

Analysis of Equipment Fault Prediction Based on the Metabolism Combined Model

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Abstract- Aiming at the difficulty of equipment fault prediction, by the combination of the validity principles and based on the grey model GM (1, 1) and linear regression model (LRM), a new combined model was established. The model was fitted by two models. It used the original data coming from constant duration measurement to simulate and predict when the system reaches the upper limit of failure data, and according to this to infer the system failure time. At the same time, the metabolism method was introduced to improve the prediction accuracy. At last, an example that output voltage of a certain type of radar transmitter data was given to verify the effectiveness and practicality of the model in failure predication.

Keywords- Analysis; Equipment Fault Prediction; Metabolism Combined Model

I. INTRODUCTION

As an important component of battle effectiveness of the army, radar is the key factor of collecting military intelligence and maintaining, recovering and improving battle effectiveness. It will have great influence over war once broken down or damaged. The scale of modern radar system is getting larger, while the performance and structure is becoming more complex. Therefore, there are imperfection and uncertainty when obtaining characteristic parameters [1-3].

The traditional maintenance modes (Run-to-breakdown Maintenance, Time Based Maintenance, etc.) can no longer meet the needs of the development of modern radar. Therefore, the Condition Based Maintenance (CBM) emerged at the right moment. It can perform controllable maintenance to the equipment in the right amount and at the right time, therefore, it is of great importance to reduce maintenance cost, improve the combat readiness and achieve mission success. Fault prediction is one of the key technologies in condition-based maintenance, and fault prediction consists of time series predicting, regression analysis predestining, neural network predicting, grey predicting, etc. [4-6]. Grey predicting model is an effective method to resolve *small samples, lack of information and uncertainty*, and it is one of the time series predicting, by analysing the past and present developing trends and combining event predicting method to estimate whether the future status of the system will reach the threshold of break-down, thus predict whether the system will break down. But basic grey GM (1, 1) predicting model has many disadvantages, therefore, there are a lot of improved grey predicting models brought up to improve the utility and prediction accuracy [7-11]. This article combines grey GM (1, 1) model and linear regression model with effectiveness principle, creates a new grey linear regression model, and based on the new grey linear regression model sets up metabolism model, using four models to predict one certain radar system future status and compare these results.

II. MODELLING

A. Grey GM (1, 1) Model

(1) Suppose $X^{(0)}$ is non-negative original sequence, $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(i), x^{(0)}(n))$, conduct accumulated generating operation to original sequence $X^{(0)}$, get a new data column $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n))$.

Which $x^{(1)}(t) = \sum_{i=1}^t x^{(0)}(i)$, $(t=1, 2, \dots, n)$.

(2) For generated sequence $X^{(1)}(t)$, there is first-order linear albinism differential equation as follows: $d x^{(1)}/dt + a x^{(1)} = b$, suppose t is time unit, first-order differential Equation's difference form equals differential form, $d x^{(1)}/dt = x^{(1)}(t+1) - x^{(1)}(t) = x^{(0)}(t)$, therefore, the differential equation of GM (1, 1) model can be represented as: $x^{(0)}(t) + a x^{(1)}(t) = b$, called the raw form of GM (1, 1) model.

(3) To make accumulation generation sequence more smooth, perform close to the average generation to $X^{(1)}$. $Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), z^{(1)}(4), \dots, z^{(1)}(n))$, in which $z^{(1)}(t) = 0.5(x^{(1)}(t) + x^{(1)}(t-1))$, $x^{(0)}(t) + a Z^{(1)}(t) = b$ is the basic form of GM (1, 1) model. Parameters: a is development coefficient; b is grey action; $Z^{(1)}$ is close to the average generating sequence of $X^{(1)}$.

(4) Solve the basic form parameters a and b of GM (1, 1) model. The value of a and b can be used least square method to get the Equation (1).

