An Optimal Equipment Replacement Model Using Logical Analysis of Data

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ABSTRACT

In this study, Logical Analysis of Data (LAD) is used to propose an optimal equipment replacement model. Unlike most classification techniques, LAD has the advantage of not relying on any statistical theory which enables it to overcome the conventional problems concerning the statistical properties of datasets. LAD is employed to estimate the equipment’s survival and failure probabilities. These probabilities are then used to build a dynamic programming model to minimize the average long-term replacement cost of the equipment. The proposed method is successfully applied on Prognostics and Health Management challenge dataset provided by NASA Ames Prognostics Data Repository. The performance of the model is compared to that of the well-known Proportional Hazards Model.

Keywords: Condition Based Maintenance (CBM), Condition Monitoring, Dynamic Programming, Logical Analysis of Data (LAD), Optimal Replacement Policy, Prognostics

1. INTRODUCTION

Condition Based Maintenance (CBM) is a maintenance program that takes into account equipment’s health condition indicators and age to optimize or improve the maintenance decisions (Jardine et al. 2006). CBM uses the equipment age and collected information concerning its health, in order to identify hidden failure, to prevent failure and/or to determine the optimal maintenance actions. Optimal maintenance action is identified by considering the cost and risk of failure and predictive replacements.

Logical Analysis of Data (LAD), first introduced in (Crama et al. 1988), is a combinatorics, optimization and Boolean logic based methodology for analysis of datasets. The typical objective of LAD is to extract knowledge hidden in records of a dataset in order to detect the sets of causes that would lead to certain effects. LAD has been broadly applied for the analysis of...
datasets from different fields such as medicine, biotechnology, economics, finance, politics, properties, oil exploration, manufacturing and maintenance. Several researchers applied LAD in medical fields such as cell growth, breast cancer, coronary risk, and electrocardiography in order to predict behavior of medical models (Abramson et al. 2005, G. Alexe et al. 2006, S. Alexe et al. 2003, and Lauer et al. 2002). Alexe et al. (2004 and 2005) used LAD on medical data such as B-cell lymphoma, and ovarian cancer in order to diagnose medical diseases. LAD is applied in various other fields such as voting, credit card scoring, housing, labor productivity, country risk, composition of soil in the oil, genotyping, and psychometric in order to discover knowledge from the data and estimate the behavior of the models (G. Alexe et al. 2008, Boros et al. 2000, A. B. Hammer et al. 1999, P. L. Hammer et al. 2006, P. L. Hammer et al. 2004, and Kim et al. 2008). Yacout et al. (2010), Bennane et al. (2012), and Mortada et al. (2011 and 2012) applied LAD to diagnose equipment failure in case studies of power transformer, oil transformer, aircraft, and rotor bearing. LAD proved to be a promising technique that provides interpretable results and its performance is comparable to pioneer techniques in equipment failure diagnostics.

Unlike the earlier applications of LAD on industrial equipment data, our focus is not on diagnostics, or predicting an imminent failure, i.e. prognostic but on developing an optimal replacement model to minimize the average long-term cost of the maintenance system. We do so by integrating the outcome of LAD prognostic and a dynamic programming model. To the knowledge of the authors, this application of LAD is untested in the literature.

In the following section, we will briefly explain LAD methodology and its application to predict equipment’s chance of survival using the age and health conditions of the equipment. Then we will introduce a replacement policy to minimize the long-term replacement cost of the equipment using a dynamic programing approach.

2. METHODOLOGY

The main objective of LAD is to extract knowledge hidden in records of a dataset in order to detect the sets of causes that would lead to certain effects. In CBM, a cause can be the monitored equipment’s age and/or health condition indicators’ values, while an effect can be the equipment’s survival or failure. Each cause is called an attribute. In order to apply the method in CBM, observations are categorized into two classes: observations that fail during the upcoming coming period, referred to as the positive class, and observations that survive at least until the end of the upcoming period, referred to as the negative class. A positive (negative) pattern is a set of attribute values that is reflected in one or more of the observations of the positive (negative) class while is not reflected in any (or many) of the observations of the negative (positive) class.

LAD patterns are constructed using available historical data on the age, health condition indicators and working status of the equipment. This data set is referred to as the “train set”. Table 1 shows a hypothetical train set which will be used in this work to explain the model. The set is composed of condition indicator data at different observation moments, and their corresponding ages. Each row corresponds to an observation moment. Class “-” is indication of survival and class “+” identifies a failure during that period.

LAD positive and negative patterns in CBM discriminate the failure and survival characteristics of the equipment by unique combinations of attribute values. For example if “age greater than 20 periods and oil particles higher than 30 ppm” is identified as a positive pattern, this combination of attributes (age and oil particle) has only (or mainly) been spotted in observations of the positive class.

By using both age and condition of equipment as LAD’s attributes, estimation of the survival probability of the equipment is made possible (Ghasemi et al. 2013). This will be more discussed in section C below.
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