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A novel prognostic model of performance degradation trend for power machinery maintenance

Dengji Zhou [a,*], Huisheng Zhang [b], Shilie Weng [b]

[a] The Key Laboratory of Power Machinery and Engineering of Education Ministry, Shanghai Jiao Tong University, Shanghai, PR China
[b] Gas Turbine Research Institute, Shanghai Jiao Tong University, Shanghai, PR China

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A B S T R A C T

Power machinery has two types of fault modes. The first type leads equipment to stop working, and the second one results in performance degradation. The second type should not be ignored, because of its safe, economic and environmental consequence. Aiming at the second type of fault modes, current prognostic model for the remaining useful life of equipment is usually based on the historical data of the equipment fault or malfunction, which can provide evidence for maintenance. However, this model just depends on the time based fault data, without taking the operation state into consideration. In this paper, a novel prognostic model of performance degradation trend is developed, which is based on current prognostic models for the remaining useful life. It combines the historical fault data and monitoring data in operation. This model can be used for maintenance optimization. Maintenance activities, according to the result of this model, actually combine the viewpoint of Time Based Maintenance and Condition Based Maintenance. Finally, compressor washing of a gas turbine engine is cited as an instance to validate this model. Maintenance strategies based on the new model infers that it not only keeps the reliability of equipment, but also reduces the maintenance cost.

1. Introduction

Maintenance, consuming a lot of time and money, is an important section for life cycle assessment of power machinery [1]. The conventional maintenance strategy is TBM (Time Based Maintenance) which divides maintenance work into routine maintenance and different levels of periodical overhaul [2]. Technical staff works as the time pre-scheduled manner, basically regardless of the health condition of the machine. This strategy with good operability will cause excessive maintenance or fault before the next pre-scheduled overhaul. The solution of these problems is to adopt CBM (Condition Based Maintenance) [3]. Performance parameters of power machine are calculated to describe the health condition of machine, with the help of monitoring parameters. The assumption for this maintenance strategy is that the deteriorated equipment works with different performance parameters from new equipment. More advanced maintenance strategies, like CBM+ (Condition Based Maintenance Plus), RCM (Reliability-centred Maintenance), Risk-based maintenance [4] and Game-theory-based maintenance [5], have been proposed and applied, for the high requirement of reliability, availability and economic of energy industrial production. Both traditional CBM and these advanced maintenance strategies need support of diagnostic and prognostic technologies. Thus the latest research results of diagnostic and prognostic technologies, are always immediately applied to energy conversion equipment operation and maintenance (e.g., fusion of support vector machine [6] and adaptive neuro-fuzzy inference system classifiers, combined pinch and exergy analysis [7]) Table 1.

To date, all fault modes have been summarized into six fault patterns [8]. For power machinery, due to different characteristics of six fault patterns, fault modes result in two different types of consequences, leading equipment to stop working in a snap or performance degradation of equipment. The main difference between the two types of consequences is the interval time between potential fault and functional fault. In order to avoid fault modes leading to the first type of consequences, equipment redundancy and diagnostic technology should be relied on. Although fault modes leading to the second type of consequences will not cause shutdown, safe, economic and environmental consequences may occur, if they are not paid attention to. In order to avoid the second type of consequences, CBM with the help of accurate prognostic model and preventive maintenance model should be adopted [9]. Therefore, the general principle for the maintenance is as follows:

* Corresponding author.
E-mail addresses: ZhouDJ@sjtu.edu.cn (D. Zhou), zhslm@sjtu.edu.cn (H. Zhang), slweng@sjtu.edu.cn (S. Weng).

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Nomenclature

E	expectation
T	time to failure
t	operating time
$Z(t)$	past condition parameter up to the current time
$Z_{hj}(\nu)$	condition parameter of the similar equipment j at time ν
E_{hj}	event data of the similar equipment j
X	performance parameter
X_T	performance parameter calculated by polynomial function
E	error term
β_i	coefficient of polynomial function
F	cumulative fault rate
i	order number of every fault
n	total number of times of fault
t_0, m, η	parameters of Weibull distribution
f	fault probability
λ	fault rate
DegX	degradation of performance parameter
k	proportionality coefficient
δ	threshold for working under common faults

(1) Accomplish fault/failure mode and effect analysis of equipment based on equipment knowledge and design and operating document, to find out all the potential faults/failures.
(2) Make maintenance schedule based on the result of fault/failure mode and effect analysis, to find suitable maintenance task for every potential faults/failures (e.g., corrective maintenance, TBM, CBM, reformative maintenance).
(3) Conduct unscheduled maintenance for fault modes prevented by CBM. This process needs the help of diagnostic and prognostic technology.

