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Using integrated mechanical diagnostics health and usage management system (IMDHUMS) data to predict UH-60L electrical generator condition

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MONTEREY, CALIFORNIA

THESIS

USING INTEGRATED MECHANICAL DIAGNOSTICS HEALTH AND USAGE MANAGEMENT SYSTEM (IMD-HUMS) DATA TO PREDICT UH-60L ELECTRICAL GENERATOR CONDITION

by

Lee Willard
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March 2006

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13. ABSTRACT (maximum 200 words)

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Goodrich has developed the Integrated Mechanical Diagnostics Health and Usage Management System (IMD-HUMS) for the practices of CBM in helicopters. Great benefits have been realized with the IMD-HUMS system in regards to several maintenance practices, readiness, and safety.

However, the total potential of the system in regards to these benefits for the multiple components observed by the IMD-HUMS is not yet achieved. The IMD-HUMS gathers a great deal of pertinent, important data on the condition of multiple components and systems, but the meaning and full potential of all this data is not yet fully realized.

The purpose of this research is to conduct and document a statistical analysis of IMD-HUMS produced data. Statistical applications of data mining, regression and classification trees are explored. The approaches used in the exploration of the IMD-HUMS acquired data sets are based on six electrical generators which displayed degradation or failure and hence required maintenance actions compared with sixty others which did not.

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USING INTEGRATED MECHANICAL DIAGNOSTICS HEALTH AND USAGE MANAGEMENT SYSTEM (IMD-HUMS) DATA TO PREDICT UH-60L ELECTRICAL GENERATOR CONDITION

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ABSTRACT

Military aircraft maintenance methods are moving from practices based on hard-time inspection and replacement intervals to one of Condition Based Maintenance (CBM). CBM allows the ability to forego scheduled maintenance on components or systems that are not in need of maintenance or replacement. CBM reduces maintenance efforts and component replacement and increases readiness and safety.

Goodrich Corporation has developed the Integrated Mechanical Diagnostics Health and Usage Management System (IMD-HUMS) to support CBM in helicopters. Great benefits in several maintenance practices, readiness and safety have already been realized by the UH-60L helicopter military unit equipped with the IMD-HUMS system.

The total potential of the system, for the components observed by the IMD-HUMS, however, has not yet been achieved. The IMD-HUMS gathers an enormous amount of data on the condition of these components and systems. The meaning and full potential of all this data has not yet been fully realized because to date, this data has never been coupled with corresponding maintenance data.

The purpose of this research is to conduct and document statistical analysis of IMD-HUMS produced data with corresponding maintenance data of observed component failures. Statistical applications of logistic regression and classification trees are explored to predict failures. The approaches used in the exploration of the IMD-HUMS acquisition data sets are based on sixty electrical generators from thirty aircraft, six of which displayed degradation or failure and hence required maintenance actions. This approach is promising. With it we accurately predict two previously undocumented failures.

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LIST OF ACRONYMS AND ABBREVIATIONS

ASAM	Aviation Safety Action Message
CART	Classification and Regression Trees
CBM	Conditional Based Maintenance
CI	Condition Indicator(s)/Indication(s)
CDU	Cockpit Display Unit
CSV	Column Separated Value
DoD	Department of Defense
DTMU	Data Transfer Memory Unit
DTU	Data Transfer Unit
Env	Envelope
Env.DF	Envelope Distributed Fault
Env.Kurt	Envelope Kurtosis
Env.P2P	Envelope Peak-to-Peak
GearMis_1	Gear Misalignment 1
GDF	Gear Distributed Fault
GSS	Ground Station System
HI	Health Indicator(s)/ Indication(s)
IMD-HUMS	Integrated Mechanical Diagnostics Health and Usage Maintenance System
IRAC	Interim Rapid Action Change
JB	Junction Box
Loess	Locally Weighted Regression
Logit	Logistic Regression
MPU	Main Processor Unit
NALDA	Naval Aviation Logistics Analysis
ND	Null Deviance
OBS	On Board System
P2P	peak-to-peak

Pdf	probability density curve
RD	Residual Deviance
RDC	Remote Data Converter
Rdf	Raw Data File
Res_P2P	Residual Peak-to-Peak
RMS	Root Mean Square
RPM	Revolutions per Minute
ROC	Receiver Operating Characteristic
SO1	Shaft Order 1
SO2	Shaft Order 2
SoFM	Safety of Flight Message
TBO	Time Before Overhaul

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EXECUTIVE SUMMARY

Military aircraft maintenance methods are moving from practices based on hard-time inspection and replacement intervals to one of Condition Based Maintenance (CBM). The latter practice allows the ability to forego scheduled maintenance on components or systems which have reached their high times but are not in need of maintenance or replacement. Benefits of CBM are the minimization of maintenance efforts and component replacement along with an increase in readiness and safety.

Goodrich Corporation has developed the Integrated Mechanical Diagnostics Health and Usage Management System (IMD-HUMS) for the practices of CBM in helicopters. Great benefits have already been realized by the using UH-60L helicopter military unit with the IMD-HUMS system in regards to several maintenance practices, readiness, and safety.

The total potential of the system, in regards to these benefits for the multiple components observed by the IMD-HUMS, however, is not yet achieved. The IMD-HUMS gathers a great deal of pertinent, important data on the condition of multiple components and systems, but the meaning and full potential of all this data is not yet fully realized.

The purpose of this research is to conduct and document the statistical analysis of IMD-HUMS produced data. Statistical applications of logistic regression and random forest of classification trees are explored. The approaches used in the exploration of the IMD-HUMS acquisition data sets are based on six electrical generators which displayed degradation or failure—and hence required maintenance actions—compared with sixty others which did not. This thesis focuses on using the combination of resulting vibratory patterns and maintenance records from one type of component, the electrical generator of the UH-60L helicopter, to forecast the need for maintenance. Data acquired from the IMD-HUMS will be used in an attempt to understand and predict health predictions of the UH-60L electrical generator, and in hopes of gaining insights in developing component health predictions from IMD-HUMS data for other components.

This thesis discusses how the resulting predicted health classifications compare to how each of the generators are currently classified. In this process, some surprising cases of generator health classification are uncovered. One generator, which was wrongly presumed to be bad and, similarly, another generator, which was wrongly assumed to be good, were predicted correctly by this study's classification scheme. The thesis demonstrates that two different models—logistic regression and random forest of classification trees—can be fit using IMD-HUMS data collected with known cases of failed generators and properly operating generators. These models can predict the overall state of a UH-60L electrical generator.

I. INTRODUCTION

There are over 12,000 aircraft in the U.S. military's inventory, with nearly 2,400 in the Navy and Marine Corps (International Institute for Strategic Studies, 2005). In Fiscal Year 2005, Congress obligated over 5.29 billion dollars toward the operation and maintenance of these Naval aircraft, with 1.08 billion dollars of this money obligated strictly to intermediate and depot-level maintenance (Office of the Undersecretary of Defense, 2005).

To put these operation and maintenance costs into perspective, consider that flying a single CH-53E helicopter for one flight hour costs $14,000 and requires 44 maintenance man-hours (http://www.aviationtoday.com, Nov 2005). A solution to these high costs may be found through the services' concerted efforts to move away from a scheduled maintenance approach toward a combination of scheduled and condition based maintenance (CBM). In fact, this has been mandated as the Department of Defense (DoD) required strategy to improve aircraft supportability (DoD Instruction 5000.2, May 2003). For helicopters, this means monitoring the conditions of the mechanical components, which account for 70% of maintenance costs (Ruben & Rossi, 2003).

Monitoring of these components is best accomplished through the collection of these components' vibratory patterns. Goodrich Corporation has developed the Integrated Mechanical Diagnostics Health and Usage Management System (IMD-HUMS) which collects and analyzes a helicopter component's vibrations for use in CBM. The system has been installed and operational for over two years in 30 U.S. Army UH-60L helicopters. This provides the opportunity, for the first time, to investigate data produced by IMD-HUMS installed in a large fleet of operational helicopters, rather than data from test stand mounted fault-induced components or test-bed aircraft.

The IMD-HUMS is worthy of study because major economic, operational and safety benefits can be realized by incorporating such CBM systems into aircraft maintenance practices. This thesis focuses on using the combination of resulting vibratory patterns and maintenance records from one type of component, the electrical generator, to forecast the need for maintenance. The data is explored and analyzed using statistical approaches in hopes of gaining insights in developing component health predictions from IMD-HUMS data.

A. LITERATURE REVIEW

Numerous papers describe the IMD-HUMS; however, very little work concerns specific analysis of operational helicopter vibratory patterns, and even less focuses on relating changes in the vibratory patterns to actual operational maintenance events.

The "Systems Users Manual for IMD-HUMS" (U.S. Army Publication, 2005) and the "P^3I VPU/DTD Software Requirements Specifications" (Goodrich Publication, 2001) provide the basic terminology, concept of operations, and an explanation of the physical measurements regarding the IMD-HUMS. Understanding the physics behind the vibratory patterns is essential for predicting component health.

Various papers and briefs written primarily by employees of Goodrich Corporation and the IMD-HUMS Program Managers Office provide an overview of the uses and issues concerning the IMD-HUMS. Hess, Duke and Kogut (2005) provide a good overview of the development history, terms, functionality, and potential of the IMD-HUMS. The master’s thesis by Revor (2004) uses discrete event simulation backed by Naval Aviation Logistics Analysis (NALDA) databases to investigate the cost benefits of incorporating the IMD-HUMS into helicopter rotor track and balance maintenance actions. Revor's simulation supports the idea that using the IMD-HUMS will decrease costs and maintenance efforts.

Several Goodrich papers also discuss the mathematical concepts and algorithmic inner workings of the IMD-HUMS in detail. These papers provide insight into the complexity and potential of the system; for example, see Bechhoefer and Power (2002) and Hochmann (2004). The latter paper addresses the issue of variability among vibratory pattern observations which originate from seemingly identical operating conditions.

The master's thesis by Elyurek (2003) presents empirical studies of vibratory patterns. Elyurek (2003) uses Box-Jenkins time series modeling with regression to determine vibration thresholds for gear fault identification. Elyurek's study is based on operational data produced by a test IMD-HUMS installed CH-53 helicopter. He concludes that his model could not match the required negligible alarm rate due to the small sample size available.

Only recently has it been possible to look at vibratory patterns matched with corresponding operational maintenance events. Wright (2005) investigates several cases of maintenance discrepancy detections made by the 30 UH-60L helicopters with IMD-HUMS installed. In three particular cases, the IMD-HUMS data indicated that the generator was about to fail before it actually did. The paper explains the subsequent investigation and facts concerning these generators. The apparent relationship between changes in vibratory patterns and the failed generators described by Wright provides the motivation for choosing UH-60L generators for this study. In addition, the paper discusses processes developed to incorporate the IMD-HUMS data into beneficial maintenance practices.

B. RESEARCH FOCUS

With the exception of Wright's paper there are no published works that empirically relate vibratory patterns to documented operational maintenance events. The full potential of CBM using IMD-HUMS in particular has not yet been fully realized. The objective of CBM is to know, from the data collected by sensor readings, when a component or system needs replacement or maintenance. A simple analogy to CBM is when a medical doctor observes a person's temperature, blood pressure and heart rate. The readings could mean many different things under different circumstances, but an experienced doctor would be able tell if that person is of good health or not, and specifically what medical actions to take. Now, imagine the first time in history a doctor listened to a heart beat. He knew this information was important and could explain a great deal concerning a patient's health, but everything the patient's heart beat can tell the doctor was not yet known. This is where we are now with much of the data resulting from the IMD-HUMS. The IMD-HUMS data tells the user something about each monitored component’s health and future health, but exactly what it tells is deserving of study.

This issue is addressed in this thesis. Data acquired from a CBM-based system (the IMD-HUMS) will be used in an attempt to understand and predict the state, condition and performance of a component (the UH-60L electrical generator).

The UH-60L electrical generators were chosen for study for two reasons. First, during the two years the helicopters were installed with IMD-HUMS there were six generators which needed to be removed from operations for some reason of fault, and there were 60 generators deemed to be working properly. This provides a data set in which generators could be classified as "bad" (removed for some fault) and "good" (working properly). Second, the electrical generators are relatively simple components to study when compared to aircraft engines or transmissions. The generators have fewer moving parts which produce vibrations and are much less likely to be affected by factors such as flight regime or torque settings.

C. APPROACH

This thesis's approach for assessing the generators' health is somewhat different than the current method of health assessment used with the IMD-HUMS. Currently a component's overall health assessment is assessed by using a Health Indicator (HI) for that component. Each component HI is computed from a subset of IMD-HUMS vibratory readings known as Condition Indicators (CI). A component's HI is a statistic which summarizes when the CI corresponding to that component have unusual values compared to the historical distributions of these CI. The CI readings are just from specific parts within the component itself. For instance, the generator's health is monitored by the HI computed from CI originating from the generator's shaft. Rather than attempt to supplant the current method by using different CI or by changing how the HI are computed from the CI, the approach used in this thesis augments the current method.

First, to assess generator health a broader set of CI are used. Not only are CI originating from the generator shaft vibratory patterns used, but CI from the vibratory patterns of the nearby supporting gear and bearing are also used. Second, for the UH-60L generators, there are two years of empirical IMD-HUMS data along with corresponding maintenance records for 30 aircraft, each with two generators. This data set should be large enough to contain examples of the most common failure modes from generators along with their corresponding vibratory patterns. The data set also contains examples of healthy generators along with their vibratory patterns. A classification scheme is developed based on these examples of good and bad generators and their vibratory patterns as measured by the approximately 170 CI related to the generator shaft, bearing and gear.

The classification scheme uses a logistic regression fit to the data which estimates the probability of the generator being bad as a function of the CI. This logistic regression fit does not explicitly take into account the time series nature of CI readings. Therefore, as a basis for classification, a loess smoother of the probabilities predicted over time by the logistic regression is used. To test the predictive ability of the classification scheme, the generator data is divided into two sets: a training set and an experimental set. Only the training set is used in the logistic regression fit. The classification scheme is then tested on the experimental data which contains a bad generator, several good generators, and generators of questionable health.

