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Development of Algorithms and Criteria for Continuous Condition Monitoring of Railroad Bearings

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DEVELOPMENT OF ALGORITHMS AND CRITERIA FOR
CONTINUOUS CONDITION MONITORING OF RAILROAD BEARINGS

A Thesis
by
SEAN MICHAEL WOODS

Submitted to the Graduate School of
The University of Texas-Pan American
In partial fulfillment of the requirements for the degree of
MASTER OF SCIENCE

December 2012

Major Subject: Mechanical Engineering

DEVELOPMENT OF ALGORITHMS AND CRITERIA FOR
CONTINUOUS CONDITION MONITORING OF RAILROAD BEARINGS

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December 2012

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ABSTRACT

Woods, Sean M., Development of Algorithms and Criteria for Continuous Condition Monitoring of Railroad Bearings. Master of Science (MS), December, 2012, 111 pp., 14 tables, 37 illustrations, 5 equations, 29 references.

This thesis summarizes research conducted at the University of Texas-Pan American to investigate the implementation of condition monitoring algorithms for use with railway roller bearings equipped with wireless temperature sensor nodes. Current temperature based condition monitoring techniques utilize wayside detection equipment intermittently located along the track to garner sporadic bearing cup temperatures. Such devices are not capable of detecting brief transient temperature trending events. The developed algorithms were tested using a fleet of ten railway freight cars instrumented with wireless sensor nodes and operated by an Australian freight transportation company. Eighteen months of continuous monitoring combined with the inspection of three setout bearings demonstrate the effectiveness and accuracy of the developed algorithms as a continuous bearing health monitoring system.

DEDICATION

The completion of my education would not have been possible with the support and love of my family. I dedicate this thesis to my mother Carol Woods, my father Floyd Woods, my brother Christopher Woods, and my sister Katherine Woods.

ACKNOWLEDGMENTS

I would like to sincerely thank Dr. Constantine Tarawneh, my advisor and thesis committee co-chair for his endless dedication to my growth as a student, a researcher, and, most importantly, an engineer. His passion for education and research is without parallel among the faculty of the University of Texas-Pan American. His high standards, demanding timelines, and an unwillingness to accept anything but my best work have helped me become the engineer I am today. All that I have learned from him will continue to benefit me for many years to come, as I progress in my career as an engineer.

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NOMENCLATURE

$\frac{dT_i}{dt}$	=	approximate bearing heating rate
$\frac{dT_i}{dt}_{limit}$	=	threshold used with bearing heating rate analysis
$N\{ \}$	=	number of data points satisfying the expression in brackets
N_i	=	total number of data points acquired
T_i	=	temperature data from a single bearing
T_{limit}	=	bearing cup temperature threshold
\bar{T}_{car}	=	average of all temperature data from a single railcar
\bar{T}_i	=	average of temperature data from a single bearing
\bar{T}_{train}	=	average of all temperature data from the train
ΔT_i	=	bearing-ambient temperature differential data from a single bearing
ΔT_{limit}	=	bearing-ambient temperature differential limit

GREEK SYMBOLS

σ_{car}	=	standard deviation of temperature data for one railcar
σ_{train}	=	standard deviation of temperature data for the entire train

ACRONYMS

<i>AAR</i>	=	Association of American Railroads
<i>CMU</i>	=	Communication Management Unit
<i>HBD</i>	=	Hot-Box Detector
<i>RCF</i>	=	Rolling Contact Fatigue
<i>TADS</i>	=	Trackside Acoustic Detector System
<i>TTCI</i>	=	Transportation Technology Center, Inc.
<i>WSN</i>	=	Wireless Sensor Node

CHAPTER I

INTRODUCTION AND MOTIVATION

1.1 Introduction

With increasing demand for freight car capacity and trains traveling at ever evolving speeds, the dangers associated with bearing failure in service are high, including possible bearing journal burn-off, derailment, and loss of human life. During the period from 2002 – 2012 there were 290 derailments attributed to bearing failure costing the railroad industry a total of \$77.7 million [1]. Additionally, railroad operators may incur significant fines for delaying traffic on main lines while performing costly field repair of less severe bearing failures.

In order to reduce the likelihood of bearing failure in service, the first attempts at wayside detection of distressed bearings were developed and implemented in the early 1960s; they utilized infrared temperature detectors stationed adjacent to the track that measure bearing cup temperature [2, 3]. These early wayside detectors, known as hot-box detectors (HBDs), continue to be the primary tool for detection of distressed bearings today. To identify bearings that are operating at elevated temperatures, HBDs compare the measured bearing cup temperature to predetermined temperature thresholds. HBDs are typically spaced 15-40 miles apart depending on track location, and can only provide sporadic monitoring of railroad bearings. Furthermore, bearing operating temperature can rise very quickly between HBDs, causing the bearing to rapidly overheat and seize, initiating journal burn-off and possible railcar derailment [4]. Consequently, the HBD system is only effective at identifying distressed bearings immediately

before or after failure has initiated. In order to develop a comprehensive condition monitoring network, research has been conducted to promote communication between existing wayside detectors; however, progress has been hindered due to divided ownership of track and wayside detector installations [5].

Despite the implementation of wayside detectors, the persistence of bearing failures in service prompted research into new methods capable of identifying distressed bearings using the existing network of HBDs. In 2002, Union Pacific employed a statistical algorithm that detects bearings whose thermal performance deviates significantly from the rest of the train [6]. This system identifies outlier bearings which are operating at temperatures below the Association of American Railroads (AAR) alarm thresholds. In the last decade, this more conservative monitoring algorithm has successfully reduced the number of bearing failures and related derailments. However, the cost of this reduction in bearing failures is a significant increase in the number of *non-verified* bearings; these are bearings removed from service which upon inspection exhibit no signs of any defects. According to data collected by Amsted Rail from 2001 to 2007, an average of nearly 40% of bearing removals were non-verified [7]. This figure approached 60% in 2003 and 2004, indicating a significant increase in the number of non-verified bearing removed from service following the introduction of Union Pacific's statistical algorithm. These non-verified bearings are a source of inconvenience and expense for railroad operators who must stop the train and either remove the car in question for maintenance or replace the entire wheel-axle assembly.

1.2 Motivation

Wayside detection has been the only widely utilized method of defect detection for freight car bearings in North America, whereas passenger rail operator Amtrak implemented on-board bearing temperature monitoring for all railcars in the 1970s [8]. On-board temperature monitoring systems have the decisive advantage of continuous sampling, allowing the observation of all transient temperature trending events as well as routine temperature fluctuations caused by changes in train speed, braking, ambient temperature, etc. The ability to sample continuously allows the application of rigorous statistical methods to determine the average operating temperature, standard deviation of temperature, skewness of temperature distribution, and other parameters of interest. Research conducted since the 1970s sought to create an on-board bearing temperature monitoring system that could be economically retrofitted to freight cars [9-11]. Unfortunately, unreliable or very expensive battery sources and wireless communication devices plagued these efforts and rendered on-board monitoring of freight car bearings economically unfeasible.

Within the last decade, major advances in wireless communications, micro-processor circuits, and battery technology has enabled engineers to create much more reliable and robust wireless temperature sensors. Using these technologies, IONX, LLC has developed low power Wireless Sensor Nodes (WSNs) capable of measuring and transmitting temperature data once per minute. Since the bearing adapter provides a convenient and secure location to mount the WSN, a correlation between adapter surface temperature and bearing cup temperature was developed prior to field testing [12]. The latter allows for comprehensive analysis of the temperature history in order to assess the bearing's current condition as well as identify and predict degradation over time. Bearing cup temperature analysis utilizes three alert levels of increasing

severity. Level 1 alarms, the most urgent, are consistent with industry standards put in place by the AAR to prevent catastrophic bearing failure in service. The two lower level alarms are generated using five statistical metrics developed at UTPA. These metrics utilize comparisons with other bearings on the same railcar as well as all other bearings on that train. This system enables rail operators to focus resources on predictive maintenance instead of reactive maintenance, resulting in fewer train stoppages, track delays, and costly field repairs [13].

The following chapters of this thesis provide a description of the research conducted at UTPA to develop an on-board condition monitoring system capable of detecting unhealthy tapered-roller bearings prior to failure. Chapter II gives a history of railroad bearing use as well as a thorough literature review discussing previous efforts to develop an on-board bearing temperature monitoring system. Chapter III describes the instrumentation of railcars for a field test of prototype wireless temperature sensors and the laboratory testing apparatus used to evaluate bearings removed from field service. Chapter IV presents the development and implementation of detailed statistical analyses used to estimate the current condition of railroad bearings as well as detection and prediction of degradation. Chapter V discusses the results of a two-year field test and presents case studies for three bearings whose performance validates the developed algorithms and criteria. Chapter VI summarizes conclusions regarding the reliability and accuracy of the developed algorithms and proposes future work in this area.

CHAPTER II

HISTORY, BACKGROUND AND LITERATURE REVIEW

This chapter will provide a brief history of roller bearings and their use in railroad applications. Background is provided in railroad bearing condition monitoring as well as a literature review of previous on-board condition monitoring technologies.

2.1 History

Rolling elements have been evolving over thousands of years now, and their development paralleled the invention of the wheel. Early civilizations utilized rudimentary rolling elements as a means of moving heavy loads over long distances. The earliest examples of this technology are cylindrical wooden logs used to transport large blocks of stone from quarries to distant construction sites. As force is applied to the block, the logs would roll; creating much less resistance to motion than static friction (Figure 1). These earliest examples of rollers are attributed to the Sumerians and date back to approximately 1,100 B.C [14].

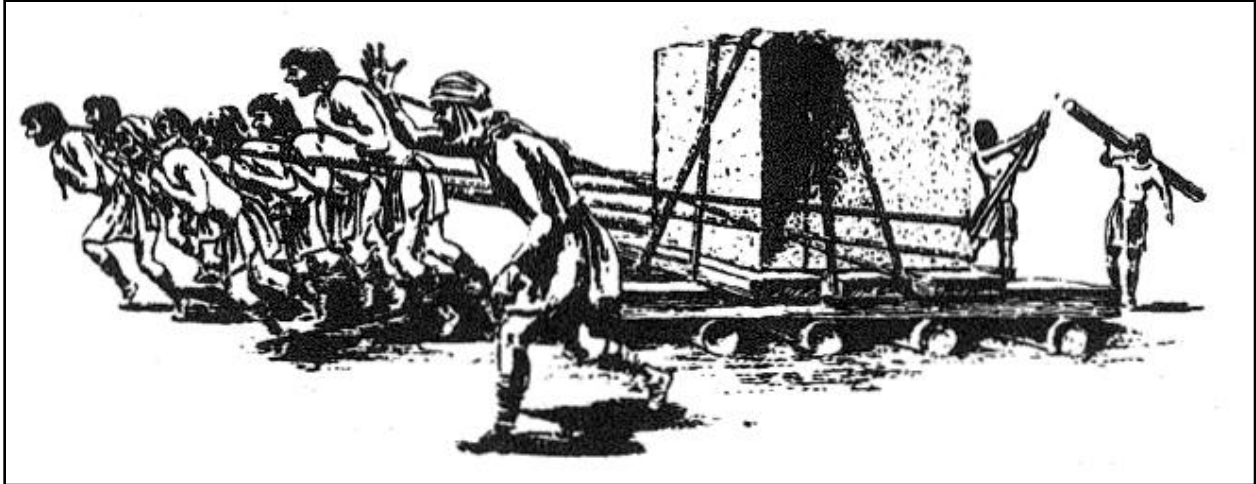


Figure 1: Wooden rollers used by the Sumerians to transport heavy stone blocks [14]

Figure 2 depicts a translational roller system with a stationary ground plate and a moving top plate used to carry a load. This primitive system was widely used to convey heavy stone blocks over long distances and is still in use today for conveyor systems in factories and warehouses. A transformation of this simple translational system yields the standard configuration of a modern enclosed roller bearing composed of two concentric circular races surrounding a set of rolling elements.

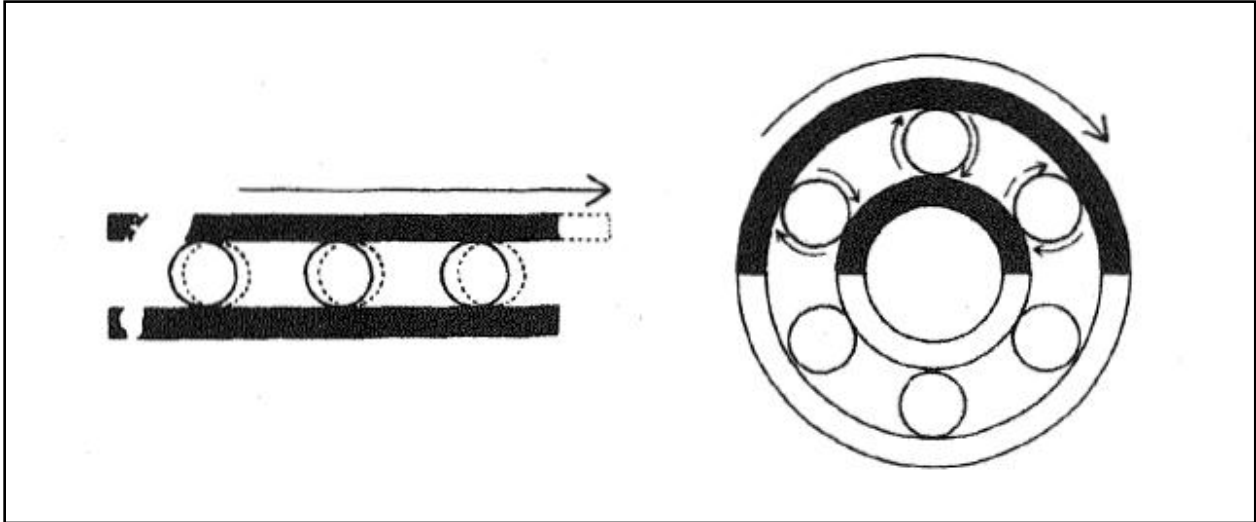


Figure 2: Translational roller systems used to support a load (left), modern enclosed roller bearing (right) [14]

Leonardo Da Vinci drew one of the first modern ball bearings during the Renaissance, although journal bearings were used almost exclusively in heavy machinery until the early 20th century. Early railroad bearing systems used journal bearings (Figure 3) to support the axle on a thin layer of lubricant, eliminating metal-to-metal contact while the axle is rotating. Journal bearings are capable of supporting large radial loads but cannot withstand axial loads due to their geometry.



Figure 3: Enclosed railcar axlebox with plain bore journal bearing [15]

These early journal bearings were housed in a metal box attached to the end of the axle, known as an axlebox, and utilized a crude system for maintaining lubrication during operation. Rags or wood chips were soaked in oil or animal tallow and packed under the journal to wipe oil

onto the axle and maintain lubrication. When these early bearings overheated, the axle boxes would occasionally catch fire and smoke excessively, providing a visual signal to alert the train operator of a failed bearing. This was given the term “hot box” referring to an overheated bearing, and this term is still commonly used in the railroad industry today. This system was only capable of identifying bearings that had already failed. Preventative maintenance required visual and manual inspection of the oil level in each axle box; a very tedious and time consuming process.



Figure 4: Several commonly used types of roller bearings [16]

Tapered-roller bearings were first used in 1895 by the Timken Company for use on horse-drawn carriages [17]. They were later adapted for use on rail cars and have proven to be more reliable than earlier journal bearing systems. Unlike other types of bearings depicted in Figure 4, tapered-roller bearings can withstand both high radial and axial loads, making them a perfect choice for railroad applications. Tapered-roller bearings are used around the world in a variety of sizes for both passenger and freight rail applications. The majority of freight cars in the United States use Class F ($6\frac{1}{2} \times 12$), Class K ($6\frac{1}{2} \times 9$), or Class G (7×12) bearings, while international railcars and passenger cars use various bearing sizes depending on local track gauge and axle load limits.

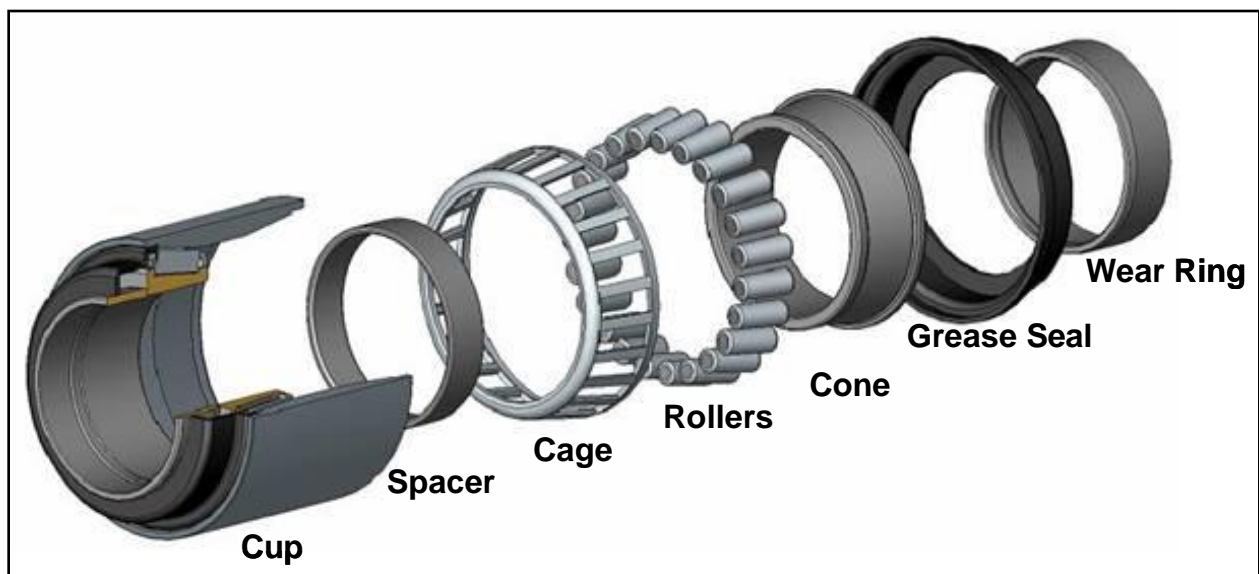


Figure 5: Expanded view of a double row tapered roller bearing [18]

Figure 5 shows a typical Class F double row tapered-roller bearing assembly commonly used on freight cars in the United States. The complete tapered-roller bearing consists of two cone assemblies (cone, 23 tapered rollers, and cage) separated by a spacer ring. This design allows the double row tapered-roller bearing to withstand large axial loads in both directions, as there are two opposing cones to prevent the cup from translating. The cones and spacer ring are

placed inside the bearing cup, grease is added, and seals are installed. The finished bearing assembly is pre-lubricated, sealed, and ready for installation onto a railcar axle journal for long reliable service life.

Although the new sealed tapered-roller bearings are more reliable than earlier journal bearings, the continual evolution of railcar weight and speed continues to stress bearings until failure. Tapered-roller bearings, like all bearings, are susceptible to rolling contact fatigue (RCF) of the cup, cone, and roller contact surfaces [19]. RCF failure causes small flakes of metal to chip out of the raceway surface and leave a depression known as a “spall”. Once a spall initiates, continued cyclic stresses combined with metal debris from the spall initiation will expedite RCF failure and enlarge the spall, resulting in increased noise, vibration, and elevated operating temperatures [19].

2.2 Background: Current Standards and Practices

As mentioned before, increased interest in detecting distressed bearings prior to failure led to the introduction of HBDs in the 1960s, and they continue to be the standard for bearing health monitoring. HBDs use an infrared scanner to measure bearing cup temperature and identify overheated bearings by utilizing a predetermined threshold. This method has been the standard for bearing condition monitoring for over 40 years and counting. The AAR has identified specific temperature thresholds that are implemented through the network of wayside hot-box detectors. These thresholds consider absolute bearing cup temperature, bearing temperature above ambient, and temperature differential between mate bearings on an axle (Table 1).

Table 1: AAR bearing temperature thresholds [20]

Absolute Bearing Cup Temperature	160°C (320°F)
Bearing-Ambient Temperature Differential	94.4°C (170°F)
Axle Mate Bearing Differential	58.3°C (105°F)

The primary disadvantage of using simple temperature thresholds to identify distressed bearings is that maintenance can only be scheduled reactively; meaning repairs can only take place once bearing failure is imminent or has already initiated. This practice results in much higher operating costs for the rail operator and increased delays for other trains using the same track.

Although the use of HBDs has reduced the number of bearing failures and related derailments, railroad engineers continue to develop more effective bearing monitoring algorithms that may be implemented using the existing network of HBDs, thus saving the substantial cost of installing new wayside detector stations.

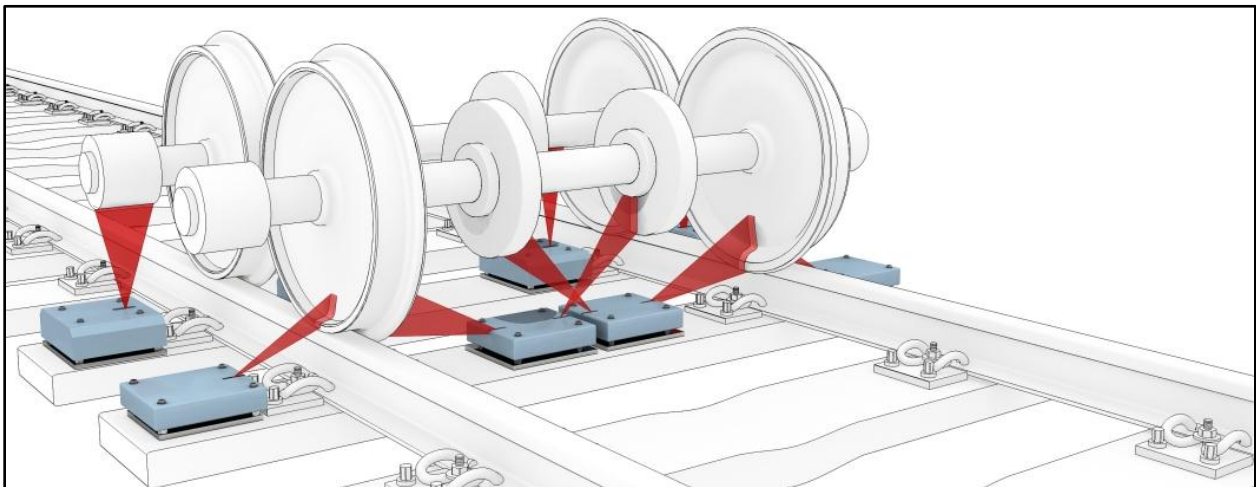


Figure 6: Illustration of a typical HBD installation with integrated wheel, and brake rim scanners [21].

In 2002, Union Pacific Railroad employed an algorithm that sorts all bearing temperatures on a train into statistical quartiles in order to identify bearings operating at significantly elevated temperatures, before they exceed AAR condemnable standards listed in Table 1 [22]. The advantage of this approach is that distressed bearings are identified before their condition necessitates immediate removal, allowing rail operators to perform more economical predictive maintenance. While this method is effective at identifying distressed bearings prior to failure, it has also resulted in a large number of non-verified bearings, which upon disassembly and inspection do not exhibit any apparent defects. Research conducted by the UTPA Railroad Research Team indicates that a significant percentage of non-verified bearings are set-out due to inaccurate infrared scanner readings. This inaccuracy is the consequence of a number of issues; namely, the scanner measures the bottom (unloaded portion) of the bearing cup, the emissivity of the cup can vary widely with dirt and grease deposits, and the scanner may read the temperature of the adjacent grease seal instead of the bearing cup, not to mention the uncertainty associated with calibrating these devices which usually only involves a one point calibration method.

2.3 Literature Review

2.3.1 On-Board Continuous Condition Monitoring

Although research has been conducted to promote communication between existing wayside detectors to develop a condition monitoring network, progress has been hindered due to divided ownership of track and wayside detector installations [5]. This has encouraged industry engineers to create an on-board bearing condition monitoring system that can be economically retrofitted to existing equipment.

Ideally, on-board condition monitoring of a roller bearing should entail a correlation of bearing temperature to railcar speed and load; this could potentially provide a more accurate method of identifying bearings operating at significantly elevated temperatures. If successful, this ideal monitoring system would even detect bearing defects at low speed operation when bearing temperatures are far below AAR condemnable standards. Furthermore, the sampling rate for the sensors in such a system would be increased dramatically in order to capture brief transient temperature trending events and accurately determine the bearing condition.

Unfortunately the sensors and instrumentation required to monitor railcar load, speed, and roller bearing temperatures is far too costly for widespread implementation in the field.

A more economically viable solution is to monitor only bearing temperature and compare an individual bearing's temperature with the performance of its peers and track these comparisons over time. This approach has been used with great success for monitoring wind turbine rotor and gearbox bearing elements [23].

2.3.2 Temperature Based Condition Monitoring

Recent efforts towards monitoring tapered roller bearing condition over an extended period of time involves storing readings from multiple consecutive HBDs in order to identify bearings that operate at higher temperatures than their peers for an extended period of time [5]. Using the existing network of approximately 5,000 HBDs is appealing for engineers and experts in the industry because of the relatively low cost to implement new monitoring algorithms. Another advantage of using stationary wayside detectors is their ability to scan many passing railcars with a single strategically placed wayside detector. The latter reduces the cost to scan each car compared to early on-board temperature monitoring systems. Unfortunately, the tradeoff for this lowered cost is reduced scanning frequency, which substantially lessens the

number of data points used to evaluate a bearing's condition. Decreasing the spacing between successive HBDs would require a dramatic increase in the number of wayside detectors nationwide, which will incur tremendous costs.

On-board bearing temperature monitoring systems have been developed and tested for both freight and passenger railcars with varying results. In 1970 Amtrak deployed wired bearing temperature sensors for their entire fleet of passenger cars, utilizing a simple temperature threshold of 93.3°C (200°F) algorithm, resulting in a significant reduction in bearing-related train delays and derailments [8]. Unfortunately, freight cars are used much differently than passenger cars, with freight cars being added and removed from a train at several stops along a specified route. Consequently, any wired monitoring system would be impractical because of the frequent connection and disconnection of sensor wiring required to change out railcars. A wireless system would have made the Amtrak system ideal; however wireless radios and battery systems of the time were unreliable and prohibitively expensive.

The DOT-STAR program was a research project initiated in 1980 with the intention of creating a system capable of continuously monitoring bearing temperatures in order to detect failures between wayside detector stations [10]. The system used a thermal sensor and a small explosive charge integrated into the bearing adapter as shown in Figure 7. A simple temperature threshold method was used to determine when the bearing temperature exceeded 250°F, triggering the explosive charge that activated the train's air brake system. Although this system was successful in field tests, it was not commercially viable due to the high equipment and installation costs associated with the non-reusable sensor design [24].

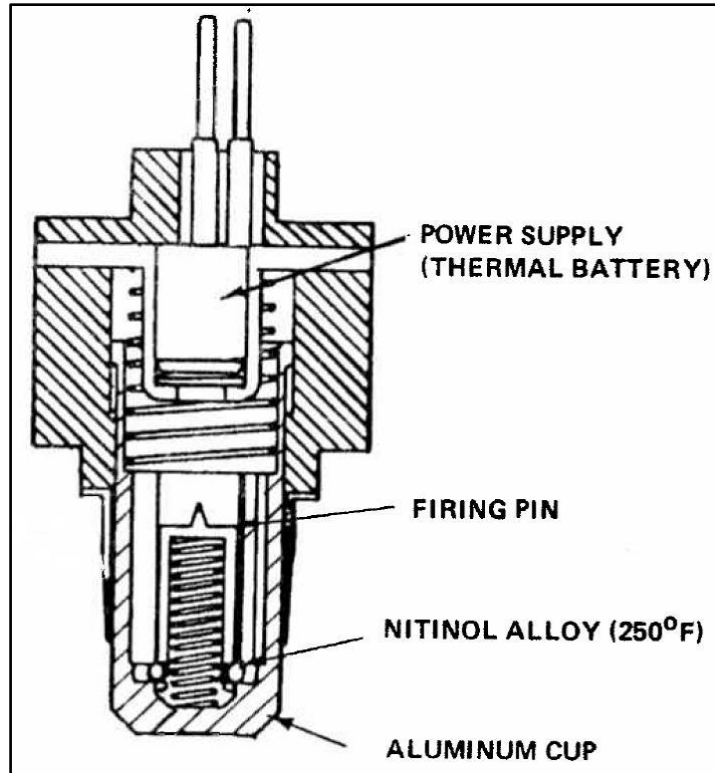


Figure 7: DOT-STAR thermal sensor design [10]

A similar initiative in 1990 produced the Smart-Bolt (Figure 8); a temperature sensor and wireless transmitter integrated into the bearing end cap bolt [9]. The wireless transmitter is intended to send an alert message to the locomotive in the event of an overheated bearing. The primary limitation of the Smart-Bolt is that the sensor measures the internal axle temperature and not the bearing cup temperature. Internal axle temperature lags far behind changes in bearing temperature and is affected by heat transfer to and from the adjacent train wheel depending on operating conditions. Furthermore, the electronic components are integrated within the end cap bolt and are subject to very high operating temperatures, above 200°C during extreme cases, which can destroy the radio transmitter and other critical electronic circuitry [24]. These factors, combined with the failure to obtain a satisfactory correlation between bearing cup and axle bolt temperatures, ultimately prevented wide-spread implementation.

