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Research on Fault Prediction of Modern Aviation Electronic Equipment Based on Improved Grey Model

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ABSTRACT

The basic principle and method of Grey Model prediction are presented. In view of the defects of general GM(1,1) model, an improved method is proposed. That is using the particle swarm optimization algorithm to obtain the best forecast dimension and using metabolism to make the model parameters adaptively change. Finally, the improved Grey Model is used to predict the fault of high voltage power supply circuit of a certain type of modern air-borne radar. The results which are computed and simulated by Matlab software show that the forecast precision of improved Grey Model is higher than that of original Grey Model.

Keywords: Grey Model; Fault Prediction; Modern Aviation Electronic Equipment

1. Introduction

With all kinds of high technology such as the microelectronic and artificial intelligence applied in modern aviation electronic equipment, its integration and complexity are greatly improved. Traditional maintenance mode, such as the breakdown maintenance and preventive maintenance, has not been adapted to it. Condition based maintenance which requires that the equipment itself must have the ability to predict fault will replace traditional maintenance mode because of its good economic affordability and small maintenance scale.

Compared with traditional maintenance mode, condition based maintenance which enabled system or components of modern aviation electronic equipment to find fault before it happened is more scientific and advisable. So we can see that fault prediction is the critical technology to realize condition based maintenance.

Because of the complex system composition, fuzzy structure and limited characteristic parameters, it's hard to predict the fault of modern aviation electronic equipment. Grey Model which supplies a new way to resolve the problems of sub-sample, poor information and uncertainty is an effective measure to predict its fault.

2. Basic Principle of Grey Model Prediction

The grey system theory, which is proposed by Professor Julong Deng in 1982, is used in studying of uncertain system with features of sub-sample and poor information. Its most prominent feature is to model with small data. The GM(1,1) model is one of the important contents in grey system theory and it has been widely used in many fields including fault prediction [1].

2.1. Accumulated Generating Operation (AGO)

Suppose the original sequence is:

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\},$$

The first order AGO sequence is:

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\} \tag{1}$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i),\ k = 1, 2, \cdots, n.$

2.2. Establish the Model

Based on $X^{(1)}$, the corresponding white equation is:

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = u \tag{2}$$

where a is the evolution coefficient and u is the grey factor.

2.3. Solve Equation

The basic formulation of GM(1,1) model is established by 1-AGO sequence $X^{(1)}$ as in

$$x^{(0)}(k) + az^{(1)}(k) = u, \tag{3}$$

$Z^{(1)}$ is the adjacent mean generating sequence of $X^{(1)}$,

$$Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n)\} \tag{4}$$

where $z^{(1)}(k) = 0.5(x^{(1)}(k) + x^{(1)}(k-1)),\ k = 2,3,\cdots,n.$ The parameter a and u can be solved with the Least Square Estimation using the following equation:

$$\hat{a} = (A^{\mathrm{T}}A)^{-1}A^{\mathrm{T}}Y_n \tag{5}$$

where

$$A = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \cdots & \cdots \\ -Z^{(1)}(n) & 1 \end{bmatrix},$$

$$Y_n = [x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)]^{\mathrm{T}},$$

The time response sequence of model (3) is

$$\hat{x}^{(1)}(k+1) = [x^{(0)}(1) - \frac{u}{a}]e^{-ak} + \frac{u}{a} \tag{6}$$

2.4. Inverse Accumulated Generating Operation (I-AGO)

Finally, we can obtain the sequence for prediction by I-AGO:

$$\begin{aligned} \hat{x}^{(0)}(k+1) &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= (1-e^{a})[x^{(0)}(1) - \frac{u}{a}]e^{-ak} \end{aligned} \tag{7}$$

3. Improvement of GM(1,1) Model

3.1. Metabolism

It is unscientific that the parameter a and parameter u in general GM(1,1) model are invariable when computed. And as the time goes by, the significance of old data information will become less and less and model forecast precision will be greatly reduced too. Therefore, the general Grey Model is not suitable for long-term prediction.

In view of the defects of general GM(1,1), metabolism is introduced here to solve the problem [2]. The thought of building metabolism model is as follows:

Firstly, use the initial sequence $\{x^{(0)}(l), x^{(0)}(2), \cdots, x^{(0)}(m)\}$ to establish GM(1,1) and to predict $\hat{x}^{(0)}(m+1)$. Secondly, use sequence $\{x^{(0)}(2), x^{(0)}(3), \cdots, \hat{x}^{(0)}(m+1)\}$ to predict $\hat{x}^{(0)}(m+2)$. Analogously, we can gain metabolism models like $\hat{x}^{(0)}(m+3)$, $\hat{x}^{(0)}(m+4)$ etc. With time passing, we get new data (a and u), and build new models. Metabolism models have a view of using a series of models to express the development and variation of system, so that they could deal with the variation of the environment [3]. It embodies the adaptability of the model for the new information and new environment.