D. OUTLINE OF STUDY

Chapter II gives the background needed to understand this study. In particular it provides an overview of CBM, IMD-HUMS, the UH-60L helicopter and its electrical generators. This chapter also provides fundamental knowledge concerning the CI and HI used in this study. This is important because the data set of flight regimes and vibratory patterns for 30 aircraft over two years of operation is very large. It contains both a large number of variables and a large number of records.

Chapter III describes the data set and how it is partitioned into the training and experimental sets. The vibratory patterns and flight regime data are also studied for both good and bad generators in the training set. This analysis chapter begins with graphical exploration to investigate differences in the training data among the good and bad generators, as well as differences among just the bad generators.

In the second part of the analysis, a parametric model, logistic regression (Montgomery, 2001), is fit to the training data. As a check of the estimated probabilities of the generator being bad, a nonparametric model, a random forest of classification trees (Berk, 2005), is also fit to the training data. These two models give respectively an estimated probability of a generator being bad and a classification of a generator being bad or good for each acquisition.

In Chapter IV the logistic regression and random forest classifiers are applied to each of the generators used in the study. The probabilities of being predicted bad from the logistic regression are plotted over time and then smoothed. These smoothed versions are used to classify each generator in the training and experimental data set as good or bad. The end of the chapter carefully discusses how these predicted classifications compare to how each of the generators are actually classified. In this process, some surprising cases of generator health classification are uncovered. One generator which was wrongly presumed to be bad and conversely another generator which was wrongly assumed to be good were classified correctly by this study's approach.

Conclusions and recommendations for further study are given in the final chapter.

II. BACKGROUND: SYSTEMS AND CONCEPTS

This section introduces and explains the concepts of scheduled maintenance, CBM and vibration analysis. A description and the principles of operation of the IMD-HUMS are given because this system acquires, manipulates and stores the data. A brief description of the UH-60L helicopter, its electrical generators and supporting components is included since they are the source of the studied data.

A. AIRCRAFT MAINTENANCE CONCEPTS

There are two very different concepts in the way military aircraft maintenance is performed. The first, scheduled maintenance, uses traditional methods based upon time of usage. The other is CBM, which is heavily dependant upon vibration monitoring and diagnostics.

1. Scheduled Maintenance

Currently, the maintenance upon most military aircraft is performed under the concept of scheduled maintenance or the idea of Time Before Overhaul (TBO). One of two cases occurs which result in a required maintenance action. A component or system noticeably fails, or is operating in a noticeably degraded mode in which case it is replaced or fixed; or the component or system reaches a pre-determined amount of usage at which time it is replaced or inspected. The inspections or replacements are based upon set hard-times of usage. For examples, there may be a requirement for a phase inspection after 100 hours of pilot logged flight time, transmission and engine replacement after a specific number of flight hours, jet engine power tests after a designated number of usage hours, or replacement of the tail-hook on a carrier-based aircraft after a specific number of traps. The number of flight hours or usage until required maintenance is determined by design engineers based upon the probability of when the component is most likely to fail and the severity of the consequences of its failure. These usage intervals are historically and purposefully set to be in a conservative to extremely conservative range. The greater the severity of the consequence of failure, the more conservative the required inspection or replacement time becomes. Design engineers will set an inspection interval or replacement time that ensures the component is inspected several times or replaced before the expected failure (Rotor & Wing Magazine, April 2005). For instance, if the bearings on a helicopter's rotor head system are expected to fail or to wear to an unacceptable level after 500 flight hours, the design engineers may dictate a phase inspection where the bearings are disassembled and inspected every 100 hours, and then replaced regardless of condition by 300 hours. An aspect of the scheduled TBO maintenance concept is that, as the name implies, maintenance actions are tied to time. Maintenance planners must adhere to dictated usage limits. Sometimes there is a window of time, an allowable plus or minus percentage of usage, permitting some flexibility in planning. The counting and tracking of usage is critical in scheduled TBO maintenance.

While the scheduled or TBO concept of maintenance practices has served the military well over many years, the concept has several inherent drawbacks. The first is that a preponderance of inspections or replacements are conducted on perfectly functioning components only because the usage time dictates so. If maintenance actions were performed only when a component was known to be in a state of unacceptable degradation or definitively failing, a great deal of time, effort and costs could be saved. Many inspections could be eliminated and perfectly functioning parts could remain in operation until they were known to be in one of the above-mentioned states. Another drawback of scheduled TBO is that it is rarely based on the history of the components. Using the prior example of the bearings in a helicopter's rotor system, if sufficient data had been collected which indicate that only 1 in 1000 bearings had degraded by the 500 flight hour TBO, perhaps an inspection interval of every 400 hours could produce the same or better safety and readiness levels with a savings in time, maintenance effort and costs. "Historical data" is rarely incorporated into the scheduled TBO maintenance concept.

2. Condition Based Maintenance

A different approach to the performance of aircraft maintenance is CBM. The underlying concept of CBM is to perform aircraft maintenance only when monitoring sensors indicate that maintenance is needed or will be needed on a component or system. Maintenance planners and maintenance actions are not tied to the counting and tracking of usage; rather the focus is on a component's state or condition. Monitoring sensors collect and record status and performance data of specific components while in use. From this data the actual condition, or state, of the components is then inferred for the user. This provides the ability to forego scheduled maintenance on components or systems which have reached their high times but are still functioning properly. Likewise, the user can specifically identify a failed or degraded component before its scheduled inspection and take immediate corrective maintenance action. Additionally, if a maintenance planner is alerted to the fact that a component is degrading, or that its performance is lessening although still operating at an acceptable level, the planner is afforded greater flexibility in the scheduling of maintenance. The maintainer not only understands that the component is wearing, but also, perhaps, at what rate and from that fact can choose the time of a required maintenance action.

In summary, the goal of the move to CBM is to rapidly and accurately identify faults in order to eliminate time-consuming inspections and unnecessary component replacements. Potential benefits of CBM are the minimization of maintenance efforts and component replacement along with an increase in readiness and safety. Thus, the CBM concept has the potential to eliminate the shortfalls of scheduled TBO maintenance.

Cases of success have already been demonstrated by the IMD-HUMS operating in the 30 UH-60L helicopters. For example the system was able to determine the cause of a persistent buzz felt by aircrew during flight. For 400 flight hours prior to the installation of the IMD-HUMS the buzz had been unidentifiable. After IMD-HUMS installation the source of the vibrations was isolated to the electrical generator. Upon removal of the generator the spline adapter was found to be severely worn. Replacement of the adapter eliminated the buzz. Other benefits have been realized in regard to several maintenance practices, readiness, and safety. During the thesis experience tour in which the system was demonstrated to the authors, maintainers expressed that when using the system the process of both "main rotor track and balance" and "tail rotor vibes" had become much simpler, quicker and reliable with respect to maintenance requirements. For more successful applications of the CBM concept refer to Collacott (1979) which lists case studies and resulting benefits of CBM in the shipping, mining, production, nuclear power and aviation industries. For a better understanding of the DoD strategy and issues of CBM see Butcher (2000). This report addresses the benefits and rewards the military services are reaping through CBM as well as issues concerning further implementation of CBM. The IMD-HUMS is one of the key CBM programs case studied in the report.

B. IMD-HUMS

1. Purpose

"...in the 22 years I've been in the Army, this is the best program as far as going from reactive to pro-active maintenance..." Sergeant First Class Reeve, Delta Co, 4th Bn, 101st AVN Div, 7 June 2005.

Coming from one of the maintainers of the 30 US Army UH-60L helicopters with IMD-HUMS, this quote by SFC Reeve lends credence to the potential and worth of the IMD-HUMS. The US Army plans to install the IMD-HUMS on all of its UH-60M helicopters. In addition, the system has been purchased by the US Navy for installation into CH-53E helicopters. The Navy is also considering installation of this system on the H-60, UH-1, AH-1, and V-22 aircraft (NAVAIR e-mail, 8 July 2005). Goodrich Corporation began development of the IMD-HUMS to perform CBM on helicopters in 1997 under the auspices of the DoD Commercial Operations & Support Savings Initiative (COSSI). The underlying purpose of the IMD-HUMS is to improve flight readiness and safety, with the added bonus of savings in maintenance effort, time and costs. (Hess, 2001)

The IMD-HUMS provides automated equipment usage tracking for life-limited components, from entry into service until retirement. The usage tracking is used not only in the continuation of scheduled TBO maintenance practices, but also for determining accurate component lifetimes and for developing component fault prediction models. Instrumentation aboard the aircraft collects usage data during aircraft operations, which is then applied to life-limited components currently installed on the aircraft (IMD-HUMS User Manual, 2005). With IMD-HUMS component usage times are automatically counted and tracked for TBO; previously this process was conducted manually. Most important, usage times may be computed from any number of variables, including time spent in various flight regimes. It stands to reason that components of aircraft which fly mostly straight and level and take off and land at improved airfields wear more slowly than components on aircraft that are used for high-stress maneuvers in harsh environments, like, for example, the deserts of Iraq. The IMD-HUMS tracks these regimes, and, through study, users may be able to determine what components wear, under what regimes and at what rate. Through this capability, flight readiness and safety are enhanced through the early identification of degraded components (IMD-HUMS User Manual, 2005).

2. Concept of Operations

The IMD-HUMS provides an automated capability to monitor, diagnose and track usage for many components of a helicopter. Sensors of the IMD-HUMS which are installed on the helicopters collect data during flight operations. The initial acquired measurements are physical in nature: motion, rates of motion, and forces. An acquisition is the record of a specific set of these measurements over a fixed period of time. For each acquisition, the IMD-HUMS manipulates these readings through proprietary algorithms to compute CI, and from these, HI for each component. The CI are values which depict a certain aspect of a component's state and are calculated from the raw data of physical measurements. The CI are aggregated to produce a components health indication (HI). This collection of CI and HI for each acquisition is then used for maintenance diagnostics.

The two main sub-systems of the IMD-HUMS are the On-Board System (OBS) and the Ground Station System (GSS). The OBS is physically located on the helicopter and is comprised of a cockpit display unit (CDU), a data transfer unit (DTU) and data transfer memory unit (DTMU), a remote data concentrator (RDC), a main processor unit (MPU), two junction boxes (JB1/JB2), 30 accelerometers, a main and tail rotor magnetic RPM sensors, a main rotor blade tracker, and engine output shaft optical tachometers. The GSS is external to the helicopter, runs on a PC and is comprised of the computer hardware and software that reads and processes the data collected from the OBS. (Figure 1) (IMD-HUMS User Manual, 2005)

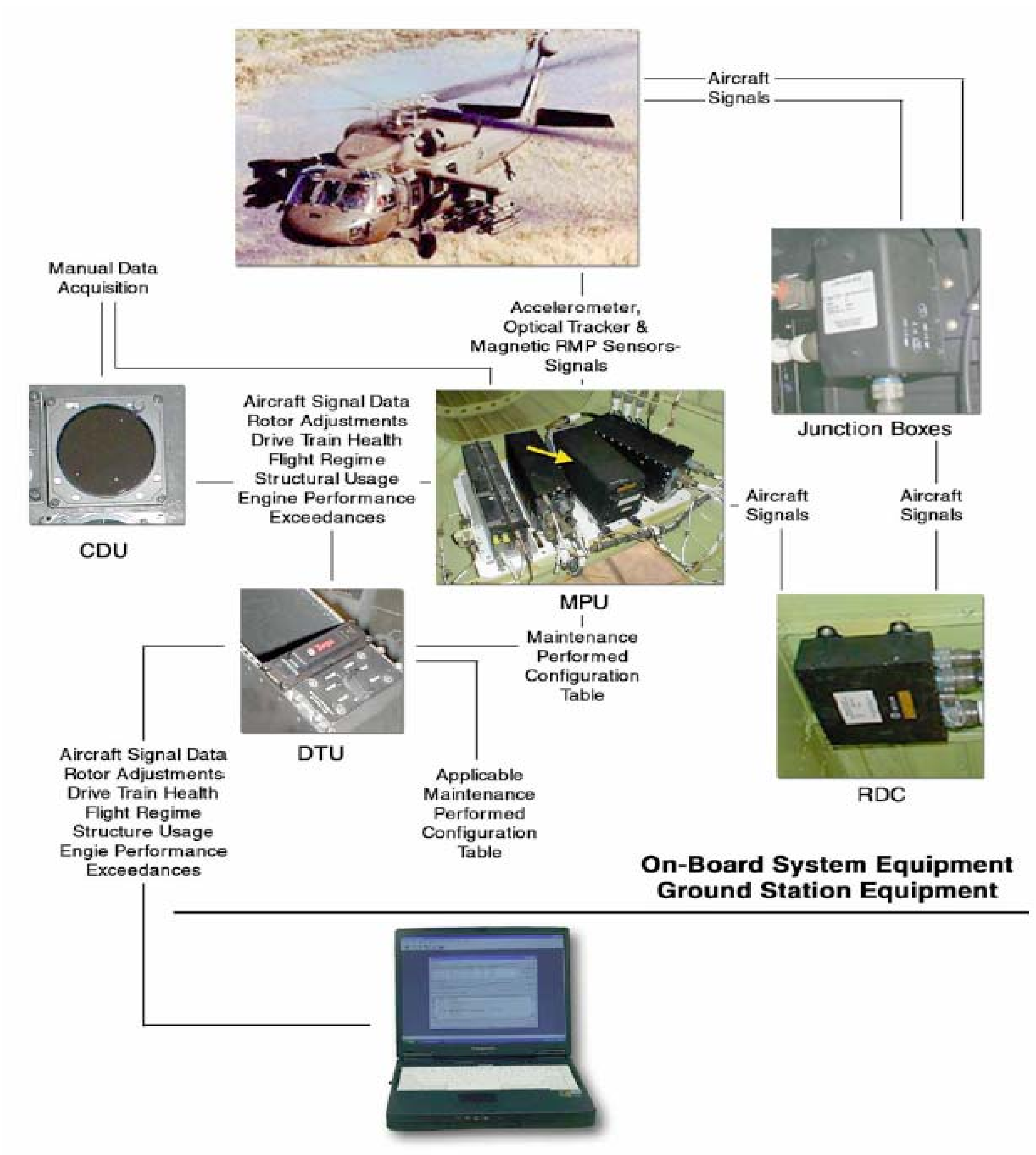

Figure 1. The Components of the IMD-HUMS (from System Users Manual for IMD-HUMS)

A helicopter component in operation results in an associated vibration. Each of the many components of an operating helicopter produces vibrations. It is these vibrations of which the IMD-HUMS takes readings. IMD-HUMS data collection begins at the various aircraft sensors. For instance, the sensors used for data collection from the electrical generators are accelerometers; they are located on the transmission accessory gear box modules, one for each of the two generators (Figure 2). These accelerometers are used to measure the specific vibrations which come from all the internal components such as gears, shafts and bearings throughout the transmission accessory gear box module, not just the electrical generators. Data collected by the accelerometers is then sent directly to the MPU for processing.

