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Multi-objective prediction of carrier-based aircraft aviation materials based on combinatorial optimization

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Abstract: **A single prediction model may have some deviations or even inaccuracies in predicting multiple data. In order to obtain more accurate prediction data of carrier-based aircraft aviation materials, multi-objective genetic algorithm, nsga2 algorithm, multi-objective particle swarm optimization algorithm are used to combinatorial optimization the three prediction models of gray prediction, quadratic exponential smoothing method, and time series three prediction models, and use the optimized model to predict the annual average flight hours, oil pumps, sensors, and seal ring data to obtain more accurate prediction data.**

Keywords: Multi-objective algorithm; Gray-scale prediction; Quadratic exponential smoothing method; Time-series analysis.

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1.Introduction

Air material consumption has received widespread attention, and how to accurately predict the consumption of aviation materials has always been a hot issue in the naval aviation material support. The single prediction method used in existing literature has certain shortcomings in predicting the accuracy of aviation material consumption, resulting in significant prediction errors. However, combination prediction methods can comprehensively utilize multiple methods to obtain more useful information, improve the accuracy and reliability of prediction, and have been widely applied in military, economic and other fields.

Currently, there are many research on single item prediction methods in the prediction of aviation material consumption both domestically and internationally, but there are not many research results in the combination prediction of aviation material consumption. Wan[1] put forward a new combination forecasting model, and used the quadratic programming algorithm to solve its weighting coefficient. In response to the seasonal and fluctuating characteristics of aviation material consumption, a generalized weighted function proportional average combination prediction model is presented for aviation material consumption based on grey system and neural network, and illustrates its prediction effect with examples. Mao[2]used combination prediction models to compare and analyze the weights of combination prediction through several weighting methods. Through practical examples, different methods for determining the weights of combination prediction were explored through various prediction models and combination prediction models. Examples demonstrate the proposed combination prediction model.

In the existing research results, there is a relatively less of research on the optimal combination model for predicting multiple air material consumption using multiple prediction methods simulataneously. In this paper, exploratory research has been developed in this area, mainly using traditional methods such as quadratic exponential smoothing method, grey system prediction method, time series analysis, and intelligent optimization methods such as genetic algorithm and particle swarm optimization algorithm, to establish the optimal combination model of air material consumption, and carried out a numerical example analysis.

2. Prediction Models

To predict the annual average flight hours, oil pump consumption, sensor consumption and seal ring consumption of a single machine in 2023, different prediction models should be established first. In this paper, grey prediction model, quadratic exponential smoothing method and time series analysis method are used to modify the parameters of each model according to the data of previous years, and then Combinatorial optimization is carried out for each model, The optimization algorithm used in this article is two multi-objective algorithms to optimize the weights of each model, and the optimized combination model is used to predict the data.

2.1 Grey prediction model

The grey prediction model GM (1,1)[3] is the most commonly used grey dynamic prediction model in grey prediction models. GM (1,1) represents a grey model with a first order equation and only one variable. This prediction model is mainly used to fit and predict the eigenvalues of a dominant factor in a complex system, in order to reveal the changing patterns of dominant factors and future development trends. Compared with many other prediction methods, it requires less historical data and is easy to calculate, making it suitable for use in

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production enterprises. The differential equations for the GM (1,1) model are

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \quad (1)$$

Where a and u are the undetermined parameter. $x^{(0)}$ is a series of data per year, $x^{(1)}$ is the generated sequence of the original sequence.

The data is arranged in chronological order to form a time series, which is used as the input to the gray prediction model, also known as the original sequence $x_0^{(0)}$.

$$x_0^{(0)} = (x_0^{(0)}(1), x_0^{(0)}(2), \cdots, x_0^{(0)}(n))^T \quad (2)$$

where n is the number of column length, generally $n \geq 4$. Data processing is to accumulate and generate the original number series. AGO requires that the initial number series must be non-negative. When the original number series collected in the actual process contains negative numbers, direct accumulation will cause information loss due to positive and negative cancellation, so that the regularity of the AGO generated number series cannot be strengthened, or even may be weakened. Therefore, the number series shown in the above formula must be mapped to non-negative number series. Therefore, exponential mapping is introduced to exchange the original data.

$$x_0^{(0)} = \exp(rx_0^{(0)}(k)), k = 1, 2, \cdots, n \quad (3)$$

The AGO generation is defined as:

$$x_0^{(1)} = AGO(x^{(0)}(k)) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, \cdots, n \quad (4)$$

$x^{(1)}$ is called generating sequence, which is obviously more regular than the original sequence $x^{(0)}$, with single increase characteristics. The purpose of gray modeling is to establish differential equations to describe the development trend of generating sequence.

