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Sophisticated Alarming Potential of Hot Box Detectors

by Scott Cummings and Harry Tournay

Summary

Information generated by Hot Box Detectors (HBD) for a particular bearing over its immediate past history has potential to benefit railroads with sophisticated alarming.

Transportation Technology Center, Inc. has produced an HBD algorithm that shows improvement over current algorithms for a limited test data set. All algorithms examined show improved performance when multiple HBD sites are linked. As "virtual AEI" and other methods of linking historical HBD data become available, it is expected that the performance of sophisticated alarming will improve and that the predictive maintenance capabilities of HBD linked to a larger database will become more apparent.

Many mechanical components have a life cycle history in which they behave reasonably consistently for a long time according to a particular set of parameters. With the onset of wear or fatigue, their behavior changes, influencing this set of parameters. This change can accelerate to ultimate failure of the component or system.

The railroad journal roller bearing exhibits this behavior pattern. Performance parameters for bearings include temperature and acoustic signature. This *Technology Digest* addresses bearing behavior related to temperature as measured by HBD's.

Existing algorithms are compared to each other and with an improved algorithm. The benefit of virtual AEI on the effectiveness of sophisticated alarming is also examined.

Suggested Distribution:

- ❑ Maintenance-of-Way
- ❑ Planning & Analysis
- ❑ Safety

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INTRODUCTION

Predictive Maintenance

Many mechanical components have a life cycle history in which they behave reasonably consistently for a long time according to a particular set of parameters. With the onset of wear or fatigue, their behavior changes, influencing this set of parameters. This change can accelerate to ultimate failure of the component or system.

The railroad journal roller bearing exhibits this behavior pattern. Performance parameters for bearings include temperature and acoustic signature. This TD addresses bearing behavior related to temperature as measured by Hot Box Detectors (HBD). Bearing temperature is an indication of friction, and therefore health. Traditionally HBD's have been used as alarming devices to detect the last portion of a bearing's life cycle, just before catastrophic failure, which sometimes results in journal burn-off. The performance of this alarming method has been fair. However, bearing thermal failure and journal burn-offs still occur. This has led to additional development of the alarming method.

Furthermore, as railroads move towards predictive maintenance, more extended history of component condition is required. For HBD data, this implies monitoring each bearing over a longer period. To do this, each bearing must be traceable not only by railcar identification code but also by its location within the railcar. As a longer historical account becomes available, the potential for predictive maintenance could be investigated.

The Nature of HBD Data

Some variance in temperature is expected among a group of properly functioning roller bearings for a given set of operating and ambient conditions.

As roller bearings become damaged, there is an increase in friction leading to higher bearing temperatures, sometimes high enough to result in bearing or axle failure. The amount of bearing degradation sufficient to take a bearing from normal temperatures to temperatures causing concern occurs in less than 1,000 miles, according to most experts in the industry.

The HBD equipment measures the temperature above ambient of each bearing as it passes the HBD site and train speed. The HBD equipment provides no information about the type or severity of the damage causing an increased temperature in a bearing. Change in bearing temperature may indicate the severity of the defect. Bearing temperature is also a function of vertical and lateral load, train operational history including speed and brake applications, track curvature, ambient temperature, and solar heat gain.

Current State of HBD

Currently, a large network of HBD's exists across North America, but many are stand-alone units that simply issue a radio warning to the train crew if a hot bearing is detected. Alarm criteria have been set and an immediate train stop is required if a bearing's temperature exceeds the criteria. These stand-alone units do not report data to a database. Some HBD's equipped with communication equipment do report bearing temperatures to a database, but individual railroads keep their own database.

Railroads also generally have a separate database for Automatic Equipment Identification (AEI) scanners. Cost considerations have kept each HBD site from being linked to a database and having an accompanying AEI scanner. Accordingly, HBD historical data is not readily searchable by car identification number. This adds a significant human factor to the predictive maintenance process. However, this information can be manually matched up to trace an individual bearing through a short sequence of HBD site readings. Several railroads are currently doing this in an effort to monitor "suspect bearings." Suspect bearings show temperatures above the normal range but below the level required for an immediate train stop. TTCI has named this process "sophisticated alarming" in which a particular bearing is "flagged" as suspect and should be removed from service by the operating railroad. This system works in parallel to the traditional HBD alarm system in which an immediate train stop is required.

