Equipment Failure Prediction based on the Improved Gray Prediction

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***Abstract*—In order to reduce the equipment failure frequency and maintenance cost, equipment failure must be effectively predicted. Consider that the actual failure interval of equipments is to contribute to maintenance planning and scheduling, it is used to statistical analysis the failure trend. According to the historical data of maintenance, the failure time distribution function can be built by gray prediction theory. This paper discussed the influence on model relative error made by the optimization of GM(1, 1) model background value. The result is that the model relative error can be reduced through adjust the value of the background. The application of PSO optimized the background value of GM(1,1) model. Finally, an engineering example verified the conclusion.**

Keywords-equipment failure; gray prediction; background values

I. INTRODUCTION

The development and utilization of mineral resources is the basic social infrastructure construction and productivity improvement. With the pervasive application of mechanical equipment, its form and scope of application are also gradually increasing, which greatly improve the reliability and availability of mining equipment operations. But it also increases the difficulty of equipment management and maintenance work. On average, the equipment maintenance budget is around 20.8% of the total plant operating budget[1]. Proper maintenance has been drawing more and more attention in contributing coal industries towards prolonging the system's effective operational lifetime.

It is well known that the position and function of production equipment in the enterprise, on the one hand is determined by the equipment itself, on the other hand turn, equipment maintenance. It is emphasized that equipment maintenance cost can even achieve 15 to 70% of the expenditure or even could be more than annual net profit in many cases[2].

In daily work, equipment failure is unavoidable, must use scientific methods to be able to accurately predict the failure time, thereby ensuring the timeliness and effectiveness of the repair. Proactive strategies utilize preventive maintenance activities to prevent the equipment failures from occurring at an early stage [3]. In class of statistical methods, analyzing the reliability is based on the observed failure data and proper statistical techniques[4].

Researchers have published many papers on failure rates of equipment maintenance policy. Burhanuddin M. A., Sami M. Halawani, and A. R. Ahmad[5] presented show that cost model can be used in failure-based maintenance systems, as it provides a powerful tool for taking into account the interaction between the frequency of failures and downtime. Reference [6] respectively performed the probabilistic failure process modeling for repairable and non-repairable items. The confidence interval of the estimated equipment reliability and availability was determined by way of the uncertainty analysis. Carazas and Souza[7] also presented the decision criterion in to minimize the equipment cost of failure. The optimal maintenance policy considering the costs and likelihood of failure scenarios was proposed for lubricating oil system availability improvement. During the past decade, large amounts of uncertainty category models has developed in a variety of directions which showed a higher degree of flexibility and practicability compared with the risk type.

This paper aims to solve the difficulty of predicting failure rate in the case of poor data and information. The maintenance decision is given based on deterioration states. The deterioration states of equipment which deteriorate stochastically from one time unit to another are discrete and modeled using Markov chains. GM (1,1) under the typical failure rate curve is applied as the base model to predict the trend of the time series so that the optimal model can be established.. And use PSO algorithm to optimize the background value of GM (1,1).

II. EQUIPMENT DEGRADATION MODEL

Most systems cannot remain in a good working condition without maintenance, since equipment deterioration is inevitable. We specify the stochastic process of the machine mode, whether operational or not. On the basis of component degradation mechanism, $X_{(t)}$can be used to meet the following conditions random process to describe the state of continuous change:

- Random variables

$$X_0, X_{t_1}-X_0, X_{t_2}-X_{t_1}, \cdots, X_{t_n}-X_{t_{n-1}}$$

are independent of each other, where

$$n=1,2,\cdots,\ t_k \in [0,+\infty), t_1<t_2<\cdots<t_n.$$

- The distribution of $(X_t - X_s)$ can be expressed as F_{st} which is only related to $t-s$, for all s, $t \in T, s \le t$.

Assume that $X_{(t)}$ is the degradation of the component state parameter at time t t. In the initial time $t=0$, $X(0)=1$, corresponding to the initial good working condition. Over time $X(t)$ is subject to certain distributed random variables. Therefore, $G(x;t)$ which is one-dimensional distribution of $X(t)$can be expressed as

$$G(x;t)=P\{X(t)\le x\} \tag{1}$$

$G(x;t)$ is a function of the degradation with time. It is assumed the existence of one-dimensional density $g(x;t)$. The density $g(x;t)$ can be written as

$$g(x;t) = \frac{\partial G(x;t)}{\partial x} \tag{2}$$

$g(x;t)$ satisfies the following properties:

- For any t, $\int_0^{+\infty} g(x;t)dx = 1$.
- $\lim_{t\to\infty} g(x;t) = 0$, within a limited range $[a,b]$, $\lim_{t\to\infty} \int_a^b g(x;t) = 0$, still, $\lim_{t\to\infty} \int_0^\infty g(x;t) = 1$.

III. GM(1,1) Model and Background Value

A. Abbreviations and Acronyms

As a matter of experience, statistical laws are established via large samples, the more the data the better will be the analysis. We predict trends from the data and a realistic data analysis should be concerned with the final destination. Furthermore, straightforward statistical modeling is often difficult to perform, and sometimes not possible. Grey system theory is inevitably to seek model built based on a small size data sample. The core of grey system prediction theory is a grey model composed of a large variety of grey differential equations.

The basic steps of GM (1,1)model is as described below. First, dilute the impact of random factors observational data series through the data accumulation process, thereby, the internal laws of observational data series is improved. Afterwards, the data sequence is build up into an approximately exponentially gray model. Here is the establishment of GM (1,1) model and solution.

Let be an original time series:

$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\}$, which reflects the changing trend of the original sequence.

And let $X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\}$ be (1-AGO)series, of which

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i),\ k = 2,3,\cdots,n \tag{3}$$

A whitening differential equation or the shadow equation of grey differential equation is given as:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{4}$$

where, *a* is development coefficient, *b* is gray predicted value, *k*=2, 3,⋯, *n*.