To obtain the development coefficient a and the gray input u, the data vector x_N and the matrix B are constructed

Using the least squares method to obtain the unknown parameters of GM (1,1):

$$\begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T x_N \quad (5)$$

Using this to find a, u .(5) Establish a time-dependent response model. After finding a, u , the solution of GM (1,1) as

$$x^{(1)}(t) = (x^{(0)}(1) - \frac{u}{a})e^{-at} + \frac{u}{a} \quad (6)$$

Obtain predicted data series:

$$x = (x(1), x(2), x(3), \cdots, x(n)), t = 1, 2, \cdots, n$$

2.2 Secondary-exponential smoothing model

The primary exponential smoothing method can only be applied to the phenomenon without obvious trend. If the time series shows a linear trend of rising or falling, the secondary exponential smoothing method[4] should be carried out. The quadratic exponential smoothing value is calculated as follows:

$$\begin{aligned} S_t^{(1)} &= \alpha Y_t + (1-\alpha) S_{t-1}^{(1)} \\ S_t^{(2)} &= \alpha S_t^{(1)} + (1-\alpha) S_{t-1}^{(2)} \end{aligned} \quad (7)$$

where $S_t^{(2)}, S_{t-1}^{(2)}$ is the quadratic exponential smoothing values for year t and year $t-1$, respectively. If $S_t^{(1)}$ and $S_t^{(2)}$ are known and the data for the next year is predicted, the prediction model can be derived from equations (1) and (2) as follows:

$$Y_{t+1} = a_t + b_t \quad (8)$$

where:

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$$a_t = 2S_t^{(1)} - S_t^{(2)}$$

$$b_t = \frac{\alpha}{1-\alpha}[S_t^{(1)} - S_t^{(2)}]$$

Obtain predicted data series:

$$\boldsymbol{y} = (y(1), y(2), y(3), \cdots, y(n)), t = 1, 2, \cdots, n$$

2.3 Analysis of time series

Remember the original time series data as $a_t(t = 1, 2, \cdots, n)$.

To construct a stationary sequence, a first-order difference operation $b_t = a_{t+1} - a_t$ is performed on the sequence $a_t(t = 1, 2, \cdots, n)$ to obtain the sequence $b_t(t = 1, 2, \cdots, n-1)$. From the time series scatter plot, the time series is stationary. The following autoregressive model ($AR(2)$ model) can be established to predict[6] b_t:

$$y_t = c_1 y_{t-1} + c_2 y_{t-2} + \varepsilon_t, \quad (9)$$

c_1, c_2 is undetermined parameter; ε_t is random disturbance term.

Using this model, the predicted value of the data is obtained:

$$\boldsymbol{z} = (z(1), z(2), \cdots, z(n)), t = 1, 2, \cdots, n$$

The above three types of models have predicted the data. Next, we will carry out combinatorial optimization on the predicted data. Since there are four kinds of prediction data, we need to carry out multi-objective optimization and establish four objective functions

Assuming $x(i)$ is the weighting coefficient of the i method, Y_{it} is the predicted value of the i method in year t, and Y_t is the predicted value of the combination prediction method in year t, the objective function of the combination prediction model is[5]

$$MinZ = \frac{1}{n}\sum_{i=1}^{n}(\sum_{i=1}^{N} x_i Y_{it} - y_t)^2 \quad (10)$$

N is the number of single prediction methods selected. The most important thing in combination prediction is to calculate the weighting coefficient, so that the results of the combination prediction model can be more accurate. In the process of solving the weighting coefficients, it is necessary to ensure that the sum of all method weighting coefficients is 1, that is $\sum_{i=1}^{N} x_i = 1$. At the same time, the condition of $x_i \geq 0$ must also be met.

Transform the constrained optimization problem into an unconstrained optimization problem using the penalty function method and solve it using intelligent algorithms. The intelligent algorithms used in this article are particle swarm optimization and genetic algorithm.

The Penalty Function Transformed into Unconstrained Optimization Problems:

$$MinZ = \frac{1}{n}\sum_{i=1}^{n}(\sum_{i=1}^{N} x_i Y_{it} - y_t)^2 + \mu(\sum_{i=1}^{N} x_i - 1)^2 \quad (11)$$

μ is a penalty parameter.