The sophisticated alarming techniques currently in practice have had a large positive impact on both safety and efficiency of operations. Since implementing a sophisticated alarming technique, one railroad has noted a reduction of 2/3 in annual journal burn-offs. In addition to this safety improvement, an operational improvement has also been realized thanks to a reduction of 1/3 in annual hot bearing alarms. These achievements are impressive and encourage additional development in this area towards the goal of maximizing the safety and operational efficiency of railroads.

Without a continent-wide, inter-railroad centralized database of HBD data, including car number, an investigation of predictive maintenance potential is impractical. Some railroads are investigating partial solutions to this problem including "virtual AEI" in which data from a single AEI scanner is automatically matched to a train as it progresses along its route past numerous HBD's. One railroad is constructing a wayside detection corridor with numerous HBD sites and AEI equipment at either end. These HBD sites will be linked to a central database searchable by car ID. As more data becomes available, the possibility of predictive maintenance could be investigated.

COMPARISON OF ALGORITHMS

Existing Algorithms

At least two railroads have produced algorithms to aid in the discovery of suspect bearings. These existing algorithms, hereafter referred to as algorithms A and B, are a piece in each railroad's sophisticated alarming system. The algorithms call attention to bearings that may be in the process of failing so that humans can decide whether or not to take action. The results of the analysis involving these algorithms represent only the performance of the algorithm and should not be confused with actual set out rates.

At least one railroad is attempting to remove the human "filter" from their sophisticated alarming system. That algorithm is not addressed here.

Algorithm A

Algorithm A is used both as an automatic pass/fail criteria applied to data from individual HBD sites and a means of identifying suspect bearings that can be manually monitored by office staff for trend analysis. Algorithm A checks for large differences between each bearing and other strategically chosen bearings in the train.

Algorithm B

Algorithm B checks for bearing temperatures far beyond the standard deviation of the train at each HBD site. Bearings are manually monitored by office staff for criteria exceedences at two separate HBD sites. When this is the case, remedial actions are taken, such as requesting the train crew to apply and release brakes to check for a stuck brake.

Improved Algorithm

The normal temperature of roller bearings in service has a large variance due to many influencing factors. This large variance makes it difficult to define normal behavior. One option would be to create a normalization algorithm that attempts to modify each bearing's temperature data based on the influencing factors. Since information about many of the factors contributing to a bearing's temperature would be extremely difficult or impractical to obtain in a meaningful way, it is not practical to generate a normalization algorithm for HBD data. Rather, it is assumed that most bearings on a train are properly functioning and inferences can be made about many factors affecting the temperature of individual bearings based on the temperature patterns of other bearings in the train. In this manner, a hybrid performance indicator (HPI) has been created that reduces the variability of the performance parameter due to many of the non-defect related variables. The goal of the HPI is to increase the effectiveness and reliability of sophisticated alarming and thus increase the amount of time/distance available to identify defective bearings while minimizing the number of "false" alarms.

Normal performance of bearings in terms of the HPI is subject to debate. Certainly, it is undesirable to stop trains unless there exists a high degree of certainty that a suspect bearing is truly a hazard. Applying the HPI to bearing temperature data results in a score. The selection of a cutoff threshold between normal behavior and non-normal behavior is a delicate balancing act between the sensitivity to find degrading bearings as early as possible and the robustness to minimize the quantity of bearings flagged. Cutoff thresholds, and thus definitions of normal performance, are suggested for the HPI that mimic the sensitivity of algorithms A and B in terms of success in selecting true suspect bearings, with an accompanying reduction in the quantity of non-suspect bearings selected. A bearing that exceeds the cutoff threshold is identified as a deviation from normal performance.