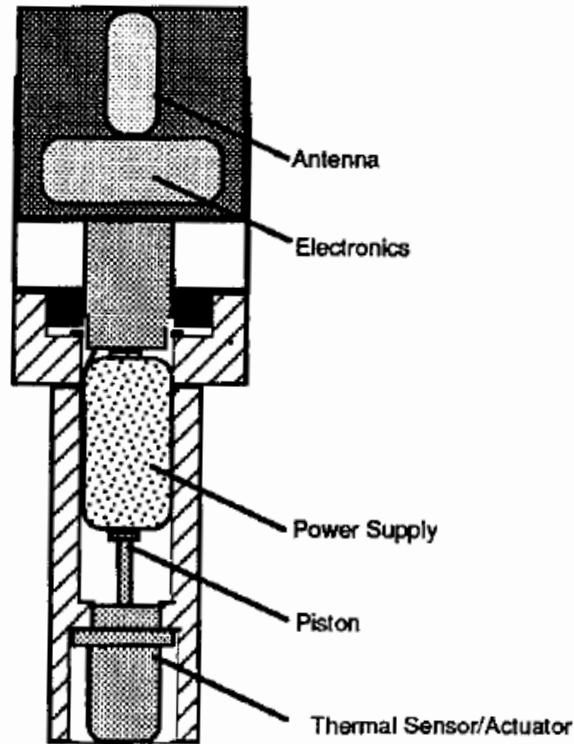


Figure 8: SMART-BOLT sensor prototype [9]

2.3.3 Frequency Domain Condition Monitoring

In recent years, vibration and acoustic sensor arrays have been developed by railroad industry engineers for defect detection in tapered roller bearings. Wayside acoustic microphone arrays are capable of early identification of defects before they grow large enough to cause the operating temperature to rise above HBD thresholds. Development of the Trackside Acoustic Detector System (TADS) was initiated by researchers at the Transportation Technology Center, Inc. (TTCI) in conjunction with the AAR in 1995 [25]. These detectors utilize computer algorithms to analyze the frequency domain characteristics of the bearing's acoustic signature. Although these systems can detect bearing defects before they become severe enough to cause overheating, some types of condemnable defects are not identifiable by acoustic detectors, such as incorrect grease fill, loss of grease, or geometric inconsistencies in the bearing raceways.

Furthermore, not all bearing defects identified by wayside acoustic detectors require removal by AAR standards.



Figure 9: Trackside Acoustic Detection System (TADS) [26]

Subsequent field testing indicated that the TADS (Figure 9) is most accurate for detection of mid-size roller and raceway defects. Additionally, TADS can detect these defects before they grow large enough to overheat and be detected by a HBD. Initial testing indicated that the TADS system became less accurate for detection of very large spalls, known in the railroad industry as “growlers” for the noise emitted during service, even though operating temperatures exceed AAR standards [27]. Subsequent research efforts improved the TADS algorithm to allow

for the detection of very severe growlers, though more research is required for the detection of small to mid-size growlers.

CHAPTER III

EXPERIMENTAL SETUP AND INSTRUMENTATION

This chapter provides a thorough description of the railcars used in the Australian field test as well as the sensors used to instrument those railcars for bearing temperature monitoring. Additionally, processing of temperature data acquired from the instrumented test fleet is discussed. Lastly, the laboratory equipment and procedures used to evaluate tapered-roller bearings removed from the Australian field test is presented.

3.1 Australian Test Fleet

Ten cars of an Australian railroad fleet were instrumented with IONX¹ Wireless Sensor Nodes (WSNs) in March 2010. Each railcar is equipped with eight Class E tapered-roller bearings making for a test fleet of 80 bearings. These railcars and bearings had been in active service for varying lengths of time prior to instrumentation, creating a test fleet composed of both healthy and potentially defective bearings. The test cars move freight between Perth and Melbourne, a round trip of approximately 4,000 miles through the hot deserts of remote Southern Australia (Figure 10) at speeds up to 120 km/h (74.6 mph). This remote section of track has only

¹ A subsidiary of Amsted Rail Industries, Inc. responsible for the development of asset monitoring technologies

one hot-box detector (HBD) and one Trackside Acoustic Detector System (TADS) installation, highlighting the need for an on-board condition monitoring system.

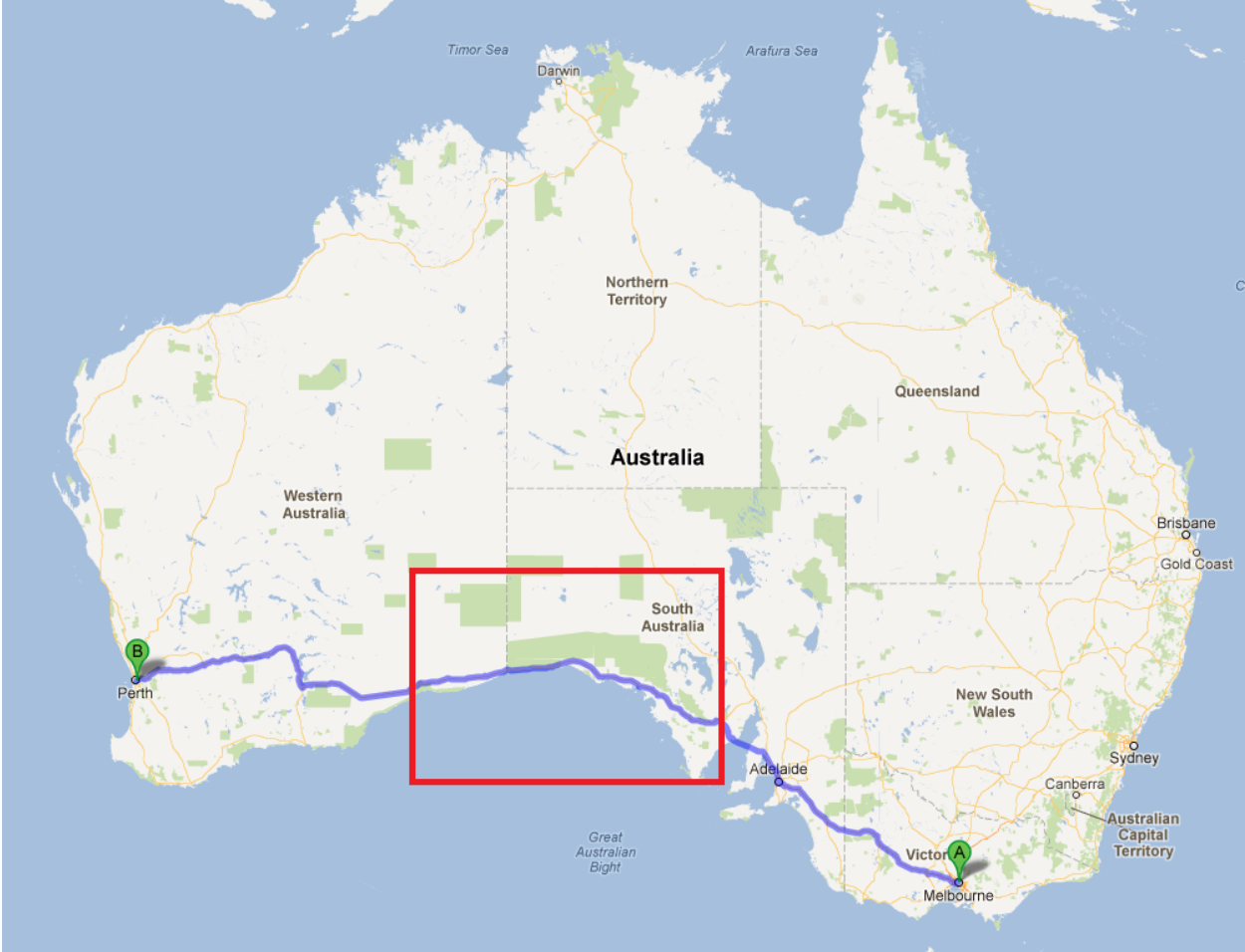


Figure 10: Map of Australia with the railroad track used by the test fleet highlighted in blue. The red box indicates territory that does not have cellular phone service.

3.2 WSN Design

IONX WSNs contain a temperature sensor, a microprocessor and related circuitry, a radio antenna, and a non-rechargeable battery encased in a weatherproof polymer housing. The temperature sensor used is a silicon based voltage output device attached to the end of a brass plug (Figure 11) selected for its high thermal conductivity. This configuration allows the temperature sensor to be safely imbedded in the core of the WSN, instead of being exposed near

the surface. The temperature sensor produces a low voltage DC signal that is processed through an 8-bit analog to digital (A/D) converter to produce a discrete integer value. This integer value, referred to herein as the number of “counts”, is then truncated to the nearest multiple of ten, and converted to a Celsius temperature. Once the bearing adapter temperature is calculated, the bearing cup temperature is estimated using a predetermined calibration function. Detailed analysis and development of the correlation between adapter surface and bearing cup temperatures is the main focus of a thesis by Zagouris [12].

All calculations required for A/D conversion and temperature correlations are performed by the imbedded microprocessor. WSNs sample the temperature sensor once every 15 seconds and average four consecutive readings to obtain an average bearing cup temperature over the past minute. The cumulative effect of reading the temperature sensor and the ensuing A/D conversion results in a theoretically calculated accuracy of approximately $\pm 6^{\circ}\text{C}$ ($\pm 10.8^{\circ}\text{F}$). The subsequent correlation of adapter surface temperature to bearing cup temperature increases the total uncertainty of the measurement to approximately $\pm 10^{\circ}\text{C}$ ($\pm 18^{\circ}\text{F}$) [12]. The bearing cup temperatures, acquired once per minute while the train is operating, are temporarily stored within the device’s internal memory until eight consecutive values are accumulated; at that time, they are transmitted via radio to the Communication Management Unit (CMU) on-board the railcar, which in turn sends this data wirelessly to specific computer servers.

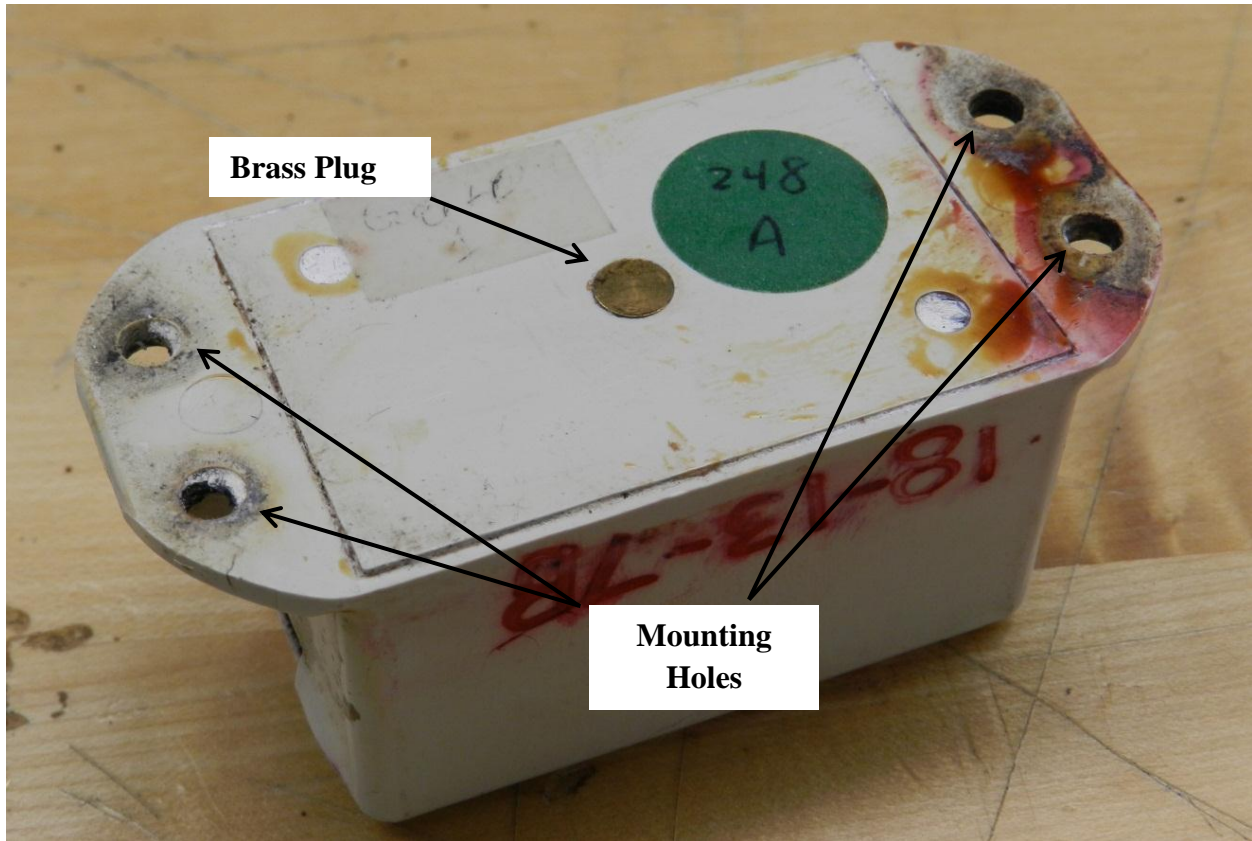


Figure 11: Bottom side of a WSN with the brass plug and mounting holes shown

3.3 WSN Field Installation

One WSN is mounted on each bearing adapter, as depicted in Figure 13, as well as one on the railcar undercarriage to record ambient temperature, for a total of nine WSNs per railcar. The WSNs are given identification numbers one through eight for the bearing positions shown in Figure 12, and WSN number nine for the ambient temperature sensor.

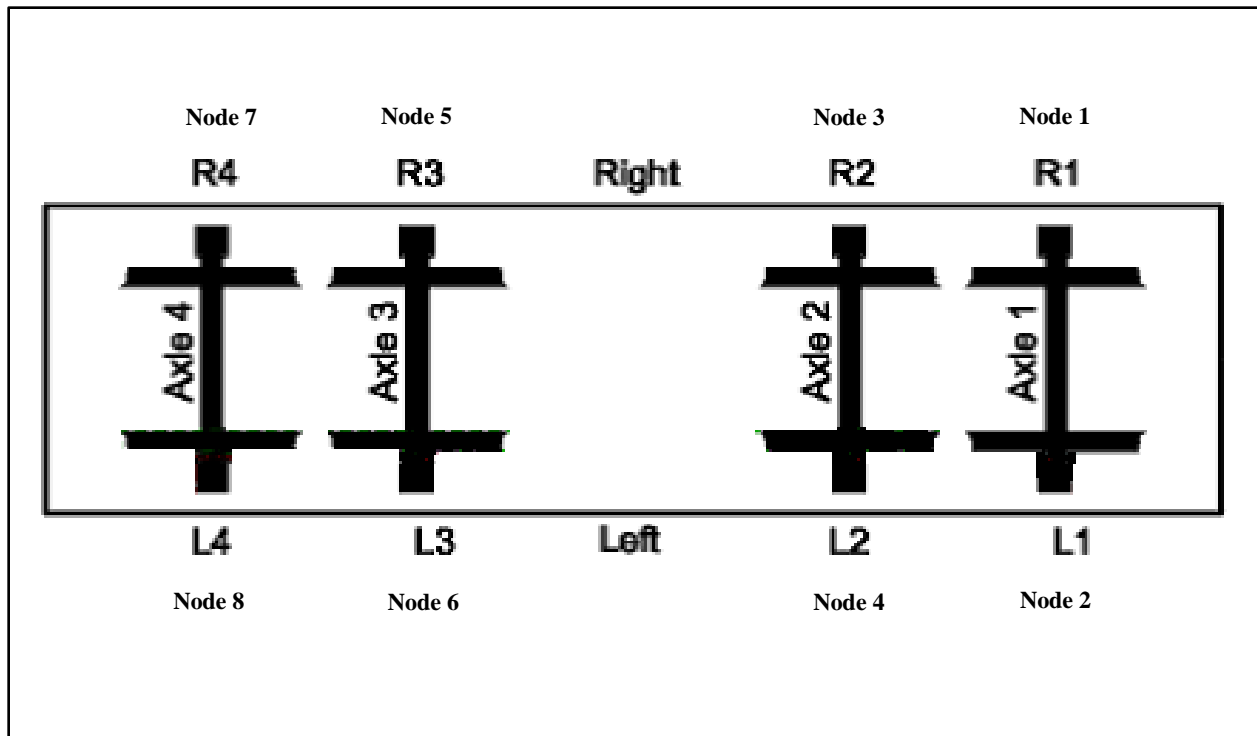


Figure 12: Diagram indicating the WSN ID numbers assigned to each railcar bearing location.

The WSNs are specifically designed to be easily retrofitted to existing railroad bearing adapters with minimum modifications. Mounting the WSN directly on the exterior surface of the bearing cup was considered, since it would allow for direct measurement of the bearing cup temperature without the need for calibration. However, this location is not suitable due to the tendency for the cup to rotate during field service. The momentary unloading of the bearing/adaptor contact when the car is traveling over uneven track causes this rotation of the bearing cup, known as *indexing* within the railroad industry. Hence, installation on the bearing adapter surface was selected for greater survivability of the WSN.

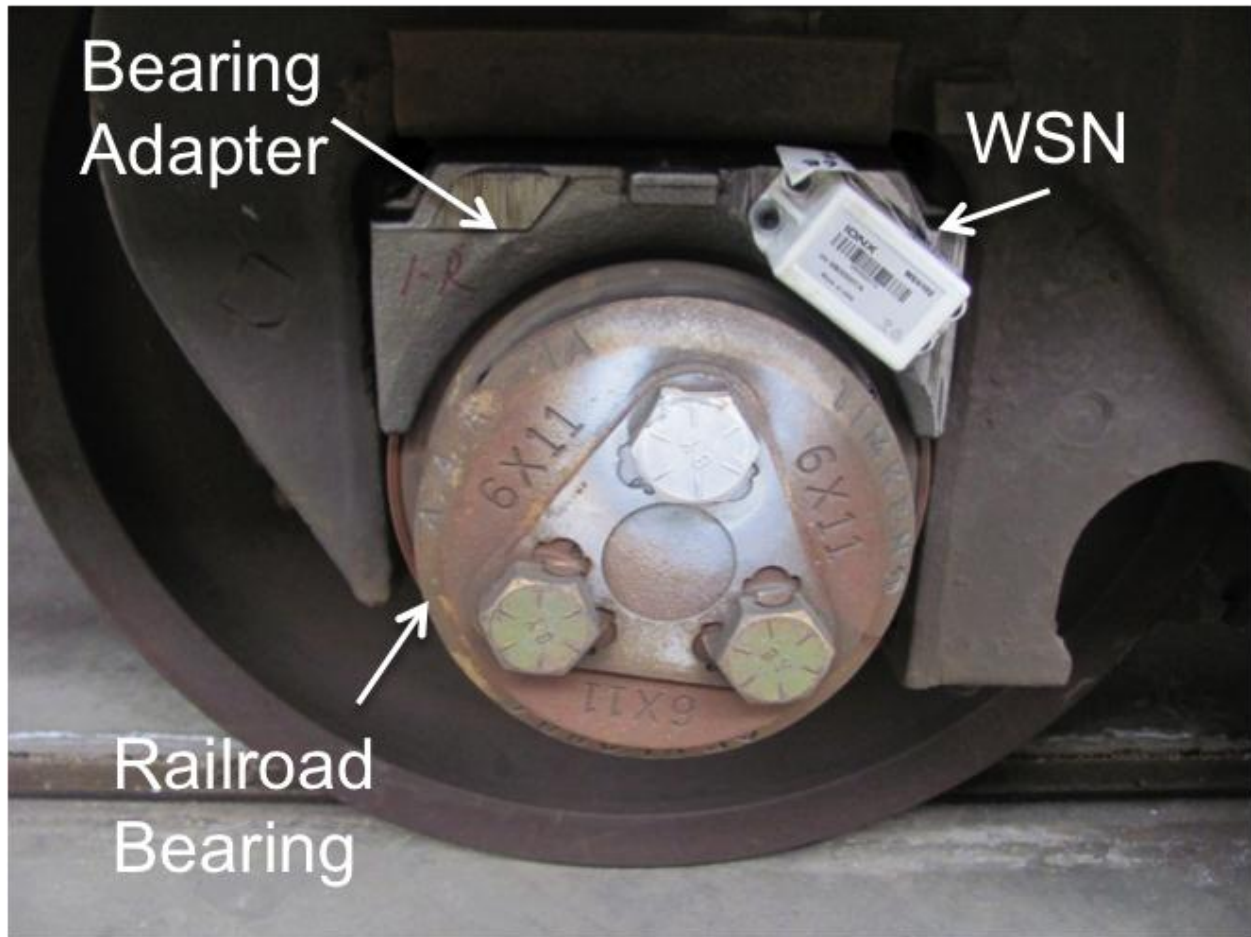


Figure 13: Typical field installation of Wireless Sensor Node [27]

Typical procedure utilized for field installation involves removing rust, dirt, and other debris from the adapter surface using a handheld grinder and wire wheel attachment. The latter is done to reduce the thermal contact resistance between the brass plug and the adapter surface, enhancing heat transfer to the sensor and improving the accuracy of the temperature readings. Following surface preparation, thermal epoxy is applied generously to the installation location, shown in Figure 14, to further reduce the thermal contact resistance. The WSN is then attached to the bearing adapter using four self-tapping metal screws driven through the device's bolt holes shown in Figure 11. The action of torquing the screws presses the WSN firmly against the adapter surface, thinning the epoxy layer. The installed WSN is given 24 hours for the thermal

epoxy to cure, improving thermal conductivity. This installation procedure results in a minimum thermal contact resistance between the temperature sensing device and the adapter surface which is critical for accurate temperature measurements.



Figure 14: Primed mounting surface with the thermal epoxy and mounting holes shown [12].

3.3 CMU Field Installation

Each railcar is equipped with one Communication Management Unit (Figure 15) with the purpose of maintaining radio communication with the nine WSNs, storing all temperature readings acquired from the WSNs, and transmitting the data from the railcar to the centralized data storage servers.



Figure 15: IONX CMU shown with mounting bracket [28]

The CMU has both cellular and satellite antennas mounted internally. This dual capability allows the unit to preferentially use the more economical cellular communication when service is available near developed areas. When the railcar is operating in remote areas without cellular service (Figure 10), satellite communication is used to transmit the temperature data as well as emergency alarm messages. The emergency alarms are generated anytime the bearing cup temperature exceeds the AAR standards (Table 1), requiring a train to be slowed or stopped to avoid catastrophic bearing failure. In order to facilitate reliable cellular and satellite communication, the CMU is mounted near the top of the railcar, as shown in Figure 16.



Figure 16: Field installation of IONX CMU on a freight car [28]

3.4 Pre-Processing Of Raw Data

Bearing cup temperature data is downloaded from centralized data storage servers in a formatted Comma Separated Value (.csv) file. This file format is selected because it is easily read by Microsoft Excel®, Notepad®, and can be readily imported using MATLAB™ for processing and analysis. By default, the raw data is sorted first by WSN sensor ID number, and second by timestamp in ascending order as shown in Table 2.

Table 2: Format of temperatures downloaded from data storage servers

Railcar ID	Date	Sensor ID	Temp (°F)
PBGY0050U	8/1/2011 15:00:15	1	81.016
PBGY0050U	8/1/2011 15:01:21	1	81.016
PBGY0050U	8/1/2011 15:02:33	1	81.016
PBGY0050U	8/1/2011 15:03:41	1	81.016
PBGY0050U	8/1/2011 15:04:43	1	83.608
PBGY0050U	8/1/2011 15:05:35	1	83.608
PBGY0050U	8/1/2011 15:00:05	2	81.016
PBGY0050U	8/1/2011 15:01:09	2	83.608
PBGY0050U	8/1/2011 15:02:24	2	83.608
PBGY0050U	8/1/2011 15:03:19	2	83.608
PBGY0050U	8/1/2011 15:04:30	2	86.2
PBGY0050U	8/1/2011 15:05:49	2	86.2
PBGY0050U	8/1/2011 15:00:36	3	78.424
PBGY0050U	8/1/2011 15:01:49	3	78.424
PBGY0050U	8/1/2011 15:02:14	3	78.424
PBGY0050U	8/1/2011 15:03:26	3	81.016
PBGY0050U	8/1/2011 15:04:15	3	81.016
PBGY0050U	8/1/2011 15:05:40	3	83.608

The WSN reporting times are not synchronized, meaning that the timestamps for temperature readings from all nodes vary by several seconds within the same minute. The latter requires that the raw data be sorted and reordered so that all bearing temperatures acquired at approximately the same time are stored together on one row of a comprehensive data array (Table 3). This process is accomplished using the MATLABTM program *data_sorter_v4* provided in the Appendix that first, rounds all timestamps to the nearest minute, next, searches for unique temperature timestamps, and then finds all temperatures recorded within each minute. All temperatures acquired within one minute are then stored on a single row for that timestamp, as shown in Table 3.

Table 3: Temperature data format after processing, with the Node ID numbers corresponding to bearing locations as depicted in Figure 12.

Date	Node# 1	Node# 2	Node# 3	Node# 4	Node# 5	Node# 6	Node# 7	Node# 8	Ambient
8/1/2011 15:00	81.06	81.03	78.424	83.608	75.832	78.424	81.016	78.424	65
8/1/2011 15:01	81.06	83.608	78.424	83.608	75.832	78.424	81.016	78.424	65
8/1/2011 15:02	81.06	83.608	78.424	83.608	75.832	78.424	81.016	81.016	65
8/1/2011 15:03	81.06	83.608	81.016	86.2	78.424	78.424	81.016	78.424	65
8/1/2011 15:04	83.608	86.2	81.016	86.2	78.424	81.016	83.608	81.016	65
8/1/2011 15:05	83.608	86.2	83.608	86.2	78.424	81.016	83.608	81.016	65

This ordered dataset allows calculation of the mean temperature for all bearings at the same time (row-wise average) and mean temperature for a single bearing during a selected timespan (column-wise average). Additionally, this reordered dataset facilitates a computationally efficient generation of temperature vs. time plots, statistical analysis, and other numerical operations using MATLAB™.

WSN power supply failures cause the CMU to interpret the WSN signal as a zero-voltage reading and the resulting A/D conversion algorithm produces readings of approximately -97°F, or -95°F for bearing cup temperatures, or 0°F for ambient temperatures as shown in Table 4. Moreover, radio communication failure between the WSN(s) and CMU results in no data being recorded, while other nodes on the same car are actively recording and transmitting. The latter leaves gaps in the sorted data set. The missing data is not used in the analysis algorithms;

however, the number of missing readings in the data set is noted and used to evaluate the reliability of the WSNs.

Table 4: Example of ordered dataset with erroneous temperature readings highlighted in yellow.

Time	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7	Node 8	Ambient
2011/06/30 22:42	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	0
2011/06/30 22:43	130.26	125.08	-95.24	104.34	140.63	145.82	-95.24	86.2	60
2011/06/30 22:44	130.26	125.08	-95.24	104.34	140.63	145.82	-95.24	86.2	60
2011/06/30 22:45	132.86	127.67	-95.24	104.34	140.63	145.82	-95.24	86.2	60
2011/06/30 22:46	132.86	127.67	-97.832	104.34	143.22	145.82	-97.832	86.2	60
2011/06/30 22:47	130.26	125.08	-97.832	106.94	143.22	145.82	-97.832	86.2	60
2011/06/30 22:48	130.26	125.08	-97.832	104.34	140.63	145.82	-97.832	86.2	60
2011/06/30 22:49	130.26	125.08	-97.832	104.34	140.63	145.82	-97.832	86.2	60
2011/06/30 22:50	127.67	125.08	-97.832	104.34	140.63	145.82	-97.832	86.2	60
2011/06/30 22:51	127.67	125.08	-97.832	104.34	140.63	145.82	-97.832	86.2	60
2011/06/30 22:52	127.67	125.08	-97.832	104.34	140.63	145.82	-97.832	86.2	60
2011/06/30 22:53	130.26	125.08	-97.832	104.34	140.63	145.82	-97.832	86.2	60
2011/06/30 22:54	130.26	125.08	-97.832	104.34	140.63	145.82	-97.832	86.2	60
2011/06/30 22:55	130.26	125.08	-97.832	104.34	140.63	143.22	-97.832	-97.832	60
2011/06/30 22:56	127.67	122.49	-97.832	-97.832	-97.832	143.22	-97.832	-97.832	60
2011/06/30 22:57	-97.832	122.49	-97.832	-97.832	-97.832	143.22	-97.832	-97.832	60
2011/06/30 22:58	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	60
2011/06/30 22:59	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	60
2011/06/30 23:00	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	61
2011/06/30 23:01	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	61
2011/06/30 23:02	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	-97.832	0

The locations of the erroneous temperature readings shown in Table 4 are identified by logical filters implemented using the MATLABTM program *data_sorter_v4*, and subsequently removed from the dataset. The reordered and filtered temperature data is analyzed using the methods presented in Chapter IV to assess the current condition of field test bearings and identify degradation in condition over time. Based on the results of these analyses, two bearings were selected for removal from active service and sent to UTPA for laboratory testing,

disassembly, and detailed visual inspection to determine the cause of the elevated operating temperatures.

3.5 Laboratory Testing of Railroad Bearings

The dynamic bearing tester, related instrumentation and data acquisition used for laboratory testing of bearings removed from active service is described in this section. The results of testing and cause of elevated operating temperatures observed in the field are discussed in Chapter V.

3.5.1 Dynamic Bearing Tester

The bearing tester housed at UTPA is designed to accommodate four tapered-roller bearings on a customized axle. The axle is driven using a 30 horsepower Baldor-Reliance Inverter Drive Motor (IDM 4104T) controlled by a Hitachi Variable Frequency Drive (Model SJ700-22) and coupled to the test axle using a V-belt and pulley system, as shown in Figure 17. This configuration allows for testing of the bearings at a range of speeds from 0 to 138.4 km/h (0 to 86mph). Additionally, the Hitachi motor controller is configured to output the motor torque, speed, and power consumption to the data acquisition system, allowing for comprehensive monitoring of the bearings during testing. Forced convection over the bearings is achieved using two 30" fans that produce air flow with an average speed of 5 m/s (11.2 mph). Vertical load is applied to the test axle using a 7" bore hydraulic cylinder capable of applying loads from 0 to 150% of a bearing's rated load capacity. For the Class E bearings tested, 100% load corresponds to 116,988 N (26,300 lb_f) per bearing.



Figure 17: Dynamic bearing tester used for laboratory experiments conducted at UTPA

3.5.2 Dynamic Bearing Tester Instrumentation

The Class E bearing adapters used to support the test axle are specifically machined at UTPA to accommodate temperature and vibration sensors, allowing for a comprehensive evaluation of the bearing performance during operation, as well as detection of degradation in condition. Three K-type thermocouples are installed on each bearing; two are bayonet-type and one is standard-wire version (Figure 18). The two bayonet thermocouples, which are centered on each cup raceway, are affixed to the bearing adapter and utilize a spring-loaded mount to maintain contact with the bearing cup. The standard-wire thermocouple is centered between the

two cup raceways and is secured using a hose clamp. Additionally, two standard-wire K-type thermocouples are used to monitor the ambient temperature of the air flow in front of and behind the test axle.