Because it is a multi-objective optimization problem, using the four types of data in this article simultaneously can ultimately be written as

$$Min\{Z^{(1)}, Z^{(2)}, \cdots, Z^{(H)}\}$$

$$Z^i = \frac{1}{n}\sum_{i=1}^{n}(\sum_{i=1}^{N} x_i Y_{it}^{(i)} - y_t^{(i)})^2 + \mu(\sum_{i=1}^{N} x_i - 1)^2 \quad (12)$$

$$\boldsymbol{Z} = \left[Z^{(1)}, Z^{(2)}, \cdots, Z^{(H)}\right]^T \quad (13)$$

Ultimately transformed into:

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$$Min\boldsymbol{Z}(x_1, x_2, \cdots, x_n) \quad (14)$$

The fitness function used in this article is the objective function of unconstrained optimization transformed from the penalty function.

3.Optimization method

3.1 genetic algorithm

Genetic algorithm[7][8] is a kind of stochastic search algorithm based on natural selection and natural genetic mechanisms in the biological world, which is very suitable for handling complex and nonlinear optimization problems that are difficult to solve by traditional search algorithms.

The steps of genetic algorithm to solve such multi-objective problems:

Initialization: First, generate an initial set of solutions (population), where the first n dimensions of individuals in the population represent the independent variables of the objective function, which is the weight of the combined model. Encoding format using real number encoding. $\boldsymbol{X} = (x_1, x_2, \cdots, x_n, \cdots)$

Non dominated sorting: Sort the solutions in the population according to non dominated relationships. A non dominated relationship refers to a solution that is no worse than another solution on all objective functions, and this solution is called a non dominated solution. The sorted solutions are divided into several non dominated levels.

Calculate crowding degree: Calculate the crowding degree of each solution within each non dominated level. Crowding degree is an indicator that measures the degree of congestion in the surrounding space of a solution. The calculation method is to calculate the distance between adjacent solutions of each solution on each objective function in the target space.

Formula for calculating crowding degree:

$$I_{distance} = \frac{(I_{i+1,m} - I_{i-1,m})}{(f_m^{\max} - f_m^{\min})} \quad (15)$$

Congestion comparison operator:

As long as any of the following conditions are true, individual i wins.

If the non dominated layer where individual i is located is better than the non dominated layer where individual j is located, i.e., $i_{rank} < j_{rank}$

If they have the same level and individual i has a larger crowding distance than individual j, that is, $i_{rank} = j_{rank}$ and $i_d > j_d$.

The winning individual enters the next operation.

Selection: Use the binary tournament selection method for selection. In this method, two solutions are randomly selected each time, their non dominated level and crowding degree are compared, and the solution with smaller non dominated level or higher crowding degree is selected.

Cross and mutation: Use cross and mutation operations to generate new solutions. These operations simulate the genetic and mutation processes in biological evolution. Calculate the fitness of the new solution:

$$\boldsymbol{Z}(x_1, x_2, \cdots, x_n) \quad (16)$$

Update population: Merge the newly generated solution with the current population, then perform non dominated sorting and calculate crowding degree again, and select the optimal solution as the new population.

Elite retention strategy:

Termination condition: If the maximum number of iterations is reached, stop the algorithm; otherwise, return to forth.

3.2 Multiple-objective particle swarm algorithm:

The multi-objective particle swarm (MOPSO)[9] algorithm is developed by CarlosA. Coello Coello et al. proposed in 2004 to apply a particle swarm algorithm (PSO) that can only be used on single targets to multiple targets.

Step 1. Initialize the particle swarm and related parameters, calculate the objective function value, and set the initial evolution algebra to 1;

Objective function value:

$$\boldsymbol{Z}(x_1, x_2, \cdots, x_n) \quad (17)$$

Step 2. Pbest=pop, obtain external archive;

Step 3. Select particles with high crowding as Gbest from the Archive based on the roulette wheel strategy;

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Roulette algorithm:

$$p(x_i)=\frac{f(x_i)}{\sum_{j=1}^{N} f_j}, q(x_i)=\sum_{j=1}^{i} p(x_j) \quad (18)$$

Step 4. Execute PSO operation to obtain the next generation population $pop(t+1)$;

Speed update:

$$vel(t+1)=w\times vel(t)+r_1\times(pbest(t)-pop(t))+ r_2\times(rep(h)-pop(t)) \quad (19)$$

Location update:

$$pop(t+1)=pop(t)+vel(t) \quad (20)$$

Step 5. Merge historical archives and $pop(t+1)$; Obtain a new Archive from it;

Step 6. Compare the dominance relationship with particle swarm $pop(t+1)$ and update Pbest;

Step 7. Termination condition: If the maximum number of iterations is reached, stop the algorithm; otherwise, return to step 3.