RESULTS

The data set used to analyze the various algorithms came from one railroad's HBD databases. The railroad sent (via email) TTCI records identifying the car number, bearing location, and HBD site identification whenever a suspect bearing was removed from service. By manually integrating AEI and HBD databases, TTCI then extracted the HBD readings for the suspect bearing and all of the other bearings in the train. This data was traced back through as many HBD sites as practicable. There were 20 suspect bearings in this data set (one per train) and the length of each suspect bearing's HBD history ranged from 5 to 74 sites for a total of 409 HBD reports.

The algorithms were compared by reviewing their success in locating or "flagging" the suspect bearing (true positive) while avoiding those bearings which were not considered suspect (false positive). This comparison was performed on a site-by-site basis and the results are shown in Figure 1.

Figure 1 shows two important points: (1) Algorithm A is far more conservative than algorithm B in that it identifies the suspect bearing less frequently but flags far fewer non-suspect bearings. This issue is a matter of preference to each railroad, but certainly the early identification of suspect bearings is crucial to the effectiveness of a predictive maintenance system and (2) The improved algorithm can be adjusted to match the suspect bearing sensitivity of either algorithm A or B. In both cases, the improved algorithm shows a marked improvement in the number of non-suspect bearings flagged. HPI flags 26 percent fewer non-suspect bearings than algorithm A and 53 percent fewer than algorithm B.

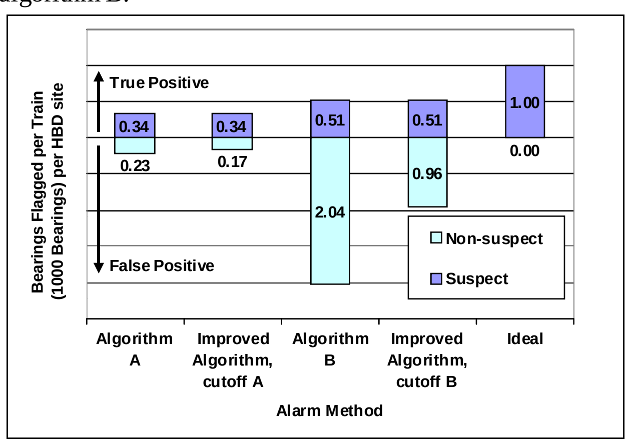

Figure 1: Single Site Algorithm Comparison

Linking HBD sites and monitoring the historical performance of a bearing can allow for sophisticated alarming and the possibility of predictive maintenance. To show the increased effectiveness of linking HBD sites, the algorithms described above were also compared by examining their performance using a 5-HBD site moving window. In this scenario, a bearing would need to exceed the particular algorithm's criteria at least twice within the five most recent HBD sites to be flagged. Results shown in Figure 2 illustrate that linking HBD sites does generally increase the sensitivity to suspect bearings while it reduces the number of non-suspect bearings flagged. For example, under the 5-HBD site moving window scenario, HPI, with "cutoff A" applied, yields a 15 percent increase in true positives and a 34 percent decrease in false positives over the same algorithm in the single site scenario (Figure 1).

