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Application of One-Step Ahead Technique and Grey Forecasting Model for Machine Health Prognostics

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ABSTRACT

The ability to forecast fault propagation of machine before it reaches the failure threshold is very important to reducing maintenance costs, operation downtime and safety hazards. In this study, the capability of one-step, two-step, and three-step-ahead techniques coupled with grey model for predicting the future condition of a machine have been investigated. Specifically, this work found that a model based on one-step-ahead techniques coupled with grey model is the superior. Furthermore, In order to improve the accuracy of prediction, a modification of basic grey model coupled with one-step-ahead technique has been made. The modified model is able to track closely the sudden change of machine degradation condition. It means the model has the potential for using as a tool in machine condition prognostics. Degraded condition data acquired from condition monitoring routine are employed for evaluating the proposed method.

Keywords: Machine condition; Prognostics; One-step ahead prediction; Grey forecasting

1. INTRODUCTION

In maintenance approaches, the condition based maintenance (CBM) is assessed as the most effective technology that can identify incipient faults before they become critical to enable more accurate planning of maintenance. Fault diagnostics and prognostics, which can estimate and forecast the machine condition, have significant roles in a CBM system. Finding an excellent model of fault diagnostics and prognostics is the key to enable CBM system to be more useful in practical applications [1]. In order to forecast the impending condition of machine and make the appropriate decision in maintenance system, numerous methods have been developed based on intelligent systems such as artificial neural network, logistic regression, relevance vector machine, etc.

The use of grey model coupled with one-step ahead for machine condition forecasting is rare [2], however grey model has been successfully applied in other areas. For instance, Zhu and Cao [3] have shown that the grey model is able to predict the occurrence of E1 Nino using the data of the chronology of E1 Nino from 1860 to 1986; Liang et al. [4] developed a grey model for evaluating the durability of concrete bridges due to carbonation damage; Yu et al. [5] demonstrated that the grey model can reasonably forecast runoff one to four hours ahead; Chang et al. [6] found that a better result of prediction can be achieved by recursive process combining the optimization method and GM(1,1) prediction model; Hsu [7] found that the grey model is better suited to short-term predictions than to mid- and long-term predictions;

Tseng et al. [8] presented that a seasonal time series should be deseasonalized first before building a GM(1,1) model; Ku and Huang [9] explored the application of grey forecasting models for predicting and monitoring production processes. Finally, Gu et al. successfully developed grey prediction model in the failure prognostics for electronics [10].

Grey model theory, which was originally proposed by Deng [11], is able to effectively deal with incomplete data for system analysis, modeling, prediction, decision making, and controlling. In a grey model, its information is neither totally clear as in a white system nor totally unknown as in a black system. Grey model sets each stochastic variable as a grey quantity that change within a given range. They deal directly with the original data and search the intrinsic regularity of data [12].
In this study, the capability of one-step, two-step, and three-step-ahead techniques coupled with grey model for predicting the future condition of machine have been investigated. Specifically, this work found that a model based on one-step-ahead techniques coupled with grey model is superior. Prognostics is the ability to access the current state of performance, forecast the future state of performance, and assess the remaining useful life (RUL) of a failing components or subsystems. With the purpose of determining the RUL, a reliable predictor for forecasting the future state is needed.

The remaining parts of this paper are organized as follows. In Section 2, we describe the basic theory of time series prediction and grey model. Section 3 shows the proposed system for machine condition prognostics, whereas Section 4 depicts the estimation of degraded performance and prediction of machine's condition. Finally, the conclusions are presented in Section 5.

2. BACKGROUND KNOWLEDGE

2.1. Time Series Prediction

Time series prediction is a problem encountered in many fields from engineering (predictive control of industrial processes) to finance (forecasting returns of shares or stock markets). Models and prediction methodologies have been proposed by a large community of researchers. The problems to be dealt with when predicting the future value is how many steps (time delays) are appropriate for obtaining the best performance?. In time-series forecasting techniques, one-step-ahead or multi-step-ahead prediction is frequently used [13]. The prediction model uses known values to forecast the *h* future value(s). Given the observation $y_t = [x_1, x_2, , x_t]$, the *h* future value(s) can be predicted by

$$\acute{y}_{t+h} = f(y_t) = f(x_1, x_2, \ldots, x_t) \quad (1)$$

One-step-ahead or multi-step-ahead prediction implies that the predictor utilizes the available observations to forecast one value or multiple values at the definite future time. The more the steps ahead is, the less reliable the forecasting operation is because multi-step prediction is associated with multiple one-step operations.