4. Problem Solving

4.1 Restatement of the problem

Table 1: The number of aircraft and tasks of aircraft carrier-borne aircraft over the years

year	average hours	Number
2018	410	12
2019	990	12
2020	970	13
2021	1010	13
2022	904	13

Table 2: The wear and tear situation of various components of the aircraft, as well as the procurement, repair and installation situation

name	model	number	repair	delivery
oil pump		4	180	300
sensor		5	30	200
gasket ring		8		30
2018	2019	2020	2021	2022
3	8	6	4	8
8	15	12	12	8
0	80	110	144	168

For the data in the table, the number of aircraft and task situation over the years are shown in Figure 1, and the installation quantity, repair cycle, supply cycle, and failure or consumption number of each component over the years are shown in Figure 2. Through the analysis of the data in the two charts, it can be found that the annual average flight hours of a single aircraft and the four data of each component are different and may fluctuate. In order to make judgments and estimates of the situation in the next year, Multiple sets of data need to be predicted, and the predicted results will have certain reference value for the prediction situation. Here, we use three prediction models to predict the data in 2023, and use multi-objective optimization algorithms to optimize the weight of the combination model, so that the combination model can make more accurate predictions of the data in 2023.

4.2 Solution results

Three methods for predicting and summarizing each (Gray prediction model, Secondary-exponential smoothing method, Time series analysis)

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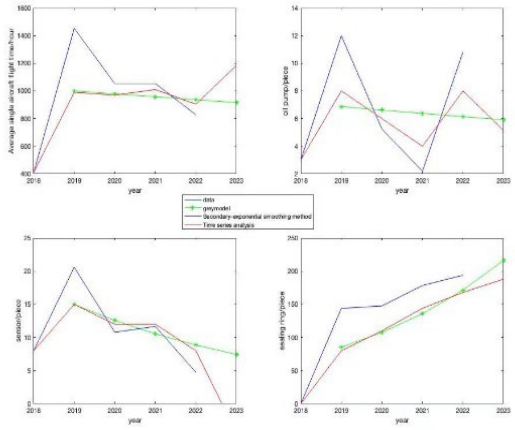

Fig 1. Grey prediction model, time series analysis, quadratic exponential smoothing method summary

According to the combined optimization model and the prediction results of each model, it can be analyzed that the error between the prediction data and the real data of the combined optimization model is smaller than the other three models, but there is still a certain gap with the real data value. Therefore, it still needs to be improved.

Through the prediction of the data in 2023, it can be found that the forecast is reasonable, but the forecast still has large fluctuations, so the forecast data still needs to be revised.

Run result (prediction 2023) (time series analysis) (multi-target particle swarm algorithm)

Combined optimization model prediction results

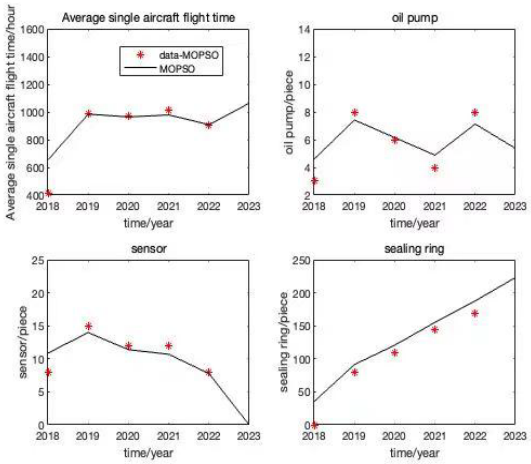

Fig 2. MOPSO for predicting images

Multi objective particle swarm optimization algorithm can perform Combinatorial optimization on the average flight time of a single machine, oil pump, sensor and seal ring according to the existing data. The optimized Combinatorial optimization data can reflect the trend of the four types of data, but it is not accurate enough

Run Results (Prediction 2023) (Time Series Analysis) (multi-target genetic algorithm)