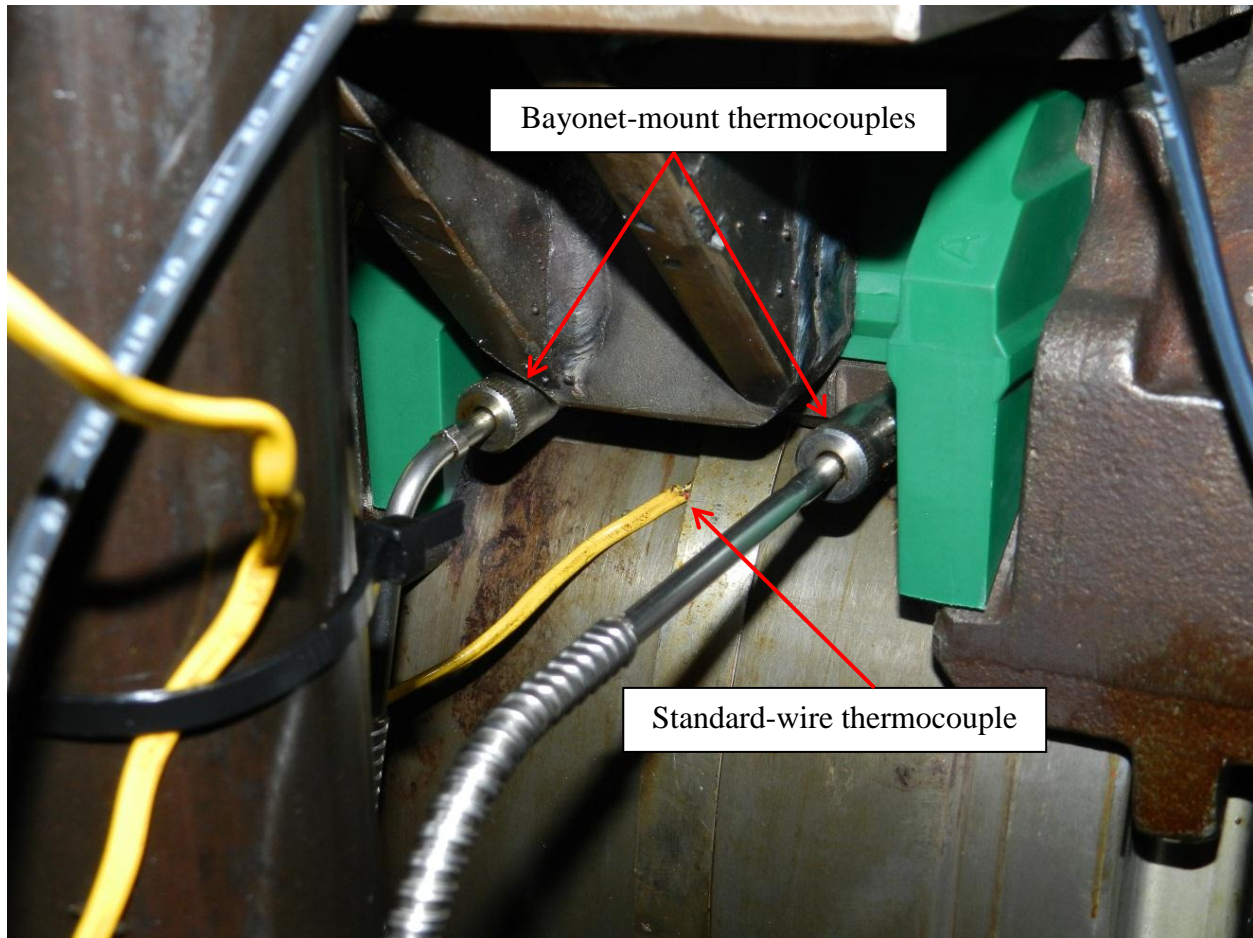


Figure 18: Sensor placement on the bearing cup with the bayonet-mount and the standard-wire thermocouples shown

Each bearing adapter is machined to accommodate one accelerometer used to capture the vibration signature of the bearing in the radial direction. The accelerometers used (PCB Piezotronics, Inc. – Model 355B02) are single axis units with a measurement range of ± 500 g and a maximum sampling frequency of 10 kHz. Data recorded from the accelerometers are processed using Fast Fourier Transform (FFT) and Power Spectral Density (PSD) techniques to

determine the intensity of vibration at specific frequencies which are known indicators of bearing condition.

The data acquisition hardware used is a National Instruments® NI cDAQ-9174 chassis with the following cards installed; one NI 9213 card connected to all fourteen thermocouples, one NI 9234 card reading four accelerometers, and one NI cRIO-9215 card to record the motor speed and power consumption signals from the Hitachi motor controller. LabView® software is used to collect and record data from the NI hardware, while MATLAB™ is utilized exclusively for post-processing and analysis of the acquired laboratory test data.

CHAPTER IV

DEVELOPED CRITERIA AND STATISTICAL METRICS

This chapter introduces *five* statistical criteria that are used to assess the thermal performance of tapered-roller bearings in the Australian SCT Logistics test fleet. These criteria are arranged into three alarm levels; the most urgent alarms, termed Level 1, are consistent with current Association of American Railroads (AAR) standards that are listed in Table 1 of Chapter II, Level 2 alarms are less urgent and used to schedule maintenance within 1-3 months, while Level 3 alarms are utilized to create a watch-list of potentially problematic bearings that require close monitoring.

4.1 Level 3 Criteria

The Level 3 Criteria presented in this section utilize statistical metrics to quantify a bearing's thermal performance. These criteria analyze absolute bearing temperature, bearing-ambient temperature differential, time rate of change of bearing temperature, as well as deviation of a bearing's operating temperature from the average temperature of the railcar, and deviation from the average temperature of the entire train. The developed Criteria identify bearings exhibiting atypical behavior by comparing the performance of a single bearing to fixed thresholds that are carefully selected based on analyses of SCT Logistics Australian field test data, current AAR standards, and extensive laboratory testing of tapered-roller bearings. The

thresholds selected for use with these methods are summarized in Table 5 and are presented in detail in Section 4.2.

Table 5: Summary of the thresholds used with Level 3 analyses and the selected threshold values

Threshold	Criterion Used	Selected Threshold Value
T_{limit}	Criterion 1 – Absolute bearing temperature limit	93.3°C (200°F)
ΔT_{limit}	Criterion 2 – Bearing-Ambient temperature differential limit	66.7°C (120°F)
–	Criterion 3 – Deviation from average of railcar operating temperatures	No Threshold Used
–	Criterion 4 – Deviation from average of train operating temperatures	No Threshold Used
$\frac{dT_i}{dt}_{limit}$	Criterion 5 – Time rate of change of bearing temperature limit	0.69°C/min (1.25°F/min)

The analysis of bearing temperature data is performed at regular intervals to assess bearing condition and identify degradation occurring in service. All bearings in the test fleet are analyzed and ranked using the five developed criteria to create a watch list of potentially unhealthy bearings that require close monitoring and may be considered for regularly scheduled maintenance.

4.1.1 Level 3 Criterion 1

Currently, the primary method utilized for health monitoring of tapered-roller bearings is measurement of bearing cup temperatures by hot-box detectors (HBDs). Considering that all bearings on a railcar are operating at the same speed, load, and ambient temperature, it is expected that bearings of comparable condition would operate at similar temperatures.

Preliminary analysis of the performance of railcar bearings consists of a visual inspection of temperature vs. time plots generated using the MATLAB™ program *RailcarTempPlot* provided

in the Appendix. The goal of this inspection is to identify bearings that are either operating at high temperatures for extended periods or operating significantly warmer than other bearings on the same railcar.

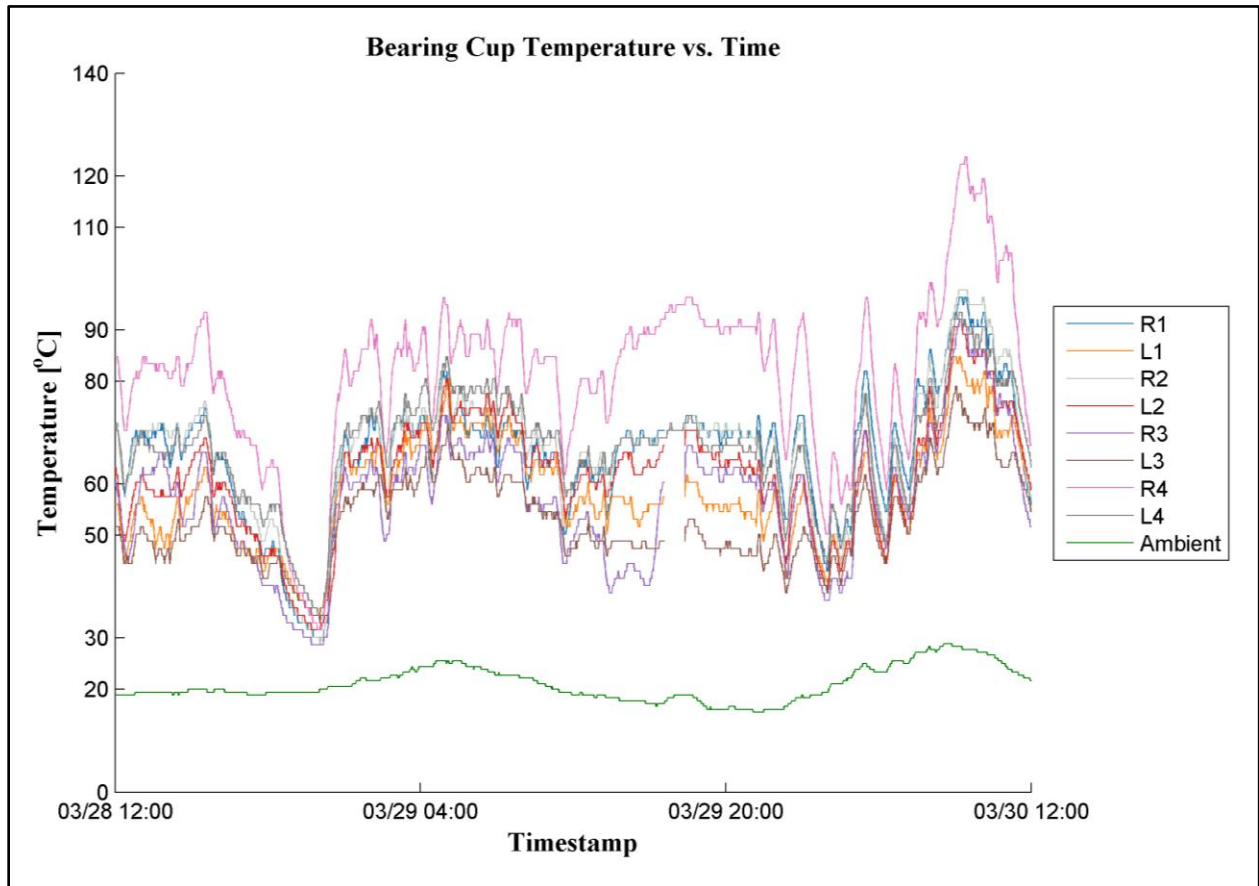


Figure 19: Plot of temperature vs. time for railcar PBGY0112N (March 28-30, 2010).

Figure 19 depicts the temperature history for railcar PBGY0112N between March 28, 2010 and March 30, 2010, and is representative of temperature vs. time plots generated for other railcars in the test fleet. The frequent rise and fall of the bearings' operating temperatures is a result of several factors; changes in the train's speed on different sections of the track, fluctuations in ambient temperature, train braking system engagement and release, and the presence or absence of sunlight warming bearings during the day. Figure 19 demonstrates that the bearing in the R4 position consistently operates 30-40°F warmer than the next hottest

bearing, and 80-90°F hotter than the coolest bearing on the same railcar. This deviation from the thermal performance of its peers is significant considering that all bearings shown are operating at the same speed, ambient temperature, and load; indicating that this bearing is likely to be unhealthy (possibly defective). Based on the performance depicted in Figure 19, the bearing in the R4 position was selected for removal from railcar PBGY0112N shortly after instrumentation of the railcars in March 2010.

Visual inspection of temperature histories proved to be effective in identifying abnormal behavior. However, this manual inspection procedure is time consuming and is not feasible for monitoring a large number of railcars. Additionally, this procedure cannot be performed in real time on a railcar in active service. In order to quantify the frequency of high temperature operation for each bearing, the percentage of temperature readings exceeding a fixed temperature threshold is calculated, according to Eq. (4.1),

$$Criterion\ 1 = \frac{N\{T_i \geq T_{limit}\}}{N\{T_i\}} \times 100\% \quad (4.1)$$

where $N\{T_i \geq T_{limit}\}$ is the number of bearing temperature readings exceeding the threshold T_{limit} , and $N\{T_i\}$ is the total number of temperature readings collected during the timespan being evaluated.

4.1.2 Level 3 Criterion 2

Bearing-ambient temperature differential is also monitored as an indicator of bearing health. Currently, this temperature differential is measured by HBDs and compared to a temperature threshold put in place by the AAR in order to identify potentially unhealthy bearings. The value of monitoring temperature differential is that it effectively normalizes bearing cup temperatures with respect to the ambient temperature, whereas absolute bearing temperature is affected by fluctuations in ambient conditions. This Criterion allows for the

detection of bearings exhibiting signs of distress before the absolute temperature increases to levels that can cause the bearing to seize and fail catastrophically. Visual inspection of bearing-ambient temperature differential plots is employed in order to identify bearings consistently exhibiting elevated temperature differentials. Figure 20 illustrates the bearing-ambient temperature differential for railcar PBGY0112N during the same timespan depicted in Figure 19.

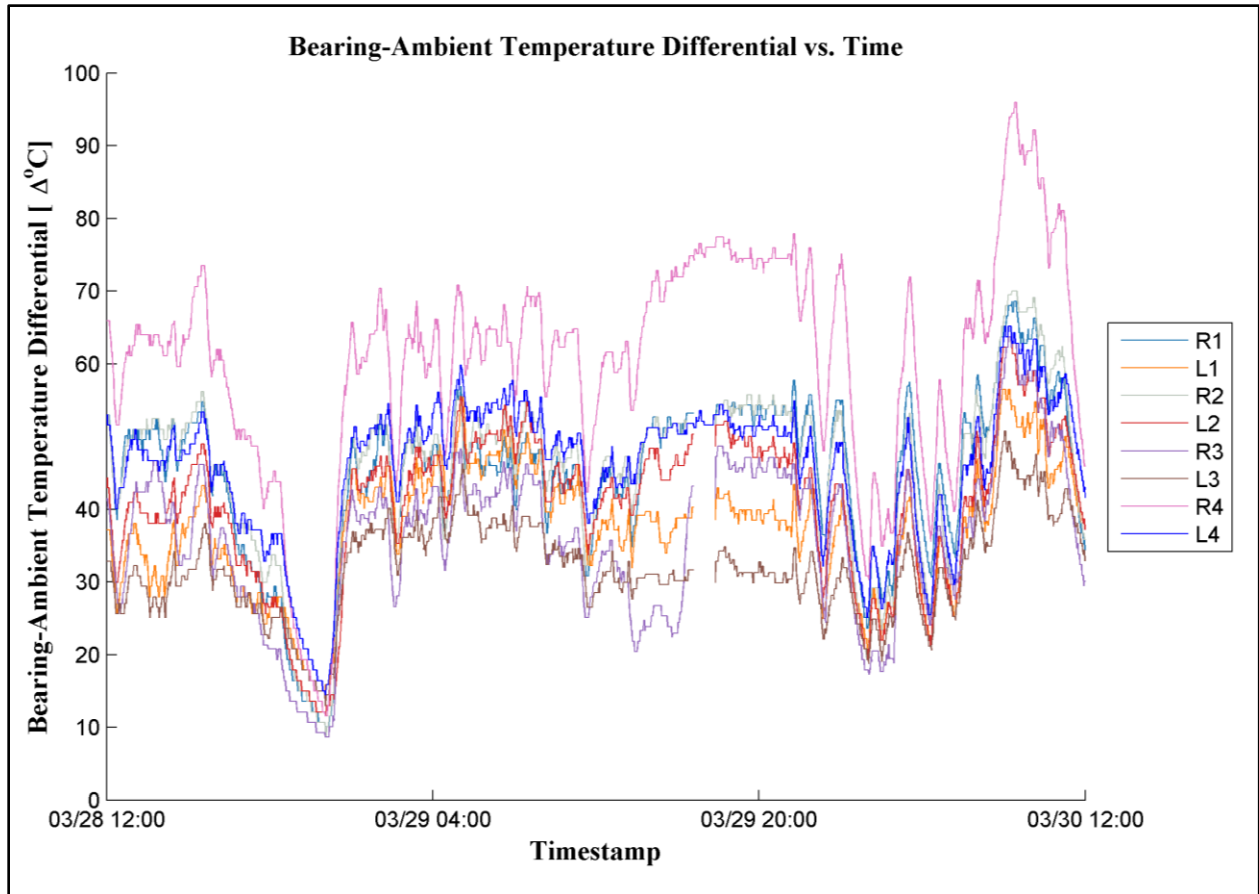


Figure 20: Plot of bearing-ambient temperature differential vs. time for railcar PBGY0112N (March 28-30, 2010).

This visual inspection procedure is quantified by calculating the percentage of bearing-ambient temperature differential readings exceeding a predetermined threshold, as shown in Eq. (4.2).

$$Criterion\ 2 = \frac{N\{\Delta T_i \geq \Delta T_{limit}\}}{N\{\Delta T_i\}} \times 100\% \quad (4.2)$$

where $N\{\Delta T_i \geq \Delta T_{limit}\}$ is the number of bearing temperature differential readings exceeding the threshold ΔT_{limit} , and $N\{\Delta T_i\}$ is the total number of temperature differential readings collected during the timespan being evaluated.

4.1.3 Level 3 Criteria 3 and 4

Fluctuations in absolute temperature and bearing-ambient temperature differential, as shown in Figure 19 and Figure 20, respectively, are affected by changes in the train's speed and the condition of the track. Without monitoring the train speed and track condition, it is not possible to determine the effect of these factors on a bearing's thermal performance. However, knowing that all bearings on one railcar operate at the same speed and experience similar excitation from the track, it is reasonable to expect that bearings of similar condition would exhibit comparable operating temperatures. Furthermore, bearings whose operating temperatures deviate significantly from their peers should be considered for detailed monitoring and possible maintenance.

Comparative distributions are utilized to visually describe the statistical distribution of temperature readings acquired from a single bearing and compare that with the distribution of temperature readings for the remaining seven bearings on the same railcar. These plots are generated by grouping temperature readings into bins with a fixed width of 2.78°C (5.0°F) for a single bearing on the railcar, as well as for the group composed of the remaining seven bearings on that same railcar. This bin width is selected in order to maximize the accuracy of the resulting distribution. This process is repeated for each of the eight bearings on the railcar, and all eight comparative distributions are grouped by axle and railcar side of the respective bearings, similar to the layout of bearing placement on the railcar illustrated in Figure 12 (Chapter II).

An example of a comparative distribution is presented in Figure 21, and is generated from data acquired from railcar PBGY0130L during the first six months of the Australian field test. In Figure 21, the red line represents the distribution of temperature readings for a single bearing, while the blue line describes the distribution of temperature readings acquired from the remaining seven bearings on that railcar. The distribution of temperature readings acquired from bearings experiencing atypical operation will be skewed to the left for lower than average operating temperatures, or to the right for above average temperatures.

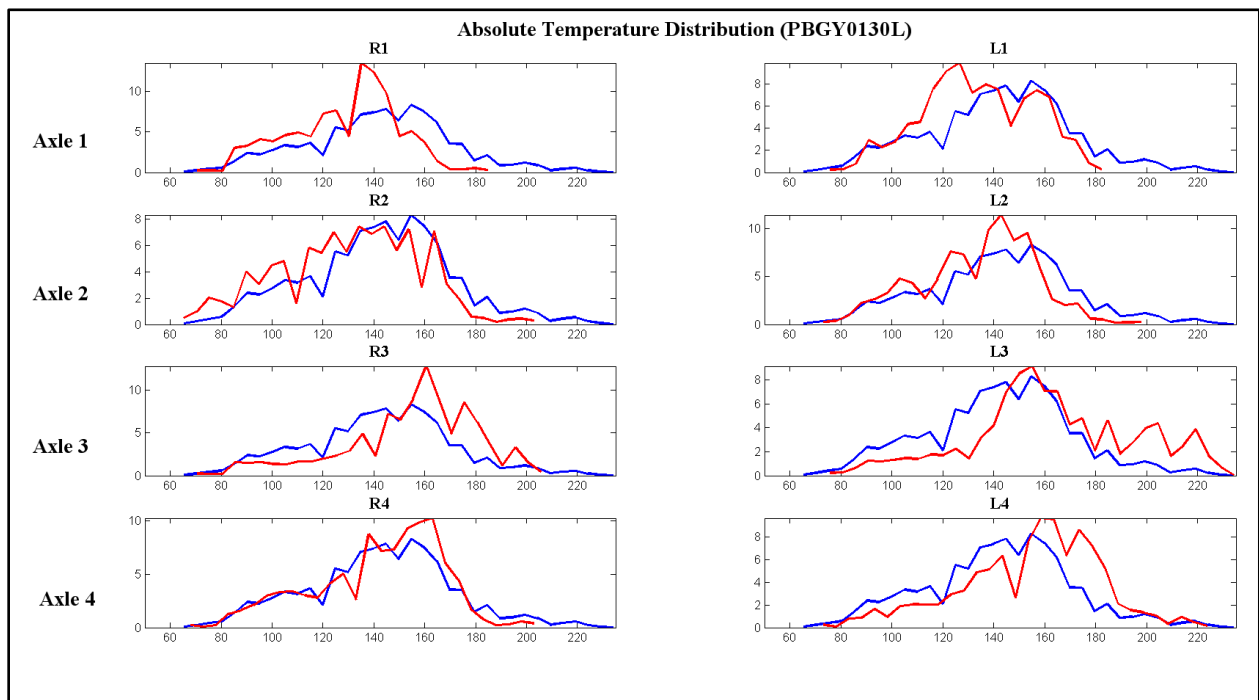


Figure 21: Comparative distribution showing bearing temperature ($^{\circ}\text{F}$) distribution in red and railcar temperature ($^{\circ}\text{F}$) distribution in blue.

Figure 21 demonstrates that several bearings exhibit a clear tendency towards relatively low temperature operation, when compared with their peers, whereas, others consistently operate at higher temperatures. For example, temperature readings acquired from the bearings in the L3 and L4 positions display a peak above and to the right of the blue railcar distribution, indicating higher than average operating temperatures. Conversely, L1 and R2 exhibit a greater number of

lower than average temperature readings, as indicated by the red line peaking to the left of the railcar distribution. It is important to note that the statistical distributions shown in Figure 21 portray the behavior of eight bearings on the same railcar, which are simultaneously subjected to the same operating speed, loads, ambient temperatures, and track excitation sources.

A quantified statistical comparison between bearings on a railcar is made in terms of the deviation of a single bearing's average temperature from the average temperature of its peers, and this is compared to the standard deviation of the peer bearings. This quantity is calculated using Eq. (4.3),

$$Criterion\ 3 = \frac{\bar{T}_i - \bar{T}_{car}}{\sigma_{car}} \quad (4.3)$$

where \bar{T}_i is the average operating temperature of an individual bearing over a predetermined time span, \bar{T}_{car} is the average temperature of the remaining seven bearings on the railcar over the same time span, and σ_{car} is the standard deviation of the remaining seven bearings. This quantity describes the number of standard deviations that one bearing varies from its peers.

The information gathered using Criterion 3 allows for identification of bearings exhibiting a significant and consistent tendency towards elevated operating temperatures, without waiting to exceed any fixed temperature thresholds. However, the use of eight bearings on a railcar represents a relatively small sample population and may be influenced by mechanical or environmental factors affecting all bearings on that railcar. Considering this possibility, the practice utilized for Criterion 3 is expanded to include all bearings on the same train, in order to obtain a larger sample population that is less susceptible to the previously mentioned factors. This statistical measure is calculated using Eq. (4.4),

$$Criterion\ 4 = \frac{\bar{T}_i - \bar{T}_{train}}{\sigma_{train}} \quad (4.4)$$

where \bar{T}_i is the average temperature of one bearing over a specified time span, \bar{T}_{train} is the average temperature of the remaining bearings on the train over the same time span, and σ_{train} is the standard deviation of the remaining bearings on the train.

4.1.4 Level 3 Criterion 5

Abrupt increases in bearing temperature, known within the railroad industry as *temperature trending*, has been shown by Maldonado [29] to be indicative of abnormal operation in tapered-roller bearings. However, the transient nature of these brief thermal events makes detection by stationary HBDs unlikely, whereas, on-board temperature monitoring is well-suited for observation of this phenomenon. In order to estimate the time rate of change of temperature increase in field service bearings, a linear curve fit is applied to an eight minute window of temperature data. The percentage of operating time that a bearing is experiencing rapid heating is calculated using Eq. (4.5),

$$Criterion\ 5 = \frac{N\left\{\frac{dT_i}{dt} \geq \frac{dT_i}{dt\ limit}\right\}}{N\left\{\frac{dT_i}{dt}\right\}} \times 100\% \quad (4.5)$$

where $N\left\{\frac{dT_i}{dt} \geq \frac{dT_i}{dt\ limit}\right\}$ is the number of heating rate values exceeding the threshold $\frac{dT_i}{dt\ limit}$, and $N\left\{\frac{dT_i}{dt}\right\}$ is the total number of heating rate values acquired for a single bearing over a specified time period.

4.2 Determination of Level 3 Thresholds

The temperature thresholds selected for Level 3 Criteria are based in part on AAR standards, statistical analyses of field test data, and insights gained from extensive laboratory testing. Additionally, one bearing was removed from the R4 position of railcar PBGY0112N shortly after instrumentation for excessively high operating temperature and significant deviation

from the performance of the remaining seven bearings on that railcar (see Figure 19 and Figure 20). Subsequent laboratory testing at UTPA demonstrated that this bearing did consistently operate at higher temperatures than its peers and a detailed visual inspection revealed that this bearing's internal clearance was not within the allowable nominal range set by AAR standards. Chapter V provides a detailed analysis of the disassembly and subsequent inspection of this specific bearing. The performance of this bearing during field service is used extensively as a benchmark for selection of other unhealthy bearings.

MATLABTM is used to process more than twenty-four million temperature readings collected over eighteen months of monitoring the instrumented test fleet. Histograms are generated that depict the statistical distribution of bearing cup temperature, bearing-ambient temperature differential, and approximate rate of temperature increase in order to determine appropriate thresholds that identify the worst performing bearings within the test fleet.

4.2.1 Criterion 1 Threshold

The statistical distribution of all bearing temperatures obtained from eighteen months of field testing is depicted in Figure 22. Bearing temperature readings are grouped into fixed width bins of 2°C (3.6°F), this bin size was selected in order to maximize the resolution of the ensuing histograms. MATLABTM is used to calculate the temperature thresholds that identify the hottest 5%, 2%, and 1% of the data points acquired. For the SCT Logistics Australian field test data considered here, the 5%, 2%, and 1% thresholds are approximately 71°C (159.8°F), 82°C (179.6°F), and 86°C (186.8°F), respectively. Based on this statistical analysis, combined with the performance benchmark set by PBGY0112N-R4, the Criterion 1 temperature threshold (T_{limit}) of 93.3°C (200°F) is selected. This temperature threshold identifies the warmest 0.3% of the

entire dataset acquired from the test fleet; therefore, any bearing whose operating temperature consistently exceeds this threshold is likely to have some defect (abnormality) present.

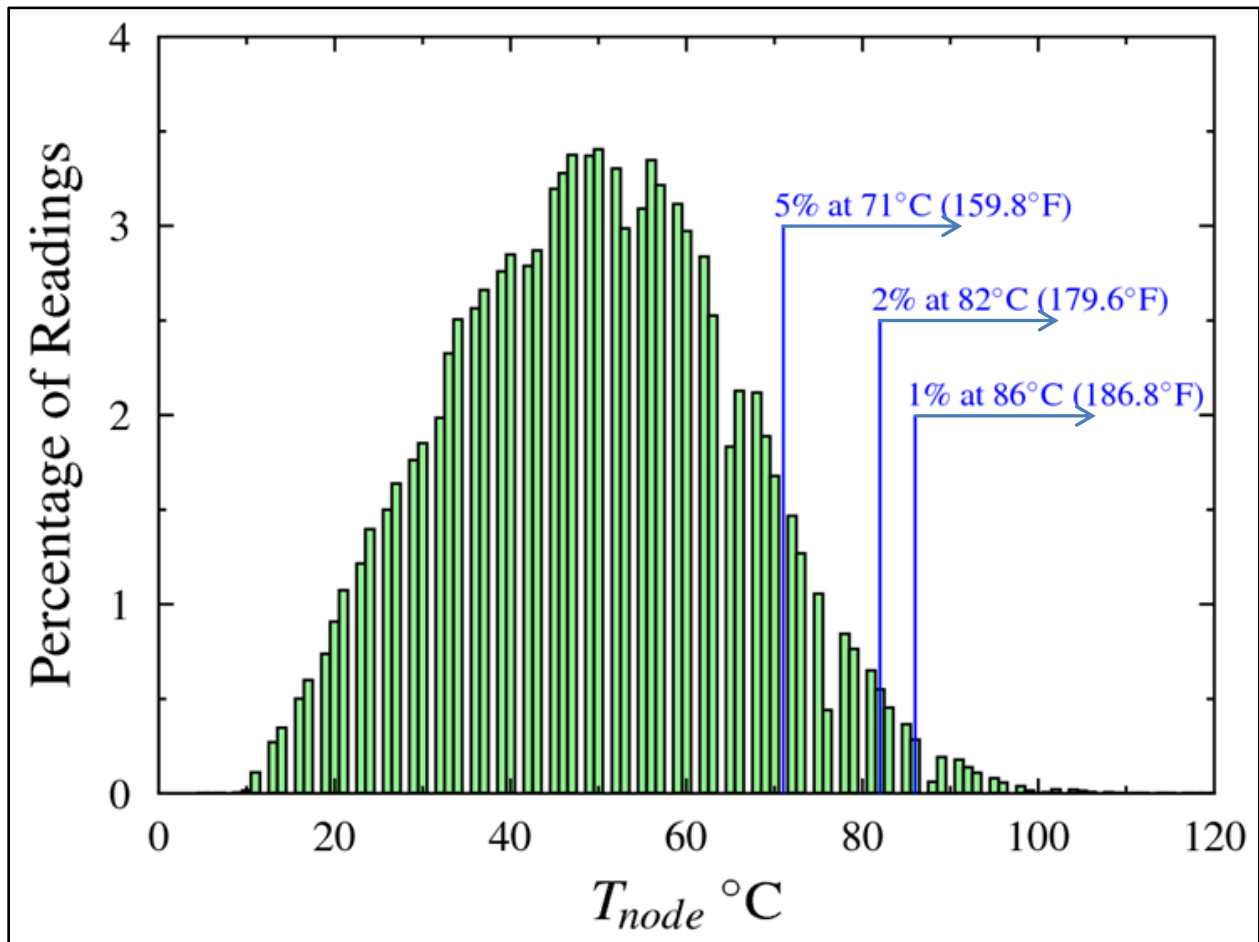


Figure 22: Statistical distribution of bearing temperatures acquired during the 18-month SCT Logistics Australian field test. Temperature readings are grouped into bins with a fixed width of 2°C.