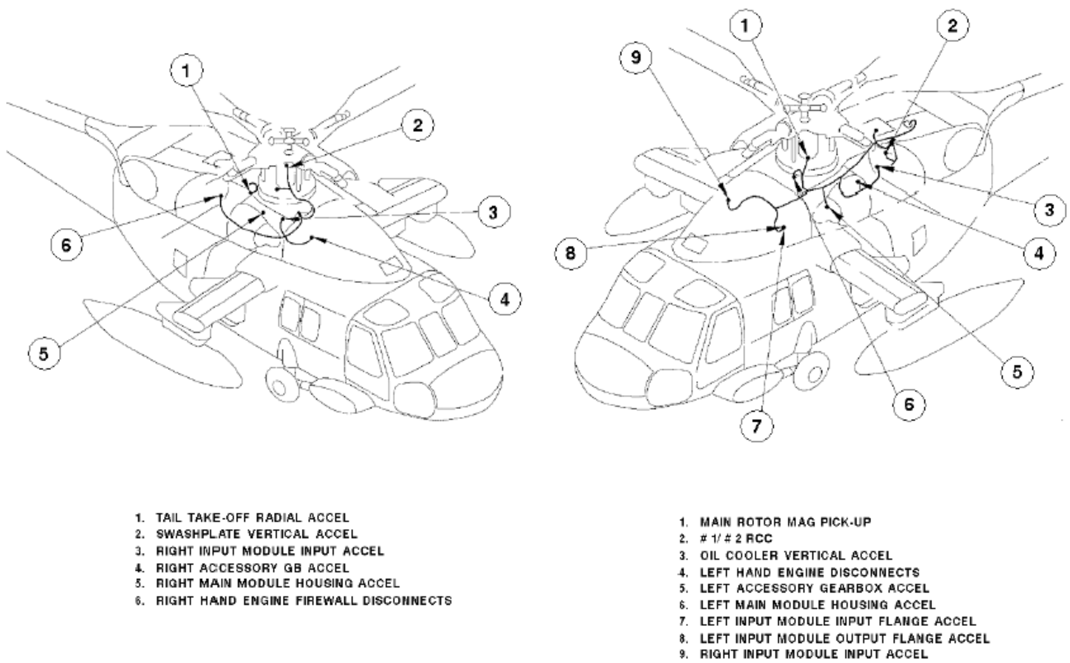

Figure 2. Location of IMD-HUMS Accelerometers on UH-60L Helicopter (from System Users Manual for IMD-HUMS)

The MPU is located in the aircraft's transition section avionics bay. It is the brain of the OBS portion of the IMD-HUMS. The MPU receives data from the accelerometers and performs the following tasks: conversion of analog data into digital data; recognition of flight regime and determination of regime duration; conversion of data into CI;

recognition of vibration exceedances; and the storage of data for transfer to the DTU. After the data has been processed by the MPU, the resulting outputs are referred to as acquisitions (IMD-HUMS User Manual, 2005). This data is in raw data file (rdf) format.

The Ground Station System consists of all the software and hardware associated with the analysis of the acquisitions not located on the helicopter. Once the acquisitions are downloaded from a DTMU, this data and all other data from all flights of all aircraft using the IMD-HUMS are available for analysis. The GSS will automatically generate some of the required maintenance actions resulting from an IMD-HUMS equipped aircraft's flight (IMD-HUMS User Manual, 2005).

C. UH-60L HELICOPTER AND ELECTRICAL GENERATORS

The UH-60L (Blackhawk) (Figure 3) is a twin turbine engine, single rotor, semi-monocoque fuselage helicopter. The primary mission capability of the helicopter is tactical transport of troops, supplies and equipment. Secondary missions include training, mobilization, development of new and improved concepts, and support of disaster relief. The US Army alone has over 1,900 H-60 helicopters in its inventory (International Institute for Strategic Studies, 2005). The incorporation of IMD-HUMS into the H-60 fleet is a major financial investment with great implications concerning the maintenance practices of these helicopters.

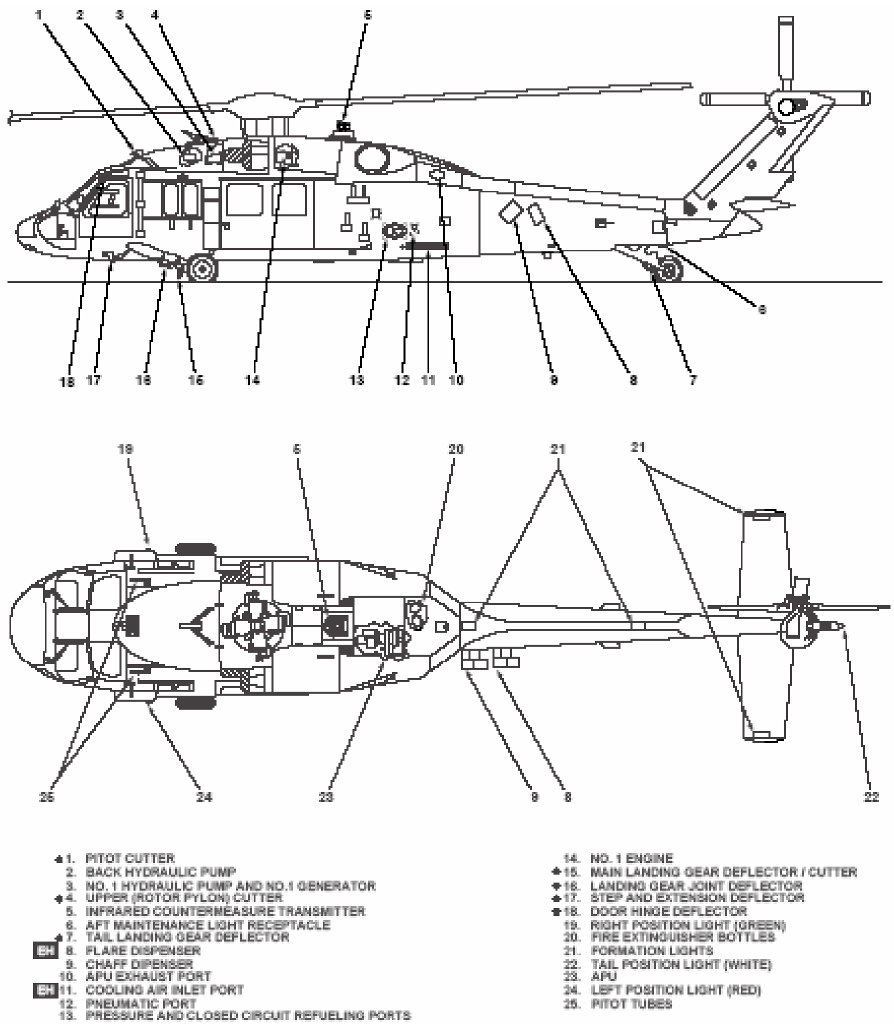

Figure 3. UH-60L Blackhawk Helicopter (from Operators Manual for UH-60L Helicopter)

There are two electrical generators in each UH-60L helicopter (Figure 4). They are mounted on and driven by the transmission accessory gear box module. Each is capable of supplying the total helicopter power requirements (Operators Manual for UH-60L Helicopter, 2003). Main components associated with the electrical generators are as follows: the spur gear located in the accessory transmission model which transfers the rotational power to rotate the generator shaft, the bearings which support and stabilize the generator shaft, and the generator shaft itself which rotates along with mounted brushes to produce electricity.

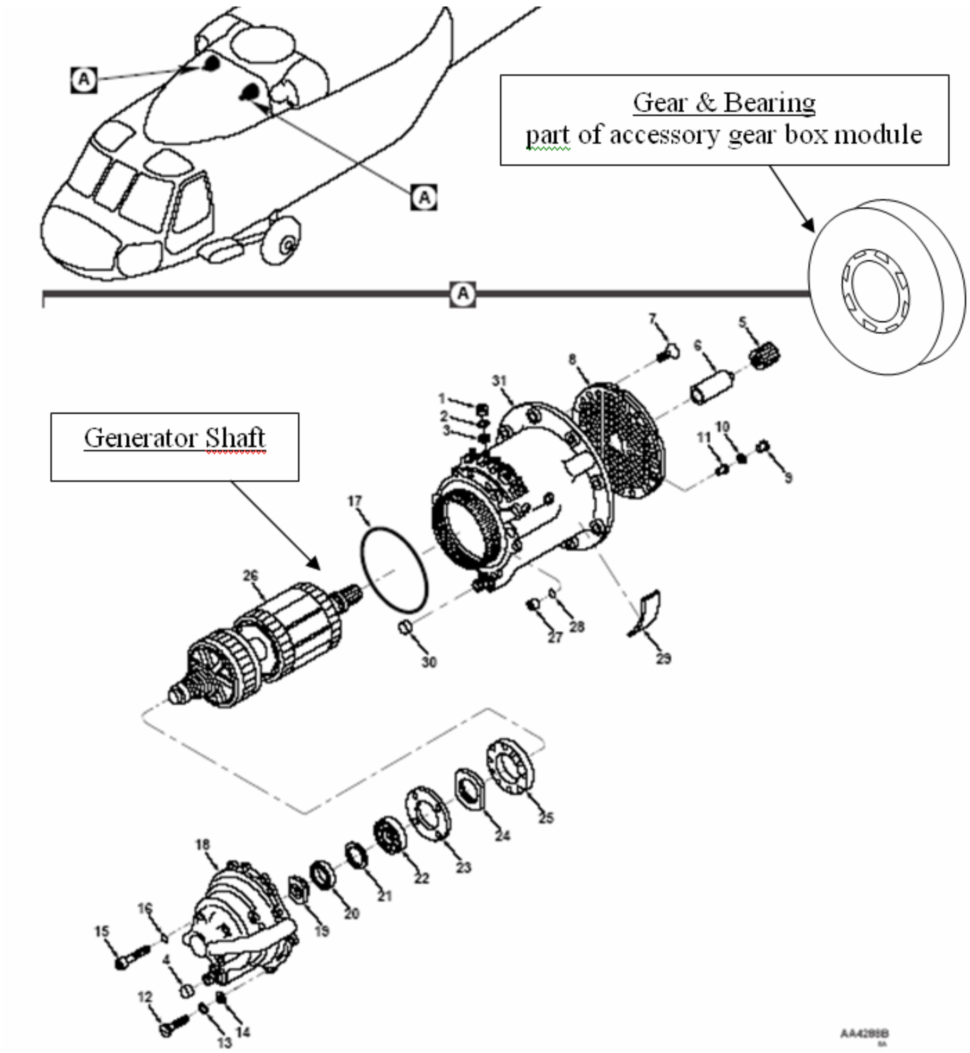

Figure 4. UH-60L Generator (after Intermediate Maintenance Repair and Special Tools List for UH-60L)

D. PHYSICS OF VIBRATIONS AND EXPLANATION OF TERMS

This section provides an overview of the basic physical concepts, terms and tools used in CBM and specifically the IMD-HUMS. These concepts are used to describe the important CI computed by IMD-HUMS and used in this thesis. Also explained is how these CI are used to assess the health of a component.

1. IMD-HUMS and Mechanical Vibrations

An oscillation is the variation, usually with time, of the magnitude of a quantity with respect to a specified reference when the magnitude is alternately greater and smaller than the reference (Harris, 2002). A vibration is an oscillation where the varying quantity is the parameter that defines the motion of mechanical system (Harris, 2002). It is the vibrations from operating components which the IMD-HUMS acquire for analysis. A rotating high-speed engine shaft, a main transmission gear turning, and a main tail rotor blade rotating, twisting, and flapping in multiple directions all produce some type of vibration. The gears, shafts and bearings of the UH-60L generators, which are the components chosen for this study, also produce vibrations when in operation.

The IMD-HUMS uses accelerometers, also known as pezio-electric transducers, to measure mechanical vibrations. Specifically they measure changes in the rate of speed of displacement, or acceleration, of a component in a particular direction. Accelerometers convert physical acceleration into analog electrical voltages. These accelerations oscillate over time hence the resulting motion is a vibration (Collacott, 1979).

The peak-to-peak (P2P) value of a vibrating quantity is the algebraic difference between the extremes of the quantity (Harris, 2002). The IMD-HUMS considers the peak-to-peak value of vibrations because this value tends to increase when vibrating components begin to fail.

The term envelope (Env) refers to the fact that the background signals are removed from a vibration leaving only the portion of the vibration which is to be focused upon or analyzed (Harris, 2002). The IMD-HUMS will extract the envelope signal for some of its outputs.

Probability Density Function (pdf) and kurtosis are statistical concepts applied to vibration analysis. All vibrations have a characteristic pdf which characterizes the probability of a specific instantaneous vibration occurring. Vibrations of good operating components usually have pdfs with a bell-shaped curve. Deviations from the bell-shaped curve can be used to indicate failing or degrading components. The fourth moment, or kurtosis, of the curve is best suited to capture these deviations. This approach has been particularly useful in the vibration analysis of bearings (Rao, 2004).

The term meshing is used to define the working contact or the fitting together and interactions of gears. Meshing of gears results in vibrations which the IMD-HUMS measures.