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (1)$$

In which: $B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix}$; $Y = (x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n))^T$;

(5) Substitute a and b 's value into albinism equation of GM (1, 1) model $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$, the time respond function of GM (1, 1) model is:

$$\hat{x}^{(1)}(t+1) = (x^{(0)}(1) - \frac{b}{a}) e^{-at} + \frac{b}{a} \quad t=1, 2, 3, \dots, n-1 \quad (2)$$

(6) Perform regressive reduction

$$\hat{x}^{(0)}(t+1) = \hat{x}^{(1)}(t+1) - \hat{x}^{(1)}(t) \quad k=1, 2, 3, \dots, n \quad (3)$$

B. Linear Regressive Model

Regression analysis is a statistical analysis method which study the dependency between random variable Y and (X) or a set of (X_1, X_2, \dots, X_k) variables. Find out and set up the correlation model between high voltage power supply circuit output voltage of radar transmitter and the number of measurements. Then based on the future value of the number of measurements (independent variable) we predict high voltage power supply circuit's output voltage. The regression model is as follow:

$$X(t) = at + \beta \quad (4)$$

parameters: t represents the number of measurements;

$X(t)$ represents voltage.

C. Build Grey Linear Regressive Model Based on Effectiveness Principle

Introduce combination weighting coefficient method from effectiveness principle to grey model and linear regressive model, build grey linear regressive model to simulate and predict the output voltage of equipment, the thought of modelling is as follows:

(1) Suppose the total number of the original data is N , x_t is the actual value of test voltage, \hat{x}_t and A_t are the simulation value and accuracy sequence respectively, E and σ are the mean value and mean square error of accuracy of sequence respectively.

$$A_t = 1 - \left| \frac{\hat{x}_t - x_t}{x_t} \right|, \quad E = \frac{1}{N} \sum_{t=1}^N A_t, \quad \sigma = \frac{1}{N} \left[\sum_{t=1}^N (A_t - E)^2 \right]^{\frac{1}{2}}$$

(2) Determine the validity of the model

$$S = E \times (1 - \sigma) \quad (5)$$

(3) Suppose the validity of grey model and linear regressive model are S_1 , S_2 , respectively, weighting coefficient are f_1 and f_2 , respectively.

$$f_i = \frac{S_i}{\sum_{j=1}^2 S_j} \quad i=1,2 \quad (6)$$

The grey linear regressive model is

$$\hat{x} = f_1 \hat{x}_{1t} + f_2 \hat{x}_{2t} \quad t=1, 2, \dots, N \quad (7)$$

parameters: \hat{x}_{1t} , \hat{x}_{2t} represent grey model simulated voltage and linear model simulated voltage respectively.

D. Build Metabolism Model

In order to increase the prediction accuracy of grey linear regressive model, build metabolism model based on this model, because as time passes by, there are random disturbance factors or driving factors which enter the system and influence the system. Generally speaking, the further the time is from zero point, the weaker the meaning of prediction is. When it comes to application, the disturbance factors or driving factors which enter the system have to be considered all along, add new data in modelling sequence while removing old data at any time, which can be regarded as data metabolism. Use dynamic metabolism model to predict system's development. The method of modelling is shown in C.

The metabolism model based on grey linear regressive model is

$$\hat{x} = f_1 \hat{x}_{1t} + f_2 \hat{x}_{2t} \quad t=1, 2, \dots, N \quad (8)$$

parameters: \hat{x}_{1t} , \hat{x}_{2t} represent simulated voltage of grey metabolism model and linear regressive metabolism model respectively.

III. INSTANCE ANALYSIS

Radar transmitter is the most expensive component in radar system, and it is a radio device which provides high power RF signal to radar. It is of great importance to provide fault prediction, therefore, it provides condition based maintenance. If the output voltage of radar transmitter alters somehow, when voltage exceeds the threshold of 25 kV, it needs maintaining to control the output voltage and avoid break-down. In one certain aviation repair shop, the output voltage of a certain type of radar transmitter is being sampled (sampled every 50 hours at a time), the sampled data of ripple voltage is shown in Table 1.

TABLE 1 ORIGINAL DATA OF OUTPUT VOLTAGE

No. of Tests	1	2	3	4	5	6	7	8	9	10
Voltage/kV	19.92	20.06	20.21	20.43	20.68	20.97	21.84	22.62	23.83	24.82

A. The Predicted Value of Grey Model

Take first 6 figures of sampling data of output voltage from Table 1 as original sequence, take last 4 figures to predict, then the GM (1, 1) model is built, perform accumulated generating operation and close to the average generation to original data, substitute into Equation (1), we get the value of B and Y .