Therefore, predicting the performance degradation trend is a necessary part of reliable maintenance for power machinery, which can guarantee the availability of the machine and give maintenance staff a priority in repair job selection. Thus there are many researchers focus on intelligent maintenance system development based on prognosis [10,11].

2. Current degradation trend prediction method

There are mainly two types of prognostic methods for maintenance, physics-based method and empirical-based method. Physics-based method combines special equipment mechanical dynamic knowledge and condition monitoring data, to predict the residual life of the equipment, like crack growth model and damage evolution tracking. Empirical-based method gains the residual life or equipment future health parameters by directly utilizing monitoring parameters and historical operating data of both this equipment and its similar equipment. Thus the expectation of residual life can be descripted as [12]

Table 1
The base load parameters of gas turbine engine.

Pressure ratio	23.1
Exhaust mass flow	84.31 kg/s
Power output	31.4 MW
Efficiency of compressor	85%

$$E\left[T - t | T > t, Z(t), \left(Z_{hj}(\nu), E_{hj}\right)\right] \tag{1}$$

where T denotes the random variable of time to failure, t is the current age, $Z(t)$ is the past condition parameter up to the current time, $Z_{hj}(\nu)$ is the condition parameter of the similar equipment j at time ν, E_{hj} is the event data of the similar equipment j.

Currently, there are two main types of prognostic methods for power machine maintenance, forecasting method and statistical method.

Forecasting method, based on the operating historical data since this machine started work, uses mathematical method to predict the trend of performance parameters, standing for the healthy state of the equipment. Engel extrapolated characteristic variables based on polynomial model, to predict the remaining useful life of helicopter gearbox [13]. Gebraeel update parameters of exponential degradation model online based on Bayesian forecasting method for accelerated life test for bearings [14]. This method has been extended and improved [15]. Li adopted a combined regression techniques, including both linear and quadratic models, to predict the remaining useful life of gas turbine engines [3]. Lee adopted Artificial neural network in multivariable prognosis and prove its advantage in calculating speed [16]. Hikmet Esen used Artificial neural network to predict the performance of ground source heat pump systems [17].

Statistical method, based on the historical fault data, uses mathematical method to predict the trend of reliability of the equipment. Wang assumed that water pump bearings have the same shape parameters as paper machine bearings, but with different scale parameters from paper machine parameters. Based on this assumption, risk function of key bearings were calculated for water pump remaining life prediction [18]. Volk presented a proportional intensity model for equipment remaining useful life prognostic [19]. Tian utilized both failure and suspension histories to train neural networks for equipment remaining useful life [20].

Both forecasting method and statistical method cannot make full use of the data in (1). Thus accurate and full utilization of data becomes the main challenge for power machine. Some efforts have been made to integrate reliability data into prognostics. Most research in this field is utilizing Proportional Hazards Model to forecast machine reliability parameters [21]. This theory assumes that hazard changes proportionately with and that the proportionally constant is the same. However this model only uses the current machine condition information rather than the whole monitoring history [22].

Due to lack of research on this problem, a novel prognostic model is proposed to make time series prediction of power machine health based on statistical data, to support maintenance decision.

2.1. Forecasting method

Forecasting method, to predict the future behaviour of equipment, uses historical performance parameters calculated by monitoring parameters since the new equipment started working. Because of different mathematical methods, there are different forecasting methods, for instance, regression method, one parameter double exponential smoothing [23], Kalman method [24], Bayesian forecasting method [25], etc.

Time regression model, relating performance parameter to polynomial function of time, is most widely used. Here the p^{th}-order polynomial trend model is given, (2) [26].

$$X = X_T + \varepsilon = \beta_0 + \beta_1 t + \beta_2 t^2 + \ldots + \beta_p t^p + \varepsilon \tag{2}$$