4.2.2 Criterion 2 Threshold

Statistical analysis of bearing-ambient temperature differentials is employed to select the temperature differential threshold (ΔT_{limit}) for use with Criterion 2, similar to the methodology followed to determine the Criterion 1 temperature threshold. Bearing-ambient temperature differentials are grouped into fixed width bins of 2°C (3.6°F) in order to maximize the resolution of the histogram portrayed in Figure 23. The statistical distribution of temperature differentials

is given in Figure 23, with the 5%, 2%, and 1% thresholds indicated for reference. The temperature differential thresholds corresponding to these cut-offs are 53°C (95.4°F), 57°C (102.6°F), and 61°C (109.8°F), respectively. Based on this statistical analysis, combined with the performance of PBGY0112N-R4, the Criterion 2 temperature threshold (ΔT_{limit}) of 66.7°C (120°F) is selected. It is important to note that the temperature differential threshold selected for Criterion 2 identifies the warmest 0.3% of bearing-ambient temperature differentials for the entire fleet, comparable to the threshold selected for Criterion 1. The latter illustrates the significance of identifying bearings that consistently operate above this threshold, and the likelihood of those bearings being potentially unhealthy.

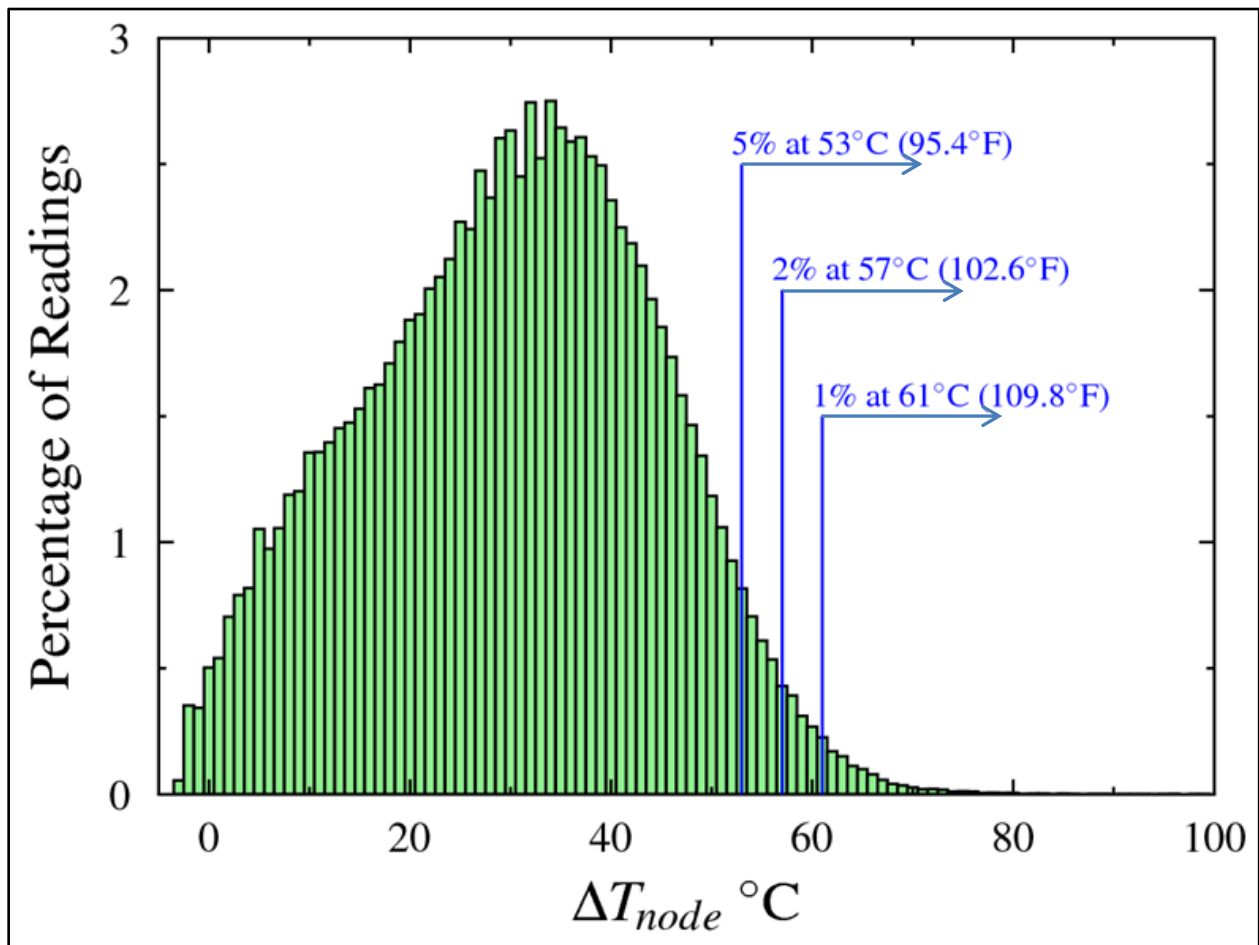


Figure 23: Statistical distribution of bearing-ambient temperature differentials collected during the 18-month SCT Logistics Australian field test. Temperature differential readings are grouped into bins with a fixed width of 2°C.

4.2.3 Criteria 3 and 4 Thresholds

The use of standard deviation as a method of identifying samples within a population which are exhibiting atypical behavior is widely accepted in statistics and engineering disciplines. However, in order for this methodology to produce meaningful results, the distribution of data within the sample population must be characterized by a Gaussian, or *normal*, distribution. Figure 24 presents the distribution of all temperature readings acquired from the Australian test fleet with a Gaussian distribution fitted to the dataset. Figure 24 suggests that the dataset used can be approximated by a normal distribution; however, this visual inspection is not sufficient to verify the use of standard deviation for identification of outliers.

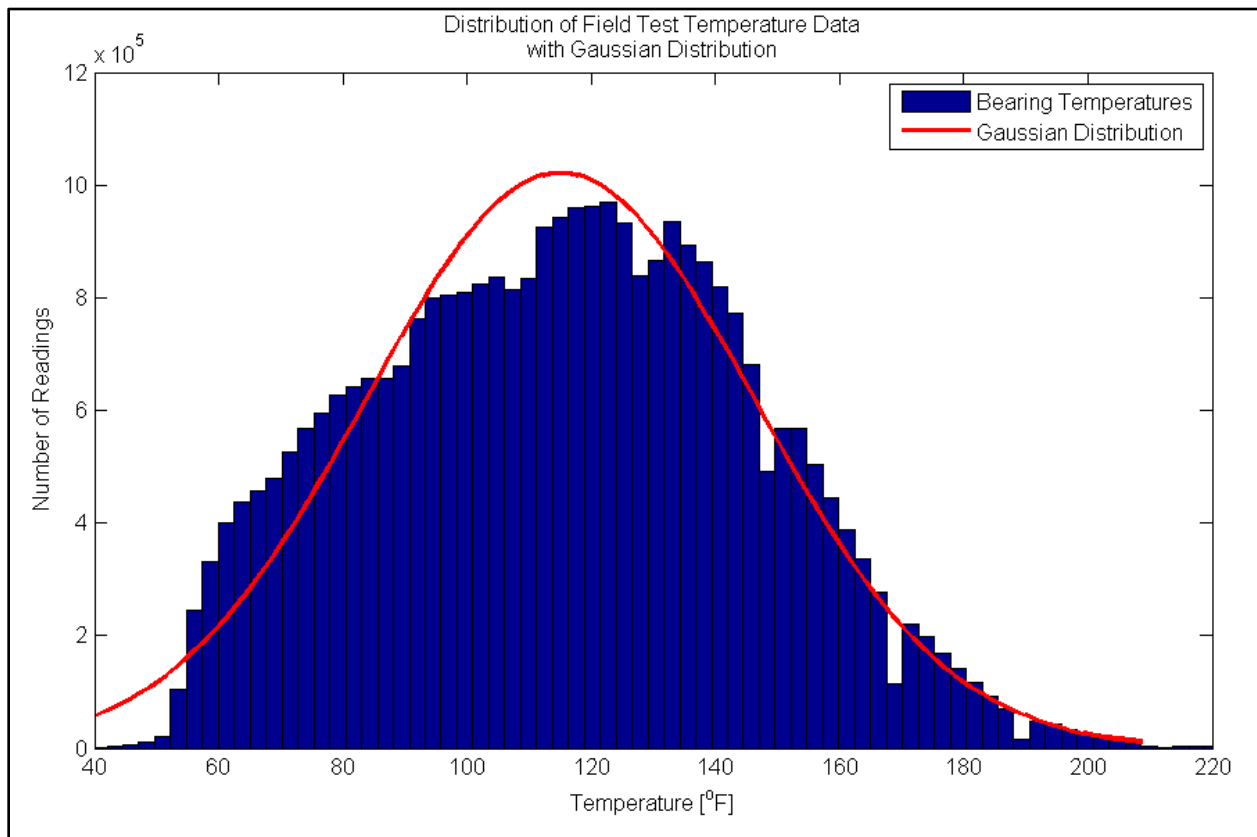


Figure 24: Histogram presenting the distribution of all bearing temperature readings with a Gaussian (normal) distribution shown in red. Temperature differential readings are grouped into bins with a fixed width of 2°C.

Proving that a given dataset can be described by a normal distribution can be a non-trivial task, especially for a small sample size. However, for a larger dataset, rigorous statistical measures such as skewness and kurtosis are employed to describe how closely a sample distribution is to a normal distribution. The skewness of a dataset quantifies the degree of symmetry about the mean value, with a skewness of zero representing a perfectly symmetric normal distribution. The dataset composed of all temperature readings acquired from the Australian field test has a skewness value of 0.1158, indicating minimal deviation from an ideal symmetric distribution. Kurtosis is another statistical measure that is used to characterize the relative width and height of a sample distribution. The kurtosis value of a Gaussian distribution is three, with a higher kurtosis value signifying a greater concentration of readings near the mean (a histogram with a taller central peak), and a lower kurtosis value representing less peaked and more widely distributed populations. The calculated kurtosis value for the bearing temperature distribution of Figure 24 is 2.447, indicating a slightly wider distribution of temperature readings, compared to a Gaussian distribution.

Considering that both the skewness and kurtosis values for the field test dataset are close to that of a normal distribution, the use of standard deviation is appropriate for identification of outliers in this case. Based on a normal distribution, a threshold of *one* standard deviation is selected for both Criteria 3 and 4 to identify bearings whose average operating temperatures are deviating significantly from the railcar and train average temperatures, respectively.

4.2.4 Criterion 5 Threshold

Statistical analysis is utilized, similar to the procedure followed for the determination of Criteria 1 and 2 thresholds, in order to specify the appropriate threshold for use in Criterion 5 analysis. For this criterion, however, the approximate time rate of change of bearing temperature

is used, as calculated by a linear fit of an eight-minute moving window of data. Figure 25 provides the statistical distribution of all heat rate data collected from the test fleet, with the 5%, 2%, and 1% thresholds shown in blue.

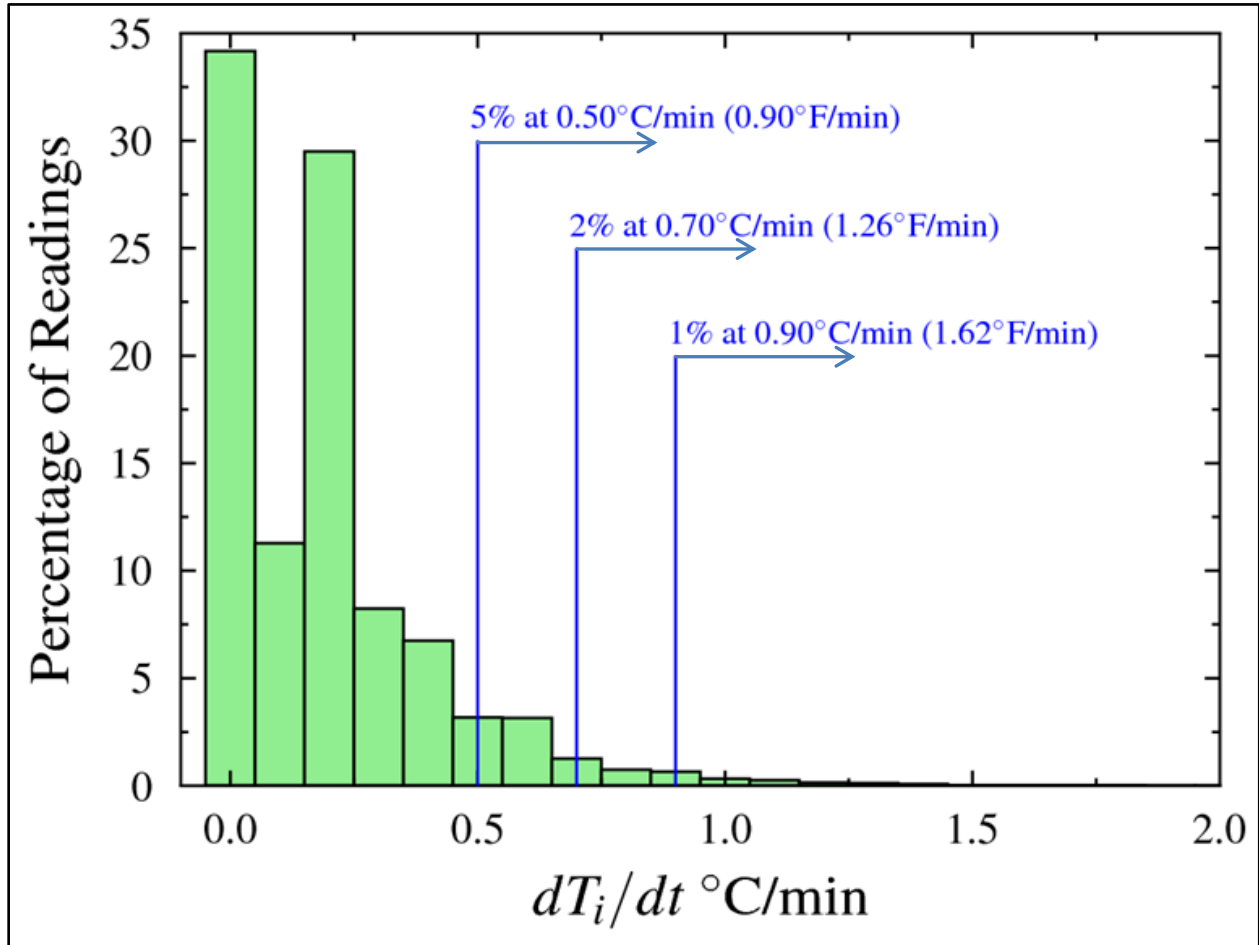


Figure 25: Statistical distribution of time rate of change of temperature data for the 18-month SCT Logistics Australian field test. Data points are grouped into bins with a fixed width of 0.1°C/min (0.18°F/min).

Utilizing an iterative procedure, several heat rate thresholds are considered and all bearings in the Australian test fleet are ranked by this Criterion to determine the effect of various threshold values on the relative ranking of bearings within the test fleet. The thresholds considered here are based on analyses of extensive laboratory testing of tapered-roller bearings with various defects present. These analyses indicate that, in more than 90% of defective

bearings tested, the rate of temperature increase observed during brief temperature trending events exceeds 1.25°F/min. However, the laboratory test data analyzed was obtained from bearings whose condition had degraded far beyond what would be allowed to operate in the field without triggering an alarm from a TADS installation. Furthermore, laboratory testing does not simulate all of the excitation sources experienced by bearings during field service. Based on the latter, the heating rate threshold, $\frac{dT_i}{dt}_{limit}$, of 0.69°C/min (1.25°F/min) is selected for use with Criterion 5. The value of this threshold identifies the warmest 2.5% of all heating rate readings, obtained from the Australian test fleet, and it is consistent with analyses of laboratory test data obtained from defective bearings.

4.3 Level 2 Alarm Thresholds

Level 2 alarms utilize the same statistical metrics as Level 3 alarms; however, additional thresholds, listed in Table 6, are integrated to serve as a performance benchmark, facilitating the identification of bearings that represent a high priority for maintenance personnel. The latter thresholds are limits placed on the results of Level 3 Criteria, which, if exceeded cause an alarm message to be generated and reviewed for consideration of further action. Level 2 alarms are less urgent than Level 1 alarms, which require a train be slowed or stopped to avoid catastrophic bearing failure, and are consistent with current AAR standards summarized in Table 1 (Chapter II).

Table 6: Level 2 performance thresholds

Criterion	Description	Level 2 Threshold
1	Percent of T_i readings $\geq 93.3^\circ\text{C}$ (200.0°F)	25%
2	Percent of ΔT_i readings $\geq 66.7^\circ\text{C}$ (120.0°F)	25%
3	$(\bar{T}_i - \bar{T}_{car})/\sigma_{car}$	1.0
4	$(\bar{T}_i - \bar{T}_{train})/\sigma_{train}$	1.0
5	Percent of dT_i/dt readings $\geq 0.69^\circ\text{C}/\text{min}$ ($1.25^\circ\text{F}/\text{min}$)	4%

Performance thresholds are established for all *five* Criteria, based in part on temperature data collected from the PBGY0112N-R4 bearing that was removed on April 7, 2010. This bearing collected data for a total of 58.6 hours of continuous operation, and, based on its performance was recommended for removal due to excessive operating temperatures and significant deviation in temperature compared to its peers on the same railcar. The developed algorithms are used to analyze this bearing's temperature data, and the resulting scores obtained from Level 3 Criteria, displayed in Table 7, were employed as performance benchmarks to identify bearings likely to be experiencing unsafe operation.

Table 7: Results of Level 3 Criteria for the PBGY0112N-R4 bearing during March 2010.

Criterion	Description	Result
1	Percent of T_i readings $\geq 93.3^\circ\text{C}$ (200.0°F)	11.02%
2	Percent of ΔT_i readings $\geq 66.7^\circ\text{C}$ (120.0°F)	25.95%
3	$(\bar{T}_i - \bar{T}_{car})/\sigma_{car}$	1.02
4	$(\bar{T}_i - \bar{T}_{train})/\sigma_{train}$	1.10
5	Percent of dT_i/dt readings $\geq 0.69^\circ\text{C}/\text{min}$ ($1.25^\circ\text{F}/\text{min}$)	5.26%

In July 2010, a second bearing was removed from field service based on analyses of the temperature readings acquired from railcar PBGY0130L. This setout bearing had been one of the worst performing bearing in the Australian test fleet for several months prior to removal, and, during April 2010 its performance, summarized in Table 8, was worse than that of the PBGY112N-R4 bearing during March 2010.

Table 8: Results of Level 3 Criteria for the PBGY0130L-L3 bearing during April 2010.

Criterion	Description	Result
1	Percent of T_i readings $\geq 93.3^\circ\text{C}$ (200.0°F)	25.07%
2	Percent of ΔT_i readings $\geq 66.7^\circ\text{C}$ (120.0°F)	28.39%
3	$(\bar{T}_i - \bar{T}_{car})/\sigma_{car}$	1.20
4	$(\bar{T}_i - \bar{T}_{train})/\sigma_{train}$	1.49
5	Percent of dT_i/dt readings $\geq 0.69^\circ\text{C}/\text{min}$ ($1.25^\circ\text{F}/\text{min}$)	6.68%

Based on the results of Level 3 analyses for the 112N-R4 and 130L-L3 bearings, the Level 2 performance threshold for Criteria 1 is set at 25%. This threshold is suitable for identification of potentially unhealthy bearings because approximately 0.3% of all absolute bearing temperatures acquired from the test fleet exceed 93.3°C (200°F), therefore, any bearing whose operating temperatures exceed 93.3°C (200°F) for at least 25% of the time is likely to be unhealthy. The same rationale is used to justify the Level 2 Criteria 2 threshold of 25% for the analysis of bearing-ambient temperature differential readings.

The Level 2 thresholds used for Criteria 3 and 4, the deviation of a bearing's average temperature from its peers, are both set at *one* standard deviation of the railcar and train, respectively. These thresholds are based primarily on the performance of the 112N-R4 and

130L-L3 bearings set out from field service, summarized in Table 7 and Table 8, as well as the widely accepted practice of identifying samples within a population that fall more than one standard deviation away from the population mean.

The Level 2 threshold selected for use with Criterion 5 requires that an alert be generated if more than 4% of the entire heating rate dataset for one bearing exceeds $0.69^{\circ}\text{C}/\text{min}$ ($1.25^{\circ}\text{F}/\text{min}$). In comparison to the performance of PBGY0112N-R4, assessed using Level 3 Criteria, this threshold is more conservative than the 5.26% result listed in Table 7. A more conservative threshold is selected because there is relatively little information available regarding the rate of temperature increase occurring in unhealthy bearings before initiation of failure in field service; of the 80 bearings monitored in the test fleet, none experienced in-service failure or any severe temperature trending events. Moreover, the current network of HBDs can only provide intermittent measurement of bearing temperatures and cannot accurately estimate the rate of temperature increase experienced by an unhealthy bearing. Experimental testing conducted at UTPA indicates that the rate of temperature increase for defective bearings exceeds $0.69^{\circ}\text{C}/\text{min}$ ($1.25^{\circ}\text{F}/\text{min}$) in more than 90% of laboratory test scenarios. Nonetheless, laboratory testing cannot simulate the excitation sources from the track and wheels which affect the rate of temperature increase. In light of these factors, a more conservative threshold is judged appropriate, considering that these condition monitoring algorithms are designed to provide early identification of potentially unhealthy bearings, not detection of impending bearing failure.

CHAPTER V

RESULTS AND DISCUSSION

The statistical metrics presented in Chapter IV are employed on a monthly basis to analyze temperature data acquired from the SCT Logistics Australian field test. The results of these metrics are utilized to assess the condition of tapered-roller bearings in service. Additionally, degradation of bearing condition occurring during field service is discussed for three case studies that validate the effectiveness of the developed algorithms as a continuous bearing health monitoring system.

5.1 Introduction

During the course of the first eight months of monitoring the SCT Logistics Australian test fleet, two Class E tapered-roller bearings were removed from active service based on the results of the analyses presented in Chapter IV. Following removal, these two bearings were sent to UTPA for laboratory testing and subsequent disassembly and detailed visual inspection. Based on this testing and inspection, it was determined that both bearings did have condemnable defects that caused the elevated operating temperatures observed during field service. In addition to these two setout bearings, one Class E tapered-roller bearing that had been assessed as healthy using Level 3 Criteria was flagged by a Trackside Acoustic Detector System (TADS) installation and subsequently replaced. However, ensuing disassembly and inspection performed by the maintenance crew of the Australian test fleet indicated that this bearing had no defects

present. This *non-verified* bearing exemplifies the inherent limitations of intermittent monitoring to identify bearings in distress or in need of maintenance.

5.2 Case Study 1: Railcar PBGY0112N-R4

Shortly after instrumentation, the bearing located in the R4 position of railcar PBGY0112N was recommended for removal based on high operating temperature, high bearing-ambient temperature differential, and significant deviation in operating temperatures when compared to its peers on the same railcar and the entire train. This bearing completed only 58.6 hours of operation before being removed from railcar PBGY0112N on April 7, 2010. The ensuing disassembly and inspection revealed that this bearing’s internal clearance was outside of the allowable range when it was originally assembled.

5.2.1 Analysis of Field Test Data

The average bearing temperatures and average bearing-ambient temperature differentials for the 58.6 hours of data collected is shown in Table 9. As shown, the average bearing-ambient temperature differential of the bearing in the R4 position is 28.64°C (51.55°F) hotter than the coolest bearing on the railcar, and 14.57°C (26.23°F) hotter than the next warmest bearing. Similarly, the average bearing temperature of the R4 bearing is 14.01°C (25.22°F) to 27.22°C (49.99°F) hotter than its peers.

Table 9: Average bearing temperature and bearing-ambient temperature differential for PBGY0112N (March 28-30, 2010)

Bearing Position	R1	L1	R2	L2	R3	L3	R4	L4
Average Bearing Temperature [°F]	150.28	136.12	151.62	142.63	134.08	126.80	178.35	152.12
Average Bearing-Ambient Differential [°F]	78.21	64.50	79.69	71.04	62.48	55.65	105.64	80.42

A plot of bearing temperature vs. time is presented in Figure 26 for the 58.6 hours of operation from March 28, 2010 to March 30, 2010. The temperatures of all eight bearings on this railcar fluctuate together as train speed, ambient conditions, and wheel braking events influence their thermal performance. However, the R4 bearing is always the hottest bearing on the railcar by a considerable margin, as demonstrated by the data in Table 9. Although the operating temperature of this bearing is significantly higher than its peers, it does not exceed the AAR temperature threshold of 160°C (320°F) at any point during the monitored period.

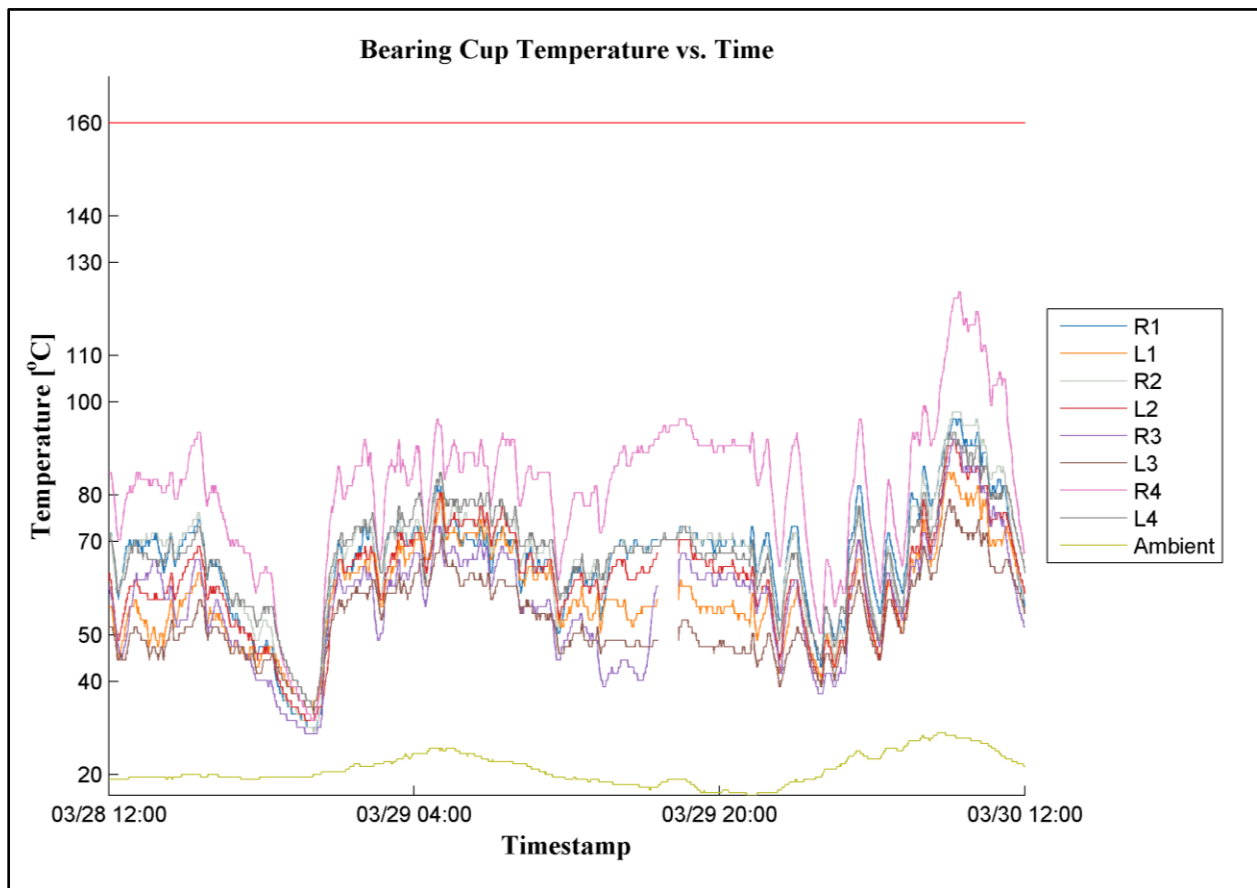


Figure 26: Bearing temperature vs. time with the AAR threshold of 160°C (320°F) shown in red (March 28-30, 2010).

A plot of the bearing-ambient temperature differential was generated for the time span of March 28, 2010 through March 30, 2010 in order to illustrate the heat generation within the R4 bearing relative to its peers. Figure 27 depicts the history of temperature differentials for all eight bearings in service on railcar PBGY0112N, and clearly shows that the R4 bearing consistently exhibited the highest temperature above ambient, indicating significantly greater heating within the bearing. Furthermore, the bearing-ambient temperature differential exceeded 94.4°C (170°F), the AAR threshold for bearing removal, for 15 minutes. If there had been an HBD installation within the 28.1 km (17.5 miles) of track covered while the temperature differential exceeded 94.4°C (170°F), this bearing would have been flagged for immediate removal. Conversely, if that HBD was located anywhere else along the 6,450 km (~4,000 mi) route, this bearing would have been allowed to continue operation. The fact that this bearing briefly exceeded the AAR standards for bearing-ambient temperature differential but not the threshold for bearing cup temperature exposes the discrepancies in the current AAR standards, and clearly highlights the need for better and more reliable condition-monitoring systems.

