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An application of DPCA to oil data for CBM modeling

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Abstract

In multivariate time series analysis, dynamic principal component analysis (DPCA) is an effective method for dimensionality reduction. DPCA is an extension of the original PCA method which can be applied to an autocorrelated dynamic process. In this paper, we apply DPCA to a set of real oil data and use the principal components as covariates in condition-based maintenance (CBM) modeling. The CBM model (Model 1) is then compared with the CBM model which uses raw oil data as the covariates (Model 2). It is shown that the average maintenance cost corresponding to the optimal policy for Model 1 is considerably lower than that for Model 2, and when the optimal policies are applied to the oil data histories, the policy for Model 1 correctly indicates almost twice as many impending system failures as the policy for Model 2.

Keywords: Maintenance; Multivariate statistics; Replacement; Dynamic principal component analysis; Proportional hazards model

1. Introduction

High complexity and sophistication of modern manufacturing systems has increased the impact of unplanned downtime caused by system failures. Unplanned downtime reduces productivity, increases product or service variability, and results in an increased maintenance spending due to breakdown maintenance. Effectively planned maintenance activities are becoming more and more important in modern manufacturing. The goal of maintenance is not only to reduce failures or minimize breakdowns, but mainly to minimize the maintenance-related operating cost (Jardine et al., 1997). Various maintenance schemes have been widely applied in industry, from corrective and time-based maintenance to condition-based maintenance

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(CBM). In a CBM system, the underlying maintenance cost model utilizes both the age information and the condition information obtained from inspections to generate a maintenance decision after each inspection. First, a statistical model describing the system deterioration is built utilizing recent data histories. Several kinds of statistical models of deteriorating systems have appeared in the maintenance literature, such as a state-space model in Christer et al. (1997), a random coefficient regression model in Lu and Meeker (1993), a hidden Markov model in Makis and Jiang (2003), and the proportional hazards model (PHM) (Banjevic, 1999; Cox, 1972; Kumar and Klefsjö, 1994a,b; Jardine et al., 1997; Love and Guo, 1991; Makis and Jardine, 1992a).

PHM, first proposed by Cox in 1972, has become very popular to model the lifetime data in biomedical sciences, and recently also in reliability and maintenance applications. In CBM modeling, PHM integrates the age information with the condition information to calculate the risk of failure (hazard rate) of a system. In the paper by Makis and Jardine (1992a), a PH decision model was considered and the structure of the optimal replacement policy minimizing the total expected average maintenance cost was obtained. The computational algorithms for this PH decision model were published in Makis and Jardine (1992b).

In this paper, the CBM modeling is based on the above PH model. The concept of CBM has been widely accepted in maintenance practice due to the availability of advanced condition-monitoring technology capable of collecting and storing large amount of data on-line, while the equipment is in operation. The inspection data can be represented in a vector form and the components in a data vector are termed as covariates in PH modeling. Usually the covariates are both cross-correlated and autocorrelated because they are related to the same deterioration process. The amount of data collected at an inspection epoch is usually very large and it is therefore important to reduce data dimensionality and capture most of the information contained in the original data set.

First, it is necessary to fit a multivariate time series model to the original data and then apply one of the recently developed dimensionality reduction methods (see e.g. Aschheim et al., 2002; Peña and Poncela, 2002) to reduce the model dimension. One of the best known traditional methods for dimensionality reduction is the principal component analysis (PCA) which can be applied when the subsequent samples are independent. Recently, PCA method was extended to the dynamic PCA to achieve the dimensionality reduction when the data exhibit both cross and autocorrelation. The applications of DPCA for multivariate process and quality control can be found e.g. in Ku et al. (1995), Li and Qin (2001), Russel et al. (2002).

In this paper, we first apply the multivariate time series methodology to fit a vector autoregressive (AR) model to the oil data histories. Then, a DPCA is performed and the principle components capturing most of the data variability are selected. These principal components are then used as the covariates to build a PH model for CBM purposes.

The paper is organized as follows. In Section 2, we describe a PH model used for the CBM modeling in this paper in more detail and provide a description of the oil data. The time series modeling of oil data is presented in Section 3 and the DPC analysis is done in Section 4. CBM modeling based on a PH model and model comparison is in Section 5 followed by conclusions from this research in Section 6.

2. The proportional hazards model and oil data description

The CBM model presented in this paper is the PH decision model considered by Makis and Jardine (1992a), controlled by the optimal replacement policy. It was proved in Makis and Jardine (1992a) that the average cost optimal policy is a control limit policy, i.e. the system is replaced (overhauled) when the value of the hazard function exceeds some optimal limit.

In the general PHM (Cox, 1972), the hazard rate is assumed to be the product of a baseline hazard rate $h_0(t)$, and a positive function $\psi(z, \gamma)$ representing the effect of the operating environment on the system deterioration, where z is a covariate vector and γ is the vector of the unknown parameters.