Combination optimization model

The genetic algorithm population contains 200 individuals

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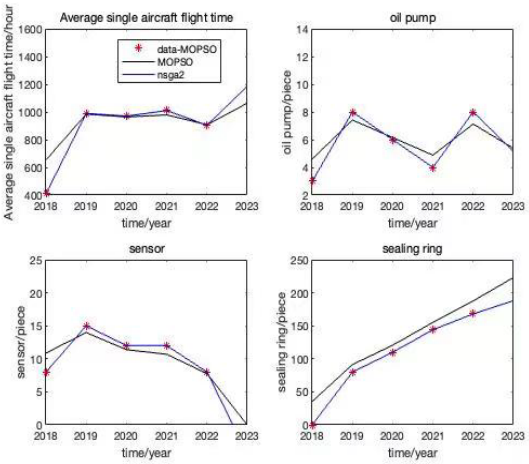

Fig 3. MOPSO and NSGA2

Final optimization results of each function

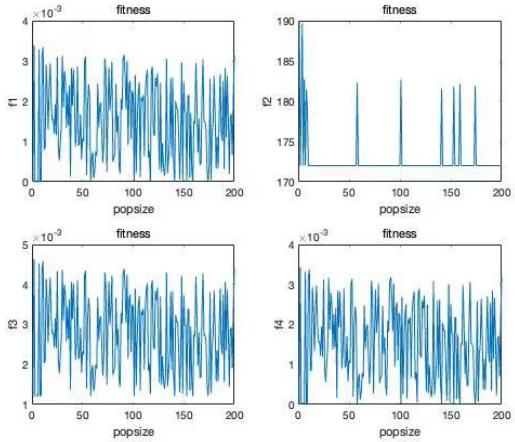

Fig4. fitness of Multi-objective genetic algorithm

The genetic algorithm population contains 25 individuals

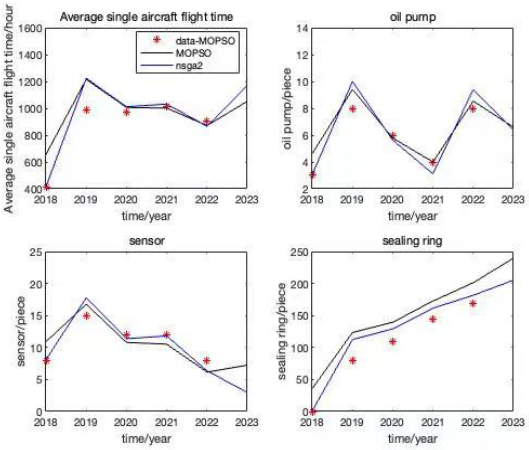

Fig 5. MOPSO and NSGA2

Table 3: The Solution Effect for Different Population Numbers

	NSGA2(200)	MOPSO(200)
Average time	9.85e-06	1.05e+03
oil pump	8.01e-10	0.84
sensor	1.39e-09	2.30
sealing ring	6.57e-07	89.72
Run time	97.25s	85.47s

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	NSGA2(25)	MOPSO(25)
Average time	1.17e+03	1.05e+04
oil pump	6.38	6.60
sensor	2.96	7.24
sealing ring	205.1725	239.62
Run time	2.86s	2.17s

Table 4: Forecast results for 2023

2023	Average time	Oil pump	sensor	Sealing ring
NSGA2	1.1852e+03	5.1428	-4.4444	188.0106
pso	1.0642e+03	5.3677	-0.0135	222.9570

According to the combined optimization model and the prediction results of each model, it can be analyzed that the error between the prediction data and the real data of the combined optimization model is smaller than the other three models. Through the prediction of the data in 2023, it can be found that the forecast is reasonable.

By using genetic algorithms with different population sizes to optimize the weights, according to the image, when the population size is less than a certain number, the algorithm cannot obtain the optimal solution. However, when the population size is 200, the solution speed will be reduced. Therefore, in the solution process, we should choose an appropriate population size to improve the solution efficiency. It can also ensure the optimal solution is obtained.

It can be seen from the image that the coincidence degree between the predicted data and the real data is high, and the prediction of future data is reasonable. For this problem, the mixed model can be used to solve the prediction. By using the PMS algorithm, nsga 2, to solve the problem, the results are shown in the figure. It can be seen that nsga 2 is better than Particle Swarm Optimization.

5. Conclusion

This article establishes the optimal model for predicting air material consumption using three single prediction methods: quadratic exponential smoothing method, grey prediction method, and time series analysis. The weight coefficients of the model in the combined prediction method are obtained through multi-objective genetic algorithm. The optimal model for predicting air material consumption proposed in this article combines traditional prediction methods and artificial intelligence methods. Examples show that the model has higher accuracy than a single prediction method, The research results of this article have certain practical significance and promotional application value.

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