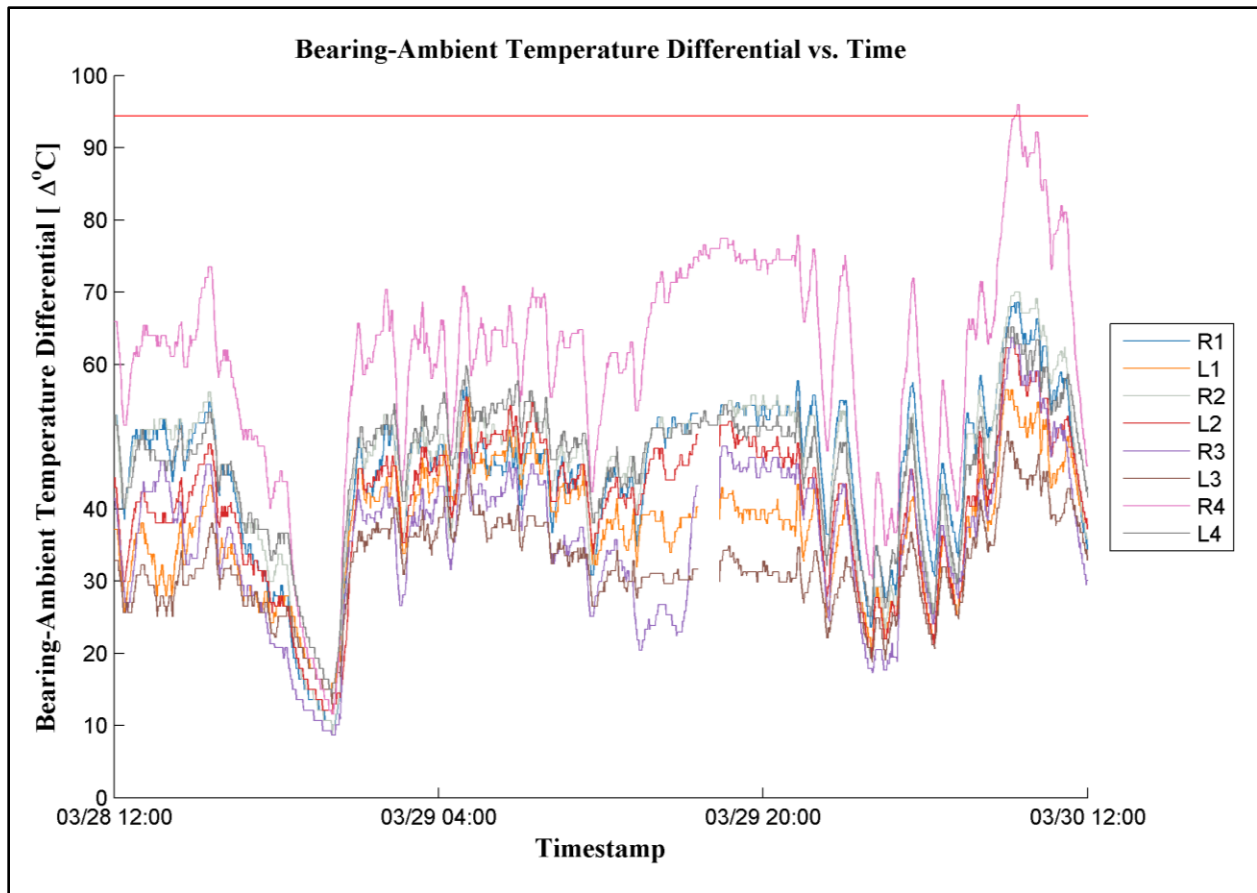


Figure 27: Bearing-Ambient temperature differential vs. time with the AAR threshold of 94.4°C (170°F) shown in red (March 28-30, 2010).

The data acquired from railcar PBGY0112N was analyzed using the Level 3 Criteria presented in Chapter IV and the results are used to assess the condition of the bearing in the R4 position before and after replacement. The condition of the R4 bearing, as evaluated by the Level 3 Criteria (see Table 10), indicated this to be a potentially distressed bearing, with high ranking among all five of the developed Criteria. The results of Criteria 3 and 4 indicate a significant deviation from the average operating temperatures of both the railcar and the entire train, suggesting that this bearing is exhibiting excessive heat generation and elevated operating temperatures in comparison to its peers.

Table 10: Condition of the bearing in the R4 position of railcar PBGY0112N as assessed by the Level 3 Criteria before and after replacement on April 7, 2010.

Month	Criterion 1	Criterion 2	Criterion 3 (σ_{car})	Criterion 4 (σ_{train})	Criterion 5
March 2010	11.02%	25.95%	1.02	1.10	5.26%
April 2010	0%	2.71%	-0.097	-0.012	2.20%

On April 7, 2010, the bearing in the R4 position was replaced based on analysis of temperature data acquired during the initial phase of the field testing of the WSNs. Following replacement, the condition of this bearing, as assessed using the Level 3 Criteria, improved markedly, as can be seen in Table 10. Specifically, the results of Criteria 1 and 2 indicate no bearing temperature readings exceeding 93.3°C (200°F) and only 2.71% of bearing-ambient temperature differentials exceeding 66.7°C (120°F), respectively. The latter is a significant improvement in comparison to 11.02% of bearing temperature readings exceeding 93.3°C (200°F) and 25.95% of bearing-ambient temperature differentials exceeding 66.7°C (120°F) prior to replacement. Furthermore, the results of Criteria 3 and 4 after replacement, with negative values for both Criteria, indicate that the replacement bearing is now operating below the average temperatures of both its railcar and the entire train. Finally, the results of Criterion 5 indicate that only 2.20% of the rate of temperature increase readings exceed 0.69°C/min (1.25°F/min) as compared to 5.26% before replacement.

Prior to replacement of the R4 bearing, its performance violated four of the five Level 2 alarms in March 2010, as shown in Table 11. In the ensuing month, April 2010, the replacement bearing in the same position did not violate any of the Level 2 alarm thresholds, signifying a substantial performance improvement.

Table 11: Summary of Level 2 alarm violations before and after replacement of the R4 bearing. A “✘” denotes that a Level 2 alarm has been violated.

Month	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5
March 2010	✓	✘	✘	✘	✘
April 2010	✓	✓	✓	✓	✓

In summary, the state of the original bearing in the R4 position and its replacement depicts a clear improvement after replacement, thus, validating the assessment that the original bearing was potentially unhealthy and in need of removal.

5.2.2 Laboratory Inspection and Analysis

Following removal and replacement on April 7, 2010, the original bearing from the R4 position was shipped to UTPA for disassembly and detailed inspection. Upon receipt of the bearing, the exterior surfaces of the bearing were inspected and showed no obvious discoloration of metal or indications of any problems. The assembled bearing was weighed prior to disassembly and inspection of all internal components. Following disassembly, the internal components were cleaned thoroughly to remove all of the grease and each component was weighed separately. Using this information, the total weight of all the components was subtracted from the weight of the assembled bearing in order to determine the weight of the grease that was present in the bearing during field service. It was determined that the grease fill at that time was 439.98 g (15.52 oz.). However, documents obtained from BRENCO² reveal that the recommended grease fill for a Class E bearing is 396.9 g to 425.2 g (14 oz. to 15 oz.). This indicates that the grease fill in the 112N-R4 bearing was 3.5% above the recommended

² A subsidiary of Amsted Rail Industries, Inc. responsible for the manufacture of tapered-roller bearings

maximum. Although this bearing only had slightly more grease than the recommended maximum, bearings with excessive grease fill have been shown to exhibit elevated operating temperatures as seen in a series of laboratory tests conducted at UTPA.

No spalls or other surface irregularities were found on any of the bearing components. However, the lateral spacing of the assembled bearing, a measure of the axial displacement of the bearing cup relative to the cones, was significantly lower than the recommended minimum value. Measurements indicate that the lateral spacing was in the range of 0.3302 mm to 0.3356 mm (0.013" to 0.014"), compared to a recommended nominal range of 0.6096 mm to 0.6604 mm (0.024" to 0.026"). This insufficient lateral spacing, known as *short lateral* within the railroad industry, is known to cause elevated operating temperatures by reducing the amount of clearance between the rollers and the cup and cone. The insufficient clearance can prevent the rollers from turning freely and may induce roller misalignment, or skidding of the rollers, which usually results in a reduced lubricating film thickness. All of these conditions are known to create elevated operating temperatures in tapered-roller bearings.

Based on this detailed inspection and analysis, it was determined that the elevated operating temperatures exhibited by this bearing during field service were caused by two compounding factors; a combination of short lateral spacing caused by incorrect bearing assembly, and excessive grease fill.

5.3 Case Study 2: Railcar PBGY0130L-L3

Following several months of careful monitoring, a second Class E bearing was recommended for removal due to inconsistent performance that varied from apparently healthy to worse than that of the first bearing removed from PBGY0112N (refer to Case Study 1).

Extensive laboratory testing conducted at UTPA accompanied by several inspections indicates that the cup of this bearing had a geometric inconsistency that is responsible for the observed elevated operating temperatures during field service and laboratory testing. Furthermore, this bearing developed one spall on each cone raceway prior to seizing after approximately 85,778 km (53,300 mi) of testing.

5.3.1 Analysis of Field Test Data

The results of the Level 3 Criteria were utilized to evaluate the condition of this bearing on a monthly basis, as well as identify degradation trends that occurred over a period of several months. The condition of this bearing appeared to fluctuate considerably from month to month, as demonstrated in Table 12, though it consistently ranked among the top five worst performing bearings in the Australian test fleet since the railcars were instrumented in March 2010.

Table 12: Condition of the bearing in the L3 position of railcar PBGY0130L as evaluated by the Level 3 Criteria prior to replacement on July 30, 2010.

Month	Criterion 1	Criterion 2	Criterion 3 (σ_{car})	Criterion 4 (σ_{train})	Criterion 5
March 2010	0.22%	0%	0.16	0.572	4.09%
April 2010	25.07%	28.39%	1.20	1.491	6.68%
May 2010	0.01%	0.91%	0.39	0.793	4.10%
June 2010	1.15%	7.00%	0.76	1.115	4.35%
July 2010	1.37%	6.96%	0.56	0.88	4.72%

During April 2010, the L3 bearing exceeded the Level 2 alarm thresholds in all five Criteria and was the worst performing bearing in the Australian test fleet. Furthermore, its performance was worse than that of the 112N-R4 bearing in March 2010. However, this bearing was not recommended for removal at the time and was allowed to continue regular operation in

order to improve understanding of the rate of degradation experienced by bearings of this condition during field service.

In May 2010, the performance of the L3 bearing appeared to improve dramatically, with almost zero temperature readings exceeding 93.3°C (200°F) and less than one percent of bearing-ambient temperature differentials exceeding 66.7°C (120°F). The deviation of this bearing's average temperature from the average operating temperatures of both the railcar and the train also decreased significantly, as described by Criteria 3 and 4 in Table 12. The cause of this behavior was not understood at the time, and the bearing was allowed to continue in service while being monitored closely for any further changes in condition.

In the ensuing month, the L3 bearing exhibited an increase in the frequency of high temperature operation, as described by the results of Criteria 1 and 2 analyses. This increase was relatively small in comparison to the noticeable increase in Criteria 3 and 4 results. Due in part to the erratic performance of this bearing over a period of four months, in addition to the fact that it violated the Level 2 alarm for Criterion 5 in every month since March 2010, it was recommended for removal and replacement the next time the railcar was available for maintenance.

On July 30, 2010, the L3 bearing was removed from service and a replacement bearing installed in its position. The performance of the replacement bearing that was installed in the L3 position, summarized in Table 13, was similar to the performance of the original bearing in August 2010. However, in the following three months, the condition of this bearing appeared to improve significantly, with a lower percentage of high temperature operation, lower deviation from railcar and train average temperatures, and steadily decreasing percentage of high heating rate readings.

Table 13: Condition of the replacement bearing in the L3 position of railcar PBGY0130L, as calculated using the Level 3 Criteria after replacement on July 30, 2010.

Month	Criterion 1	Criterion 2	Criterion 3 (σ_{car})	Criterion 4 (σ_{train})	Criterion 5
August 2010	2.82%	5.33%	0.77	0.98	4.96%
September 2010	0.45%	0.93%	0.44	0.68	5.51%
October 2010	0.92%	0.86%	0.45	0.58	4.75%
November 2010	8.71%	8.20%	0.40	0.92	3.85%

This initial high temperature operation immediately after a new bearing is put into service is a commonly observed phenomenon known as the *break-in* period. Following the initial break-in period, operating temperatures will gradually approach a steady operating range. Generally, a bearing will continue to operate within this predictable range until it approaches the end of its life and begins to degrade, resulting in elevated operating temperatures.

5.3.2 Laboratory Testing and Inspection

The bearing that was removed from the L3 position was shipped to UTPA for laboratory testing followed by disassembly and detailed inspection. Unlike the 112N-R4 bearing, which was disassembled and inspected immediately, the 130L-L3 bearing was installed onto a test axle with three other defective Class E bearings, used as controls to reference the performance of the setout bearing. One control bearing was built with short lateral spacing, comparable to the 112N-R4 bearing removed from the field test. The second control had four cone spalls, and the third control had four cup spalls and multiple roller spalls. These bearings were used in order to compare the operating temperature of the L3 bearing to other bearings with known defects that would require removal by current AAR bearing maintenance standards. All four bearings were

pressed onto one customized Class E axle and tested using the dynamic bearing tester described in Chapter III.

During the first series of laboratory tests performed on this bearing, the vertical load applied to the bearing was alternated between two conditions; 17% load to simulate an empty railcar, as this scenario is known to promote roller misalignment and temperature trending, and 100-110% load to simulate a fully loaded railcar, increasing the stress placed on the bearing's internal components. Additionally, the test speed was varied between 106.2 km/h (66 mph) and 138.4 km/h (86 mph). Figure 28 presents the temperature history of the L3 bearing along with the three defective bearings for reference, under these varied testing conditions. This figure illustrates that the L3 bearing exhibited the highest operating temperature under 100-110% loading at both test speeds, and consistently operated warmer than the two spalled bearings, but cooler than the bearing with short lateral, under all other load and speed conditions utilized.

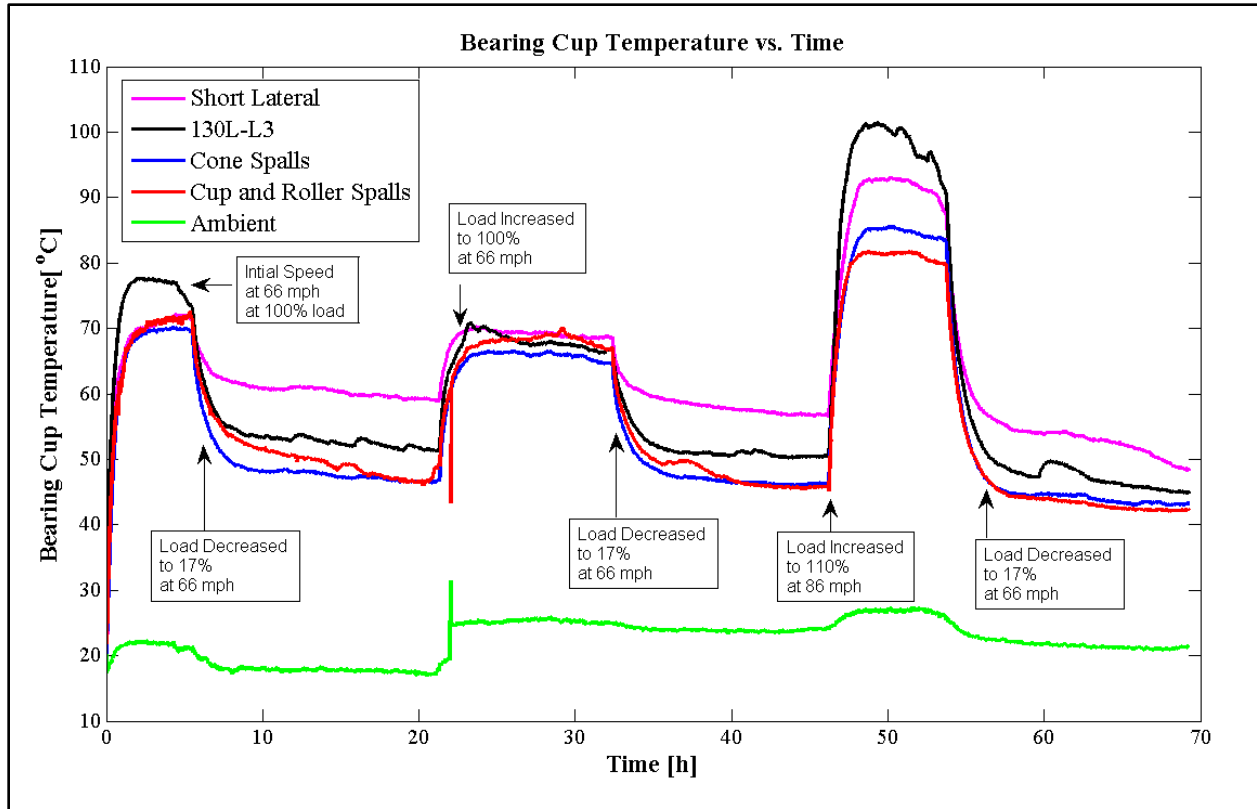


Figure 28: Bearing cup temperature vs. time for the first series of laboratory testing of the L3 bearing following removal from the Australian field test.

Following this initial phase of testing, totaling 39,107 km (24,300 mi), the L3 bearing was removed from the test setup for disassembly and detailed inspection. Visual inspection of the bearing cup revealed an abnormal wear pattern, shown in Figure 29, along the surface of both raceways. This abnormal wear pattern was present along the entire circumference of both cup raceways, however, its width varied considerably with position, as can be seen in Figure 30. This abnormal wear pattern present on the bearing cup raceways, and the change in width with raceway position, is indicative of a geometric inconsistency created during manufacturing. This inconsistency results in reduced contact area between the bearing cup and the rollers, causing a thinning of the hydrodynamic film thickness, which greatly increases heat generation and wear.

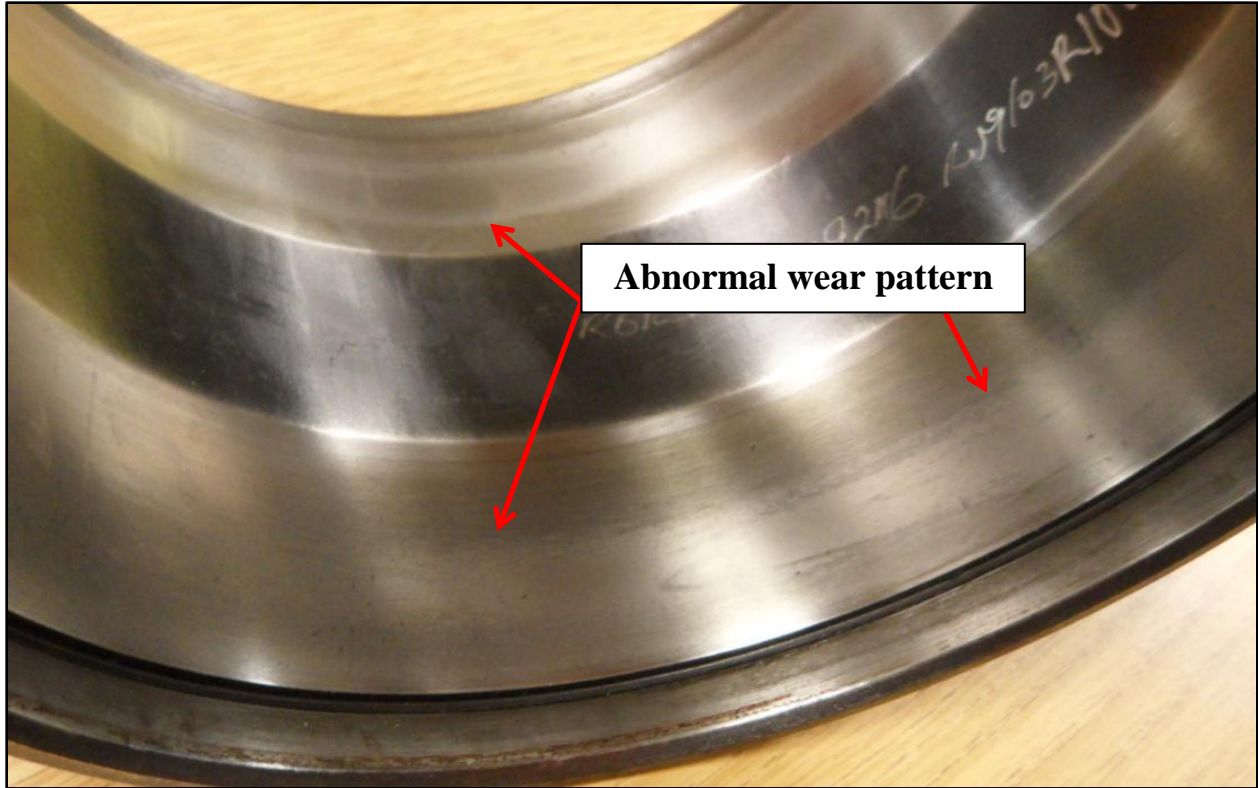


Figure 29: Abnormal wear pattern present on both raceways of the L3 bearing cup after the first teardown and inspection.



Figure 30: Detailed view of one raceway of the L3 bearing cup with the varied width of the wear pattern indicated.

The L3 bearing was rebuilt and packed with new grease before being installed on the dynamic bearing tester to resume the evaluation process. After careful inspection of the results from the first teardown, it was believed that the L3 bearing cup had a geometric inconsistency causing the abnormal wear patterns seen in Figure 29 and Figure 30. Therefore, in the second series of the conducted tests, the test speeds and loads were systematically varied in order to determine their effect on the operating temperatures of the L3 bearing. The vertical load was maintained at either 100% or 115%, and the speed was alternated between 106.2 km/h (66 mph) and 138.4 km/h (86 mph). Additionally, the bearing cup was rotated periodically in order to load sections of the cup raceway exhibiting the greatest signs of distress. The rotation of the cup through several positions indicated that one particular orientation resulted in a higher operating temperature. The second iteration of tests were completed with this configuration.

The operating temperature of the L3 bearing under these conditions, depicted in Figure 31, clearly indicates that it was the hottest bearing when tested at 106.2 km/h (66 mph), in comparison to the two spalled bearings and one bearing with short lateral spacing. It is worth noting that while the 130L-L3 bearing was cleaned and rebuilt with fresh grease during the first teardown, the other three bearings referenced in Figure 31 were tested in the same condition as in the first series of tests. The fact that the L3 bearing continued to exhibit higher operating temperatures than its peers supports the assessment that it was unhealthy at the time of removal from field service.

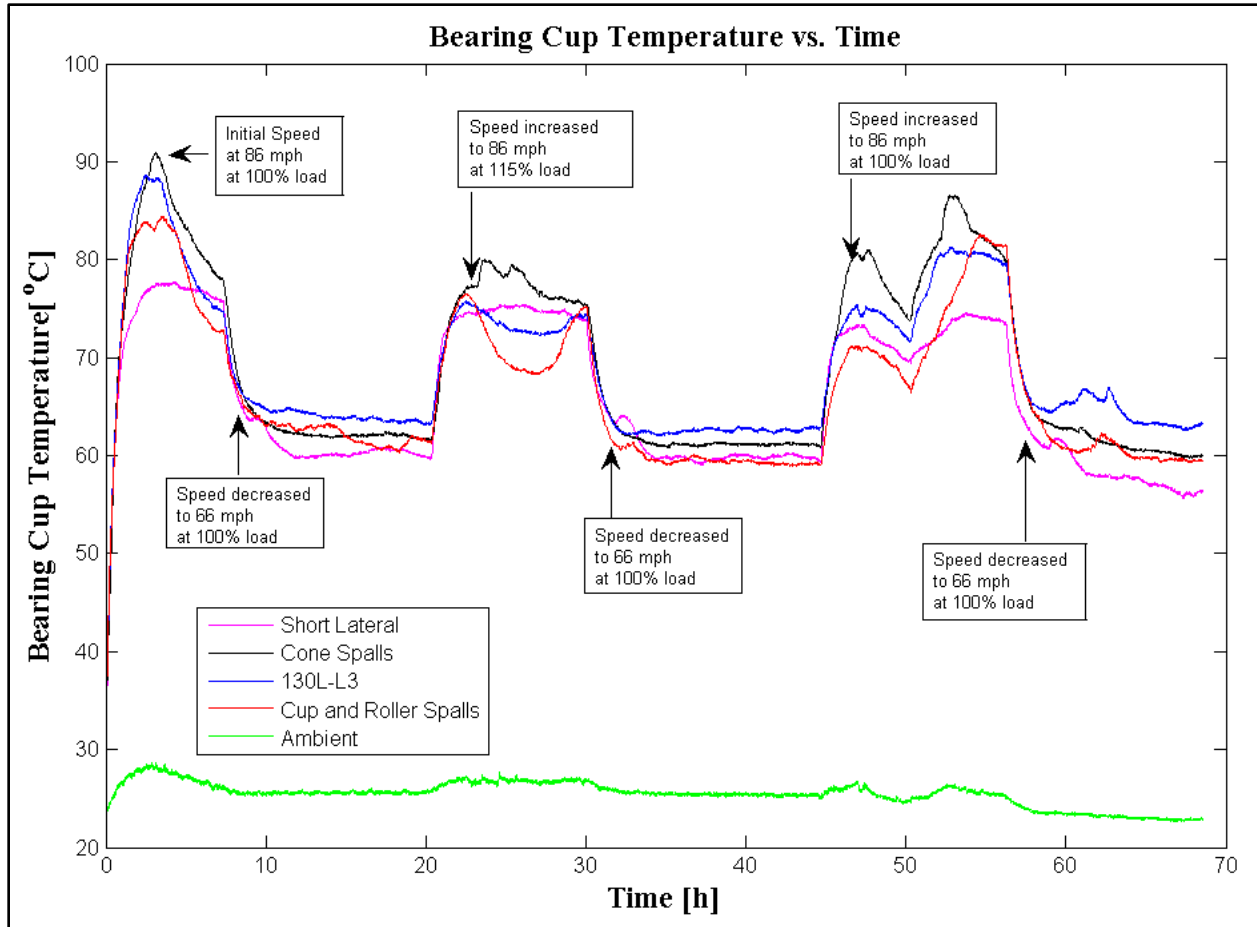


Figure 31: Bearing temperature vs. time for tests conducted with vertical loads of 100-115% load and speeds of 106.2-138.4 km/h (66-86 mph).

The difference in operating temperature of the L3 bearing between tests conducted at 106.2 km/h (66 mph) and 138.4 km/h (86 mph) is considerably greater than that of healthy Class E bearings tested at UTPA (~50°C). Moreover, the process of rotating the bearing cup that was performed during laboratory testing, known as *indexing* within the railroad industry, occurs commonly in the field due to the dynamic vertical motion of the railcar and momentary unloading of the friction between the bearing cup and adapter. The indexing of the bearing cup, combined with an increased sensitivity to higher operating speeds and loads, is the most likely cause of the significant variation in the performance of this bearing that was observed in the months prior to removal (see Table 12)

On November 12, 2010, after a total of 79,663 km (49,500 mi) of laboratory testing, the L3 bearing was removed from the tester and disassembled for the second time. Detailed inspection of the internal components revealed that the abnormal wear patterns on both cup raceways had become more evident. Additionally, one of the raceways exhibited a very shiny surface with brown circumferential streaks indicative of substantial metal-to-metal contact friction, as pictured in Figure 32. This discoloration, referred to as heat tint, is likely caused by a significant reduction or absence of the lubricating film between the rollers and bearing cup raceway. Similar brown streaking is present on the rollers corresponding with the discolored cup raceway, as seen in Figure 33.

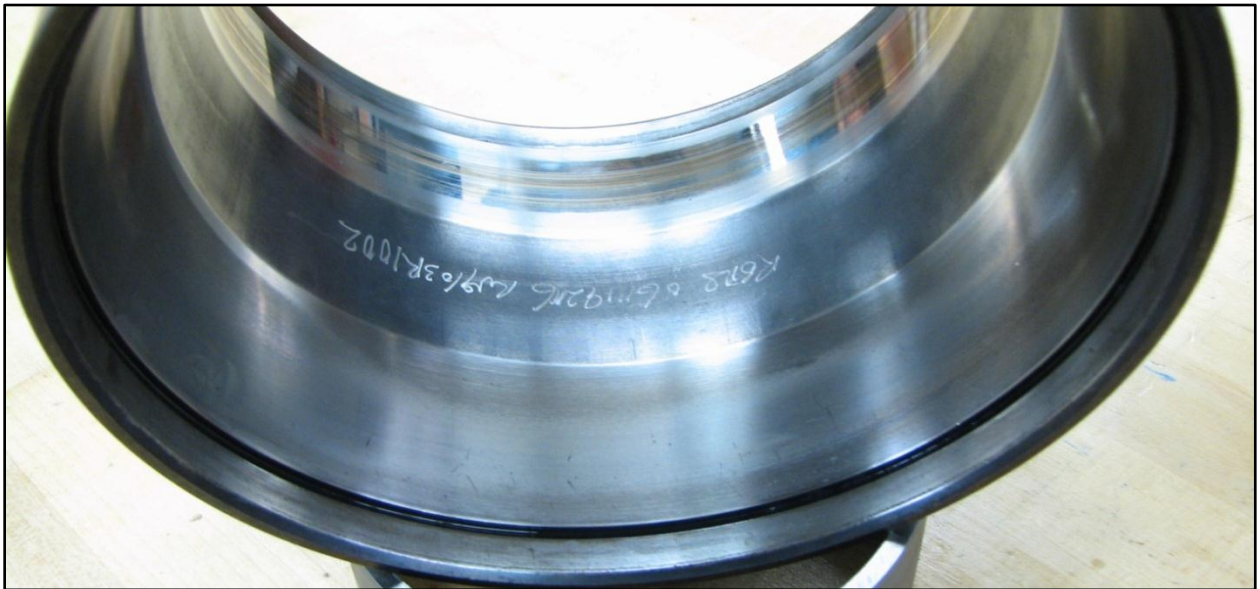


Figure 32: Picture showing the abnormal wear pattern present on one cup raceway and the brown heat tint present on the second raceway.

