Transportation Research Part C 45 (2014) 17–26

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Improving rail network velocity: A machine learning approach to predictive maintenance

Hongfei Li [a,*], Dhaivat Parikh [b], Qing He [c], Buyue Qian [a], Zhiguo Li [a], Dongping Fang [a], Arun Hampapur [a]

[a] IBM T.J. Watson Research Center, Yorktown Heights, NY, United States
[b] IBM Global Business Services, Dallas, TX, United States
[c] The State University of New York at Buffalo, Buffalo, NY, United States

A R T I C L E I N F O

Article history:
Received 8 May 2013
Received in revised form 31 March 2014
Accepted 21 April 2014
Available online 16 May 2014

Keywords:
Big data
Condition based maintenance
Multiple wayside detectors
Information fusion
Predictive modeling
Rail network velocity

A B S T R A C T

Rail network velocity is defined as system-wide average speed of line-haul movement between terminals. To accommodate increased service demand and load on rail networks, increase in network velocity, without compromising safety, is required. Among many determinants of overall network velocity, a key driver is service interruption, including lowered operating speed due to track/train condition and delays caused by derailments. Railroads have put significant infrastructure and inspection programs in place to avoid service interruptions. One of the key measures is an extensive network of wayside mechanical condition detectors (temperature, strain, vision, infrared, weight, impact, etc.) that monitor the rolling-stock as it passes by. The detectors are designed to alert for conditions that either violate regulations set by governmental rail safety agencies or deteriorating rolling-stock conditions as determined by the railroad.

Using huge volumes of historical detector data, in combination with failure data, maintenance action data, inspection schedule data, train type data and weather data, we are exploring several analytical approaches including, correlation analysis, causal analysis, time series analysis and machine learning techniques to automatically learn rules and build failure prediction models. These models will be applied against both historical and real-time data to predict conditions leading to failure in the future, thus avoiding service interruptions and increasing network velocity. Additionally, the analytics and models can also be used for detecting root cause of several failure modes and wear rate of components, which, while do not directly address network velocity, can be proactively used by maintenance organizations to optimize trade-offs related to maintenance schedule, costs and shop capacity. As part of our effort, we explore several avenues to machine learning techniques including distributed learning and hierarchical analytical approaches.

1. Introduction

Rail network operators across the world are seeing an increase in demand for services driven by increased global trade and increasing cost of fuel. Accommodating this increased load on relatively fixed rail networks requires increase in network velocity without compromising safety. Network velocity is defined as system-wide average speed of line-haul movement

* Corresponding author. Address: IBM T.J. Watson Research, 1101 Kitchawan Rd., Yorktown Heights, NY 10510, United States. Tel.: +1 914 945 2656.
E-mail address: liho@us.ibm.com (H. Li).

http://dx.doi.org/10.1016/j.trc.2014.04.013
0968-090X/

between terminals and is calculated by dividing total train-miles by total hours operated. Higher network velocity represents efficient utilization of capital-intensive assets, and it is one of the most important metrics to measure performance of a railroad. Among many determinants of overall network velocity, service interruption is a key driver, which includes lowered operating speed due to track/train condition and delays caused by derailments. Railroads have put significant infrastructure and inspection programs in place to avoid service interruptions. One of the key measures is an extensive network of rolling stock or train monitoring detectors. Each of these detector systems consists of multiple sensors (temperature, strain, vision, infrared, weight, impact, etc.) and processing software and hardware. Detectors are installed along rail tracks and inspect the rail cars and locomotives passing over them to monitor and detect equipment health conditions (Ouyang et al., 2009). The detectors are primarily designed to alert for conditions that violate regulations set by government rail safety agencies.