2.2. Grey Prediction

The grey forecasting model uses the operations of accumulated generation to construct differential equations. Intrinsically speaking, it has the characteristics of requiring less data. The grey model GM(1,1), i.e., a single variable first-order grey model, is summarized as follows [14]:

Step 1: For an initial time sequence,

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

where $x^{(0)}(i)$ denotes the time series data at time ith.

Step 2: On the basis of the initial sequence $X^{(0)}$, a new sequence $X^{(1)}$ is set up through the accumulated generating operation in order to provide the middle message of building a model and to weaken the variation tendency, i.e.

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(i), \ldots, x^{(1)}(n)\}, \tag{3}$$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \qquad k = 1, 2, \ldots, n. \tag{4}$$

Step 3: The first-order differential equation of grey model GM(1,1) is then the following

$$\frac{\mathrm{d}X^{(1)}}{dt} + aX^{(1)} = b, \tag{5}$$

and its difference equation is

$$x^{(0)}(k) + aZ^{(1)}(k) = b \qquad k = 2, 3, \ldots, n, \tag{6}$$

and from Eq. (6), it is easy to get

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}, \tag{7}$$

where a and b are the coefficients to be identified.
Let

$$Yn = [x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)]^{\mathrm{T}} \tag{8}$$

$$B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \tag{9}$$

where Yn and B are the constant vector and the accumulated matrix respectively.
also take

$$Z^{(1)}(k+1) = \tfrac{1}{2}(x^{(1)}(k) + x^{(1)}(k+1)),$$
$$k = 1, 2, \ldots, (n-1) \tag{10}$$

where $Z^{(1)}(k+1)$ is the $(k+1)$th background value.
and

$$A = [a, b]^{\mathrm{T}}. \tag{11}$$

Applying ordinary least-square method to Eq. (7) on the basis of Eqs. (8) – (11), coefficient A becomes

$$A = (B^{\mathrm{T}}B)^{-1}B^{\mathrm{T}}Yn. \tag{12}$$

Step 4: Substituting *A* in Eq. (3) with Eq. (9), the approximate equation becomes the following

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - b/a)\, e{-ak} + b/a\ , \tag{13}$$

where $\hat{x}^{(1)}(k+1)$ is the predicted value of $x^{(1)}(k+1)$ at time $(k+1)$.

After the completion of an inverse accumulated generating operation on Eq. (10), $\hat{x}^{(1)}(k+1)$, the predicted value of $x^{(0)}(k+1)$ at time $(k+1)$ becomes available and therefore,

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k). \tag{14}$$

3. THE PROPOSED SYSTEM

In term of forecasting the future state of machine, firstly a process of data acquisition that records the useful information of the machine's condition must be carried out. After acquiring the useful data, the grey method is applied to predict the future states of machine health. This proposed model is shown in Fig.1 and is summarized as follows:

Step 1 (Machine degraded data): The acquired time series data are first made into the degraded data before being applied by the grey model.
Step 2 (Splitting data): The machine degraded data are divided into two parts: training data and testing data. Training data are employed to build the model whereas testing data are used to evaluate performance of the model.
Step 3 (Building model): Training data are employed to build the prediction model.
Step 4 (Predicting): After the adequate model is achieved, predicting is performed to predict the future condition of machine health.

In order to evaluate the predicting performance, the root-mean square error (*RMSE*) and linear correlation (*R*) are utilized as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2}{n}} \tag{15}$$

where *n* represents the total number of data points in the test set, *yi* is the actual value, and $\tilde{y}_i$ represents the predicted value of the model.

$$R = \frac{Cov(y,\tilde{y})}{\sigma_y \sigma_{\tilde{y}}},$$

$$Cov(y,\tilde{y}) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})(\tilde{y}_i - \bar{\tilde{y}}) \tag{16}$$

where *Cov(y,ỹ)* is covariance between actual and predicted value. $\bar{y}$ is the mean of actual value and $\bar{\tilde{y}}$ is the mean of predicted value.