2. Condition Indicators and Health Indicators

Condition Indicator/Indication(s) (CI) and Health Indicator/Indication(s) (HI) are terms developed by Goodrich Corporation. The CI are variables computed by IMD-HUMS from the raw vibratory data. They are used as a measure of a component's state at the time of acquisition. There are several types of CI. The important CI used in this study are described in the following paragraphs. Up to eight different CI are used by the IMD-HUMS to calculate a value which summarizes a component's overall state, known as a HI. For each specific component there is a proprietary algorithm developed by Goodrich Corporation which determines exactly how its HI is computed. HI are scaled to have values between 0 and 1. During the time period in which data is collected, a HI value between 0.0 and 0.32 is normal (operating fine), between 0.33 and 0.66 is called a warning, and between 0.67 and 1.0 is called an alarm (software changes subsequent to the data collection period have resulted in changes to the HI scale).

Shaft Order 1 (SO1) is a measurement used to detect dynamic imbalances and shaft misalignment with supporting structures (usually bearings) of a shaft. It has dimensions of distance per unit time, measured in IPS (inches per second). A single oscillation in the resulting vibration occurs (order 1) for each complete shaft revolution when an imbalance and/or misalignment exists. These imbalances and misalignments are a result of wearing and degrading shafts and bearings (Harris, 2002).

Shaft Order 2 (SO2), like SO1, is a measure used in detecting shaft misalignment with supporting structures in a shaft. It has dimensions of distance per unit time, measured in IPS. Two oscillations in the resulting vibration (order 2) for each complete shaft revolution results when a misalignment exists (Harris, 2002).

Residual Peak-to-Peak (Res_P2P) is a measurement of displacement (distance dimension) in a vibration. The term "residual" speaks to the fact that the strong tones are first removed from the vibration leaving only the portion of the peak-to-peak displacement which results from regularly existing background vibration (Harris 2002, P^3I VPU/DTD Software Requirements Specifications, 2001).

The ball energy measurement results from defects of a spinning ball bearing. This measurement is used to detect defects or wear in the bearings and is in the dimensions of force, distance and time (Rao, 2004).

Envelope peak-to-peak (Env.P2P) is a measure of the periodic impulses due to bearing defects. Background signals within the vibration are first removed from the vibration, leaving only the portion of the vibration which best depicts the bearing defect. Envelope peak-to-peak is in the dimension of distance (Rao, 2004).

Envelope Kurtosis (Env.Kurtosis) is a measurement of how the periodic impulses due to bearing defects affect the curve of the pdf of the bearings' total vibration. Kurtosis measures the thickness of the tails of the distribution of bearing vibrations after the background signals have been removed (Harris, 2002).

Envelope Distributed Fault (Env.DF) is a dimensionless ratio of the standard deviations of the envelope data (data after background signals are removed) and all raw data (the total vibration). This measurement is used in the analysis of bearing defects. The term "distributed" refers to the fact that all possible directions of displacement are considered in this measurement (Harris, 2002).

Gear Distributed Fault (GDF) is a dimensionless measurement resulting from the ratio of unexplained and explainable variances of a vibration resulting from the meshing of gears. It is believed that this measurement is an indication of gear teeth wear and cracks (Harris, 2002).

The G2-1 measurement is a result of an algorithm which considers the average peak-to-peak and energy output of a vibration resulting from the meshing of gears. It is used in the analysis of gears. The term was developed by Goodrich Corporation and the algorithm which determines its value is proprietary (P^3I VPU/DTD Software Requirements Specifications, 2001).

Gear Misalignment 1 (GearMis_1) is a dimensionless measurement resulting from the ratio of the energies of the vibrations produced when gears mesh (Harris, 2002).

III. DATA ANALYSIS

This section details the process of data analysis for this thesis. It begins with an explanation and description of the data and how the data are partitioned into a training data set and an experimental data set. Next, for the training data a brief graphical exploration of the differences between good and bad generators as well as differences among bad generators is given. The remainder of the chapter deals with variable selection and the fitting of the logistic regression and forest of trees models.

A. DATA

1. Data Collection

The authors first visited the US Army unit conducting the operational test of the IMD-HUMS. The soldiers of this unit, 4th Regiment 101st AVN Division, are the operators and maintainers of the 30 UH-60L helicopters which have IMD-HUMS installed. During the ten-day visit the components and concept of operations of the system were explained, the operation of the system was witnessed, and the IMD-HUMS data output was shown. The authors were permitted to fly aboard one of the helicopters during which time the data collection process from beginning to end was demonstrated and explained in detail. The soldiers then explained the unit-level data analysis and maintenance practices which result from these data collections. They also provided several specific cases of successful implementation of the system and cases of interest for possible study. Of particular interest were six electrical generators which have been replaced for cause. The IMD-HUMS data concerning these replaced generators provided an opportunity to determine whether the data can predict the cause and/or need for generator replacement.

In the two years of IMD-HUMS use in the 30 UH-60L helicopters, data has been collected on 66 different electrical generators. In these two years six generators were removed from operations for some reason of fault; the remaining 60 generators were deemed to be working properly. Where available, pre-fault data, maintenance records and photographs were used to explain the circumstances of the faulted generators. Photographs show that some of the faulted generators had worn or totally broken components. In addition, the maintenance history of each of these faulted generators was investigated. Table 1 provides a summary of the cases of each of these six faulted generators. The failure of two of the generators, numbers 9 and 33, were detected during operation by a generator warning light. Faults in the remaining four generators, numbers 22, 31, 53 and 56, did not trigger the generator warning light. However each of the four generators had unusually high SO1 readings upon removal. Three of these generators, numbers 22, 31 and 53, showed evidence of fault or wear. The removal of generator number 56 resulted from the case of an identifiable buzz explained earlier in Chapter II.

Table 1. Confirmed Bad Generators

Confirmed Bad Generators		
Aircraft / Side	**Generator #**	**Reported Comments**
450 Left	**9**	# 1 generator failed during shutdown upon APU generator coming on during start; replaced #1 generator [1]
829 Left	**33**	# 1 generator bad; replaced generator [1]
518 Left	**22**	SO1 near 2 IPS so replaced Spline Adapter Coupler during next scheduled maintenance. Evidence of wear and possible improper installation. SO1 returned to .05 IPS after replacement. [2]
549 Left	**31**	Replaced Spline Adapter Coupler due to SO1 at 3 IPS. Adapter severly worn and two 1 inch cracks found. IPS still high after Adapter replacement so generator also replaced. [2]
515 Right	**53**	While getting modified with IMD-HUMS, vibration was noted, found to have SO1 at 3 IPS. Adapter Coupler was replaced (had some wear) and SO1 vibrations dropped below .05 IPS. [2]
518 Left	**56**	3 Jan 04 Mosul: had a weird buzz on left-hand side ceiling, isolated to generator (found to have SO1 over 4 IPS). Generator and coupling replaced. [2]
Source: **1** Maintenance Records **2** Johnny Wright and Ground Station Team, IMD-HUMS Fault Detections, Goodrich Corporation. Draft 5/25/2005 (Ver 117)		

2. Data Description

More than 60GB of data, which consists of acquisition data for all the helicopters' monitored components, was sent to NPS in rdf format. The data readings concerning all the generator shaft, spur gear and bearing were then extracted and converted to column separated value (csv) format for data exploration and analysis. Each IMD-HUMS acquisition concerning the shaft, spur gear and bearings of a generator results in 169 variables. The 169 variables are listed in Appendix A.

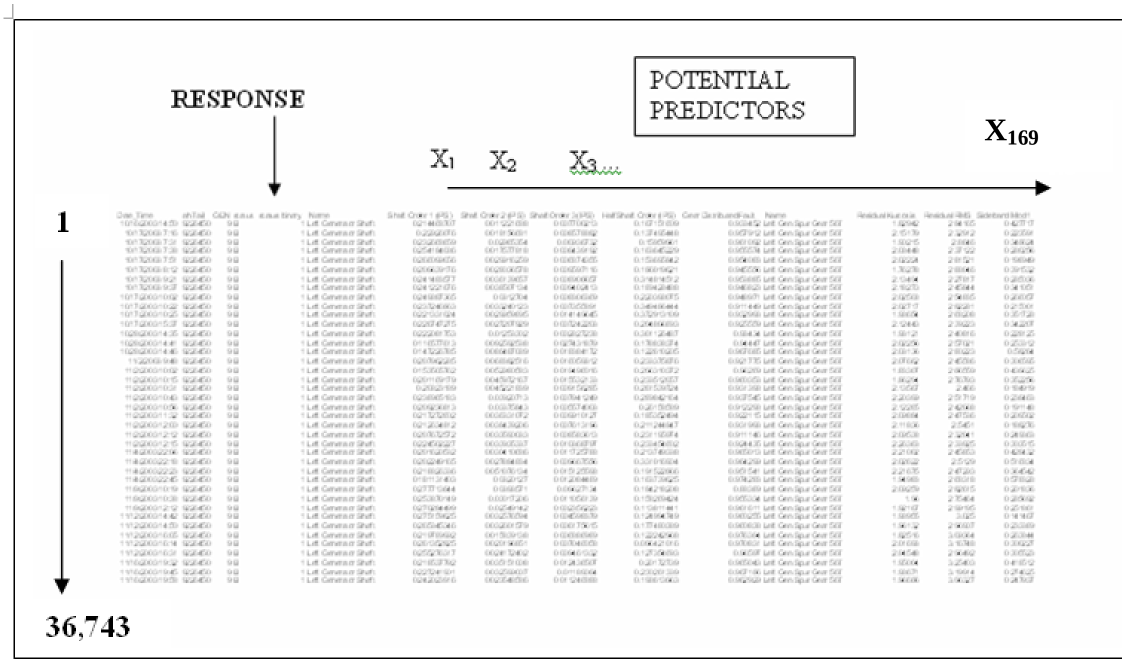

Figure 5. Example of the IMD-HUMS Data in CSV Format

Each generator is assigned a number, 1 through 66, for ease of identification and data manipulation. These numbers were then incorporated into the data set. Among the 169 variables recorded for each acquisition are the Health Indicators for the gear, bearing and shaft. Some generators had acquisitions which numbered in the tens, others in the hundreds, and others in the thousands. In total, for all 66 generators, there are 36,743 separate data acquisitions from the two-year period during which the IMD-HUMS were installed. Two generators, numbers 23 and 34, were removed because these two generators have less than 20 acquisitions during their time of operation, leaving data from 64 generators.

The data set is divided into two separate groups; the "training" set to be used to develop models which predict whether a generator is faulty or not based on CI, and an "experimental" set used to test how well these models actually predict whether a generator is faulty or not.

3. Training Data Set

Each generator in the training set is assigned a binary value of 1 or 0 to classify their known state. The value of one is given to the generators removed for fault, henceforth referred to as bad generators. The value of zero is given to the generators not removed, referred to as good generators.

A complication of this binary classification system is that there may be bad generators, ones which will eventually fail, classified as good because their faulty condition has not yet been identified. The large number of good generators included in the training set serves as protection from these errors, diminishing the influence of any incorrectly classified generators. This is a critical assumption in the analysis. The fact that each generator is assigned a state of 0 (good) or 1 (bad) does not mean these generators are actually in the assigned state. The assigned state of 0 (good) or 1 (bad) is based strictly upon whether a generator was removed for fault or not. A generator with an undetected fault would be assigned a state of 0 (good). Likewise a generator which was replaced for a reason of fault and assigned a state of 1 (bad) could actually have been mechanically good; perhaps the electrical contacts or wiring could have had a short-circuit. This is the reason the authors investigated the circumstances and maintenance actions of each of the replaced generators.

The training set consists of data from 52 of the 64 generators. Five of the training set generators had been taken off their helicopters for fault and are classified as bad; the remaining 47 training set generators had no known faults throughout their data history and are classified as good.

Only CI computed in the last 20 acquisitions of each generator of the training set were used in the development of the prediction models. This is because the faulted generators, classified as bad, most likely were not bad throughout their entire two-year history. By restricting analysis to the last 20 acquisitions the risk of including observations from bad generators gathered before the fault occurred is reduced. The choice of 20 acquisitions is a judgment call made by the authors after inspecting the general trend of CI and HI. This reduced the training set to a total of 1040 acquisitions.

4. Experimental Data Set

The experimental set consists of data from the remaining 12 generators. One generator, number 33, was taken off its helicopter for fault and the remaining 11 generators in the experimental set worked properly throughout their data history. However, six of these 11 generators were put on what the users called the "watch list," the list of generators with questionable status (Table 2). The watch list consists of generators which show generator shaft CI or HI values which indicate that perhaps these generators are beginning to degrade. Two of the generators, numbers 30 and 21, are considered to be in a priority status due to shaft order 1 (SO1) readings above 2.0 IPS. The other four watch-list generators have SO1 readings above 1.5 IPS. These generators are included in the experimental set to make a final determination of their status using the prediction model.

The five remaining good generators in the experimental data were on the opposite side of the four watch list generators and the one faulty generator.

Table 2. Generator Watch List

Generator Watch List		
Aircraft / Side	**Generator #**	**Shaft Order 1 Vibrations (IPS) As of 5/27/2005 RTH (Rotor Turn Hours)**
545 Left	**30**	reached 2.3 IPS and is increasing at 2.2 IPS per 100 RTH
516 Left	**21**	reached 2.5 IPS and is increasing at 0.5 IPS per 100 RTH
441 Left	**6**	reached 1.5 IPS and increasing at 0.4 IPS per 100 RTH
516 Right	**55**	reached 1.78 IPS and is increasing at 0.1 IPS per 100 RTH
493 Right	**48**	reached 1.85 IPS and is not increasing
519 Left	**24**	reached 1.55 IPS and is increasing at less than 0.1 IPS per 100 RTH
Source: Harrison Chin, Dave Green, Eric Mayhew, Johnny Wright, Generator Shaft Analysis: Expanded Survey Including #441, #515, #516, #518, #519 and #545, Goodrich Corporation, Draft 5/27/2005 (Ver 3)		

B. GRAPHICAL ANALYSIS

Projection Pursuit (Hastie, Tibshirani & Friedman, 2001) implemented by the statistical software Ggobi, is used to gain a visual perspective of the relationship among the variables. Ggobi plots two-dimensional projections of multi-dimensional data. The projection pursuit algorithm numerically searches for two-dimensional projections which maximize one of several possible measures of interest. These projections are displayed graphically and the plot is continually updated as the algorithm pursues “optimal” projections. The display is interactive, and Ggobi allows the user to stop the display and manually change the projection at any point. By using projection pursuit several insights are gained concerning the data.

