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A novel grey prognostic model based on Markov process and grey incidence analysis for energy conversion equipment degradation

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ABSTRACT

Maintenance strategy for energy conversion equipment degradation is now experiencing the transformation from fail-and-fix to predict-and-prevent due to the equipment complexity and the strict requirements for equipment reliability. Actually, the current situation of world class maintenance is providing never-before-seen opportunities and challenges for the maintenance specialists. For this problem, the essence is to optimize present PM (preventive maintenance) strategies, so as to avoid some common maintenance problems, such as insufficient proactive maintenance, frequent problem repetition, and unnecessary and conservative PM. Besides, accurate prognostic methodology is the core section of this optimization. Considering the data uncertainty and the requirements for long-term forecast, grey model serves as an attractive and effective prognostic model for equipment degradation prognosis. To compensate the limitation of traditional grey model resulting in the unfitness of fluctuant data, the Markov model is introduced into traditional grey model. In order to expand the dimension of the original data, the grey incidence model is adopted, so as to further employ the additional time series data similar to the target series. Then, the scheme of the novel grey prognostic model, based on the Markov process and the grey incidence analysis, is proposed. Finally, the fouling process of a gas turbine compressor is chosen as an instance to validate this novel model. In addition, the study has been conducted on the relationship between model parameters and the prognostic accuracy, and the best parameters for this case are suggested. Comparative study results of different prognostic models show that considering the prognostic accuracy and fluctuations, this novel model is better than some other prognostic models.

1. Introduction

The sustainable, efficient and safe operation of energy conversion equipment, due to appropriate maintenance strategy, can exert great effects on the productivity and competitiveness of institutions and companies [1]. People have struggled against failures of the energy conversion equipment for a long period of time. Early years have witnessed efforts to eliminate failures and guarantee reliability [2]. With the wide application of the increasingly complex equipment, like IGCC (Integrated Gasification Combined Cycle) and SOFC-MGT (Solid Oxide Fuel Cell–Micro Gas Turbine), it is impossible to eliminate all failures of equipment currently [3]. Therefore, CBM (Condition based Maintenance) is widely adopted for complex equipment maintenance, so as to manage the degradation of equipment performance caused by failures. CBM recognizes the uncertainty of the equipment and the certainty of failures, after which it implements the equipment health management via condition monitoring, diagnosis and prognosis.

Currently, there are a lot of advanced maintenance strategies, like RCM (Reliability-centred Maintenance), to increase equipment reliability and reduce the maintenance cost. CBM is still the kernel part of these advanced maintenance strategies [4]. For instance, as a maintenance analysis method, RCM affirms the merits of corrective maintenance, TBM (Time based Maintenance), CBM, and reformative maintenance, while at the same time it can choose the suitable maintenance strategy for every potential failure based on failure analysis and logical decision [5]. CBM is the priority in the RCM logical decision process.

The task of CBM is defined as an objective assessment of the current condition through the classification into a known category, providing a causal explanation of this condition and identifying its present stage as well as its predicted development [6]. For possible CBM, it is necessary to diagnose the health condition of equipment and forecast its degradation trend [7–9]. In addition, prognostics is

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Nomenclature

PM	Preventive Maintenance
CBM	Condition based Maintenance
RCM	Reliability-centred Maintenance
TBM	Time based Maintenance
$X^{(0)}$	original series
$x^{(0)}(k)$	k-th point in the original series
$X^{(1)}$	generated series
$x^{(1)}(k)$	k-th point in the generated series
D	operator of grey generation
a,b	parameters of the whitening differential equation
B	a data matrix
Y_N	a data vector
$\hat{x}^{(1)}(k)$	k-th point in the prognostic generated series
$\hat{x}^{(0)}(k)$	k-th point in the prognostic original series
a_i	corresponding state
$P_{ij}^{(k)}(n)$	k-step transition probability
$P^{(k)}$	k-step transition probability matrix
M_i	sample number of the original series in i-state
$M_{ij}(k)$	sample number of points in i-state transiting to j-state after k steps
E_i	mean absolute incremental value of the original series
$\partial_i(t_k)$	relative incremental value of series from t_{k-1} to t_k
$\gamma(x_{0i}(t_{k-1},t_k))$	grey relational coefficient of two series at corresponding moment
$\gamma(X_0,X_i)$	grey relational degree of two series
w_i	the confidence degree of the prognostic result of every reference series
RE_{GMPM}	relative error of the grey Markov prognostic model
RE_{GIPM}	relative error of the grey incidence prognostic model
$\widehat{x_0^{GMPM}}(t_n)$	prognostic result of the grey Markov prognostic model
MRE	mean relative error
NARNN	Nonlinear Autoregressive Neural Network
ARIMA	Autoregressive Integrated Moving Average

superior to diagnostics in the sense that prognostics can prevent faults or failures, and be ready (with prepared spare parts and planned human resources) for the problems if possible. In this way, extra unplanned maintenance cost can be saved [10]. Thus, prognosis is the core technology of CBM. However, compared to diagnostics, the literature of prognostics is much scanter, along with insufficient research due to existing difficulties [7,11].

Grey model is usually used for prognosis of systems with partial unknown structure, parameters or characteristics. Energy conversion equipment degradation process, with both the certainty of increase and the uncertainty leading to fluctuation, seems to be suitable for grey model. Therefore, grey model is introduced to degradation process prognosis in this paper, so as to further support the implementation of their CBM strategy. Additionally, the traditional grey model is improved in this paper, to increase the prognostic accuracy.

2. Background

The grey model is usually written as GM(c,d). Where, c is the order of the differential equation in the model, and d is the number of variables. GM(1,1) is the mostly used one [12].

If $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$ is the original series composed of history data, and $X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\}$ is the generated series.

$$X^{(1)} = X^{(0)}D \tag{1}$$

In the equation, D is the operator of grey generation for the series. The most common operators are the summation operator, the subtraction operator, the buffer operator, the initializing operator and the averaging operator. Equipment degradation parameters have shown an obvious increasing trend in the process. Thus, the summation operator is the most suitable one which can make the generated series show exponential growth.

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

The whitening differential equation of grey prognostic model can be established as follows [13].

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{3}$$

According to the generated series, estimate the parameters of the whitening differential equation:

$$\left[\hat{a}\hat{b}\right]^T = \left(B^T B\right)^{-1} B^T Y_N \tag{4}$$

Where,

$$B = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(1)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2) + x^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(k-1) + x^{(1)}(k)\right] & 1 \end{bmatrix} \tag{5}$$

$$Y_N = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(k) \end{bmatrix} \tag{6}$$

Then, the solution of whitening differential equation is:

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right) e^{-\hat{a}(k-1)} + \frac{\hat{b}}{\hat{a}}, \quad k = 2, 3, \ldots \tag{7}$$

With the subtraction operator, the prognostic value of the original series can be acquired:

$$\hat{x}^{(0)}(k) = \left(1 - e^{\hat{a}}\right)\left(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right) e^{-\hat{a}(k-1)}, \ k = 2, 3, \ldots \tag{8}$$

Traditional grey model has been widely used in many different fields. El-Fouly completed wind speed forecasting and wind power prediction for wind energy conversion by using the grey prediction model GM(1,1) [14]. Zhang adopted an unequal interval revised grey model to fit and forecast the wear trend of diesel engines, with