The standard deviation of the actual and predicted values, σy and $\sigma\tilde{y}$, respectively, can be calculated as

$$\sigma y = \left[\frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2\right]^{1/2},$$

$$\sigma\tilde{y} = \left[\frac{1}{N-1}\sum_{i=1}^{N}(\tilde{y}_i - \bar{\tilde{y}})^2\right]^{1/2} \tag{17}$$

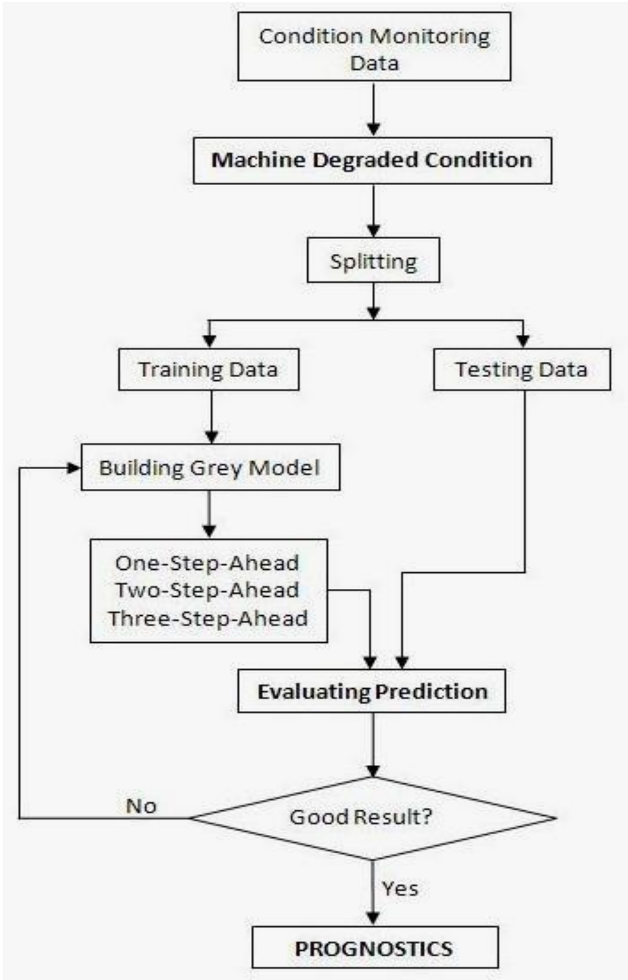

Fig.1. The proposed system

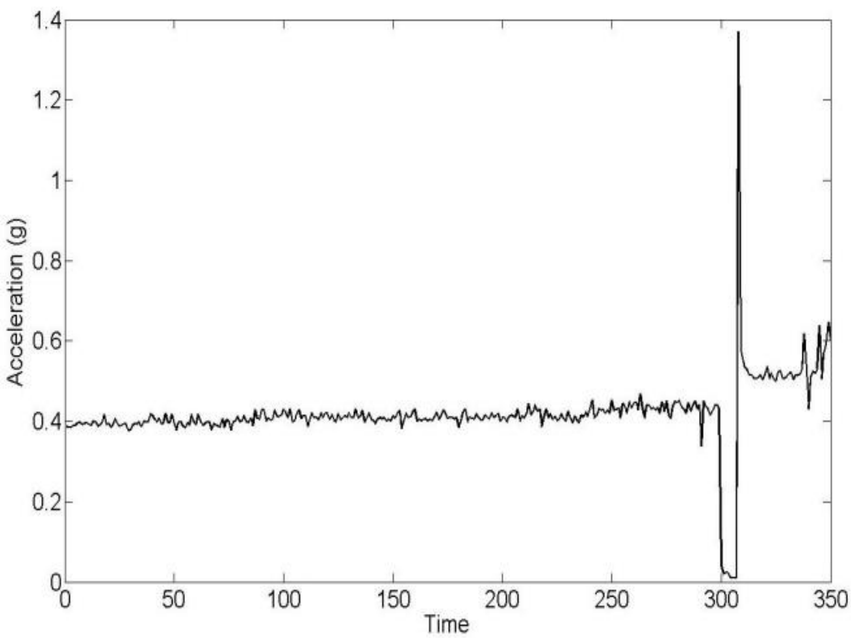

Fig.2. The peak acceleration data

4. APPLICATION AND RESULT

The proposed method is applied to forecast the health condition of the real system of the low methane compressor in a petrochemical plant based on peak acceleration data as shown in Fig.2 [13]. The compressor is driven by a 440kW motor, 6600 V, 2 poles and operating at a speed of 3565 rpm. The applied data shown in Fig. 4 were recorded every 6 hours. It contained information of machine history during the states of normal condition and fault condition with respect to time sequence. Consequently, it can be classified as time series data.

