADM Approach," *Russian Aeronautics*, Vol. 66, No. 2, 2023, pp. 349–386.

[14] Gao, Y., Tian, Y., Liu, H., and Sun, X., "Gaussian Fitting Based Optimal Design of Aircraft Mission Success Space Using Multi-Objective Genetic Algorithm," *Chinese Journal of Aeronautics*, Vol. 33, No. 12, 2020, pp. 3318–3330.

[15] Saaty, T. L., and Peniwati, K., "Group Decision Making: Drawing Out and Reconciling Differences," RWS Publications, 2013.

[16] Tzeng, G.-H., and Huang, J.-J., "Multiple Attribute Decision Making: Methods and Applications," CRC Press, 2011.

[17] Yoon, K., "A Reconciliation Among Discrete Compromise Solutions," *Journal of the Operational Research Society*, Vol. 38, No. 3, 1987, pp. 277–286.

[18] Hwang, C.-L., Lai, Y.-J., and Liu, T.-Y., "A New Approach for Multiple Objective Decision Making," *Computers & Operations Research*, Vol. 20, No. 8, 1993, pp. 889–899.

[19] Roy, B., "Classement et choix en présence de points de vue multiples."

[20] Mahmoudi, M., Aydi, A., and Ibrahim, H., "Site Selection for Artificial Recharge with Treated Wastewater with the Integration of Multi-Criteria Evaluation and ELECTRE III," *Environmental Science and Pollution Research*, Vol. 28, No. 34, 2021, pp. 46748–46763.

[21] Lahdelma, R., and Salminen, P., "Stochastic Multicriteria Acceptability Analysis (SMAA)," *Trends in Multiple Criteria Decision Analysis*, edited by M. Ehrgott, J. R. Figueira, and S. Greco, Vol. 142, Springer US, Boston, MA, 2010, pp. 285–315.

[22] Yang, J., and Hu, X., "Evaluation of new quality combat capability based on system simulation test bed," *Military Operations Research and Systems Engineering*, Vol. 30, No. 3, 2016, pp. 5–9.

[23] Rong, M., Hu, X., and Yang, J., "Research on Assessment of Operation System's Resilience Based on Test Bed," *Journal of System Simulation*, Vol. 30, No. 12, 2018, pp. 4711–4717.

[24] Sepulveda, J., Rabelo, L., Jaebok Park, Riddick, F., and Peaden, C., "Implementing the High Level Architecture in the Virtual Test Bed," In *2004 Winter Simulation Conference, 2004.*, Vol. 2, Washington, D.C., 2004, pp. 380–387.

[25] Zhu, Q., and Luo, J., "Generative Transformers for Design Concept Generation," *Journal of Computing and Information Science in Engineering*, Vol. 23, No. 041003, 2023.

[26] Zhu, Q., Zhang, X., and Luo, J., "Biologically Inspired Design Concept Generation Using Generative Pre-Trained Transformers," *Journal of Mechanical Design*, Vol. 145, No. 041409, 2023.

[27] Ma, K., Grandi, D., McComb, C., and Goucher-Lambert, K., "Conceptual Design Generation Using Large Language Models," presented at the ASME 2023 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Boston, Massachusetts, USA, 2023.