Reducing the number of derailments attributed to mechanical faults in car and locomotive as primary cause and reducing intermediate maintenance calls due to false alarms can significantly improve rail network velocity. The extensive sensor network provides information sources to enable the solutions. One approach is to use machine learning techniques to automatically "learn rules" from historical sensor measurements and then better predict which rail cars are likely to have problems and thus maximize the hit rate of rail operator's setouts. Machine learning techniques allow systematic classification of patterns or relationships contained in data and identification of the attributes, containing information about condition of physical assets that contribute associated failure mode, or class (Hastie et al., 2001).

Considering the complexity of sensor network, there are several challenges in developing machine-learning techniques for predictive maintenance in railway operations.

1. The first challenge is caused by spatio-temporal incompatible information collected through multiple detectors, which are not always co-located. The detector system consists of multiple detectors measuring temperature, strain, vision, weight/impact, etc. Existing systems issue alerts primarily using one or two types of detectors at a time and only partial information is used. For example, when the bearing temperature is above 170 °F, the system issues an alert to request an immediate train-stop. The rule is simple but does not consider measurement errors or impact of environmental variables on detectors, which may lead to high false alarms and lower hit rate of rail operator's setouts. To better understand the conditions of a railcar, it is essential to integrate the information collected from various detectors. Since these detectors are not co-located, the measurements coming out of them are spatially and temporally incompatible, posing challenges when combining the information. We use bad truck/bad wheel prediction model as an example to show how we address this issue in Section 3.2.
2. The second challenge is big data. The ubiquity of connectivity and the growth of sensors have opened up a large storehouse of information. The bearing temperature detectors, for Class I railroad under this study, generate 3 terabytes of data in a year. Other industries offer possibilities of even larger amount of data generated under normal operating conditions, e.g., a Boeing jet generates 10 terabytes of information per engine every 30 min of flight-time (Higginbotham, 2010). The amount of data is only going to continue to rise. There has been a lot of recent progress in big data warehousing to manage, store and retrieve this information including Netezza and Teradata, but the true value is realized only if we are successful in mining and using the signals contained in the information effectively. In this paper, we will show a customized support vector machine (SVM) technique that effectively utilizes large-scale data and provides valuable tools for operational sustainability as described in the scenario of alarm prediction in Section 3.1.
3. The third challenge comes from the need to learn and create alarm rules in the context of industry operations, so that the rules generated can be interpreted by operators easily leading to efficient operational decision support. On one hand, subject matter experts (SME) can derive rules based on their knowledge and expertise in concert with industry standards. Those rules are easy to interpret, but do not accommodate the complexity required for accurate prediction based on large, spatially and temporally incompatible and dirty, heterogeneous data coming from multiple detectors. On the other hand, machine learning techniques provide good approaches to learn efficient rules to predict failures. But those rules are usually complicated and thus not easily understood by human operators. To facilitate predictive maintenance operations in railway, it is important to set proper trade-off in learning system to create efficient but human-interpretable rules. We address this issue by using two different approaches. One is to extract logicalized rules from the complex machine-learning based algorithm outputs, and the other is to use certain machine learning techniques, such as decision tree, to derive rules that are easily to understand and implement. The approaches are described with more details in the two scenarios in Section 3.1 and 3.2, respectively.

In the area of condition monitoring and predictive maintenance, some work has been done to provide failure predictions using statistical and machine learning approaches. Lin and Tseng et al. (2005) presents reliability modeling to estimate machine failures. Saxena and Saad (2007) uses neural network classifier for condition monitoring of rotating mechanism systems. In railway applications, Yella et al. (2009) adopts a pattern recognition approach to classify the condition of the sleeper into classes (good or bad). Yang and Létourneau (2005) proposes an approach to predict train wheel failures but only using one type of detectors, Wheel Impact Load Detector (WILD), without considering the impacts of multiple detectors. Recently, Hajibabai et al. (2012) develops a logistic regression model to classify wheel failures based on WILD and Wheel Profile Detector (WPD). They claim that the classification accuracy is 90% with 10% false alarm rate. However, only two detectors are taken into account in that study. The problems that those papers have worked on are not as complicated as what we face and none of them has addressed all the challenges we describe above.