Projection Pursuit is first used to study the five bad generators from the training set. Five variables, the CI: SO1, SO2, Env.P2P, GearMis_1, and Ball Energy, from the 169 variables relating to generators are used as input variables. The SO1 and SO2 variables are accepted common indications for shaft conditional state. The remaining three variables are used to address the conditional state of the gears and bearings.

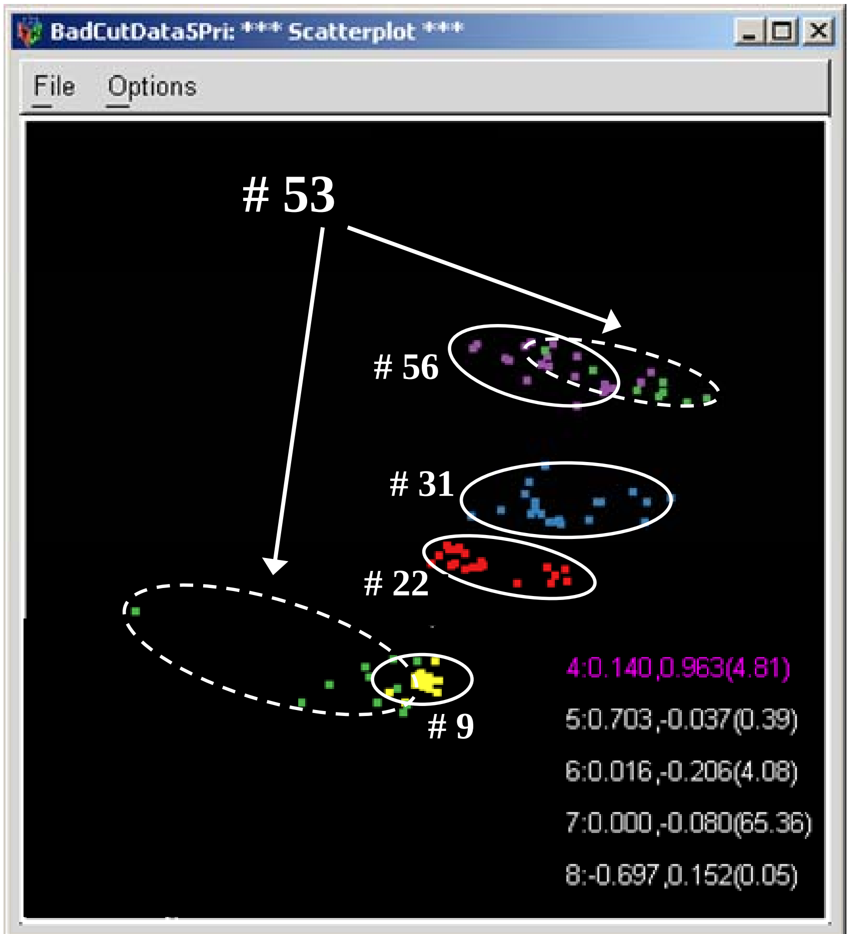

Figure 6. Ggobi Dispaly - Clusters of Bad Generators

Figure 6 shows the Ggobi graphical display of the projection of these five variables for the five bad generators of the training set. The figure shows that four of the five bad generators form single clusters. Only one of the generators, number 53, forms two clusters, one in the upper right of the display, the other in the lower left of the display. From this display, one might be tempted to propose that the two clusters represent two different time periods. However, this is not the case.

Let y_1 and y_2 be the linear functions of the five CI computed by Ggobi in Figure 6. Further, consistent with Figure 6, let

$x_4 \equiv$ SO1

$x_5 \equiv$ SO2

$x_6 \equiv$ Env.P2P

$x_7 \equiv$ GearMis_1

$x_8 \equiv$ Ball Energy.

Then y_1 and y_2 can be computed as

$$y_1 = \left(0.140 \times \frac{x_4}{4.81}\right) + \left(0.703 \times \frac{x_5}{0.39}\right) + \left(0.016 \times \frac{x_6}{4.08}\right) - \left(0.697 \times \frac{x_8}{0.05}\right)$$

$$y_2 = \left(0.963 \times \frac{x_4}{4.81}\right) - \left(0.037 \times \frac{x_5}{0.39}\right) - \left(0.206 \times \frac{x_6}{4.08}\right) - \left(0.08 \times \frac{x_7}{65.36}\right) + \left(0.152 \times \frac{x_8}{0.05}\right)$$

Plotting y_1 and y_2 in acquisition time sequence, Figure 7 clearly shows that the y_1 and y_2 values of generator number 53 oscillates between the two groups depicted in Figure 6 over time.

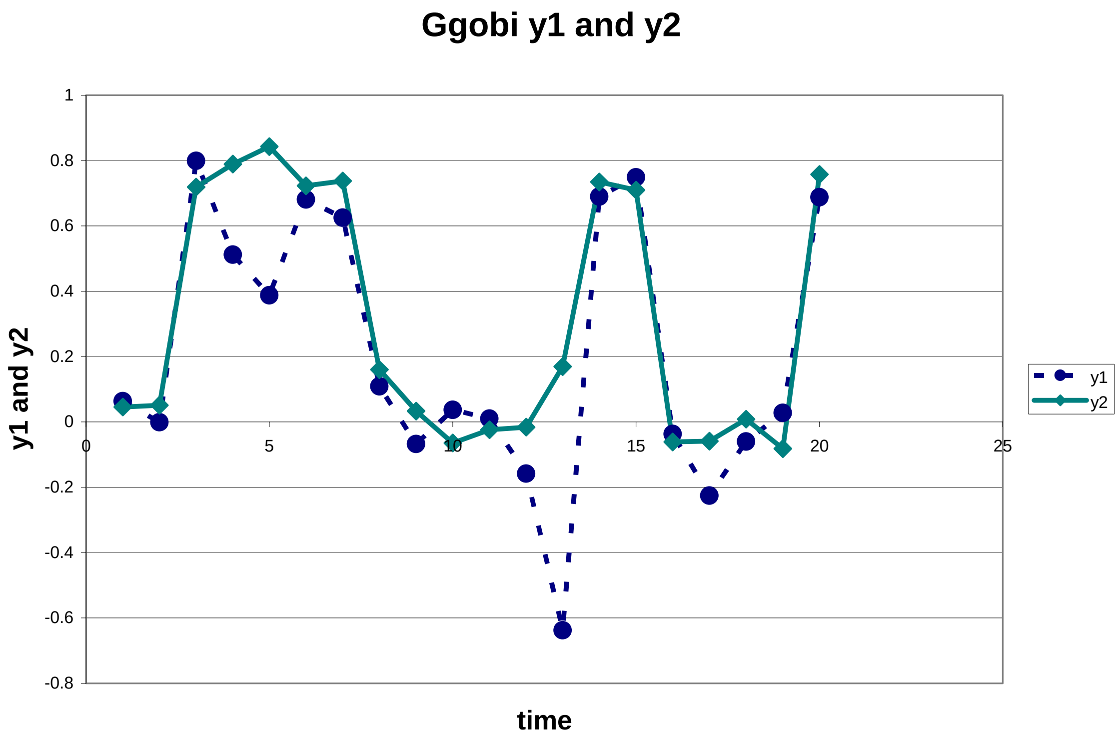

Figure 7. Variability of Generator Number 53

Ggobi is also used to investigate clustering of generators classified as good and bad. The five same CI are again used as input variables. The resulting display, Figure 8, shows a definite difference in grouping of variables between most of the good generators (light grey dots if viewed in the non-color copy or yellow dots if viewed in the color copy) and the bad generators (dark grey dots if viewed in the non-color copy or purple if viewed in the color copy). However, one bad generator, number 9, seems to be clustered with the good generators.

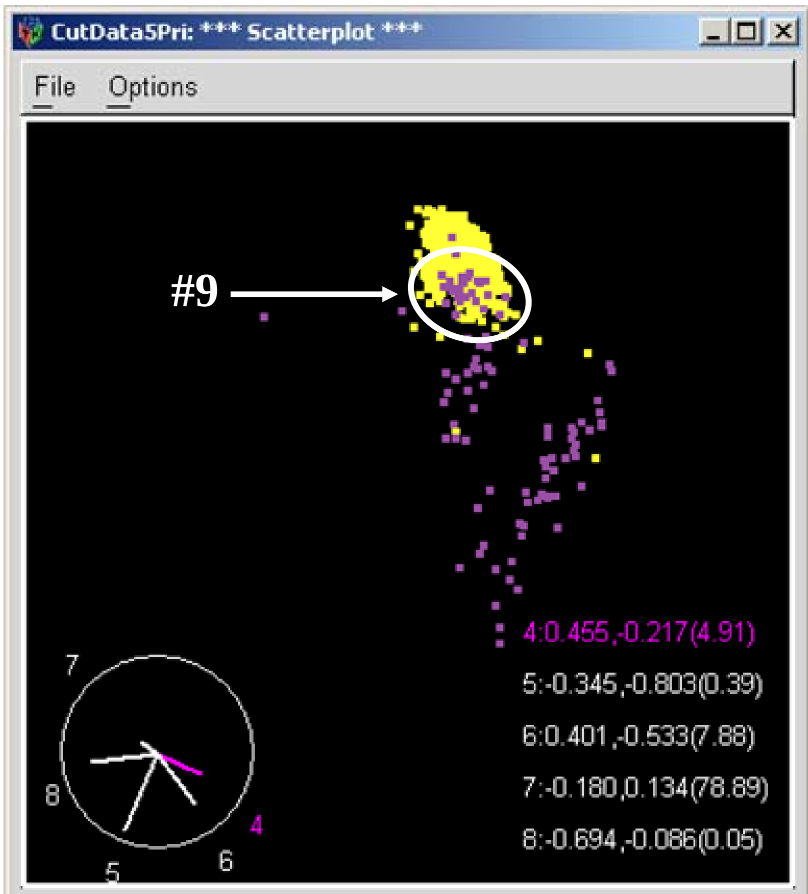

Figure 8. Ggobi Display - Light gray (yellow) dots are good generators, dark gray (purple) dots are bad generators

C. INITIAL VARIABLE SELECTION PROCESS

With 169 variables initially in the training data set, we reduced the number of potential predictors based upon an understanding of the IMD-HUMS, the physical operation of the helicopter and generators, and the vibrations they produce. This variable reduction is necessary when fitting parametric models such as logistic regression. It is also desirable but not strictly required when using certain data mining techniques. The 169 variables include the HI for the shaft, gear and bearing. The current practice is to rely heavily upon the HI of the generator shaft to assess the overall health of the generator. A single model incorporating acquisitions from all three components, however, might better detect other modes of fault or degradation.

The classification models are based on variables that describe the state of the three main components involved in the operation of the generator: the generator's shaft, supporting bearings and supporting spur gear. The authors believe doing so explains the overall state of the generator better than separately tracking and assessing each component's HI.

The first step in variable reduction is to eliminate any variables which do not originate from, or directly address, one of these three components and their physics of operation. For example, consider torque (a measure of power output) readings of each engine at the time of acquisition. Once up and running, the electrical generators turn at a nearly constant speed, under a nearly constant force, regardless of engine torque. The transient run-up time to generator rotational speed is minimal. Therefore the engine torque readings are eliminated as possible predictors. Explained another way, changes in engine torque are not expected to result in significant changes of generator speed or forces. The same reasoning is applied to eliminate other variables. For example, acquisition date/time, aircraft tail number, airspeed, main rotor speed, outside air temperature, main gear box temperature, and flight regime are all eliminated.

It seems this reasoning should also be applied in determining whether position of the generator (left or right side of the helicopter) should be included as a variable. The left and right generators are identical and interchangeable in all physical aspects. The only distinction between them is their name "left" or "right" given by the side of the helicopter they are installed on. However, graphical analysis of certain CI, particularly Residual Peak-to-Peak, show clear differences in both mean and variance of these values between left and right generators. (Figure 9).

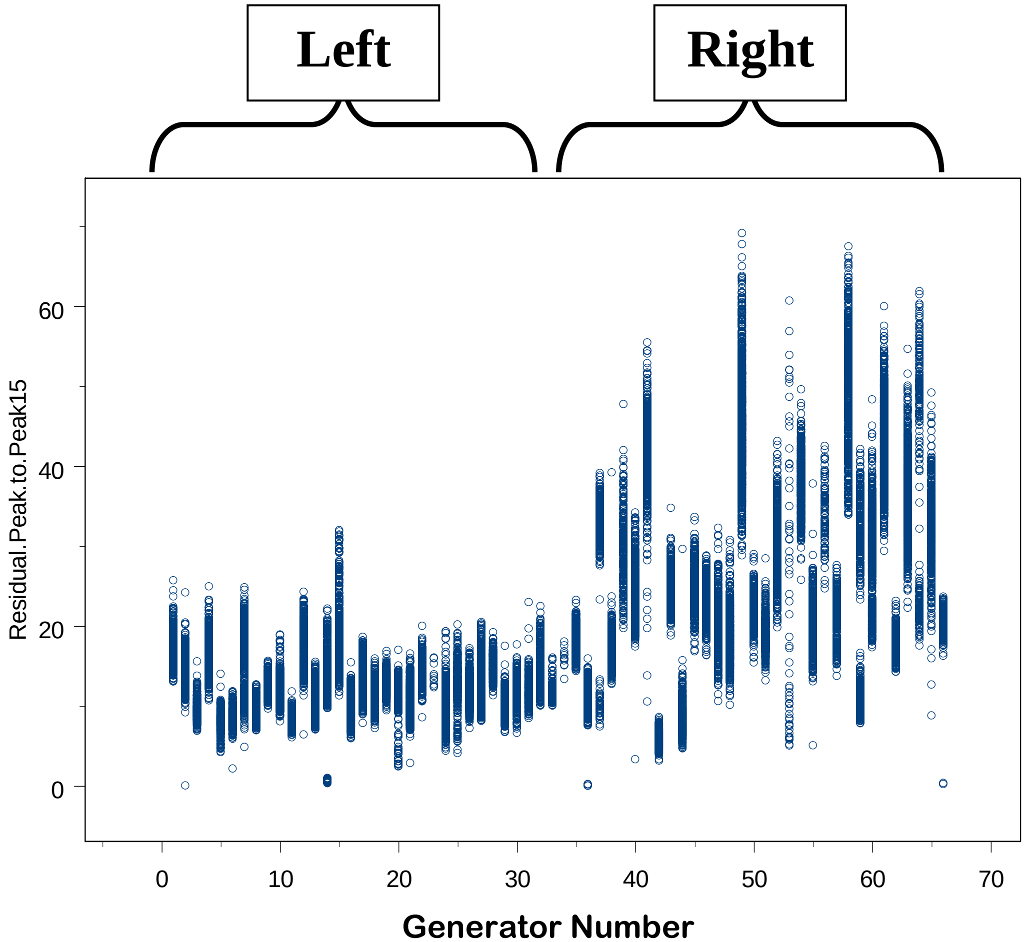

Figure 9. Dot Plot of the Residual Peak-to-Peak CI for Each Generator

The differences may be caused by slight variations in the way that complicated vibrations are transmitted from the accelerometer to the MPU. While the variables indicating left or right side of aircraft is not explicitly included in the analysis, the left/right position is implicitly captured with variables such as residual peak-to-peak and envelope distributed fault.