4.1. Estimation of Degraded Performance

The machine is in normal condition during the time correlated with the first 291 points. After that time, the data drastically changed, which means degradation state just has occurred. The final failure occurred at time of 308, after that some maintenance actions were applied.

In term of forecasting the future condition of machine, firstly a performance curve that indicates the degraded condition of the machine must be carried out. Based on the peak acceleration data, the degraded condition of machine can be estimated by survival function as shown in Fig.3.

4.2. Prediction of Machine's Condition

The third step of this method is to build a grey model, and predict the future value of machine's condition. When the machine's condition decreases and then reaches the incipient failure threshold, the future condition must predict immediately. Finally, Fig.4 depicts both actual and prediction of machine's condition from time of 291 to 308.

In the aim of investigating the capability of multi-step-ahead forecasting, Fig.4 shows the prediction results of one-step-ahead, two-step-ahead, and three-step-ahead techniques, and Table 1 also shows the *RMSE* and *R* values of each forecasting technique. According to the both results, this work found that a model based on one-step-ahead techniques coupled with grey model is the superior.

Although the model has good values for *RMSE* and *R*, the model needs a modification in order to improve the accuracy of prediction. The current model may not a good prediction model because it is not able to track well the sudden change of degraded condition of machine.

Finally, Fig. 5 shows the result of a modified version of the grey model coupled with one-step-ahead forecasting. According to the result, it can closely track the sudden change of machine's degradation. Especially, it is able to predict the actual final failure occurring at time of 308. Predicting the time of final failure is very crucial in machine prognostics problem.