$$B = \begin{bmatrix} -29.95 & -40.125 & -40.455 & -40875 & -41.38 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}^T$$

$$Y = (20.06, 20.21, 20.43, 20.68, 20.97)^T$$

Use Matlab software to substitute B and Y into equation, the value of a and b are: $a = -0.05288$, $b = 18.43106$, substitute the value of a and b into time response function (2)

$$\hat{x}^{(1)}(t+1) = 368.456E^{0.05288t} - 348.536$$

Perform regressive reduction to Equation (3), get the simulation value of original sequence from GM (1, 1) model:

$$\hat{X}^{(0)} = (\hat{x}^{(0)}(2), \hat{x}^{(0)}(3), \hat{x}^{(0)}(4), \hat{x}^{(0)}(5), \hat{x}^{(0)}(6)) = (20.01, 21.09, 22.24, 23.45, 24.72)$$

We can get the predicted value of $(\hat{x}^{(0)}(7), \hat{x}^{(0)}(8), \hat{x}^{(0)}(9), \hat{x}^{(0)}(10))$:

$$(\hat{x}^{(0)}(7), \hat{x}^{(0)}(8), \hat{x}^{(0)}(9), \hat{x}^{(0)}(10)) = (26.06381, 27.47916, 28.97136, 30.54459)$$

B. The Predicted Value of Linear Regressive Model

Take first 4 figures from Table 1 as original sequence, last 4 figures to predict, build linear regressive model. Use least square method to solve the value of α and β in linear regressive Equation (2): $\alpha = 0.209$; $\beta = 19.645$, substitute them into Equation (3), we get linear regressive equation:

$$\hat{x}(t) = 0.209t + 19.645$$

The simulation value of linear regressive model to original sequence:

$$X^{(0)} = (x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), x^{(0)}(5), x^{(0)}(6)) = (20.06, 20.27, 20.48, 20.69, 20.90)$$

We can get the predicted value of $(x^{(0)}(7), x^{(0)}(8), x^{(0)}(9), x^{(0)}(10))$:

$$(x^{(0)}(7), x^{(0)}(8), x^{(0)}(9), x^{(0)}(10)) = (21.11, 21.32, 21.53, 21.74)$$

C. The Predicted Value of Grey Linear Regressive Model Based on Effectiveness Principle

The simulated value and actual value of grey model and linear regressive model can be used to get the value of E and σ , Equation (5) can be used to calculate the validity of grey model and linear regressive model.

(1) The mean value of sequence accuracy of grey model is $E=0.91046$, mean square error is $\sigma=0.028$. The validity of grey model:

$$S=E \times (1-\sigma) = 0.885$$

(2) The mean value of sequence accuracy of linear regressive model is $E=0.99808$, mean square error is $\sigma=0.0006$. The validity of linear regressive model:

$$S=E \times (1-\sigma) = 0.9975$$

Based on the validity of grey model and linear regressive model, Equation (6) can be used to calculate the weighting coefficient of grey model and linear regressive model, the weighting coefficient of grey model is $f_1=0.47$, the weighting coefficient of linear regressive model is $f_2=0.53$. The combined model (7) is:

$$\hat{x} = 0.47 \hat{x}_{1t} + 0.53 \hat{x}_{2t}$$

We can get the predicted value of $(x^{(0)}(7), x^{(0)}(8), x^{(0)}(9), x^{(0)}(10))$:

$$(x^{(0)}(7), x^{(0)}(8), x^{(0)}(9), x^{(0)}(10)) = (23.43, 24.21, 25.02, 25.87)$$

D. The Predicted Value of Metabolism Model

After putting one new figure $x^{(0)}(7)$ into the system, remove $x^{(0)}(1)$, still use grey linear regressive model to simulate the 6 sets of test figures, according to A, B, C , the concrete forms of 3 models are shown in Table 2.

TABLE 2 METABOLISM MODEL

Grey model		Linear regressive model		Grey linear regressive model	
$a=-0.01836$	$b=19.51556$	$\alpha=0.666$	$\beta=18.93$	$f_1=0.496$	$f_2=0.504$
$\hat{x}^{(1)}(t+1)=1082.85e^{0.01836t}-1062.79$		$\hat{x}(t)=0.666t+18.93$		$\hat{x}=0.496\hat{x}_{1t}+0.504\hat{x}_{2t}$	

We can get the predicted value of $(x^{(0)}(7), x^{(0)}(8), x^{(0)}(9), x^{(0)}(10))$ from metabolism model:

$$(x^{(0)}(7), x^{(0)}(8), x^{(0)}(9), x^{(0)}(10))=(21.93, 22.46, 23.00, 23.54)$$

E. Analyse the Voltage Predicted Values of 4 Models

Compare the predicted values and actual values of linear regressive model, grey model, grey linear regressive model and metabolism model, calculate mean relative error, predicted value and actual value, the results are shown in Table 3.