Another method of eliminating variables is to drop any redundant or nearly redundant variables. For instance, shaft orders one, two, three and one-half are all calculated in three different scales: IPS, OBS, and G forces. Each is a constant multiple of the other. Thus the shaft order readings in the scale of IPS were kept while the others were dropped. Normalized versions of the variables ball energy, cage energy, inner race energy, outer race energy and total bearing energy were also dropped since non-normalized readings for each of these exist in the data set.

By eliminating redundant variables and those not directly involved with the generator shaft, gear and bearing, the 169 variables were reduced to 65 variables. Appendix A is a listing of all 169 variables with the 65 remaining variables highlighted.

However, redundancies still exist among the remaining variables. For example, computation of the sample correlations between the 65 predictor variables gives 16 pairs of variables with sample correlations greater than 90%. These high correlations are an indication of multicollinearity among the predictors. In addition, the principle components of the standardized variables (Hastie, Tibshirani & Friedman, 2001) indicate that the first 10 principle components account for 68% of the variability of the 65 variables (Figure 10). Over 95% of the variability can be captured with 34 components. This confirms our suspicion that generator condition can be captured in fewer dimensions than the current data set. Figure 10 shows the percentage of variance captured in the first ten principle components of the 65 standardized predictor variables.

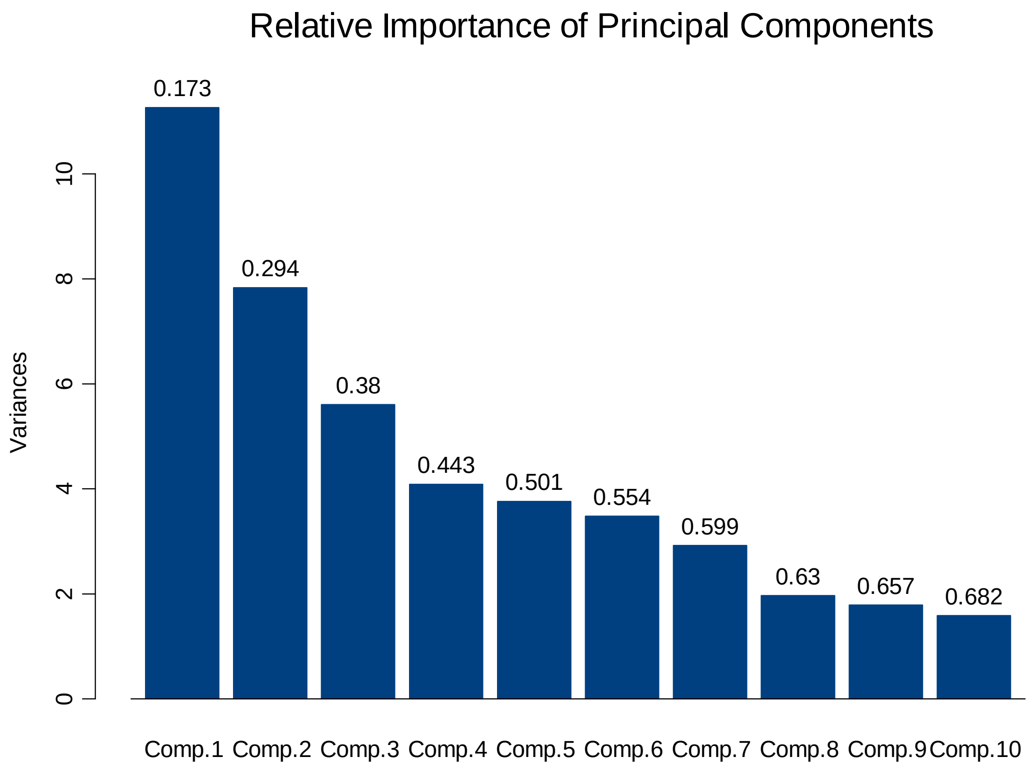

Figure 10. Variance Captured in First Ten Components of Data Set Containing 65 Predictor Variables

Table 3. Pairwise Sample Correlations

CI	CORRELATION	CLASSIFICATION
SHAFT ORDER 2	0.690	STRONG
SHAFT ORDER 1	0.654	MEDIUM
SHAFT ORDER 3	0.491	MEDIUM
ENVELOPE PEAK TO PEAK	0.376	MEDIUM
GEAR DISTRIBUTED FAULT	-0.305	WEAK
BASE ENERGY	0.275	WEAK
BALL ENERGY	0.252	WEAK
BEARING ENERGY	0.197	WEAK

Pairwise sample correlations of the 65 predictors with the binary response variable indicating good or bad are also computed. Of these, the variables with the highest correlation are given in Table 3. Correlations from 0.0 to 0.33 are classified as weak, correlations from 0.34 to .66 are classified as medium, and correlations from 0.67 to 1.00 are classified as strong.

This analysis of correlation provides indications of useful variables for the models. They are shaft orders 1, 2 and 3 which result from vibrations of the generator shaft, and in the case of shaft order 1 from the bearings also. Shaft order 2 has the strongest correlation with the response variable of all 65 predictors. Shaft orders 1 and 3 have the next highest correlations, classified as medium. Envelope Peak-to-Peak which result from vibrations of the bearings shows the next highest correlation, also classified as medium. The remaining predicators have differing measures of weak correlation with respect to the response.

D. LOGISTIC REGRESSION MODEL

Let $n = 1{,}040$ be the total number of observations in the training data set; and let Y_i, $i = 1, 2, 3, ..., n$, represent the binary random variable indicating whether the i^{th} observation comes from a bad generator ($Y_i = 1$) or a good generator ($Y_i = 0$). The logistic regression model assumes that Y_i are independent Bernoulli variables with $\pi_i = P(Y_i = 1)$ for $i = 1, 2, 3..., n$. In addition the logistic regression model "links" π_i to the observed values of the k predictors for the i^{th} observation $x_{i1}, x_{i2}, x_{i3}, ..., x_{ik}$ as follows:

$$\ln\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{i1} + ... + \beta_k x_{ik} \quad i = 1, 2, 3, ..., n,$$

where $\beta_0, \beta_1, \beta_2, ..., \beta_k$ are the $k+1$ parameters or coefficients to be estimated.

The benefit of using logistic regression in the model is it can be used to estimate π, the probability that the observation comes from a bad generator rather than a good generator.

There is one assumption for logistic regression which our application of the model violates heavily. Logistic regression requires that the Y_i be independent of one another. Time-series collections, and the method of classifying an entire generator, not each individual acquisition, as good or bad create an unusual dependency between acquisitions within each generator. To fit the models, the last 20 acquisitions from each generator in the training set are used, thus violating independent sampling. For instance, a single worn or damaged ball bearing wears more and more with continued operation. Further acquisitions depicting more wear and damage will result. Therefore the state of a component is dependent upon its past state. However, here logistic regression is used to compute summary statistics rather than for inference. Thus the real proof of the utility of using this approach lies in how well it predicts problems in the generators in both the training and experimental data sets.

Two approaches are used to fit the logistic regression model. The first method creates a compact model which has no correlation or left/right generator issues; however, the second method is chosen for the final model due to better performance.

The first method forces inclusion of shaft, gear, and bearing CI. Three logistic regression models are fit: one with CI originating only from the bearings, another with CI originating only from the gear, and still another with CI originating only from the shaft. Backwards elimination is used to select variables for each of these models, i.e. the CI with the greatest p-value is eliminated from the model at each step of the backwards elimination procedure. The end result is 20 variables for the bearings, 14 variables for the gear and 5 variables for the shaft. The purpose of fitting separate models based on CI from the three separate components is to ensure that potential predictors for each component are included in the final model. These three sets of variables are then combined, and another logistic regression model is fit using backwards elimination for variable selection. With each logistic regression printout Null Deviance (ND) minus Residual Deviance (RD) is considered. In logistic regression fits where all modeling assumptions such as independence apply, a small RD is desired but not at the expense of an over-fit model. Including all or too many of the potential variables would result in over-fitting; the resulting model would predict the training data set very well but would include unnecessary variables and may not be usable for predictions on other data.

This process gives a model with only five predictors: SO1, SO2, GearMis_1, Ball Energy, and Env.P2P. These CI have low pairwise correlation and the variable indicating left/right generator is not needed, but the performance compared to the final model is inferior (Table 4).

Table 4. Comparison of Logit Model Performance

Model	Logit Model Fitting Criteria		
Over Fit 65 variables	Null Deviance: **658.4219** on 1039 degrees of freedom Residual Deviance: **0** on 974 degrees of freedom		
Under Fit 5 variables	Null Deviance: **658.4219** on 1039 degrees of freedom Residual Deviance: **213.6768** on 1034 degrees of freedom		
Final Model 10 variables (fitted with generator # 7 classified as bad, explained in Results Chapter)	Null Deviance: **743.8645** on 1039 degrees of freedom Residual Deviance: **77.71993** on 1029 degrees of freedom		
Likelihood Ratio Test	**Chi-Square**	**degrees of freedom**	**Significance**
	666.145	10	.000

The second logistic regression model was fit by the following process. We begin with the 65 variables determined after initial variable elimination. Further elimination of redundant or similar variables led to the removal of 16 bearing and 2 gear predictors. These variables were eliminated because the pool of predictors included other variables derived from the same vibration, differing only from the dropped variables by the algorithm from which they are derived. For instance, the gear variable "AM kurtosis" is dropped because "derivative AM kurtosis" is also present.

A logistic regression model was then fit in Clementine using the 47 variables left in the predictor pool. Backwards elimination was again used to eliminate variables further, leaving 12 CI. At this point the classification error rate of the model was also monitored so as to choose the final number of predictor variables in a backwards-stepwise fashion. Variables continued to be eliminated from the model as long as the misclassification rate stayed low. When the output shows an increase in the misclassification rate, the last eliminated variable is re-installed in the model and that model is deemed best. Using this method, "Envelope Crest Factor" and "Shaft Order 3" were eliminated resulting in a final logistic regression model with an overall correct classification rate of 99%, and only one observation from a bad generator classified as good.

Table 5. Logit Model Classification Rate

Classification			
Observed	Predicted		
	0 (bad)	1 (good)	Percent Correct
0 (bad)	919	1	99.9%
1 (good)	9	111	92.5%
Overall Percentage	89.2%	10.8%	99.0%

Table 6. Logit Model Fitting Information

Model Fitting Information				
Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	743.864			
Final	77.720	666.145	10	.000

Goodness-of-Fit			
	Chi-Square	df	Sig.
Pearson	6525.330	1029	.000
Deviance	77.720	1029	1.000

Pseudo R-Square	
Cox and Snell	.473
Nagelkerke	.926
McFadden	.896

Table 7. Logit Model Likelihood Ratio Tests

Likelihood Ratio Tests				
	Model Fitting Criteria	**Likelihood Ratio Tests**		
Effect	**-2 Log Likelihood of Reduced Model**	**Chi-Square**	**df**	**Sig.**
Intercept	119.540	41.820	1	.000
Shaft Order 1 (IPS)	145.015	67.295	1	.000
Shaft Order 2 (IPS)	144.412	66.692	1	.000
Gear Distributed Fault	138.842	61.122	1	.000
G2-1	80.286	2.566	1	.109
Residual Peak to Peak	141.611	63.891	1	.000
Gear Misalignment 1	94.404	16.684	1	.000
Ball Energy	78.850	1.130	1	.288
Envelope Peak to Peak	184.416	106.696	1	.000
Envelope Kurtosis	117.695	39.975	1	.000
Envelope Distributed Fault	79.924	2.204	1	.138
The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.				

Table 8. Logit Model Parameter Estimates

	B	Std. Error	Wald	df	Sig.
Intercept	37.010	7.225	26.242	1	.000
Shaft Order 1 (IPS)	-9.369	2.025	21.407	1	.000
Shaft Order 2 (IPS)	-98.357	20.245	23.603	1	.000
Gear Distributed Fault	-39.442	8.025	24.153	1	.000
G2-1	.019	.013	2.370	1	.124
Residual Peak to Peak	1.004	.207	23.473	1	.000
Gear Misalignment 1	.189	.054	12.223	1	.000
Ball Energy	-96.958	124.581	.606	1	.436
Envelope Peak to Peak	-6.652	1.244	28.571	1	.000
Envelope Kurtosis	3.979	.975	16.653	1	.000
Envelope Distributed Fault	61.703	44.512	1.922	1	.166

E. TREE MODELS

Due to the large number of possible predictor variables (CI) available in the data set, a nonparametric, data mining approach is used to augment and check the predictions of the logistic regression model. We use a procedure based on Classification and Regression Trees (CART) developed by Breiman, Friedman, Olshen and Stone in 1984. CART searches all predictors in a data set, making a split in each predictor which reduces variability of the dependent variable to the minimum within the resulting subsets. This creates two leaves, each of which can be split again. This continues until a minimum threshold is reached.