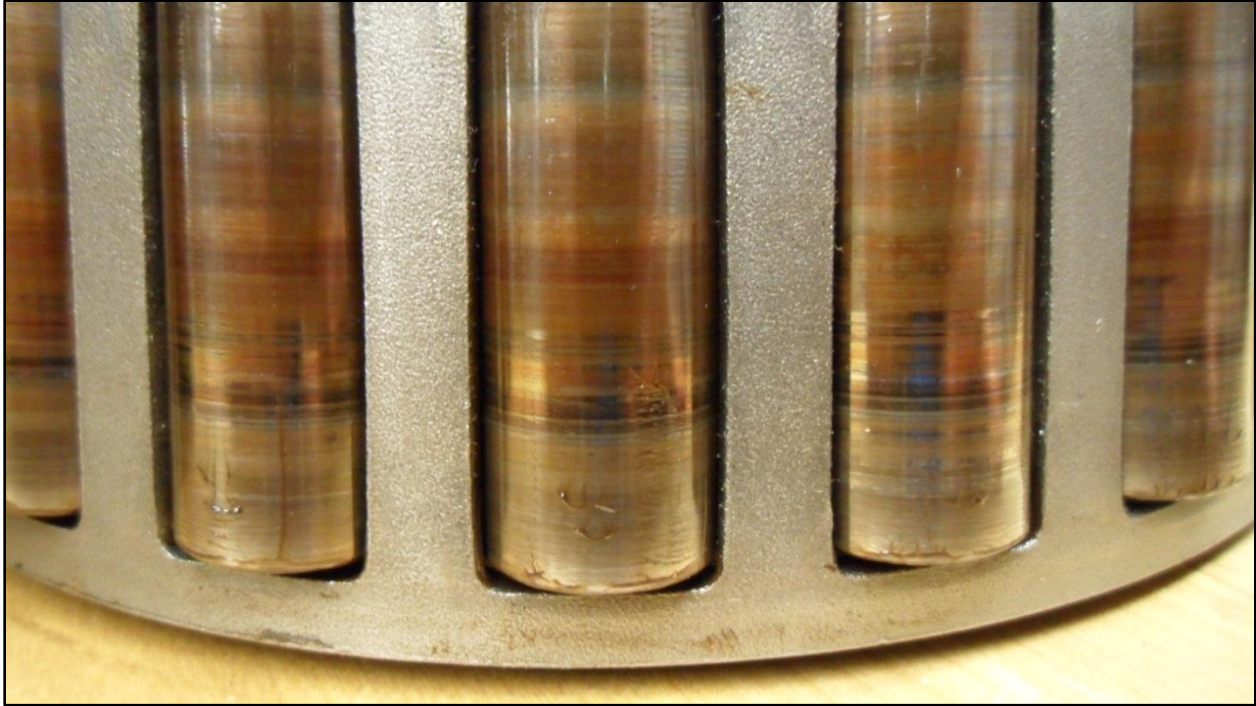


Figure 33: Picture depicting the brown heat tint that was present on the set of rollers associated with the discolored cup raceway (second raceway) of Figure 32.

Following the second teardown and inspection, it was decided to run the bearing to failure in order to estimate the usable service life remaining from the time of removal from field service. To this end, the L3 bearing was reinstalled on the test axle along with two new Class E bearings and the defective bearing with cup and roller spalls that was tested previously. This test configuration was subjected to accelerated service life testing at 130% load and 138.4 km/h (86 mph). Approximately 60 hours into the accelerated service life testing, the bearing seized abruptly, causing the axle to crack, and preventing further testing. The temperature history of this test is provided in Figure 34. Note that the L3 bearing operated considerably hotter than the bearing with multiple cup and roller spalls, and on par with the two brand new bearings that were experiencing elevated operating temperatures during the *break-in* period. The results of this test further support the evaluation that the 130L-L3 bearing was unhealthy at the time of removal from field service.

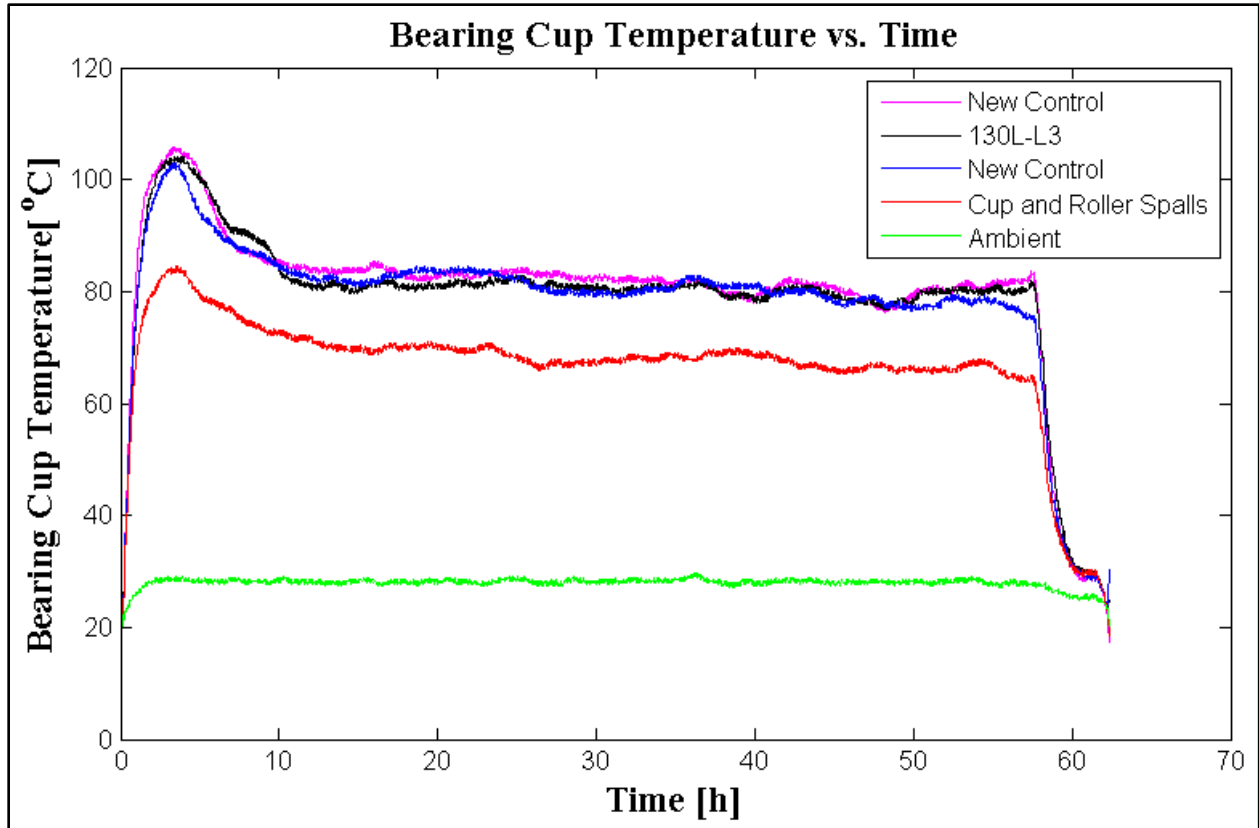


Figure 34: Plot of bearing cup temperature vs. time for the final 60 hours of testing prior to failure of the L3 bearing.

Subsequent to the failure of the L3 bearing, all test bearings were removed from the axle for disassembly and detailed inspection in order to determine the cause of the sudden failure. Upon inspection of the L3 bearing, it was discovered that the brown heat tint that had been previously observed on one raceway of the bearing cup had become more pronounced. Additionally, several small indentations had formed on the tinted raceway, as illustrated by Figure 35. This pitting of the raceway is indicative of metal debris in the grease, typically from fragments that have flaked out of a developed spall on the bearing's raceways or rollers.

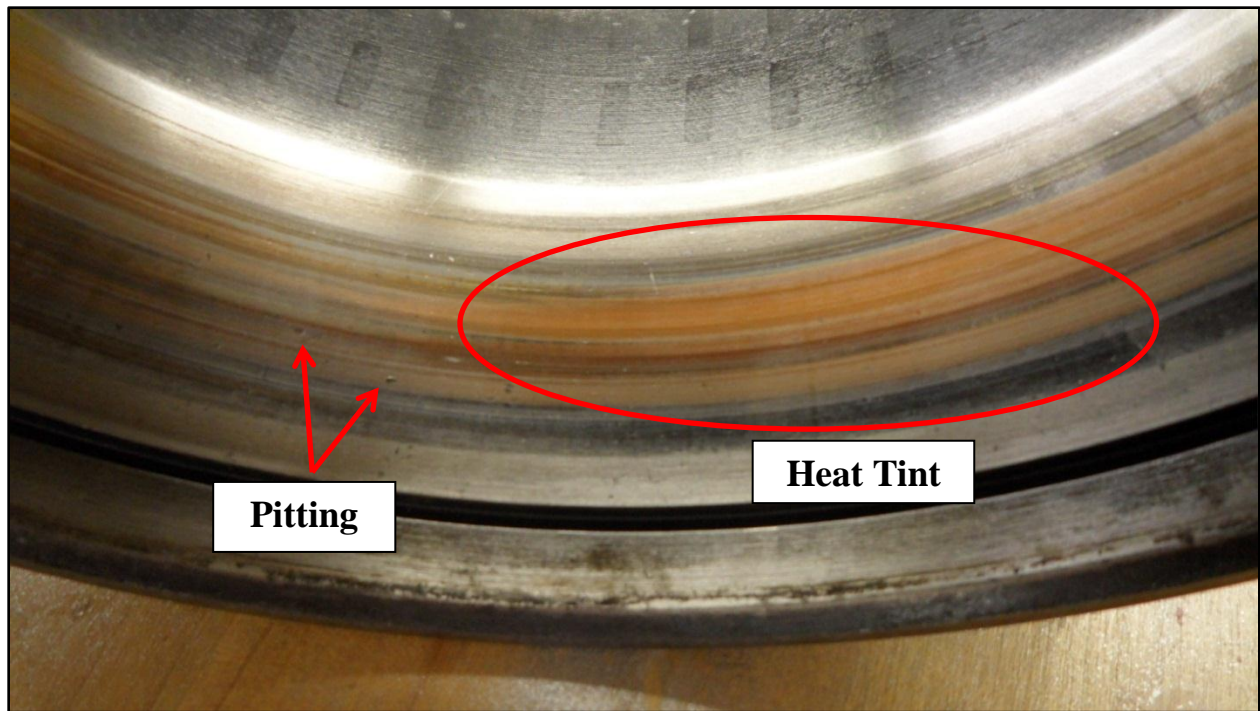


Figure 35: One raceway of the L3 bearing cup illustrating the brown heat tint and pitting that developed during the final series of tests.

The second cup raceway exhibited extensive pitting, as pictured in Figure 36, although no visible signs of discoloration due to heat tint were present. The more extensive pitting that was discernible on the non-tinted raceway suggested the presence of a significant spall within the bearing; however, there were no spalls on either cup raceway. In order to determine whether any spalls had formed on the bearing's cones (inner raceways), the steel cages were cut off, allowing for the inspection of the cone raceways. The inspection revealed that one spall had formed on *each* cone raceway, in addition to a noticeable brown heat tint along the middle of one raceway, as portrayed in Figure 37. The cone with the larger spall corresponds to the heavily dimpled cup raceway depicted in Figure 36, while the cone with the smaller spall and visible brown heat tint corresponds to the discolored cup raceway shown in Figure 35. Both spalls that developed during laboratory testing were large enough to warrant removal under AAR bearing maintenance standards.

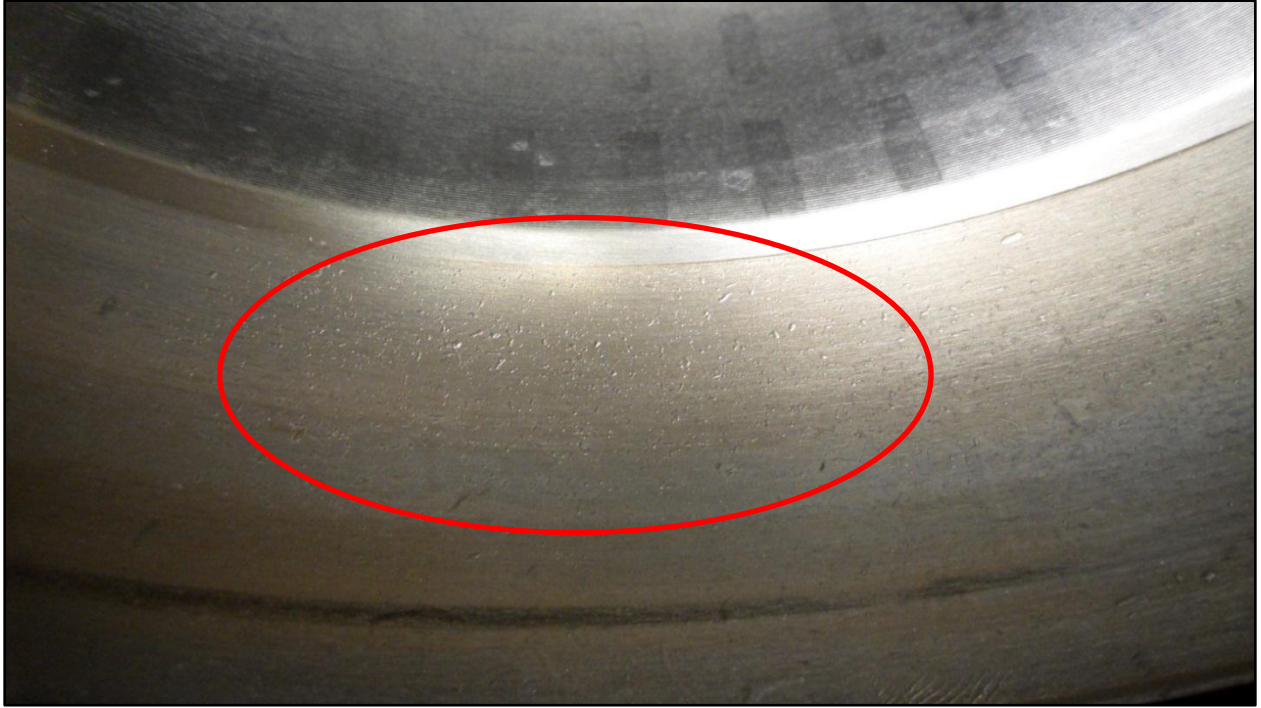


Figure 36: One of the cup raceways in the L3 bearing after the third and final teardown exhibiting extensive pitting.

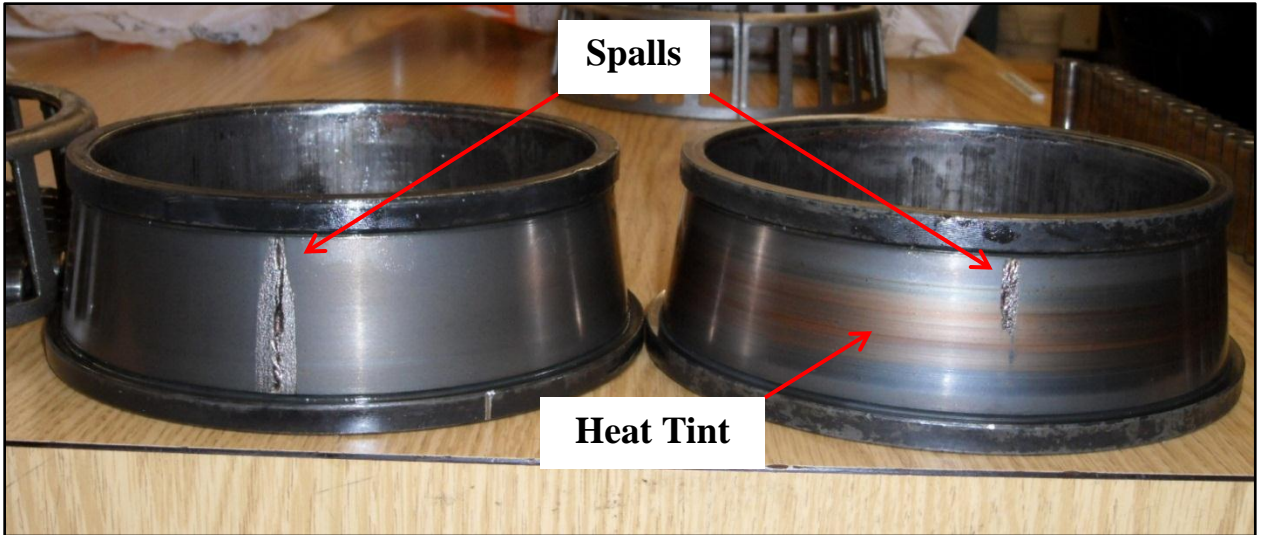


Figure 37: Both cones removed from the 130L-L3 bearing with large spalls and heat tint indicated.

The formation and rapid growth of the cone spalls seen in Figure 37 led to failure after approximately 85,778 km (53,300 mi) of laboratory testing. This distance is relatively small in comparison to the average mileage covered by freight cars in active service. For example, the railcar that this bearing was removed from covered approximately 6,450 km (~4,000 mi) during one round trip across Southern Australia, and completed this route every four to six days. This means that the 130L-L3 bearing, had it been allowed to continue in service undetected, could have failed catastrophically in eight to ten weeks of normal service. Furthermore, the seizing of this bearing on the test axle is analogous to a full burn-off failure in field operation, and could have resulted in a catastrophic derailment.

5.4 Case Study 3: Railcar PBGY0130L-R1

On November 24, 2010, the bearing in the R1 position of railcar PBGY0130L was flagged for removal by a Trackside Acoustic Detector System (TADS) installation. This bearing was removed from service when the railcar was available for maintenance, and a replacement bearing was installed. The bearing removed from the R1 position was subsequently disassembled and thoroughly inspected for defects by the Australian test fleet maintenance crew. Following this inspection it was determined that this setout bearing did not have any defects present and it was rebuilt and returned to active service.

The condition of this bearing, prior to being flagged by the TADS installation, demonstrates that it did not exhibit any signs of atypical operation. On the contrary, this bearing operated below the average temperatures of both railcar PBGY0130L and the entire train, as demonstrated by the results of Criteria 3 and 4 listed in Table 14. Furthermore, this bearing had never been highly ranked among Level 3 Criteria and had not triggered any Level 2 alarms prior

to being flagged for removal by the TADS installation. Detailed analysis of this bearing's temperature data, summarized in Table 14, indicates that the replacement bearing installed in the R1 position exhibited a slightly greater percentage of high temperature operation than the original bearing, as characterized by Criteria 1 and 2. The results of the remaining three Criteria indicate that the performance of the replacement bearing was comparable to the healthy bearing that was removed.

Table 14: Condition of the bearing in the R1 position, as assessed by the Level 3 Criteria, before and after replacement on November 24, 2010.

Month	Criterion 1	Criterion 2	Criterion 3 (σ_{car})	Criterion 4 (σ_{train})	Criterion 5
September 2010	0%	0%	-0.36	0.01	1.72%
October 2010	0%	0%	-0.40	-0.11	2.10%
November 2010	0.66%	0%	-0.09	0.50	2.53%
December 2010	4.19%	3.23%	0.16	0.39	2.41%
January 2011	2.47%	0%	-0.12	0.40	2.68%

This *non-verified* bearing highlights the potential inaccuracies associated with assessing the health of in-service bearings based on intermittent monitoring by wayside equipment. In comparison, the on-board condition monitoring system installed on this railcar indicated that this bearing was healthy at the time of removal, consistently operating below the average temperature of its peers; an assessment that is validated by the subsequent teardown and inspection performed by the maintenance crew of the Australian test fleet. The expense incurred by SCT Logistics related to this non-verified bearing removal is considerable, including labor costs and shop time to remove the original bearing, the cost of a new replacement bearing, as well as the revenue that was lost while this car was not in service.

CHAPTER VI

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

The current system utilized for condition monitoring of tapered-roller bearings in service is composed solely of stationary detector installations placed on the wayside of the railroad track. In North America, this system consists of approximately 5,000 hot box detectors (HBDs) and 20 Trackside Acoustic Detector System (TADS) installations, illustrating the overwhelming preference within the railroad industry for the use of thermal detection as an indicator of bearing health. However, the spacing between successive HBDs may be 24-64 km (15-40 mi) apart, depending on the location and amount of traffic on the track. The intermittent monitoring provided by these wayside installations is not capable of detecting brief temperature trending events, which have been shown through extensive laboratory testing to be an indicator of a potentially unhealthy bearing. Continuous monitoring of bearing temperatures has been proven an effective method of detecting potentially unhealthy bearings for passenger rail operator Amtrak. However, the wired temperature sensors utilized by Amtrak are not practical for freight car applications due to the frequent exchange of railcars on a train.

The development of IONX Wireless Sensor Nodes (WSNs) represents the first low-cost, durable, and accurate wireless temperature sensing device that can be easily retrofitted to existing freight car hardware. This system allows for continuous monitoring of bearing and ambient temperatures, facilitating detailed statistical analyses of the acquired temperature data in

order to assess the condition of bearings in service. Furthermore, the observation of brief temperature trending events, and determination of the frequency of these occurrences, greatly improves the accuracy of bearing condition assessments and identification of degradation trends occurring in service.

The statistical criteria and algorithms presented in Chapter IV have been organized into three levels, facilitating the classification of in-service bearings based on their maintenance priority. Level 1 alarms indicate a potential imminent failure, requiring immediate attention by the train controller, and, are consistent with the Association of American Railroads (AAR) standards that are currently implemented using the network of HBDs. Level 2 alarms are used to identify bearings that will require attention within a specified time span (e.g., 3-6 months out), while Level 3 alarms function as a means of generating a watch list of potentially problematic bearings. Statistical analyses of more than 24 million temperature readings acquired over the course of 18 months of monitoring the Australian test fleet support the temperature thresholds established for use with Level 3 Criteria, as well as the performance benchmarks utilized in Level 2 Criteria.

During the 18 month Australian field test, two Class E tapered-roller bearings were removed from service based on the results of the developed algorithms. Following removal, these two bearings were sent to the University of Texas-Pan American (UTPA) for testing and subsequent disassembly, detailed visual inspection, and measurement of all internal dimensions and clearances. These inspections revealed that both bearings had defects present at the time of removal, and these defects were responsible for the elevated operating temperatures observed during field service. In a staggering validation of the developed algorithms, the second Class E bearing removed from the Australian test fleet failed on the dynamic tester after only 85,778 km

(53,300 mi) by abruptly seizing on the axle. This distance is relatively small, equivalent to approximately eight to ten weeks of normal service for this bearing. The seizing of this bearing on the test axle is analogous to a full burn-off failure in field operation, and could have resulted in a catastrophic derailment.

Moreover, a third Class E bearing was removed from service after being identified as defective by a Trackside Acoustic Detector System (TADS) installation. This removal was in contradiction with the assessment that the bearing was healthy at the time of removal, based on the analysis of the temperature data acquired from this bearing utilizing the algorithms presented in Chapter IV. Subsequent disassembly and inspection performed by maintenance technicians verified that this bearing did not have any defects present, and it was later returned to active service. This *non-verified* bearing highlights the inherent limitations and inaccuracies associated with the use of intermittent monitoring to assess the health of bearings in service.

The current IONX system provides a proven, ready-to-use continuous bearing health monitoring system that can be readily installed onto existing freight car bearing adapters. This system allows railcar operators to transition from high-cost reactive maintenance scheduling to a more cost-effective predictive maintenance system. The latter facilitates more efficient use of railroad assets and infrastructure, reduced delays of trains and cargo, and safer operation of the railroad network. The financial benefits associated with this increase in efficiency more than offsets the costs associated with the implementation of a continuous bearing health monitoring system.

6.2 Future Work

The IONX system, in its current state, has proven to be an effective continuous bearing health monitoring solution for Class E bearings and the service conditions experienced by SCT Logistics' freight cars in Australia. Although the basic statistical metrics and comparisons, which comprise the core of the developed algorithms, may be readily applied to railcars across the globe, the temperature limits and performance thresholds must be refined for other classes of bearings and different types of freight service. The refinement of these thresholds would follow a methodology similar to the one described in Section 4.2, using temperature data acquired from the deployment of the IONX system in other services.

The existing prototype condition monitoring system records minute-by-minute and each minute of data is uploaded to the database. To extend battery life, future systems may utilize a reduced sampling rate on the order of one reading every four to eight minutes. This reduced sampling rate is relatively less than the time constant of a tapered-roller bearing, thus, allowing for the observation of brief temperature trending events. In an effort to further extend battery life, full datasets may not be uploaded to the database, instead more sparse periodic measurements or metric calculations may be reported. Work must be done to scale application of the existing metrics to a sparser data set while preserving the accuracy in the assessment of bearing condition.

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APPENDIX

APPENDIX

MATLAB™ COMPUTER CODE

MATLAB™ Program 1: The function *data_sorter_v4.m* is used to import the raw temperature data files (.csv format), and reorder the temperature readings so that all readings acquired within the same minute are stored on a single row of a master temperature data array. Additionally, all temperature readings acquired from a single WSN are arranged into one column. Logical filters are implemented in order to identify and remove erroneous temperature data from the ordered data array. Statistical distributions are generated in order to visually depict the thermal performance of single bearings as well as groups of bearings on one railcar or within the entire train.

```
function data_sorter_v4(filename,Alertfilenames)
%% Function Settings
Visibility='on';
PlotToggle=0;
PlotToggleCombined=1;
dTLimit=100;
format long
%% Import SCT Temperature data report
ImportTempFile(filename); %User-defined func, returns 'data','textdata'
fprintf('\n<%s> has been imported into MATLAB succesfully\n',filename)
%% Create Master Data File Header
NodeID=cell(1,10);
NodeID(1)={'Time'};
for z=2:9
    n=num2str(z-1);
    NodeID(1,z)={strcat('Node #',n)};
end
NodeID(1,10)={'Ambient'};
%% Extract Railcar name from filename
RailcarName=textdata(2,1);
assignin('base','RailcarName',RailcarName)
DirName=strcat(pwd,'\Results\',RailcarName);
%% Assign Imported Raw Data to workspace
DataName={strcat(RailcarName,'_RawTempData')};
TextDataName={strcat(RailcarName,'_RawTempText')};
TextDataName{1};
assignin('base',char(DataName{1}),data)
assignin('base',char(TextDataName{1}),textdata)
%% Convert time string dates to date numbers. Remove repeated time/dates
time_str=char(textdata(2:end,2));
timeVec=datevec(time_str,'mm/dd/yyyy HH:MM:SS PM');
```

```

assignin('base','TimeVectors',timeVec)
timeVec(:,5)=timeVec(:,5)+(timeVec(:,6)>=30);
timeVec(:,6)=0;
timeVec(:,4)=timeVec(:,4)+(timeVec(:,5)>=60);
timeVec(:,5)=timeVec(:,5).*(~(timeVec(:,5)>=60));
if any(timeVec(:,4)>=24)
    timeVec(:,3)=timeVec(:,3)+(timeVec(:,4)>=24);
    timeVec(:,4)=timeVec(:,4).*(~(timeVec(:,4)>=24));
end
times=datenum(timeVec);
assignin('base','TimeNumbers',times)
sensorID=data(:,1);
temps=data(:,2);
UT=unique(times);
mast_data=zeros(length(UT),12);
mast_data(:,1)=UT;
%% Calculate time step between adjacent data points
TimeDifference=diff(mast_data(:,1));
TimeLimit=1/24;
DataBreaks=(TimeDifference>TimeLimit);
SplitPoints=find(DataBreaks==1);
NTimePlots=length(SplitPoints);
%% Arrange all temperature values by reading time
length_data=length(data);
OverwriteCount=0;
DuplicateCount=0;
for i=1:length_data
    SID=sensorID(i);
    index=find(times(i)==UT);
    if mast_data(index,SID+1)==0
        mast_data(index,SID+1)=temps(i);
    elseif (mast_data(index,SID+1)~=temps(i))&&(mast_data(index,1)==times(i))
        mast_data(index,SID+1)=temps(i);
        OverwriteCount=OverwriteCount+1;
    elseif (mast_data(index,SID+1)==temps(i))
        mast_data(index,SID+1)=temps(i);
        DuplicateCount=DuplicateCount+1;
    end
end
mast_data(mast_data==0)=NaN;
mast_data(mast_data<0)=NaN;
NaNCount=sum(sum(isnan(mast_data)));
TemperatureCount=size(mast_data,1)*(size(mast_data,2)-1)-NaNCount;
CountDiff=length_data-TemperatureCount;
if (CountDiff~=0)
    ResultsDirName=fullfile(pwd,'Results');
    if ~exist(ResultsDirName,'dir')
        mkdir(ResultsDirName)
    end
    ErrorLogFileName=strcat(pwd,'\Results\ErrorLog_',date,'.txt');
    ErrorLogFileID=fopen(ErrorLogFileName,'a');
    fprintf(ErrorLogFileID,'Data File <%s> contains %6.0f temperature readings.\n',filename,length_data);
    fprintf(ErrorLogFileID,'Reordered Data array contains %6.0f temperature readings.\n',TemperatureCount);
    fprintf(ErrorLogFileID,'%5.0f temperature readings were lost\n',CountDiff);
    fprintf(ErrorLogFileID,'Total Data Overwrite Errors Counted = %4.0f\n',OverwriteCount);
    fprintf(ErrorLogFileID,'Total Duplicate Temperature Readings = %4.0f\n',DuplicateCount);
end