TABLE 3 THE COMPARISON OF PREDICTED VALUE AND ACTUAL VALUE

Number of measurements	Actual value	Linear regressive model	Grey model	Grey linear regressive model	metabolism model
		Predicted value	Predicted value	Predicted value	Predicted value
7	21.84	21.11	26.06381	23.43	21.93
8	22.62	21.32	27.47916	24.21	22.46
9	23.83	21.53	28.97136	25.02	23.00
10	24.82	21.74	30.54459	25.87	23.54
Mean relative error (%)		7.8%	21.3%	5.9%	2.43%

By analysing the predicted values of 4 models, we can find out that combine metabolism algorithm and the original model, removing old data and putting in new data can make prediction more accurately, and the accuracy is obviously higher than other models.

IV. CONCLUSION

By using effectiveness principle to combine linear model and grey model, set up a new grey linear regressive model, which essentially is combined model. It has a lot of information such as linear model and index model, it also has characteristic of these two models, meanwhile, it uses metabolism to self-adjust the parameters, keep the system updating and developing. Use equal-interval measurement data of radar transmitter output voltage as original data, use 4 models to simulate and predict the original data to estimate when system will reach the upper threshold of break-down, therefore, estimate the fault time. Instance analysis shows that metabolism combined model improved a lot in prediction accuracy and adaptive, it can predict equipment break-down more accurately, and it has certain values to preventive maintenance and practical applicability.

REFERENCES

- [1] G.Y. Zhang, Y.Q. Su, and A.Q. Xu, "Applications of grey model to predict in equipment fault analysis", *J. Measurement and control technology*, vol. 31, pp. 20-22, Jun. 2012.
- [2] Z.C. Xu, *Supportability Engineering and Management for Equipment*, Beijing, China: National Defense Industry Press, 2006.
- [3] S.J. Xu, X.S. Tan, H.Z. Wang, and H. Zhang, "A MUGM(1,m,w) Model of Radar Fault Prediction", *J. Modern Radar*, vol. 33, pp. 25-28, Aug. 2011.
- [4] J.J. Zhou, D.G. Wang, and S. Chang, "Research on Fault Prediction of Radar Based on Improved GM(1,1) Model", *J. Technology of Equipment Maintenance*, vol. 3, pp. 16-18, Mar. 2010.
- [5] P. Shi, S. Gao, and Y.Q. Su, "Application Analysis of Improved GM (1, 1) Model in Equipment Fault Prediction", *J. Computer Measurement & Control*, vol. 20, pp. 1176-1178, May 2012.
- [6] D.R. Huang, and L.F. Huang, "The application status of the grey system theory in fault prediction and its development trend", *J. Journal of Gun Launch & Control*, vol. 33, pp. 88-92, Mar. 2009.
- [7] G.X. Zhou, and M. Wu, "Fuzzy neural network based on improved grey prediction control ", *J. Journal of System Simulation*, vol. 22, pp.2333-2336, Oct. 2010.
- [8] H.Z. Wang, J.P. Yang, and M.R. Huang et al, "An improved non-equidistance grey prediction model ", *J. Journal of Air Force Engineering University(Natural Science Edition)*, vol. 11, pp. 75-79, Jun. 2010.
- [9] X.L. Li, Y.J. Li, and K. Zhang, "Improved grey forecasting model of fault prediction in missile applications", *J. Computer Simulation*, vol. 27, pp. 33-37, Aug. 2010.
- [10] S.F. Liu, T.B. Guo, and Y.G. Dang et al, *Research and application on grey theory on cost forecasting*, Beijing, China: Science Press, 2010.
- [11] S.Y. Chen, and W. Wang, "Grey neural network forecasting for traffic flow", *J. Journal of South-East University (Natural Science Edition)*, vol. 34, pp. 541-544, Apr. 2004.



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