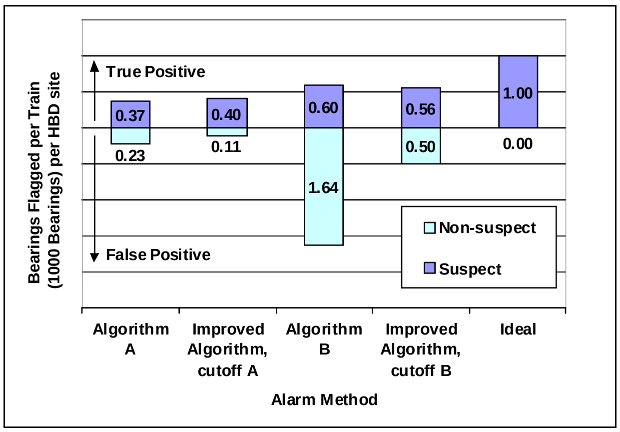

Figure 2: Effect of Linking Five Sites and Waiting for Two Criteria Exceedences

The results presented thus far pertain to all 409 HBD site histories. This means that equal weighting has been given to the results of an HBD scan that occurred immediately prior to suspect bearing removal and to the results of an HBD scan that occurred 30 or even 70 HBD sites prior to removal of the suspect bearing. However, if the data set is limited to the five HBD sites prior to the removal from service of each of the 20 suspect bearings, the algorithms are much more successful at selecting the suspect bearing. Again using the scenario of linking five HBD sites and requiring at least two exceedences to be flagged, the results from this restricted data set are shown in Figure 3. False positive results are not plotted in Figure 3 because any difference from the false positive results in Figure 2 is coincidental.

DISCUSSION

Roller bearings at the end of the life cycle degrade quickly in terms of temperature increase. It is the goal of sophisticated alarming to increase the time available for operational and maintenance intervention by earlier identification of the problem. In this manner, sophisticated alarming may allow cars with suspect bearings to be cutout of trains more conveniently at yards as opposed to mainlines. The goal of the HPI is to increase the effectiveness and reliability of sophisticated alarming.

Maintenance planning can be thought of as the continuous spectrum shown in Figure 4. On this spectrum, the right side represents advance notification to conveniently repair or replace a component prior to an impending failure and the left side represents an alarm that requires immediate setout of a car with a component that has failed. On this spectrum, somewhere closer to the left side would be the sophisticated alarming technique.

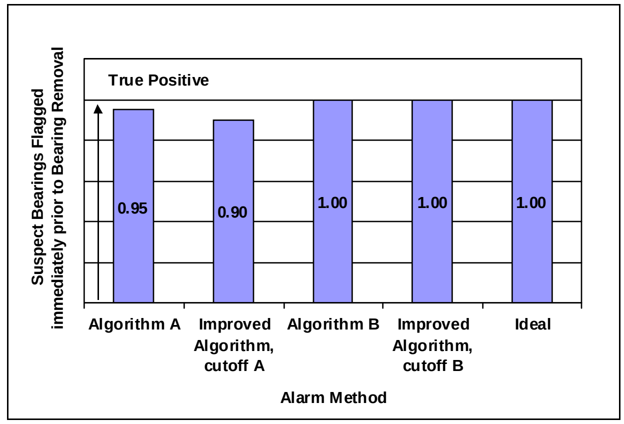

Figure 3: Results at the Sites Immediately Prior to Suspect Bearing Removal

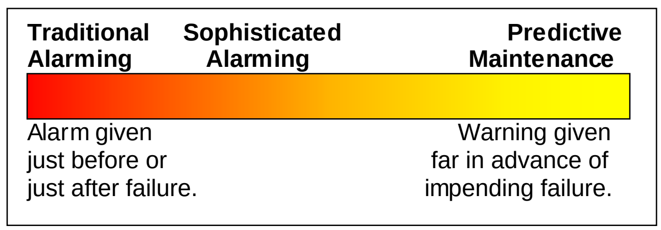

Figure 4: Spectrum of Maintenance Planning

All three algorithms examined report a binary type of result; i.e., black/white, pass/fail. Future work on this subject could include an algorithm with a continuous type of result; i.e., shades of gray, such that defect severity could be more accurately assessed. Such an algorithm could allow the process to move towards the right of the maintenance planning spectrum. Another means of moving towards the right side of the spectrum is the linking of individual railroad databases into a central storage facility, such as *Inte*RRIS™, accessible by all participating railroads. Longer term trending could be investigated and the potential for more accurate scheduling of maintenance exists.

At least three of the Class I North American railroads are already working towards some sort of integrated HBD/AEI databases. Therefore, it would seem that there is need of further exploration into the economics of the methodology of sophisticated alarming and predictive maintenance. The improved algorithm can be applied to current 'manual' methods and others once 'virtual AEI' is introduced.