A grey differential equation is given as:

$$x^{(0)}(k) + az^{(0)}(k) = b \tag{5}$$

where, $z^{(1)}(k)$ is the background value at time k.

$$z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(0)}(k-1)\right) \tag{6}$$

$$k = 2,3,\cdots,n$$

$$Y = \left[x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\right]^T \tag{7}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{8}$$

The grey differential equation is given as:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{9}$$

where, the estimated parameters column is

$$\hat{a} = (B^T B)^{-1} B^T Y \tag{10}$$

Time response sequence of grey differential equation (5) is

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \quad k = 1,2,\cdots,n \tag{11}$$

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad k = 1,2,\cdots,n \ \ n \tag{12}$$

B. Optimization Model for Modeling Algorithm

After the above theoretical analysis, the use of background value is calculated for newly constructed data modeling. To obtain data sequence simulation and predicted values, the algorithm steps are as follows:

Input the original sequence:

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

The simulated output value and prediction functions:

$$\hat{x}^{(0)}(k+1) = (1 - e^{a})\left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} \quad k = 1,2,\cdots,n$$

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

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), \qquad k = 1,2,\cdots,n$$

2) Calculation of the background value $z^{(1)}(k)$, if $x^{(1)}(k) \neq x^{(1)}(k-1)$, then

$$z^{(1)}(k) = \frac{x^{(0)}(k)}{L(k)} + x^{(0)}(1) - \frac{x^{(0)}(k)}{e^{L(k)(k-1)}}\left[\frac{x^{(0)}(k)}{x^{(0)}(k-1)}\right]$$

where,

$$L(k) = lnx^{(0)}(k) - lnx^{(0)}(k-1)$$

if not ,

$$z^{(1)}(k) = x^{(1)}(k),\ k = 2, 3, \cdots, n.$$

3) According to (7) (8) calculate Y and matrix B.

4) Calculate parameter value a and b. Set parameters of the column $\hat{a} = [a, b]^T$, then, $\hat{a} = (B^T B)^{-1} B^T Y$.

5) Output value according to (12) calculate $\hat{x}^{(0)}(k)$.

IV. CASE STUDY

According to the scheduling statistical records of Anjialing mine, shovel modeling at intervals for the original sequence modeling. This type of equipment due to fewer experimental data, statistical and other processing methods can not be used for large data sets, so that the equipment can only be predicted by existing data processing .

We can interpret the results of the traditional model and the improved model as in the following sections. We have 16 raw data, as shown in Table 1. we obtain the prediction model based on actual data through gray prediction method. Figure 1 is the forecast graph. We set the initial background value as $P_0 = (0.5, 0.5, \cdots, 0.5)$, $[L_d, U_d] = [0,1]$, $c_1 = c_2 = 2$. Using MATLAB and GM (1,1) model to predict the two sets of data, model is obtained in which a=3.5324, b=0.0368.

Then the background value is optimized by PSO, the number of iterations of 1000 to get a new model in which a=3.6542, b=0.0342. The differences of relative error between the traditional model and improved model are statistically significant.

TABLE I. TABLE TYPE STYLES

Serial Number	Actual Value	Predicted Value		Relative error	
		p=0.566	*p=0.5*	*p=0.564*	*p=0.5*
1	4.3	4.30	4.30	0.00	0.00
2	4.1	3.84	3.87	-0.06	-0.06
3	3.8	3.98	4.01	0.05	0.06
4	4.2	4.12	4.15	-0.02	-0.01
5	3.9	4.27	4.30	0.09	0.10
6	4.3	4.42	4.45	0.03	0.04
7	4.9	4.58	4.61	-0.07	-0.06
8	5.2	4.74	4.77	-0.09	-0.08
9	4.5	4.91	4.94	0.09	0.10
10	5.4	5.08	5.12	-0.06	-0.05
11	5.2	5.26	5.30	0.01	0.02
12	6.3	5.45	5.49	-0.13	-0.13
13	5.5	5.64	5.68	0.03	0.03
14	6.3	5.84	5.88	-0.07	-0.07
15	6.8	6.05	6.09	-0.11	-0.10
16	6.5	6.26	6.30	-0.04	-0.03
17	6.3	6.48	6.53	0.03	0.04
18	7.4	6.71	6.75	-0.09	-0.09
19	6.6	6.95	6.99	0.05	0.06
20	6.9	7.19	7.24	0.04	0.05

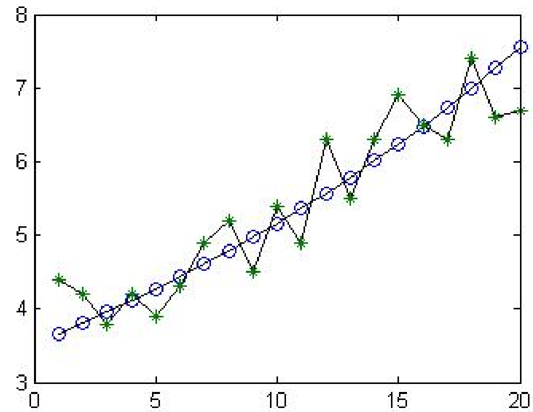

FIGURE I. FORECAST GRAPH

V. CONCLUSIONS

As indicated from the analyzed results of the above application, the actual data of failure interval is used to calculate the failure distribution of equipment. The smoothness of the sequence was improved through the optimization of the original GM(1,1) model. The prediction accuracy of failure interval was significant. Besides, this paper is just focused on failure distribution analysis methods. Therefore, analysis of multiple component states and cost-effective configuration optimization aimed at mitigating in unreliable equipment is needed for further study.

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