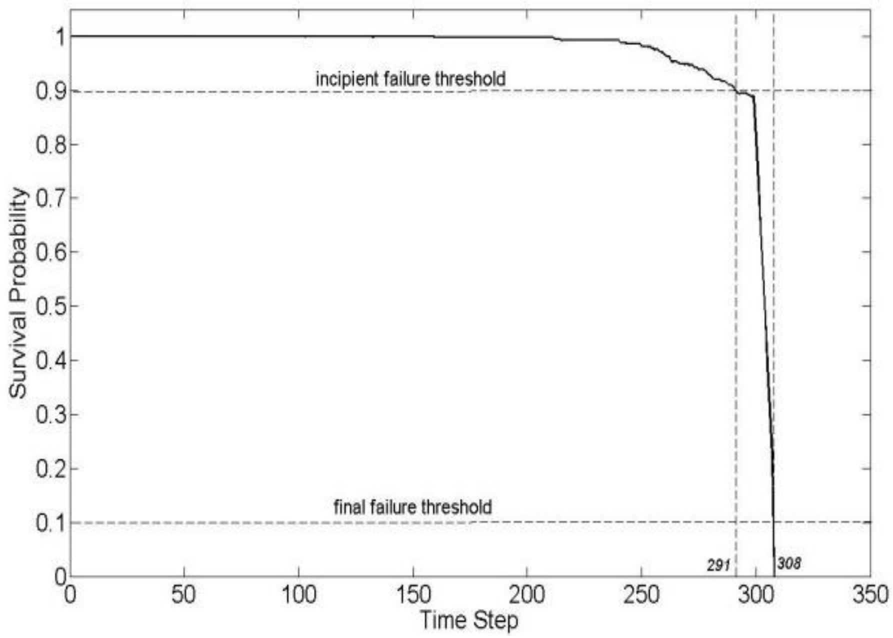

Fig.3. The degraded condition data

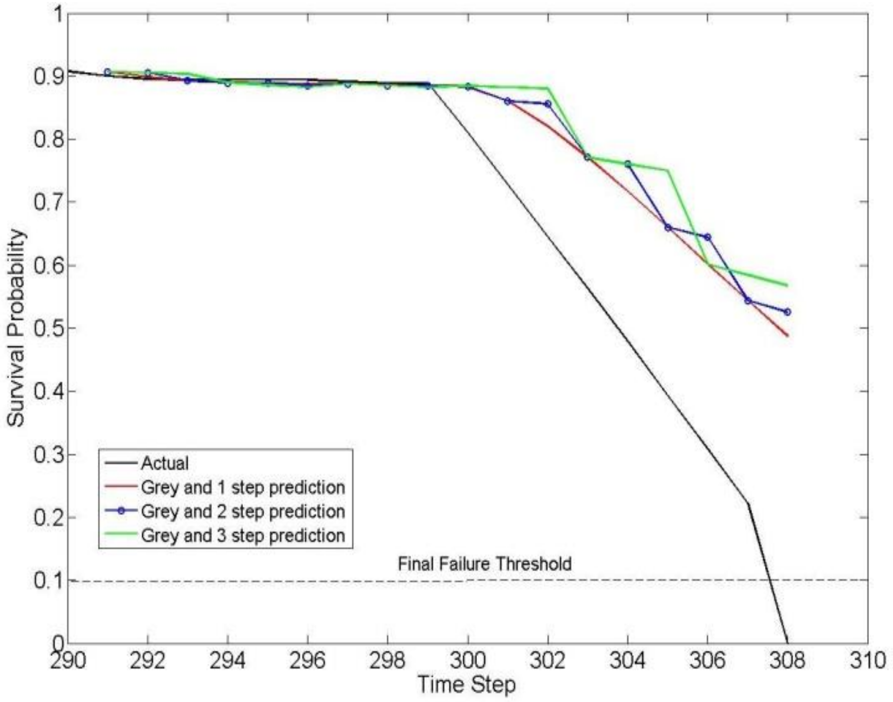

Fig.4. Grey predictions of machine's condition using one-step-ahead, two-step-ahead, and three-step-ahead techniques.

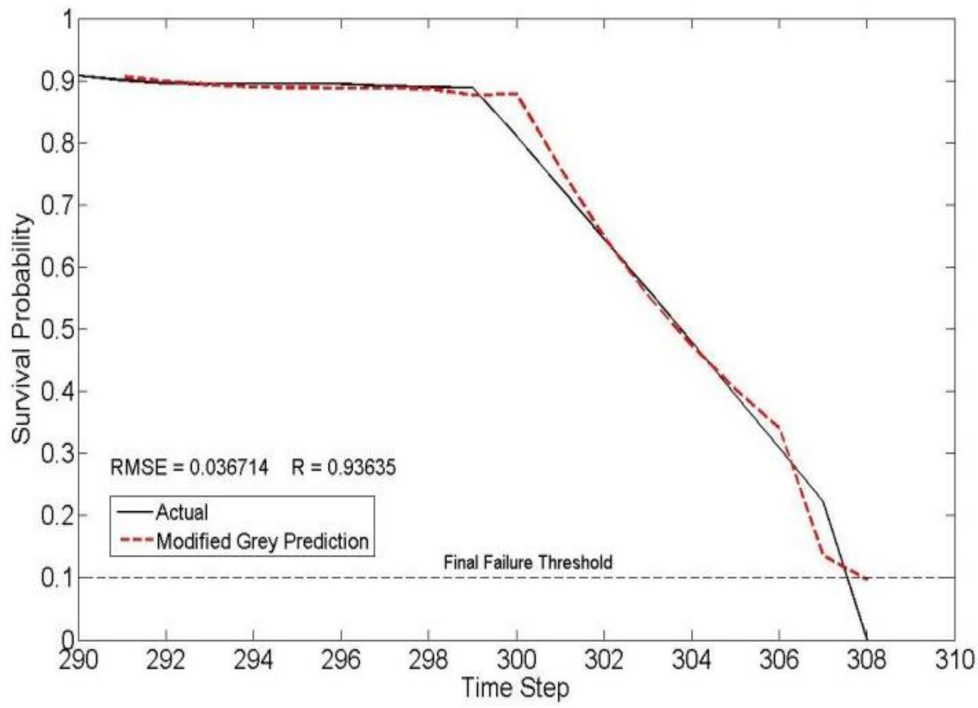

Fig.5. Modified grey prediction coupled with one-step-ahead technique.

Table 1 The *RMSE* and *R* values by using the multi-step-ahead prediction

Number of Step-Ahead	RMSE	R
1	0.19028	0.93338
2	0.20462	0.92141
3	0.22041	0.90326

5. CONCLUSIONS

Machine condition prognostics is very important in forecasting the degradation of machine conditions and trends of fault propagation before they reach the final failure threshold. The capability of one-step-ahead, two-step-ahead, and three-step-ahead prediction coupled with grey model have been investigated. This work found that a model based on one-step-ahead techniques coupled with grey model is the superior. The models are validated by its ability to predict future conditions of a low methane compressor using the peak acceleration data. Furthermore, a modified model is able to track the change of machines' operating conditions with high accuracy. The tracking-change capability of operating conditions is of crucial importance in estimating the remaining useful life of industrial equipments. This means that grey model with one-step-ahead technique have the potential for using as a tool to machine condition prognostics.

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