The tree-fitting process provides information about predictor importance as well as a decent prediction. However, it is vulnerable to over-fitting and thus requires cross-validation and pruning (limiting the number of splits). Figure 11 shows the un-pruned classification tree created from the last 20 acquisitions of each generator in the training set. The 65 CI determined by initial variable elimination are used to fit this tree. Appendix F displays the remaining S-Plus training set classification tree output.

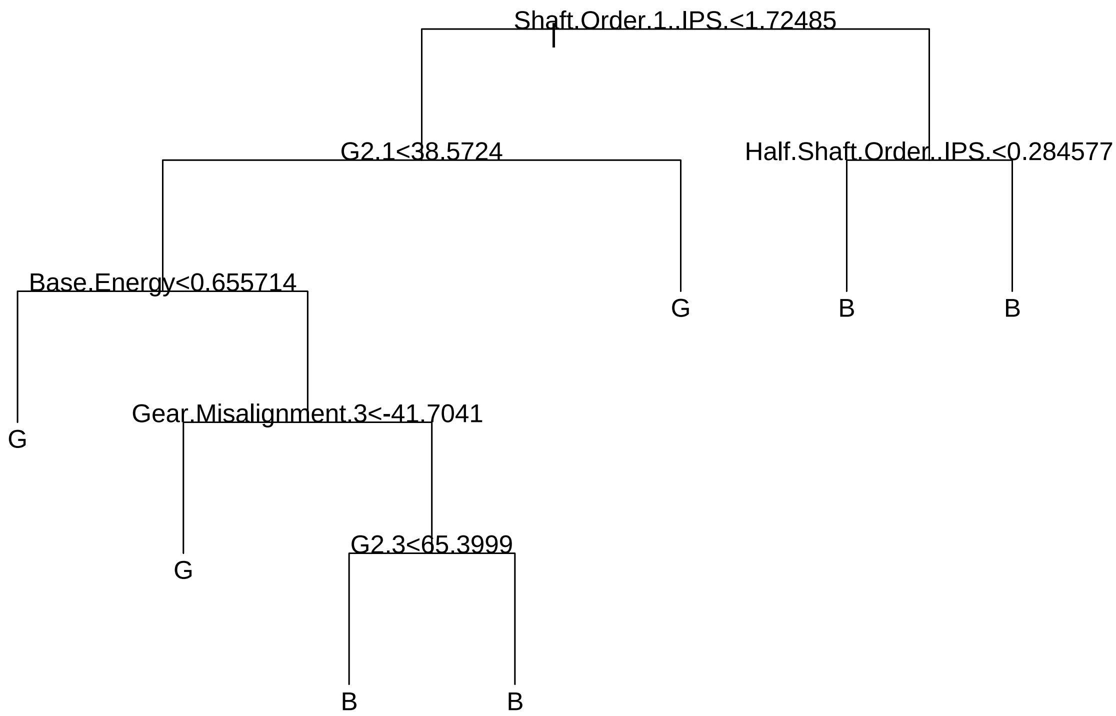

Figure 11. S-Plus Classification Tree using Training Set. The inequality above each split corresponds to the left branch. At each leaf "G" indicates a leaf with a higher proportion of good generators and similarly "B" indicates a leaf with a higher proportion of bad generators.

Classification trees are an intuitive way to see how the data can be split into subsets capable of predicting the dependant variable. However, their accuracy is not always satisfactory. Leo Breiman introduced the concept of aggregating many different trees and allowing them to each “vote” on their prediction of the dependant variable (Berk, 2005). Different aggregation methods have been developed which create the multiple trees, or forests, in different ways. Bagging builds trees on many bootstrap samples. Boosting is a more complicated method which first seeks out errors while re-sampling from original data in order to focus on the marginal boundaries. Accurate trees are then given more weight to their vote; this process creates predictions with excellent misclassification rates. Here, the random forests method is used as a nonparametric cross check to the logistic regression model because it builds new trees by randomly choosing a subset of predictor variables each time. Pruning is not required as the aggregated voting process protects against over-fitting. This algorithm is ideal for the large IMD-HUMS data set. Five hundred trees are fitted to the last 20 acquisitions from each generator in the training set and allowed to vote using the random Forest function in the R statistical environment. The resulting misclassification rate is 0.00673.

The forest model is then used to predict the entire training set (misclassification rate 0.01420) as well as the experimental set (see Results section). One drawback to the random forest is its "black box" nature which restricts insight into how predictions are made, although variable importance is obtainable.

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IV. RESULTS

In the final phase of the study, for both the training and experimental data we compare the status of the generators to the estimated probability of being a bad generator based on the logistic regression model and the classification of being bad or good based on the forest of trees. In addition, we track the three HI (the HI for the shaft, gear, and bearing) provided by IMD-HUMS.

Only the last 20 acquisitions for each generator are used to construct the logistic regression and forest of trees models. As a check of these methods, probabilities of bad are estimated for each acquisition in the entire two-year period for which IMD-HUMS data is available. As an example of how we compare results, consider generator number 43. Generator number 43 is in the training set and classified as a good generator. The plot of estimated probability of bad (circular dots) based on logistic regression and classification of being good (0) or bad (1) (triangles) based on forest of trees is given in Figure 12.

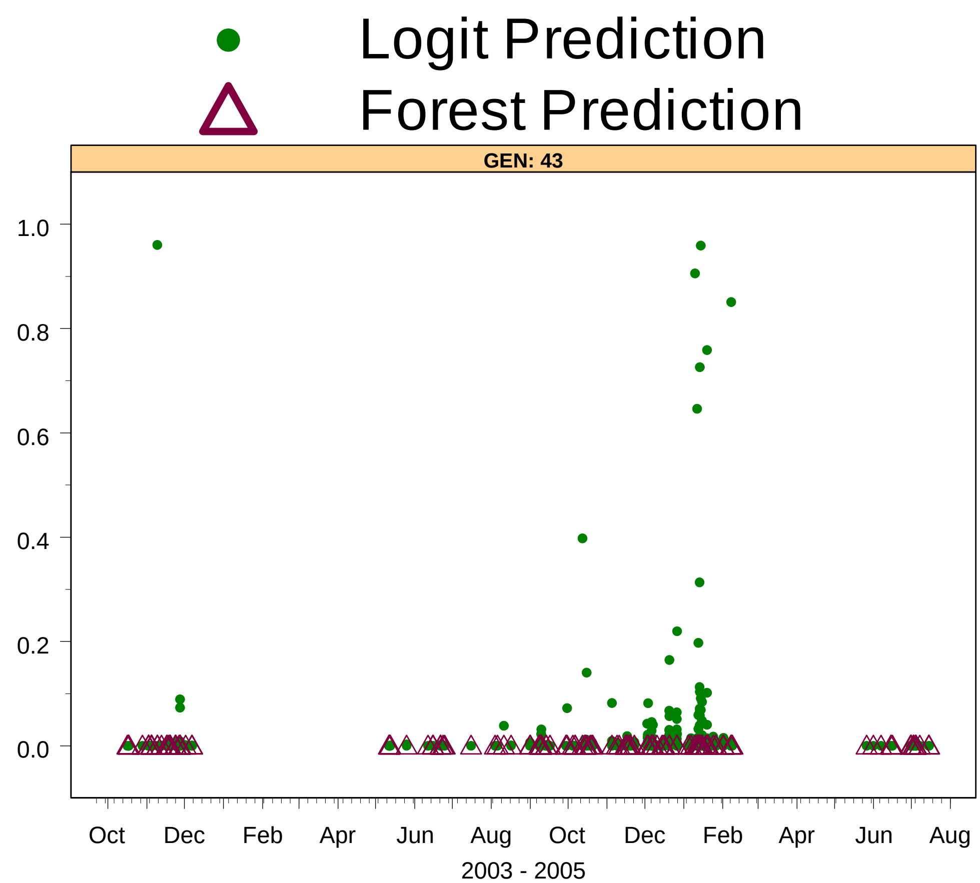

Figure 12. Generator Number 43: Plot of Estimated Probability of Bad from the Logistic Regression Model and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

Notice that the estimates of the probability of being bad based on the logistic regression vary from acquisition to acquisition, even rising above 0.5, but for the most part are small with the majority of estimates below 0.1. For this generator the forest of trees classifies the generator as good for every acquisition.

To see the trends in the estimated probabilities from the logistic regression more clearly, in Figure 13 we superimpose a smooth nonparametric fit of the estimated probabilities using a loess smoother (Montgomery, 2001). At each acquisition, the loess smoother fits a weighted regression using only the nearest neighbors to that acquisition.

The number of nearest neighbors used is governed by the span, or proportion of total number of observations in the data set. The larger the span, the more extensive the smoothing. For most generators, the loess fit with a span of .3 gives a smooth estimate of probability of bad which can in turn be used to predict the generator status. However, loess fits with a span of .3 for generators numbers 7, 53, and 56 are not smooth; thus cross-validation is used to automatically set span parameters between .3 and .5. This cross validation is implemented by default when using the S-Plus function. For consistency, all graphs of the training set generator predictions in the remainder of the chapter are all shown with the S-Plus "auto" span parameter. Experimental set generator predictions are all shown with a .3 span parameter. Figure 13 shows the loess fit for generator number 43. For this generator, the loess fit is a straight line at zero. Thus, the logistic regression results indicate that the generator should be classified as good.

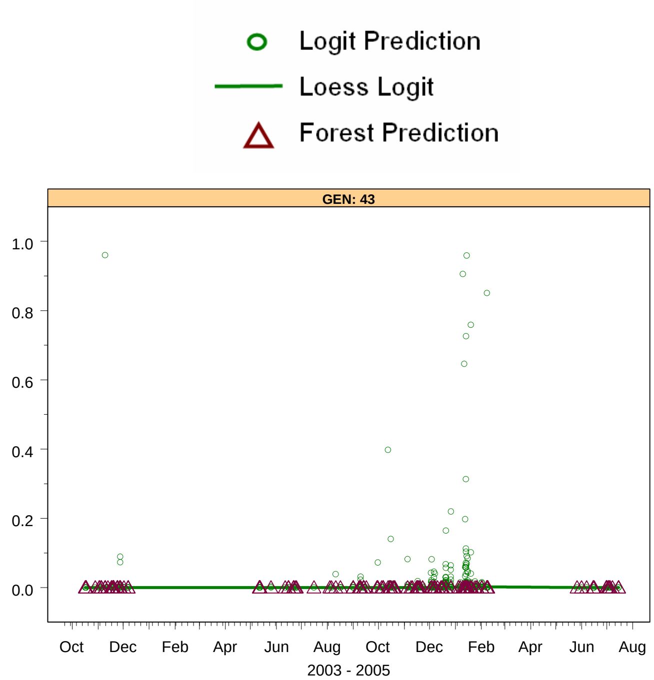

Figure 13. Generator Number 43: Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

Analogous to the health indicators, we use the loess smooth of the estimated probabilities to indicate that a generator is good, or assign a strong, moderate, or weak classification to a generator that is bad. When the loess fits have values greater than .66, then we say that the logistic regression strongly indicates the generator as bad. When the loess fit has estimated fits greater than .33 but smaller than .66, we say that the logistic regression moderately indicates the generator as bad. A value between 0 and .33 shows a weak indication, and a straight loess fit line of 0 indicates good. A summary of the results is given in Table 9 for the training data and special cases are discussed in detail in this chapter.

Table 9. Classification of Training Set Generators Based On the Logistic Regression Fit. (>.66 - 1.0 Strong, >.33 - .66 Moderate, >0.0 - .33 Weak, 0.0 Good)

Prior Classification	Logit Predictions				
	Good	Weak	Moderate	Strong	Total
Good	40	6	0	0	46
Bad	0	0	1	5	6*
					52

* includes additional generator discovered during model formulation

The rule used for the results of the forest of trees is a majority of 1.0 predictions is a strong classification and a minority of 1.0 predictions is a moderate classification.

A. RESULTS FOR GENERATORS IN THE TRAINING SET

After fitting the logistic regression model and forest of trees to the last 20 acquisitions of each generator in the training set, the models are used to predict generator state throughout the entire two-year period in which the training set was collected. This serves as additional validation of the models, as well as providing additional information about behavior of the faulty generators. Appendix B provides an overview, while subsequent subsections cover specific findings for generators in the training set.

1. Four Bad Generators: Numbers 22, 31, 53, 56

Of the 52 generators in the training set five are classified as bad. Four of these (numbers 22, 31, 53, 56) are similar in that they have high SO1 CI. For all four of these, the generator was determined to be faulty upon inspection. Figures 12 and 13 provide an example of the plot for a good generator. In contrast, Figure 14 shows the corresponding plots for the four generators from the training set for which damage was found upon inspection. It is not surprising that both the logistic regression and forest of trees models classify generators with proven damage as bad, since these generators were used for model fitting and their CI have values which form clusters separated from the values of the CI from the rest of the training set(see Figure 6). In particular, these generators have high SO1 and SO2 CI compared to the good generators in the training set. Generator number 53 is unusual in the amount of variation present between acquisitions, shown on the next page in Figure 14. There may be something different about the failure mode for this generator, but no clear-cut, specific cause has been identified, which accounts for this variation and is a phenomenon worthy of study.