```

```

    fclose(ErrorLogFileID);
end
assignin('base','MasterTempData',mast_data)
assignin('base','MasterData',mast_data)
%% 8 Minute Moving Average
rows=size(mast_data,1); cols=size(mast_data,2);
MovingAverage=zeros(rows,cols);
MovingAverage(:,1)=mast_data(:,1);
for r=1:rows
    for c=1:cols
        if r<=8
            MovingAverage(r,c)=mean(mast_data(1:r,c));
        else
            MovingAverage(r,c)=mean(mast_data((r-7):r,c));
        end
    end
end
end
assignin('base','MovingAverage',MovingAverage)
%% Identify Temperature readings > 200 F
Z=size(mast_data,1);
row=1; iter=1;
OverTemp=[]; PlotTemps=[]; PlotTimes=[];
if ~exist('Results','dir')
    mkdir('Results')
end
HighTempFileName1=fullfile(pwd,'Results','HighTempData1.txt');
HighTempFileName2=fullfile(pwd,'Results','HighTempData2.txt');
if exist(HighTempFileName1,'file')
    HighTempFileID1=fopen(HighTempFileName1,'a');
else
    HighTempFileID1=fopen(HighTempFileName1,'a');
    fprintf(HighTempFileID1,'RailcarName,Time,NodeID,AmbientTemp,BearingTemp\n');
end
if exist(HighTempFileName2,'file')
    HighTempFileID2=fopen(HighTempFileName2,'a');
else
    HighTempFileID2=fopen(HighTempFileName2,'a');

fprintf(HighTempFileID2,'RailcarName,Time,Ambient,Node#1,Node#2,Node#3,Node#4,Node#5,Node#6,Node#7,
Node#8\n');
end
RailcarName=char(RailcarName);
for z=1:Z
    if any(mast_data(z,2:9)>=200)
        OverTemp(row,:)=mast_data(z,:); %[Time {Nodes1-8}]
        Time=datestr(mast_data(z,1),'mm/dd/yyyy HH:MM PM');
        fprintf(HighTempFileID2,'%s,%s,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f\n',...
            RailcarName,Time,OverTemp(row,10),...
            OverTemp(row,2),OverTemp(row,3),OverTemp(row,4),...
            OverTemp(row,5),OverTemp(row,6),OverTemp(row,7),...
            OverTemp(row,8),OverTemp(row,9));
        INDEX=find(mast_data(z,2:9)>=200)+1;
        ambient=mast_data(z,10);
        Y=length(INDEX);
        for y=1:Y
            BearingTemp=mast_data(z,INDEX(y));
        end
    end
end

```



```

        BearingID=char(NodeID(INDEX(y)));
        OutlierBearingNames(iter,1)=strcat(RailcarName,'_',NodeID(INDEX(y)));
        fprintf(HighTempFileID1,'%s,%s,%s,%s,%4.2f,%3.4f\n',RailcarName,...
            Time,BearingID,ambient,BearingTemp);
        PlofTimes(iter,1)=mast_data(z,1);
        PlofTemps(iter,1)=BearingTemp;
        iter=iter+1;
    end
    row=row+1;
end
end
HighTempCountFileName=fullfile(pwd,'Results','HighTempCount.txt');
HighTempCountFileID=fopen(HighTempCountFileName,'a');
fprintf(HighTempCountFileID,'RailcarName,NodeID,Temp.Count,Percent,n-Sigma\n');
K=length(mast_data);
all_temps=mast_data(1:end,2:9);
all_temps=all_temps(all_temps>0);
CarAverage=mean(all_temps);
CarSTD=std(all_temps);
for z=2:9
    HighTempCount(1,(z-1))=sum(mast_data(:,z)>=200);
    Percentage=HighTempCount(1,(z-1))/(sum(~isnan(mast_data(:,z))))*100;
    NodeTemps=mast_data(:,z);
    NodeTemps=NodeTemps(NodeTemps>0);
    NodeAverage=mean(NodeTemps);
    nSigma=(NodeAverage-CarAverage)/CarSTD;
    fprintf(HighTempCountFileID,'%s,%s,%4.0f,%2.3f,%1.3f\n',RailcarName,...
        char(NodeID(z)),HighTempCount(1,(z-1)),Percentage,nSigma);
end
fclose(HighTempFileID1);
fclose(HighTempFileID2);
fclose(HighTempCountFileID);
assignin('base','OverTemp',OverTemp)
%% Calculate Bearing Temperature above Ambient
delTempFileName1=fullfile(pwd,'Results','delTempData1.txt');
if ~exist(delTempFileName1,'file')
    delTempFileID1=fopen(delTempFileName1,'w');
    fprintf(delTempFileID1,'RailcarName,Time,NodeID,AmbientTemp,BearingTemp,deltaTemp\n');
else
    delTempFileID1=fopen(delTempFileName1,'a');
end
delTempFileName2=fullfile(pwd,'Results','delTempData2.txt');
if ~exist(delTempFileName2,'file')
    delTempFileID2=fopen(delTempFileName2,'w');
    fprintf(delTempFileID2,'RailcarName,Time,Ambient,dT#1,dT#2,dT#3,dT#4,dT#5,dT#6,dT#7,dT#8\n');
else
    delTempFileID2=fopen(delTempFileName2,'a');
end
delTempCountFileName=fullfile(pwd,'Results','delTempCount.txt');
delTempCountFileID=fopen(delTempCountFileName,'a');
fprintf(delTempCountFileID,'RailcarName,NodeID,delTempCount,Percent\n');
Z=size(mast_data,1);
row=1; iter=1;
delTemp=[];
for z=1:Z
    del_Temp=mast_data(z,2:9)-mast_data(z,10);

```

```

TempRise(z,:)=cat(2,mast_data(z,1),del_Temp,mast_data(z,10));
if any(del_Temp>=dTLimit)
    delTemp(row,:)=cat(2,mast_data(z,1),del_Temp,mast_data(z,10));%[Time {Nodes1-8} Ambient]
    Time=datestr(mast_data(z,1),'mm/dd/yyyy HH:MM PM');
    fprintf(delTempFileID2,'%s,%s,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f\n',...
        RailcarName,Time,delTemp(row,10),delTemp(row,2),delTemp(row,3),...
        delTemp(row,4),delTemp(row,5),delTemp(row,6),delTemp(row,7),...
        delTemp(row,8),delTemp(row,9));
    INDEX=find(delTemp(row,2:9)>=dTLimit); INDEX=INDEX+1;
    ambient=mast_data(z,10);
    Y=length(INDEX);
    for y=1:Y
        NODEdt=delTemp(row,INDEX(y));
        BearingID=char(NodeID(INDEX(y)));
        BearingTemp=mast_data(z,INDEX(y));
        fprintf(delTempFileID1,'%s,%s,%s,%3.2f,%3.2f\n',RailcarName,...
            Time,BearingID,ambient,BearingTemp,NODEdt);
        iter=iter+1;
    end
    row=row+1;
end
end
Z=size(TempRise,1);
for z=Z:-1:1
    if all(isnan(TempRise(z,2:10)))
        TempRise(z,:)=[];
    end
end
end
if (~isempty(delTemp))
    for z=2:9
        delTempCount(1,(z-1))=sum(delTemp(:,z)>=dTLimit);
        Percentage=delTempCount(1,(z-1))/(sum(~isnan(mast_data(:,z))))*100;
        fprintf(delTempCountFileID,'%s,%s,%4.0f,%2.3f\n',RailcarName,char(NodeID(z)),delTempCount(1,(z-1)),Percentage);
    end
end
fclose(delTempFileID1);
fclose(delTempFileID2);
fclose(delTempCountFileID);
assignin('base','DeltaTemp',TempRise)
%% Histograms-Per Wheel
if PlotToggle
    DirName=strcat(pwd,'\Results\',RailcarName);
    if exist(DirName,'dir')
        rmdir(DirName,'s')
        mkdir(DirName)
    else
        mkdir(DirName)
    end
end
for z=2:10
    figure('Visible',Visibility)
    set(gcf,'PaperSize',[6 5],'PaperPositionMode','auto')

    nbins=round((max(mast_data(:,z))-min(mast_data(:,z)))/5);
    [n,xout]=hist(mast_data(:,z),nbins);
    n=n/sum(n)*100;
end

```

```

bar(xout,n)
if z==10
    axis([45 125 -Inf Inf])
else
    axis([50 235 -Inf Inf])
end
NTotal=sum(n);
if NTotal<99.95 || NTotal>100.05
    warning('Error plotting %s histogram in %s\n',char(NodeID(z)),filename);
end
TitleName=char(strcat('Temperature Distribution - ',NodeID(z)));
SubTitleName=char(strcat('Rail Car ID (',RailcarName,')'));
title({ TitleName;SubTitleName },'FontWeight','bold',...
    'FontName','Times','FontSize',14)
xlabel({'Temperature (^oF)'},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
ylabel({'Time Distribution (% of Readings)'},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
FigFileName=strcat(RailcarName,'_',char(NodeID(z)));
FullFileName=fullfile(DirName,FigFileName);
saveas(gcf,FullFileName,'pdf')
saveas(gcf,FullFileName,'fig')
close(gcf)
end
end
%% Histograms-Bearing & Ambient
if PlotToggle
figure('Visible',Visibility)
set(gcf,'PaperSize',[12 10],'PaperPositionMode','auto')
for z=2:10
    nbins=round((max(mast_data(:,z))-min(mast_data(:,z)))/5);
    [n,xout]=hist(mast_data(:,z),nbins);
    n=n/sum(n)*100;
    if z==10
        subplot(3,3,1)
    else
        subplot(3,3,z)
        axis([50 235 -Inf Inf])
    end
    bar(xout,n)
    NTotal=sum(n);
    TitleName=char(NodeID(z));
    title(TitleName,'FontWeight','bold','FontName','Times','FontSize',14)
end
FigFileName=strcat(RailcarName,'_AllvsAmbient');
FullFileName=fullfile(DirName,FigFileName);
saveas(gcf,FullFileName,'pdf')
saveas(gcf,FullFileName,'fig')
close(gcf)
end
%% Histograms-Per Axle
AxleName={'Axle #1';'Axle #2';'Axle #3';'Axle #4'};
if PlotToggle
for z=1:4
    Z=2*z;
figure('Visible',Visibility)

```

```

set(gcf,'PaperSize',[6 5],'PaperPositionMode','auto')
AxleData=cat(1,mast_data(:,Z),mast_data(:,Z+1));
nbins=round((max(AxleData)-min(AxleData))/5);
[n,xout]=hist(AxleData,nbins);
n=n/sum(n)*100;
bar(xout,n)
axis([50 235 -Inf Inf])
NTotal=sum(n);
TitleName=char(strcat('Temperature Distribution - ',AxleName(z)));
SubTitleName=char(strcat('Rail Car ID (',RailcarName,')'));
title({TitleName;SubTitleName},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
xlabel({'Temperature (^oF)'},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
ylabel({'Time Distribution (% of Readings)'},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
FigFileName=strcat(RailcarName,'_',char(AxleName(z)));
FullFileName=fullfile(DirName,FigFileName);
saveas(gcf,FullFileName,'pdf')
saveas(gcf,FullFileName,'fig')
close(gcf)
end
end
%% Histograms-Per Railcar
if (1)%PlotToggle
all_temps=mast_data(1:end,2:9);
all_temps=all_temps(all_temps>0);
figure('Visible',Visibility)
set(gcf,'PaperSize',[6 5],'PaperPositionMode','auto')
nbins=round((max(all_temps)-min(all_temps))/5);
[N,allTout]=hist(all_temps,nbins);
N=N/sum(N)*100;
bar(allTout,N)
axis([50 235 -Inf Inf])
NTotal=sum(n);
if iscell(DirName)
    DirName=char(DirName);
end
TitleName=char(strcat('Temperature Distribution for all wheels'));
SubTitleName=char(strcat('Rail Car ID (',RailcarName,')'));
FigFileName=strcat(RailcarName,'_All Wheels');
FullFileName=fullfile(DirName,FigFileName);
title({TitleName;SubTitleName},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
xlabel({'Temperature (^oF)'},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
ylabel({'Time Distribution (% of Readings)'},'FontWeight','bold',...
    'FontName','Times','FontSize',14)
close(gcf)
end
%% Histograms-Bearing & RailCar
if PlotToggleCombined
FigHandle=figure('Visible',Visibility);
set(gcf,'PaperSize',[10 12],'PaperPositionMode','auto')
%set(gcf,'PaperPosition',[0 0 9 5.5],'PaperPositionMode','manual')
for z=2:9

```

```

position=z-1;
subplot(4,2,position)
hold on;
CarHandle=plot(allTout,N,'-b','LineWidth',2);
nbins=round((max(mast_data(:,z))-min(mast_data(:,z)))/5);
[n,xout]=hist(mast_data(:,z),nbins);
n=n/sum(n)*100;
BearingHandle=plot(xout,n,'-r','LineWidth',2);
box on
axis([50 235 0 Inf])
TitleName=NodeNameID(position);
title(TitleName,'FontWeight','bold','FontName','Times','FontSize',14,...
'BackgroundColor',[1 1 1])
end
TitleHandle=uicontrol('Style','text','String',...
    strcat('Absolute Temperature Distribution (',RailcarName,')'),...
    'HorizontalAlignment','center','Units','normalized',...
    'Position',[0.38 .9 .28 .05],'BackgroundColor',[1 1 1]);
set(TitleHandle,'FontName','Times','FontSize',18,'FontWeight','Bold');
Axle1Handle=uicontrol('Style','Text','String','Axle 1',...
    'horizontalAlignment','left','Units','normalized',...
    'Position',[.05 .8 .05 .03],'BackgroundColor',[1 1 1]);
set(Axle1Handle,'FontName','Times','FontSize',18,'FontWeight','Bold');
Axle2Handle=uicontrol('Style','Text','String','Axle 2',...
    'horizontalAlignment','left','Units','normalized',...
    'Position',[.05 .58 .05 .03],'BackgroundColor',[1 1 1]);
set(Axle2Handle,'FontName','Times','FontSize',18,'FontWeight','Bold');
Axle3Handle=uicontrol('Style','Text','String','Axle 3',...
    'horizontalAlignment','left','Units','normalized',...
    'Position',[.05 .36 .05 .03],'BackgroundColor',[1 1 1]);
set(Axle3Handle,'FontName','Times','FontSize',18,'FontWeight','Bold');
Axle4Handle=uicontrol('Style','Text','String','Axle 4',...
    'horizontalAlignment','center','Units','normalized',...
    'Position',[.05 .14 .05 .03],'BackgroundColor',[1 1 1]);
set(Axle4Handle,'FontName','Times','FontSize',18,'FontWeight','Bold');
hold off;
FigFileName=strcat(RailcarName,'_Bearing_Temp_Comparison');
FullFileName=fullfile(pwd,'Results',FigFileName);
saveas(gcf,FullFileName,'fig')
close(gcf)
end
%% Histograms-DeltaTemp Per RailCar
all_delTemp=TempRise(1:end,2:9);
all_delTemp=all_delTemp(all_delTemp>0);
nbins=round((max(all_delTemp)-min(all_delTemp))/5);
[N,alldTout]=hist(all_delTemp,nbins);
N=N/sum(N)*100;
%% Histograms-DeltaTemp Overlaid Plots
if PlotToggleCombined
FigHandle=figure('Visible',Visibility);
set(gcf,'PaperSize',[10 12],'PaperPositionMode','auto')
for z=2:9
    CarHandle=[];
    BearingHandle=[];
    position=z-1;
    subplot(4,2,position)

```

```

hold on;
CarHandle=bar(alldTout,N);
set(get(CarHandle,'children'),'facea',0.75)
nbins=round((max(TempRise(:,z))-min(TempRise(:,z)))/5);
if (nbins~=0)
[n,xout]=hist(TempRise(:,z),nbins);
n=n/sum(n)*100;
BearingHandle=bar(xout,n,'FaceColor','yellow');
set(get(BearingHandle,'children'),'facea',0.5)
end
box on;
TitleName=char(NodeID(z));
title(TitleName,'FontWeight','bold','FontName','Times','FontSize',10)
axis([0 150 -Inf Inf])
NTotal=sum(n);
end
TitleHandle=uicontrol('Style','text','String',...
    strcat("Temperature Increase Comparison ('",RailcarName,')"),...
    'HorizontalAlignment','center','Units','normalized',...
    'Position',[0 .95 1 .025],'BackgroundColor',[.8 .8 .8]);
set(TitleHandle,'FontName','Times','FontSize',14,'FontWeight','Bold');

Axle1Handle=uicontrol('Style','Text','String','Axle 1',...
    'horizontalAlignment','left','Units','normalized',...
    'Position',[.05 .8 .05 .03],'BackgroundColor',[.8 .8 .8]);
set(Axle1Handle,'FontName','Times','FontSize',10,'FontWeight','Bold');

Axle2Handle=uicontrol('Style','Text','String','Axle 2',...
    'horizontalAlignment','left','Units','normalized',...
    'Position',[.05 .58 .05 .03],'BackgroundColor',[.8 .8 .8]);
set(Axle2Handle,'FontName','Times','FontSize',10,'FontWeight','Bold');

Axle3Handle=uicontrol('Style','Text','String','Axle 3',...
    'horizontalAlignment','left','Units','normalized',...
    'Position',[.05 .36 .05 .03],'BackgroundColor',[.8 .8 .8]);
set(Axle3Handle,'FontName','Times','FontSize',10,'FontWeight','Bold');

Axle4Handle=uicontrol('Style','Text','String','Axle 4',...
    'horizontalAlignment','center','Units','normalized',...
    'Position',[.05 .14 .05 .03],'BackgroundColor',[.8 .8 .8]);
set(Axle4Handle,'FontName','Times','FontSize',10,'FontWeight','Bold');
hold off;
FigFileName=strcat(RailcarName,'_Bearing_DeltaTemp_Comparison');
FullFileName=fullfile(pwd,'Results',FigFileName);
saveas(gcf,FullFileName,'fig')
close(gcf)
end
%% TimeSeries-Temperature vs. Time
if PlotToggle
figure('Visible',Visibility)
set(gcf,'PaperSize',[12 10],'PaperPositionMode','auto')
plot(mast_data(:,1),mast_data(:,2),mast_data(:,1),mast_data(:,3),...
    mast_data(:,1),mast_data(:,4),mast_data(:,1),mast_data(:,5),...
    mast_data(:,1),mast_data(:,6),mast_data(:,1),mast_data(:,7),...
    mast_data(:,1),mast_data(:,8),mast_data(:,1),mast_data(:,9),...
    mast_data(:,1),mast_data(:,10))

```

```

set(findobj('Type','line'),'MarkerSize',0.25)
tmin=min(mast_data(:,1)); tmax=max(mast_data(:,1));
ymin=min(mast_data(:,10)); ymax=max(max(mast_data(:,2:9)));
axis([tmin tmax ymin ymax])
datetick('x',2)
TitleName=char(strcat('Node Temperature vs. Time'));
SubTitleName=char(strcat('Rail Car ID (',RailcarName,')'));
title({TitleName;SubTitleName},'FontWeight','bold','FontName','Times','FontSize',14)
xlabel('Time','FontWeight','bold','FontName','Times','FontSize',14)
ylabel('Temperature (^oF)','FontWeight','bold','FontName','Times','FontSize',14)
FigFileName=strcat(RailcarName,'_',TimeSeries_TempPlot');
FullFileName=fullfile(DirName,FigFileName);
saveas(gcf,FullFileName,'pdf')
saveas(gcf,FullFileName,'fig')
close(gcf)
end
%% TimeSeries-Temperature increase vs. time
if PlotToggle
figure('Visible',Visibility)
set(gcf,'PaperSize',[6 5],'PaperPositionMode','auto')
plot(TempRise(:,1),TempRise(:,2),TempRise(:,1),TempRise(:,3),...
TempRise(:,1),TempRise(:,4),TempRise(:,1),TempRise(:,5),...
TempRise(:,1),TempRise(:,6),TempRise(:,1),TempRise(:,7),...
TempRise(:,1),TempRise(:,8),TempRise(:,1),TempRise(:,9))
set(findobj('Type','line'),'LineWidth',0.5)
tmin=min(TempRise(:,1)); tmax=max(TempRise(:,1));
ymin=min(TempRise((size(TempRise,1)+1):end));
ymax=max(TempRise((size(TempRise,1)+1):end));
axis([tmin tmax ymin ymax])
datetick('x',2)
TitleName=char(strcat('Temperature Above Ambient vs. Time'));
SubTitleName=char(strcat('Rail Car ID (',RailcarName,')'));
title({TitleName;SubTitleName},'FontWeight','bold','FontName','Times','FontSize',14)
xlabel('Time','FontWeight','bold','FontName','Times','FontSize',14)
ylabel('Temperature (^oF)','FontWeight','bold','FontName','Times','FontSize',14)
legend('Node #1','Node #2','Node #3','Node #4','Node #5','Node #6',...
'Node #7','Node #8')
FigFileName=strcat(RailcarName,'_',TimeSeries_TempRise_Plot');
FullFileName=fullfile(DirName,FigFileName);
saveas(gcf,FullFileName,'pdf')
saveas(gcf,FullFileName,'fig')
close(gcf)
end
%% TimeSeries-Temperatures > 200F vs. Time
if PlotToggle
figure('Visible',Visibility)
set(gcf,'PaperSize',[6 5],'PaperPositionMode','auto')
plot(PlotTimes,PlotTemps,'.r')
set(findobj('Type','line'),'MarkerSize',5)
tmin=min(OverTemp(:,1)); tmax=max(OverTemp(:,1));
ymin=min(OverTemp((size(OverTemp,1)+1):end));
ymax=max(OverTemp((size(OverTemp,1)+1):end));
axis([tmin tmax ymin ymax])
datetick('x',2)

TitleName=char(strcat('Temperature > 200F vs. Time'));

```

```

SubTitleName=char(strcat('Rail Car ID (',RailcarName,')'));
title({ TitleName;SubTitleName },'FontWeight','bold','FontName','Times','FontSize',14)
xlabel('Time','FontWeight','bold','FontName','Times','FontSize',14)
ylabel('Temperature (^oF)','FontWeight','bold','FontName','Times','FontSize',14)

FigFileName=strcat(RailcarName,'_',TimeSeries_HighTemp_Plot');
FullFileName=fullfile(DirName,FigFileName);
saveas(gcf,FullFileName,'pdf')
saveas(gcf,FullFileName,'fig')
close(gcf)
end

%% TimeSeries-8 Minute Moving Average vs. Time
if PlotToggle
figure('Visible',Visibility)
set(gcf,'PaperSize',[6 5],'PaperPositionMode','auto')
plot(MovingAverage(:,1),MovingAverage(:,2),MovingAverage(:,1),MovingAverage(:,3),...
    MovingAverage(:,1),MovingAverage(:,4),MovingAverage(:,1),MovingAverage(:,5),...
    MovingAverage(:,1),MovingAverage(:,6),MovingAverage(:,1),MovingAverage(:,7),...
    MovingAverage(:,1),MovingAverage(:,8),MovingAverage(:,1),MovingAverage(:,9))
datetick('x',2)

TitleName=char(strcat('8 Minute Moving Average vs. Time'));
SubTitleName=char(strcat('Rail Car ID (',RailcarName,')'));
title({ TitleName;SubTitleName },'FontWeight','bold','FontName','Times','FontSize',14)
xlabel('Time','FontWeight','bold','FontName','Times','FontSize',14)
ylabel('Temperature (^oF)','FontWeight','bold','FontName','Times','FontSize',14)

FigFileName=strcat(RailcarName,'_',TimeSeries_MovingAverage_Plot');
FullFileName=fullfile(DirName,FigFileName);
saveas(gcf,FullFileName,'pdf')
saveas(gcf,FullFileName,'fig')
close(gcf)
end

%% Save data file as .CSV
%% All Data

FullFileName=fullfile(DirName,RailcarName,'_Sorted_Data.csv');
%% Temperatures over 200F
FullFileName=fullfile(DirName,RailcarName,'_HighTemp_Data.csv');
fprintf('<%s> was analyzed succesfully\n',filename)
close('all');
fclose('all');
end
%% Function Functions
function ImportTempFile(fileToRead1)
%IMPORTFILE(FILETOREAD1)
% Imports data from the specified file
% FILETOREAD1: file to read

% Auto-generated by MATLAB on 25-May-2010 12:01:12

% Import the file
newData1 = importdata(fileToRead1);

```



```
% Create new variables in the base workspace from those fields.
vars = fieldnames(newData1);
for i = 1:length(vars)
    assignin('caller', vars{i}, newData1.(vars{i}));
end
end
```

```
function ImportAlertFile(fileToRead1)
%IMPORTFILE(FILETOREAD1)
% Imports data from the specified file
% FILETOREAD1: file to read
```

```
% Import the file
newData1 = importdata(fileToRead1);
```

```
% Create new variables in the base workspace from those fields.
vars = fieldnames(newData1);
for i = 1:length(vars)
    assignin('caller', vars{i}, newData1.(vars{i}));
end
end
```

MATLAB™ Program 2: The *RailcarTempPlot.m* program is used to generate temperature vs. time plots for a single railcar. The program loads the master temperature data file created using *data_sorter_v4* and prompts the user to select a railcar from with fleet, followed by the desired start and end times of the plot.

```

%% RailcarTempPlot.m plots railcar temperature data for a specified timespan
% Written by Sean Woods (updated 2/20/2011)
% This script loads the processed FleetData temperature datafile and plots
% the temperature history for the selected railcar and during
% the specified time period.
%% Function Settings
PrintData=0; %PrintData=1 will create csv data file
RemoveNegs=0; %RemoveNegs=1 will remove negative values from data
DirName='Plots';
%% Intialize Data and Create Output Directory
if ~exist('FleetData','var');load FleetData;end
if ~exist(DirName,'dir');mkdir(DirName);end
if ~exist(fullfile(pwd,DirName,'CSVs'),'dir');mkdir(fullfile(pwd,DirName,'CSVs'));end
%% Set Node Colors
NodeNames=['R1';'L1';'R2';'L2';'R3';'L3';'R4';'L4'];
NodeColors=[31 119 180;255 127 14;...
            188 200 188;214 39 40;...
            148 103 189;140 86 75;...
            227 119 194;127 127 127;...
            188 189 34;1 1 1]/255;
%% Print List of Cars to Plot
sheets=size(FleetData,3);
N=size(FleetData,3);
for n=1:N
    fprintf('%2.0f - %s\n',n,FleetData{1,1,n})
end
%% Select Car from List
Page=input('Select Railcar # from list above\n');
CarName=FleetData{1,1,Page};
if Page<1 || Page>N
    error('Invalid Railcar Selection\n')
end
%% Input Specified Timespan to Plot
time1=input('Enter Start Date (mm/dd/yyyy HH:MM (Military Time)):\n','s');
time2=input('Enter End Date (mm/dd/yyyy HH:MM (Military Time)):\n','s');
%% Convert input time sprting to time number
if ischar(time1);time1=datenum(time1,'mm/dd/yyyy HH:MM');end
if ischar(time2);time2=datenum(time2,'mm/dd/yyyy HH:MM');end
%% Find indices of specified times in CarData
[~,index1]=min(abs(FleetData{1,3,Page}(:,1)-time1));
[~,index2]=min(abs(FleetData{1,3,Page}(:,1)-time2));
%% Select Data to be Plotted
plotTimes=FleetData{1,2,Page}(index1:index2,1);
plotNodeTemps=FleetData{1,2,Page}(index1:index2,2:end);
plotTempDiff=FleetData{1,4,Page}(index1:index2,2:end);
%% Prompt for Trip Direction
Direction=questdlg('Is this trip East or westbound?','Select Direction',...
    'Eastbound','Westbound','Unknown','Unknown');
%% Remove Negative Readings

```

```

if RemoveNegs;plotNodeTemps(plotNodeTemps<=0)=NaN;end
%% Plot Absolute Temp
h=figure;
set(gcf,'PaperPosition',[0 0 9 5.5],'PaperPositionMode','manual')
hold on
h1=plot(plotTimes,plotNodeTemps,[min(plotTimes) max(plotTimes)],[320 320],r');
hold off
% Set Axes
axis([-Inf Inf 60 330])
% Set Axis Labels and Tickmarks
xTicks=get(gca,'XTick'); yTicks=get(gca,'YTick');
xTicks=linspace(xTicks(1),xTicks(end),4);
yTicks=linspace(yTicks(1),yTicks(end),10); yTicks=round(yTicks/10)*10;
set(gca,'XTick',xTicks); set(gca,'YTick',yTicks);
datetick('x','mm/dd HH:MM','kepticks','keplimits')
legend('R1','L1','R2','L2','R3','L3','R4','L4','Ambient','Location','EastOutside')
xlabel('Timestamp','FontWeight','bold','FontName','Times','FontSize',12)
ylabel({'Temperature [^oF]','FontWeight','bold','FontName','Times','FontSize',12)
for z=1:(length(h1)-1)
    set(h1(z),'Color',NodeColors(z,:))%,'MarkerSize',6)
end
% Create Figure Filename
switch Direction
case 'Unknown'
    TitleName='Temperature vs. Time';
    title(TitleName,'FontWeight','bold','FontName','Times','FontSize',12)
    FigID=strcat(upper(CarName),'_Temps_',...
        datestr(plotTimes(1),'mm.dd'),'_',...
        datestr(plotTimes(end),'mm.dd'),'png');
    FigID=fullfile(pwd,DirName,FigID);
otherwise
    TitleName='Temperature vs. Time';
    SubTitleName=char(Direction);
    title([TitleName;SubTitleName],'FontWeight','bold','FontName','Times','FontSize',12)
    FigID=strcat(upper(CarName),'_Temps_',...
        datestr(plotTimes(1),'mm.dd'),'_',...
        datestr(plotTimes(end),'mm.dd'),'_',Direction,'png');
    FigID=fullfile(pwd,DirName,FigID);
end
% Save figure
print(h,'-dpng','-r300',FigID)
%% Plot Temp-Ambient Differential
h=figure;
set(gcf,'PaperPosition',[0 0 9 5.5],'PaperPositionMode','manual')
hold on
h1=plot(plotTimes,plotTempDiff,[min(plotTimes) max(plotTimes)],[170 170],r');
hold off
% Set Axes
if max(max(plotTempDiff))>135
    axis([-Inf Inf min(min(plotTempDiff))-5 max(max(plotTempDiff))+10])
else
    axis([-Inf Inf min(min(plotTempDiff))-5 140])
end
% Set Axis Labels and Tickmarks
xTicks=get(gca,'XTick'); yTicks=get(gca,'YTick');
xTicks=linspace(xTicks(1),xTicks(end),4);