3.2. PSO Algorithm

Generally forecast dimension m is determined by experience or iterative trials. In this paper, it is computed by particle swarm optimization (PSO) algorithm. PSO is initialized with a population of random solutions (particles). Each particle has two states, the current position x and the current velocity v. Particle has an ability of memory to the best position (*pbest*) itself experienced and the best position (*gbest*) swarm experienced. At each generation, the velocity and position of each particle is updated using following formulas [4,5]:

$$\begin{aligned} v_i(t+1) = \omega * v_i(t) + c_1 * r1 * (pbest^t - x_i^{\,t}) \\ + c_2 * r2 * (gbest^t - x_i^{\,t}) \end{aligned} \tag{8}$$

$$x_i^{t+1} = x_i^{\,t} + v_i^{t+1} \tag{9}$$

where t is the current time, ω is called the inertial weight, c_1 and c_2 are the acceleration constants, r_1 and r_2 are the random numbers uniformly generated from [0,1]. A limit velocity called $v_{\max}$ is imposed on particles. If calculated velocity of a certain particle exceeds this value, it will be reset to the maximum velocity.

4. Case Analysis

Here a certain type of air-borne radar is taken for an example to specify the whole process of fault prediction by improved Grey Model. We have acquired the values of high voltage power of radar transmitter from an aviation repair factory by equal interval sampling. As is shown in **Table 1**.

From **Table 1** we can see that with the increase of working time of high voltage power, its performance gradually decreased and the slow-wave line voltage increased. The working range of slow-wave line is between 10 to 15 kV. It would break down when the voltage which is able to reflect the characteristics of fault trend of high voltage power, has exceeded 15kV. So the voltage of slow-wave line is selected as the object for prediction.

Table 1. Measured values of slow-wave line.

Times of Test	1	2	3	4	5	6	7	8	9
Voltage/kV	10.02	10.10	10.22	10.31	10.45	10.66	10.57	10.55	10.88
Times of Test	10	11	12	13	14	15	16	17	18
Voltage/kV	10.79	11.34	11.77	12.39	12.88	13.27	13.58	14.04	14.55

4.1. Determination of Forecast Dimensionl

Set initial population of particles as 20, maximum iteration times as 20, maximum invalid iteration times as 10, inertial weight as 0.5 to 1.2, forecast dimension as 4 to 15, particle velocity as -2 to 2. Programmed and computed by Matlab software, we know the forecast precision is optimum when m = 5.

4.2. Metabolic GM(1,1) Prediction

Choose the first 5 values for prediction and the remainder 13 values for inspection. And then use GM(1,1) model and the improved model to predict. Finally, the results simulated by Matlab software are shown in **Figure 1**:

Different kinds of error and precision level of the two models computed by Matlab software are shown in **Table 2** [6]:

From **Figure 1** and **Table 2** we can see that in short-term prediction, the gap in precision discrepancy of the two models is not too wide. With the time passing, data predicted by general GM(1,1) model only linearly increased. However, the improved GM(1,1) model has been updating and developing dynamically. When the newest information is added, the oldest one is subtracted simultaneously. Therefore, its precision and self-adaptability are greatly improved.

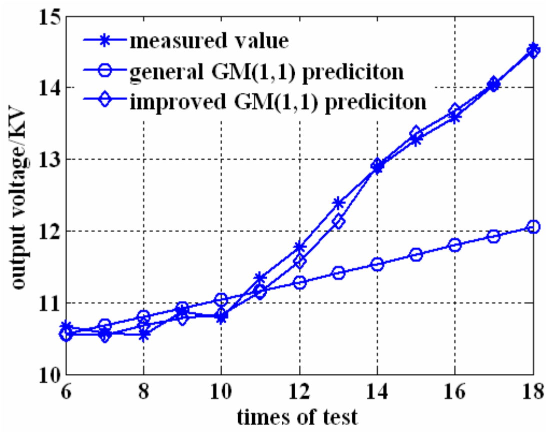

Figure 1. Prediction curve of the two models.

Table 2. Comparison between the two models.

Model	General GM(1,1) Prediction	Improved GM(1,1) Prediction
relative error	0.0769	0.0085
ratio of mean square error	0.4492	0.0547
error probability	76.92%	100%
precision level	3	1

5. Conclusion

The improved GM(1,1) model that has been updating and developing dynamically has overcome the defects of general GM(1,1) model and enhanced its self-adaptability and forecast precision, which provides a new way for modern aviation electronic equipment to predict its fault.

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