```

```

yTicks=linspace(yTicks(1),yTicks(end),10); yTicks=round(yTicks/10)*10;
set(gca,'XTick',xTicks); set(gca,'YTick',yTicks);
datetick('x','mm/dd HH:MM','keepticks','keeplimits')
legend('R1','L1','R2','L2','R3','L3','R4','L4','Location','EastOutside')
xlabel('Timestamp','FontWeight','bold','FontName','Times','FontSize',12)
ylabel({' Bearing-Ambient Temperature Differential [
\Delta^oF]'},'FontWeight','bold','FontName','Times','FontSize',12)
for z=1:(length(h1)-1)
    set(h1(z),'Color','NodeColors(z,:)','MarkerSize',6)
end
% Create Figure Filename
switch Direction
case 'Unknown'
    TitleName='Bearing-Ambient Temperature Differential vs. Time';
    title(TitleName,'FontWeight','bold','FontName','Times','FontSize',12)
    FigID=strcat(upper(CarName),'_TempDiff_',...
        datestr(plotTimes(1),'mm.dd'),'_',...
        datestr(plotTimes(end),'mm.dd'),'png');
    FigID=fullfile(pwd,DirName,FigID);
otherwise
    TitleName='Bearing-Ambient Temperature Differential vs. Time';
    SubTitleName=char(Direction);
    title({TitleName;SubTitleName},'FontWeight','bold','FontName','Times','FontSize',12)
    FigID=strcat(upper(CarName),'_TempDiff_',...
        datestr(plotTimes(1),'mm.dd'),'_',...
        datestr(plotTimes(end),'mm.dd'),'_',Direction,'png');
    FigID=fullfile(pwd,DirName,FigID);
end
% Save figure
print(h,'-dpng','-r300',FigID)
%% Write CSV file with Node-Temperature Data for Selected Timespan
if PrintData==1

filename=strcat(upper(CarName),'_Temps_',datestr(plotTimes(1),'mm.dd'),'_',datestr(plotTimes(end),'mm.dd'),'csv')
;
    filename=fullfile(pwd,DirName,'CSVs',filename);
    TempFileID=fopen(filename,'w');
    fprintf(TempFileID,'RailcarName,Time,Node1,Node2,Node3,Node4,Node5,Node6,Node7,Node8,Ambient(F)\n');
    Times=datestr(plotTimes,'mm/dd/yyyy HH:MM');
    Z=length(plotNodeTemps);
    for z=1:Z
        fprintf(TempFileID,'%s,%s,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f\n',...
            CarName,Times(z,:),plotNodeTemps(z,1:9));
    end
    fclose(TempFileID);
end
end

```

MATLAB™ Program 3: The MATLAB™ *Level3* function is used to split the processed master temperature data array into discrete time periods based on dates supplied by the user. These intervals of temperature data are subsequently evaluated using the algorithms and thresholds presented in Chapter IV. The output of this function is a qualitative ranking of the thermal performance of all bearings in the instrumented test fleet.

```
function Level3 (EndDate,varargin)
% Created by Sean Woods
%This program is used to divide processed temperature data array into
% discrete time segments and evaluate the condition of all bearings
% within the fleet of railcars using the developed Level 3 algorithms
tic
%% Initialize variables and load files
if ~exist('FleetData','var');load FleetData;end
load NetData
%% Input Temperature Thresholds
global TempLimit dTLimit SlopeLimit
SlopeLimit=1.25; %Moving Average threshold
TempLimit=200; %Absolute Bearing Temperature Threshold
dTLimit=120; %Bearing Temperature above ambient threshold
%% Check for/create old directories
if ~exist('Checklists','dir');mkdir('Checklists');end
%% Calculate Fleet Average and Standard Deviation
Z=size(FleetData,3);
FleetTemps=[];
DataRange=10*24*60;
for z=1:Z
    [~, EndIndex(z)]=min(abs(FleetData{1,3,z}(:,1)-EndDate));
    if isempty(varargin)
        StartIndex(z)=EndIndex(z)-DataRange;
        if StartIndex(z)<1
            StartIndex(z)=1;
        end
    else
        [~, StartIndex(z)]=min(abs(FleetData{1,3,z}(:,1)-varargin{1}));
    end
    StartDate(z)=FleetData{1,3,z}(StartIndex(z),1);
    DataEndDate(z)=max(FleetData{1,3,z}(:,1));
    FleetTemps=cat(1,FleetTemps,FleetData{1,3,z}(StartIndex(z):EndIndex(z),[2:10]));
end
% Remove Temperatures when dTemp<20F
indexA=cat(2,(FleetTemps(:,1:8)-repmat(FleetTemps(:,9),1,8))<20,false(size(FleetTemps,1),1));%find dTemps<20F
indexB=cat(2,isnan(FleetTemps(:,1:8)),false(size(FleetTemps,1),1));%find NAN temps, excluding ambient
indexD=FleetTemps(:,end)<=1;
index=logical(indexA+indexB);
indexC=or(all(index(:,1:8),2),indexD);
FleetTemps(:,end)=[];%remove ambient readings before computing FleetAvg and FleetSTD

fprintf('Fleet average temp with ambient bearing temps is %3.3f\n',mean(FleetTemps(~isnan(FleetTemps))))
fprintf('Fleet standard deviation with ambient bearing temps is %3.3f\n',std(FleetTemps(~isnan(FleetTemps))))
FleetTemps(indexC,:)=[];

StartDate=mean(StartDate);
global FleetAvg FleetSTD
```

```

FleetAvg=mean(FleetTemps(~isnan(FleetTemps)));
FleetSTD=std(FleetTemps(~isnan(FleetTemps)));

fprintf('The average temperature for the fleet was %3.2f F between %s and %s\n',...
    FleetAvg,datestr(StartDate,'mm/dd/yy'),datestr(EndDate,'mm/dd/yy'))
fprintf('The standard deviation of the temperature for the fleet was %2.3f F between %s and %s\n',...
    FleetSTD,datestr(StartDate,'mm/dd/yy'),datestr(EndDate,'mm/dd/yy'))
%save 'FleetStats.mat' FleetAvg

%% Identify data window for each RailCar

if exist('Phase1Checklist.mat','file');delete('Phase1Checklist.mat');end
Phase1Checklist=cell(1,8);save('Phase1Checklist.mat','Phase1Checklist')

if exist('Phase2Checklist.mat','file');delete('Phase2Checklist.mat');end
Phase2Checklist=cell(1,4);save('Phase2Checklist.mat','Phase2Checklist')

for z=1:Z
    [~, EndIndex(z)]=min(abs(FleetData{1,2,z}(:,1)-EndDate));

    if isempty(varargin)
        if EndIndex(z)>14400
            StartIndex(z)=EndIndex(z)-14400;
        else
            StartIndex(z)=1;
        end
    else
        [~, StartIndex(z)]=min(abs(FleetData{1,2,z}(:,1)-varargin{1}));
    end
    CarName(z,:)=FleetData{1,1,z};
    StartEndDate(z,1)=FleetData{1,3,z}(StartIndex(z),1);
    StartEndDate(z,2)=FleetData{1,3,z}(EndIndex(z),1);

    TempData=FleetData{1,3,z}(StartIndex(z):EndIndex(z),[1:10]);
    indexA=cat(2,(TempData(:,2:9)-repmat(TempData(:,10),1,8))<20,false(size(TempData,1),1));%find dTemps<20F
    indexB=cat(2,isnan(TempData(:,2:9)),false(size(TempData,1),1));%find NAN temps, excluding ambient
    indexD=TempData(:,end)<=1;
    index=logical(indexA+indexB);

    indexC=or(all(index(:,1:8),2),indexD);

    TempData(indexC,:)=[];

    fprintf('%6.0f rows removed from railcar %s data\n',sum(indexC),FleetData{1,1,z})

    MovingAvgData=FleetData{1,5,z}(StartIndex(z):EndIndex(z),[1:9]);
    MovingAvgData(indexC,:)=[];

    PHASE1_10Day(FleetData{1,1,z},z,TempData);
    PHASE2(FleetData{1,1,z},MovingAvgData);
end

%% Load and store unsorted results of Phase 1 Analysis
load Phase1Checklist

CarNameList=Phase1Checklist{1,1};

```

```

NodeList=Phase1Checklist{1,2};
HighTempPercent=Phase1Checklist{1,3};
TempRisePercent=Phase1Checklist{1,4};
nSigma=Phase1Checklist{1,5};
nSigmaFleet=Phase1Checklist{1,6};
ReadCount=Phase1Checklist{1,8};

K=length(NodeList);
OutlierNodeScore=zeros(size(NodeList));

%% Sort and Score Bearings by Phase 1.1 Analysis (Temp>200F)
% Replace NaNs with Zeros
index=isnan(HighTempPercent);
HighTempPercent(index)=0;
% Sort
[sHighTempPercent Index11]=sort(HighTempPercent,'descend');
snHighTempPercent=sHighTempPercent/max(sHighTempPercent)*100;
% Assign Scores
N=find(snHighTempPercent<=0,1,'first');
for n=1:N
    OutlierNodeScore(Index11(n))=snHighTempPercent(n);
end
%% Sort and Score Bearings by Phase 1.2 Analysis (>+120F)
% Replace NaNs with Zeros
index=isnan(TempRisePercent);
TempRisePercent(index)=0;
% Sort
[sTempRisePercent Index12]=sort(TempRisePercent,'descend');
snTempRisePercent=sTempRisePercent/max(sTempRisePercent)*100;
% Assign Scores
N=find(sTempRisePercent<=0,1,'first');
for n=1:N
    OutlierNodeScore(Index12(n))=OutlierNodeScore(Index12(n))+snTempRisePercent(n);
end
%% Sort and Score Bearings by Phase 1.3 Analysis (# Sigmas deviation)
% Replace NaNs with Zeros
index=isnan(nSigma);
nSigma(index)=0;
% Sort
[sSigma Index13]=sort(nSigma,'descend');
snSigma=sSigma/max(sSigma)*100;
% Assign Scores
N=find(sSigma<=0,1,'first');
for n=1:N
    OutlierNodeScore(Index13(n))=OutlierNodeScore(Index13(n))+snSigma(n);
end
%% Sort and Score Bearings by Phase 1.4 Analysis
% Replace NaNs with Zeros
index=isnan(nSigmaFleet);
nSigmaFleet(index)=0;
% Sort
[sSigmaFleet Index14]=sort(nSigmaFleet,'descend');
snSigmaFleet=sSigmaFleet/max(sSigmaFleet)*100;
% Assign Scores
N=find(sSigmaFleet<=0,1,'first');
for n=1:N

```

```

    OutlierNodeScore(Index14(n))=OutlierNodeScore(Index14(n))+snSigmaFleet(n);
end
%% Store Phase 1 Analysis Outlier Scores in "Phase1Checklist"
OutlierNodeScore=OutlierNodeScore/4;
Phase1Checklist(1,7)={OutlierNodeScore};
save('Phase1Checklist.mat','Phase1Checklist')

%% Sort Bearings by Total Score
[sOutlierScore Index1]=sort(OutlierNodeScore,'descend');
sOutlierScorePercent=sOutlierScore;

%% Create Output Directory
if ~isempty(varargin)
    Date=(varargin{1}+EndDate)/2;
    DirName=datestr(Date,'mmmmmyyyy');
    DirName=strcat(datestr(varargin{1},'mmddyy'),'_',datestr(EndDate,'mmddyy'));
    DirName=fullfile(pwd,'Checklists',DirName)
else
    DirName=fullfile(pwd,'Checklists',datestr(EndDate,'mmddyy'))
end

%% Print Level 3 Analysis Statistics, Window Start/End Dates
% Create Output Directory
if ~exist(DirName,'dir');mkdir(DirName);end

% Open Text file and print headers/titles
L3Statsfn=fullfile(DirName,'Level3Stats.csv');
L3Statsfid=fopen(L3Statsfn,'w');

fprintf(L3Statsfid,'Average Fleet Temperature (F),Fleet Standard Deviation(F)\n');
fprintf(L3Statsfid,'%3.2f,%3.2f\n',FleetAvg,FleetSTD);

% Print Node Statistics
fprintf(L3Statsfid,'Railcar,Node,Start Date,End Date,Average Temp(F),Standard Deviation(F),Average Delta
Temp(F),Standard Deviation(F),nSigma from Fleet,# Total Readings,Valid Readings,Negative
Readings(%),Missing readings(%),Reliability(%),R-S-L,IsLive(%)\n');
for z=1:Z
    CarTemps=FleetData{1,3,z}(StartIndex(z):EndIndex(z),[1:10]);
    indexA=cat(2,(CarTemps(:,2:9)-repmat(CarTemps(:,10),1,8))<20,false(size(CarTemps,1),1));% find
dTemps<20F
    indexB=cat(2,isnan(CarTemps(:,2:9)),false(size(CarTemps,1),1));% find NAN temps, excluding ambient
    index=logical(indexA+indexB);
    indexC=all(index(:,1:8),2);
    CarTemps(indexC,:)=[];

    Car_dTemps=FleetData{1,4,z}(StartIndex(z):EndIndex(z),[1:9]);
    Car_dTemps(indexC,:)=[];

    for c=2:10
        Temps=CarTemps(:,c);
        if (c<10)
            dTemps=Car_dTemps;
        elseif (c==10)
            dTemps=nan(size(Temps));
        end
    end
end

```



```

TotalReadings=EndIndex(z)-StartIndex(z)+1;% Count total readings (time intervals) in dataset
ValidReadings=sum(~isnan(Temps));% count total number of valid, processed readings
NegativeReadings=100*(sum(FleetData{1,2,z}(StartIndex(z):EndIndex(z),c)<=0)/TotalReadings);% count
number of negative/zero readings
NaNReadings=100*(sum(isnan(FleetData{1,2,z}(StartIndex(z):EndIndex(z),c)))/TotalReadings);% count
missing readings in original dataset

Temps(isnan(Temps))=[];
dTemps(isnan(dTemps))=[];

% Find NetData indices
[~, NetEnd]=min(abs(NetData{1,2,z}(:,1)-EndDate));
if isempty(varargin)
    [~, NetStart]=min(abs(NetData{1,2,z}(:,1)-(EndDate-10)));
else
    [~, NetStart]=min(abs(NetData{1,2,z}(:,1)-varargin{1}));
end

% Parse NetData for time window
Data=NetData{1,2,z}(NetEnd:NetStart,:);

NodeMatches=Data(:,2)==(c-1);
Data=Data(NodeMatches,3:end);
Averages=mean(Data,1);

StartDateStr=datestr(FleetData{1,3,z}(StartIndex(z),1),'mm/dd/yy');
EndDateStr=datestr(FleetData{1,3,z}(EndIndex(z),1),'mm/dd/yy');
if (c<10);NodeName=strcat('Node#',num2str(c-1));
elseif (c==10);NodeName='Ambient';dTemps=NaN;end

fprintf(L3Statsfid,'%s,%s,%s,%s,%s,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%3.2f,%s,%3.3f\n',...
    FleetData{1,1,z},NodeName,StartDateStr,EndDateStr,...
    mean(Temps),std(Temps),mean(dTemps),std(dTemps),...
    (mean(Temps)-FleetAvg)/FleetSTD,...
    TotalReadings,ValidReadings,NegativeReadings,NaNReadings,...
    abs(100*(ValidReadings/TotalReadings)),...
    strcat(num2str(Averages(1),3),' - ',num2str(Averages(2),3),...
    ' - ',num2str(Averages(3),3)),100*Averages(4));
end
fprintf(L3Statsfid,'\n');
end

%% Create Array to store results (rank+percent) of L3C1-L3C5
Results=zeros(K,10);

%% Print detailed results of Level 3 Crit 1 (Phase 1.1 Analysis)

L3C1fn=fullfile(DirName,'Level3Criteria1.csv');
L3C1fid=fopen(L3C1fn,'w');
fprintf(L3C1fid,'Railcar,Node,Rank,Score(%%),%% Counts>%3.0fF,Counts\n',TempLimit);

N=find(snHighTempPercent<=0,1,'first')-1;
for n=1:K
    J=Index11(n);
    if isnan(sHighTempPercent(n))

```

```

    Value=0;
else
    Value=sHighTempPercent(n);
end
Results(J,[1 2])=[n Value];
if n<=N
    fprintf(L3C1fid,'%s,%s,%2.0f,%2.3f,%2.3f,%5.0f\n',char(CarNameList(J:)),...
        strcat('Node#',num2str(NodeList(J))),n,snHighTempPercent(n),Value,ReadCount(J));
    end
end

%% Print detailed results of Level 3 Crit 2 (Phase 1.2 Analysis)
L3C2fn=fullfile(DirName,'Level3Criteria2.csv');
L3C2fid=fopen(L3C2fn,'w');
fprintf(L3C2fid,'Railcar,Node,Rank,Score(%),%%Counts>%3.0fF,Counts\n',dTLimit);
N=find(sTempRisePercent<=0,1,'first')-1;
for n=1:K
    J=Index12(n);
    if isnan(sTempRisePercent(n))
        Value=0;
    else
        Value=sTempRisePercent(n);
    end
    Results(J,[3 4])=[n Value];
    if n<=N
        fprintf(L3C2fid,'%s,%s,%2.0f,%2.3f,%2.3f,%5.0f\n',char(CarNameList(J:)),...
            strcat('Node#',num2str(NodeList(J))),n,snTempRisePercent(n),Value,ReadCount(J));
    end
end

%% Print detailed results of Level 3 Crit 3 (Phase 1.3 Analysis)
L3C3fn=fullfile(DirName,'Level3Criteria3.csv');
L3C3fid=fopen(L3C3fn,'w');
fprintf(L3C3fid,'Railcar,Node,Rank,Score(%),#StdDev,Counts\n');
N=find(sSigma<=0,1,'first')-1;
for n=1:K
    J=Index13(n);
    if isnan(sSigma(n))
        Value=0;
    else
        Value=sSigma(n);
    end
    Results(J,[5 6])=[n Value];
    if n<=N
        fprintf(L3C3fid,'%s,%s,%2.0f,%2.3f,%2.3f,%5.0f\n',char(CarNameList(J:)),...
            strcat('Node#',num2str(NodeList(J))),n,snSigma(n),Value,ReadCount(J));
    end
end

%% Print detailed results of Level 3 Crit 4 (Phase 1.4 Analysis)
L3C4fn=fullfile(DirName,'Level3Criteria4.csv');
L3C4fid=fopen(L3C4fn,'w');
fprintf(L3C4fid,'Railcar,Node,Rank,Score(%),#StdDev,Counts\n');
N=find(sSigmaFleet<=0,1,'first')-1;
for n=1:K
    J=Index14(n);

```

```

        if isnan(sSigmaFleet(n))
            Value=0;
        else
            Value=sSigmaFleet(n);
        end
        Results(J,[7 8])=[n Value];
        if n<=N
            fprintf(L3C4fid,'%s,%s,%2.0f,%2.3f,%2.3f,%5.0f\n',char(CarNameList(J,:)),...
                strcat('Node#',num2str(NodeList(J))),n,snSigmaFleet(n),Value,ReadCount(J));
        end
    end
end

%% Phase 2 (Level 3 Critrion 5)

%% Load and store unsorted results of Phase 2 Analysis
load Phase2Checklist %Needs Rank and %Slope>1.25 when Phase 2 is integrated

CarNameList=Phase2Checklist{1,1};
NodeList=Phase2Checklist{1,2};
HighSlopePercent=Phase2Checklist{1,3};

K=length(NodeList);

%% Sort and Score Bearings by Phase 2.1 Analysis (Moving Average Slope > SlopeLimit)
%Replace NaNs with Zeros
HighSlopePercent(isnan(HighSlopePercent))=0;

%Sort
[sHighSlopePercent Index1]=sort(HighSlopePercent,'descend');
sHighSlopePercentScore=sHighSlopePercent/sHighSlopePercent(1)*100;

%% Store Phase 2 Analysis Outlier Scores in "Phase2Checklist"
Phase2Checklist(1,4)={sHighSlopePercentScore};
save('Phase2Checklist.mat','Phase2Checklist')

%% Print Level 3 Criteria 5 Results (Phase 2)

L3C5fn=fullfile(DirName,'Level3Criteria5.csv');
L3C5fid=fopen(L3C5fn,'w');
fprintf(L3C5fid,'Railcar,Node,Rank,% %Slope>%1.2f,Score(% %)\n',SlopeLimit);
%Print top ranking outlier bearing information
N=length(Index1);
for n=1:K
    J=Index1(n);
    if isnan(sHighSlopePercent(n))
        Value=0;
    else
        Value=sHighSlopePercent(n);
    end
    Results(J,[9 10])=[n Value];
    if n<=N
        fprintf(L3C5fid,'%s,%s,%2.0f,%3.2f,%3.2f\n',char(CarNameList(J,:)),...
            strcat('Node#',num2str(NodeList(J))),n,...
            sHighSlopePercent(n),sHighSlopePercentScore(n));
    end
end
end

```

```

%% Print Level 3 Summary CSV from "Results" array
L3Sfn=fullfile(DirName,'Level3Summary.csv');
L3Sfid=fopen(L3Sfn,'w');
%Print Header

fprintf(L3Sfid,'Railcar,Node,Rank,%% Counts>200F,Rank,%% Counts>120F,Rank,#StdDev,Rank,#StdDev,Rank,%%
%Slope>1.25F/min\n');
for k=1:K
    fprintf(L3Sfid,'%s,%s,%2.0f,%2.3f,%2.0f,%2.3f,%2.0f,%2.3f,%2.0f,%2.3f,%2.0f,%2.3f\n',...
        char(CarNameList(k,:)),strcat('Node#',num2str(NodeList(k,:))),...
        Results(k,1:10));
end

%% Close Phase 2 Checklist text file
fclose('all');
toc
fprintf('\n\n')
end

%% Function Functions
%%
function PHASE1_10Day ( RailcarName, iter, mast_data )
%% PHASE1_10Day Evaluates Phase 1 Bearing Health Analysis Algorithms
% Phase 1 function and algorithm developed and implemented by
% UTPA - Railroad Research Team
% Sean Woods
% Dr. Tarawneh
% Dr. Kypuros
%This function requires that the temperature input "mast_data" have reading
%times in the first column, bearing node readings in the next column, and
%the last column must be ambient temperatures
%% Input Temperature Thresholds
global TempLimit dTLimit nCars
%% Initialize Variables
load Phase1Checklist
global FleetAvg FleetSTD
%Count the number of nodes
nNodes=size(mast_data,2)-2;
nReadings=size(mast_data,1);
if nReadings==0
    fprintf('warning: Zero Temperature readings for <%s>\n',RailcarName)
end
%Create arrays to be appended to "Phase1Checklist"
CarNodes=zeros(nNodes,1);
HighTempCount=zeros(nNodes,1);
PercentCount=zeros(nNodes,1);
nSigma=zeros(nNodes,1);
nSigmaFleet=zeros(nNodes,1);
dTPercent=zeros(nNodes,1);

%% Phase 1.1 - Percent of Temperatures above 200F
%Calculate number of readings > 200F and percent of total readings
for z=2:nNodes+1
    HighTempCount(z-1,1)=sum(mast_data(:,z)>=TempLimit);%Count # of readings > Temperature Limit
    ReadingCount(z-1,1)=sum(~isnan(mast_data(:,z)));

```

```

PercentCount(z-1,1)=HighTempCount(z-1,1)/ReadingCount(z-1,1)*100;%Calculate percent
CarNames(z-1,:){RailcarName};%Stores RailcarName
CarNodes(z-1,1)=z-1;%Stores Node Number
end

%% Phase 1.2 - Percent of Readings > 120F above Ambient
Z=size(mast_data,1);
TempRise=zeros(Z,nNodes+1);
TempRise(:,1)=mast_data(:,1);
for c=2:nNodes+1
    %Calculate (node temperature-ambient)
    TempRise(:,c)=mast_data(:,c)-mast_data(:,end);
    %Calculate the percent of readings with temp increase (>=dTlimit)
    dTPercent(c-1,1)=sum(TempRise(:,c)>=dTlimit)/...
        sum(~isnan(TempRise(:,c)))*100;
end

%% Phase 1.3 - Calculate the number of standard deviations between node
% average temperature and railcar average temperature
for z=2:nNodes+1
    %Calculate average temp of one bearing
    NodeTemps=mast_data((~isnan(mast_data(:,z))),z);
    if size(NodeTemps,2)~=1
        NodeTemps=reshape(NodeTemps,[],1);
    end
    index=isnan(NodeTemps);
    NodeTemps(index)=[];
    NodeAverage(z-1,1)=mean(NodeTemps);

    %Store all readings for other 7 bearings
    CarTemps=mast_data(:,2:9);
    CarTemps(:,z-1)=[];
    %Reshape temperature matrix into column vector
    CarTemps=reshape(CarTemps,[],1);
    %Remove Empty readings (NaNs)
    CarTemps(isnan(CarTemps))=[];
    size(CarTemps);
    any(isnan(CarTemps));

    %Calculate Standard Deviation of the other 7 bearings
    CarSTD=std(CarTemps);
    CarAverage=mean(CarTemps);

    %% Phase 1.4 - Calculate number of standard deviations between node and fleet
    %Calculate the # of stds between car and bearing averages
    if isnan(NodeAverage(z-1,1))
        nSigma(z-1,1)=0;
        nSigmaFleet(z-1,1)=0;
    else
        nSigma(z-1,1)=(NodeAverage(z-1,1)-CarAverage)/CarSTD;
        nSigmaFleet(z-1,1)=(NodeAverage(z-1,1)-FleetAvg)/FleetSTD;
    end
end
end
%% Store Existing PHASE 1 Results from "Phase1Checklist"
if ~isempty(Phase1Checklist{1,1})
    CarNameList=Phase1Checklist{1,1}; %size(CarNameList)

```

```

end
NodeList=Phase1Checklist{1,2}; %size(NodeList)
HighTempList=Phase1Checklist{1,3}; %size(HighTempList)
TempRiseList=Phase1Checklist{1,4}; %size(TempRiseList)
stdList=Phase1Checklist{1,5}; %size(stdList)
stdFleetList=Phase1Checklist{1,6};
FleetReadingsCount=Phase1Checklist{1,8};

%% Append Results of Phase 1 Analysis to "Phase1Checklist"
if isempty(Phase1Checklist{1,1})
    CarNameList=CarNames;
else
    CarNameList=cat(1,CarNameList,CarNames);
end
NodeList=cat(1,NodeList,CarNodes);
HighTempList=cat(1,HighTempList,PercentCount);
TempRiseList=cat(1,TempRiseList,dTPercent);
stdList=cat(1,stdList,nSigma);
stdFleetList=cat(1,stdFleetList,nSigmaFleet);
FleetReadingsCount=cat(1,FleetReadingsCount,ReadingCount);

%% Replace Phase 1 Analysis Results and return to workspace
Phase1Checklist(1,1)={CarNameList};
Phase1Checklist(1,2)={NodeList};
Phase1Checklist(1,3)={HighTempList};
Phase1Checklist(1,4)={TempRiseList};
Phase1Checklist(1,5)={stdList};
Phase1Checklist(1,6)={stdFleetList};
Phase1Checklist(1,8)={FleetReadingsCount};

%% Save Modified "Phase1Checklist"
save('Phase1Checklist.mat','Phase1Checklist')
end

function PHASE2 (RailcarName, MovingAverage)
%% PHASE2 Evaluates Phase 2 Bearing Health Analysis Algorithms
% Phase 2 function and algorithms developed and implemented by
% UTPA - World Bearing Research Centre
% Sean Woods
% Dr. Tarawneh
% Dr. Kypuros
%
%This function requires that the temperature input "mast_data" have reading
%times in the first column, bearing node readings in the next column, and
%the last column must be ambient temperatures
%% Input Temperature Thresholds
global SlopeLimit

%% Initialize Variables
load Phase2Checklist
%Count the number of nodes
nNodes=size(MovingAverage,2)-1;
%Create arrays to be appended to "Phase2Checklist"
CarNodes=zeros(nNodes,1);
HighSlopeCount=zeros(nNodes,1);
HighSlopePercent=zeros(nNodes,1);

```

```

%% Phase 2.1 - Percent of moving Average Slope Values > Threshold ("T" Method)
%Calculate number of readings > 200F and percent of total readings
for z=1:nNodes
    HighSlopeCount(z,1)=sum(MovingAverage(:,z+1)>=SlopeLimit);
    HighSlopePercent(z,1)=HighSlopeCount(z,1)/sum(~isnan(MovingAverage(:,z+1)))*100;
    CarNames(z,:)={RailcarName};%Stores RailcarName
    CarNodes(z,1)=z;%Stores Node Number
end
%% Load Existing PHASE 2 Results from "Phase2Checklist"
if ~isempty(Phase2Checklist{1,1})
    CarNameList=Phase2Checklist{1,1};
end
NodeList=Phase2Checklist{1,2};
HighSlopeList=Phase2Checklist{1,3};

%% Append Results of Phase 2 Analysis to "Phase2Checklist"
if isempty(Phase2Checklist{1,1})
    CarNameList=CarNames;
else
    CarNameList=cat(1,CarNameList,CarNames);
end
NodeList=cat(1,NodeList,CarNodes);
HighSlopeList=cat(1,HighSlopeList,HighSlopePercent);
%% Store New Phase 2 Analysis Results
Phase2Checklist(1,1)={CarNameList};
Phase2Checklist(1,2)={NodeList};
Phase2Checklist(1,3)={HighSlopeList};

%% Save Modified "Phase2Checklist"
save('Phase2Checklist.mat','Phase2Checklist')

end

```

BIOGRAPHICAL SKETCH

Sean Michael Woods was born on May 21, 1984 in Pasadena, California to Floyd and Carol Woods. He moved to Texas at the age of 13 where he graduated from McAllen High School in 2002. He received his Bachelor of Science from the Mechanical Engineering Department at the University of Texas-Pan American in August 2011. He continued his education at the University of Texas-Pan American and earned a Master of Science degree in Mechanical Engineering in December 2012. In addition to serving as a teaching assistant for one year, he served as a Research Assistant on the Railroad Research Team for three years, performing research in support of a project funded by Amsted Rail Industries, Inc. During his tenure on the Railroad Research Team, he was responsible for many aspects of the project ranging from design and construction of laboratory testing apparatus, to data analysis, and the formulation of condition monitoring algorithms. Sean Michael Woods may be reached at 2104 E. 20th Ave., Mission, TX, 78572.