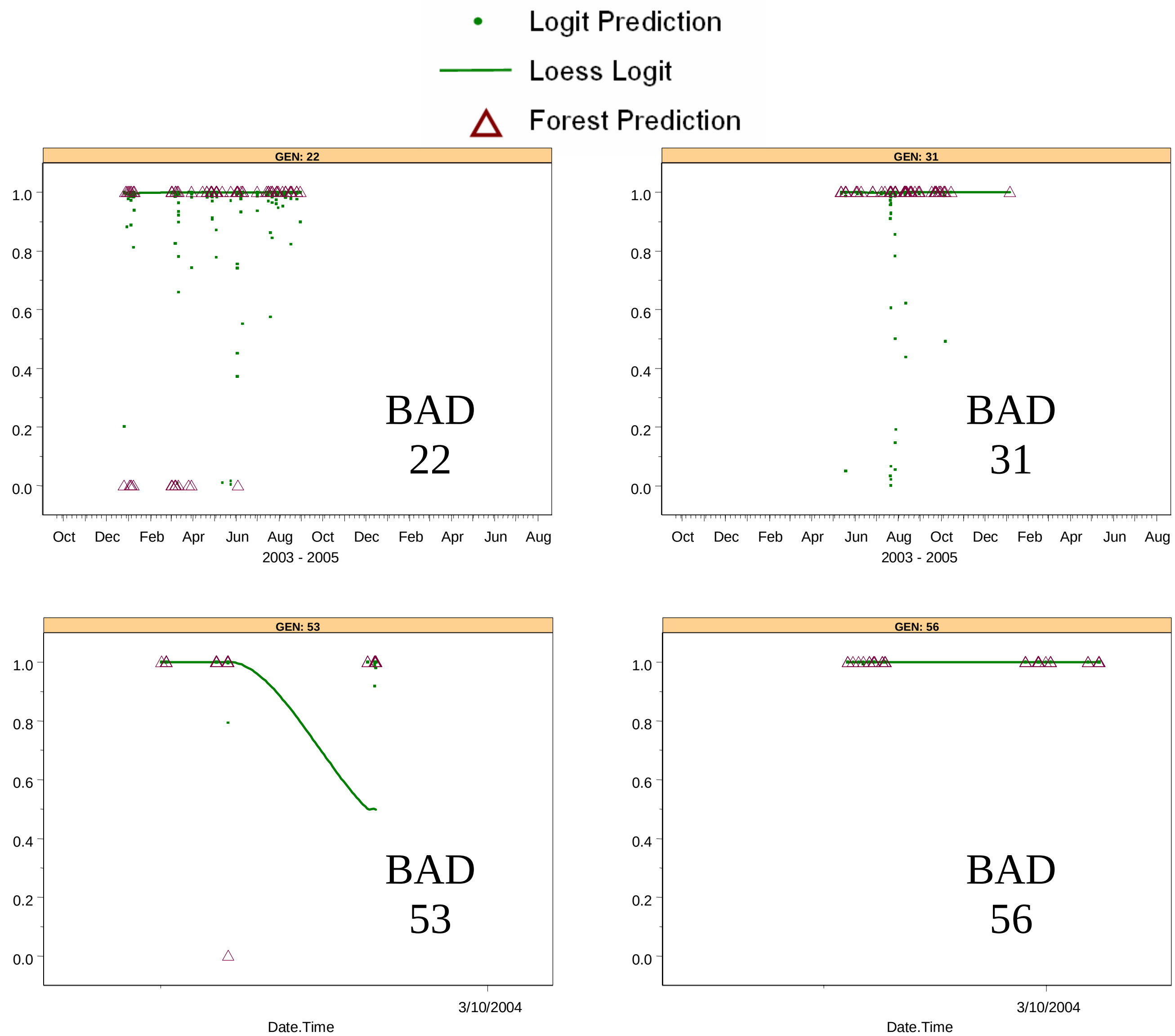

Figure 14. Generators Numbers 22, 31, 53, 56: Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

2. Generator Number 9

Generator number 9 is classified as a bad generator because of an actual failure. During operation the helicopter did not receive electrical power from this generator resulting in the illumination of a generator-fail warning light. After replacing the generator with a new one the problem went away. Both the logistic regression and forest of trees models classify the number 9 generator as bad, but not strongly (see Figure 15). These results are consistent with the plot in Figure 6 which shows that generator number 9 is not easily distinguished from the good generators. The figure depicts good generator data points (light grey dots if viewed in the non-color copy or yellow dots if viewed in the color copy) and bad generator data points (light grey dots if viewed in the non-color copy or purple dots if viewed in the color copy) using five important CI as variable inputs. The dark grey dots intermingled with the good generator data points are primarily from generator number 9. This raises the question: Was the generator failure merely electrical in nature (such as an electrical short-circuit) and not mechanical and therefore undetectable by the IMD-HUMS CI? This generator may be classified as bad in the logistic regression and forest of trees models only because it is in the training set and was used to build both the logistic regression and forest of trees models. Perhaps it is detected in the logistic and forest of trees models due to over-fitting as a result of its binary bad classification.

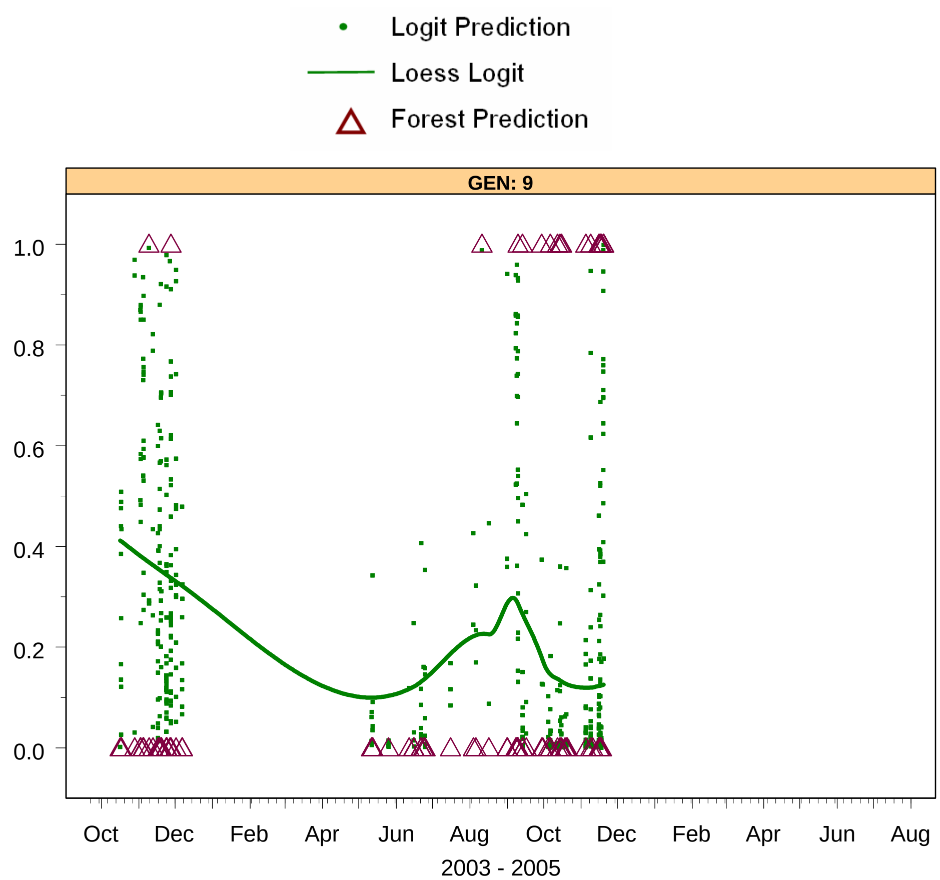

Figure 15. Generator Number 9: Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

For generator number 9 there are some acquisitions for which the bearing HI is in the warning range, but these warnings are present on many good generators. To justify inclusion of generator number 9 on the bad generator list, two mini-experiments are performed. In the first, the data is perturbed by giving a binary classification of good (0) to generator number 9 and fitting a new logistic regression model. Alarmingly, generator number 9 is then predicted to be a perfectly good generator. In this modified data the only bad generators are the four generators with high SO1 CI (numbers 22, 31, 53, 56). In the second mini-experiment, the data is then perturbed further by giving a binary classification of bad (1) to a perfectly good generator, generator number 26. The new logistic regression model gives estimates of being bad to this good (classified bad) generator no higher than .3, yet now gives estimates of probabilities to generator number 9 (still classified as good) values in the .5 to .95 range. This suggests generator number 9 is not a case of a good generator misclassified as a bad generator. Therefore generator number 9 is retained as a bad generator and is an important element of the logistic and forest of trees model. The mode of failure of generator number 9 may be different from the other failure modes and unique to the data set.

3. Generator Initially Classified as Good

One generator initially classified as good in the training set is detected by the logistic regression model as being misclassified. For generator number 7 the logistic model gives strong estimates of being bad (values of 1.0, much stronger than generator number 9) and then rapidly drops off to estimates of being good (values of 0.0) around July 2005, see Figures 16. Figure 17 plots in EXCEL the three IMD-HUMS produced health indicators and depicts the dramatic change from a bad conditional state to a good conditional state for generator number 7.

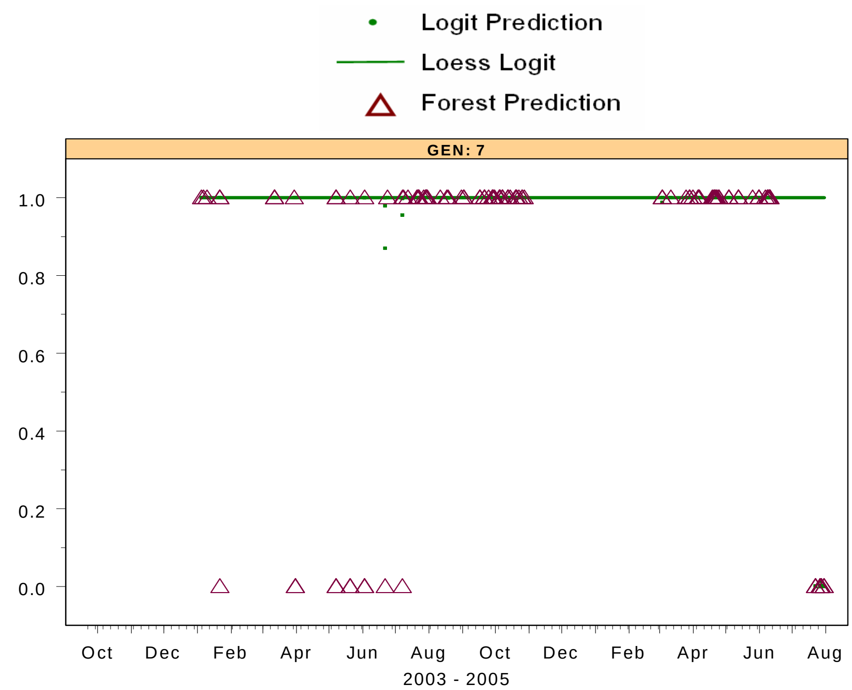

Figure 16. Generator Number 7: Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

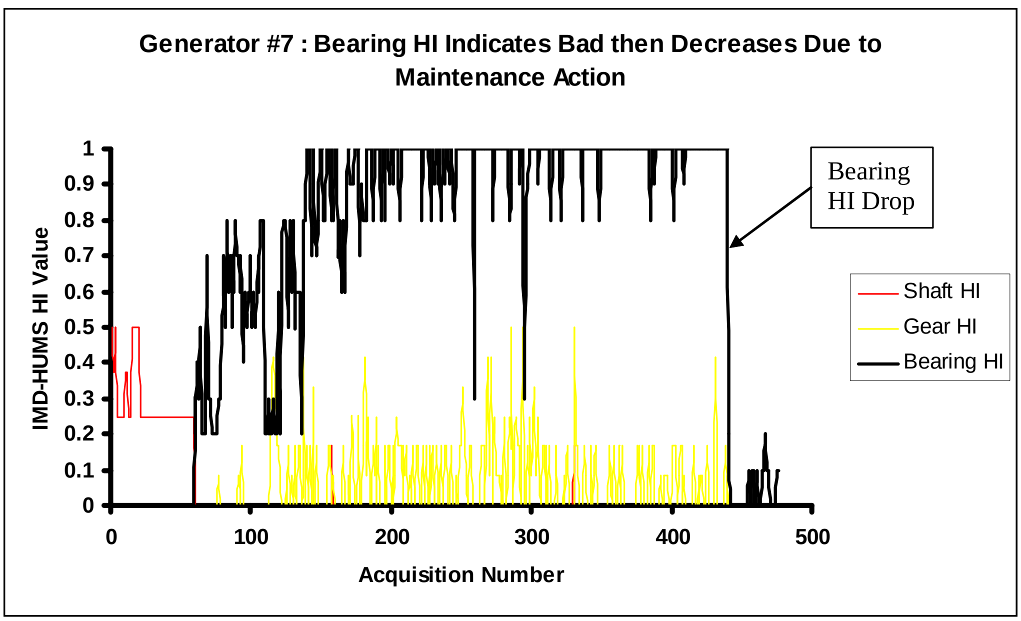

Figure 17. Generator Number 7: EXCEL Plot of IMD-HUMS Produced Shaft, Gear and Bearing HI (note the change from bad to good HI)

The generator also had strong bearing HI indications which drop off at the same time as the logistic regression model. Based on these results Goodrich Corporation re-examined the records for generator number 7 and confirmed that the accessory gearbox, which houses the gear and bearing for the generator, had been replaced on the aircraft (Bechhoefer, 2005). The model has properly predicted a generator to be in an unhealthy condition, and likewise predicts the post-maintenance health as good. The pre-maintenance acquisitions of generator number 7 were then reclassified as bad and the logistic regression model was refitted. The null deviance increased from 658.42 to 743.86. The residual deviance decreased slightly from 77.76 to 77.72. The final forest of trees model is then also refit including generator number 7 as a bad generator.

4. Loess Smoothing and "Weak" or "Scattered" Logistic Regression Predictions goes under Loess

The CI's behavior is complex and highly variable in nature. Spikes which are not easily linked to a specific cause can occur; further it is difficult to determine the periodicity. This complex behavior can be seen in varying degrees on many generators and it affects HI calculations and logistic regression predictions. The forest of trees appears more robust to these fluctuations than the logistic regression, possibly due to its repetitive re-sampling and voting process. To avoid high false alarm rates, loess smoothing is performed on the logistic regression using S-Plus (smoothing parameter 0.3 or auto-default for the training set, 0.3 for the experimental set). Generator logistic prediction results are considered bad if their loess curve ever moves above .33 with anything over .66 being considered a strong prediction. A "weak" prediction occurs when there are enough spikes to pull the loess curve above zero. A "scattered" classification occurs when there are one or more spikes before the loess smoothes them down to zero. Figure 18 shows examples of "weak" and "scattered" logistic regression examples.

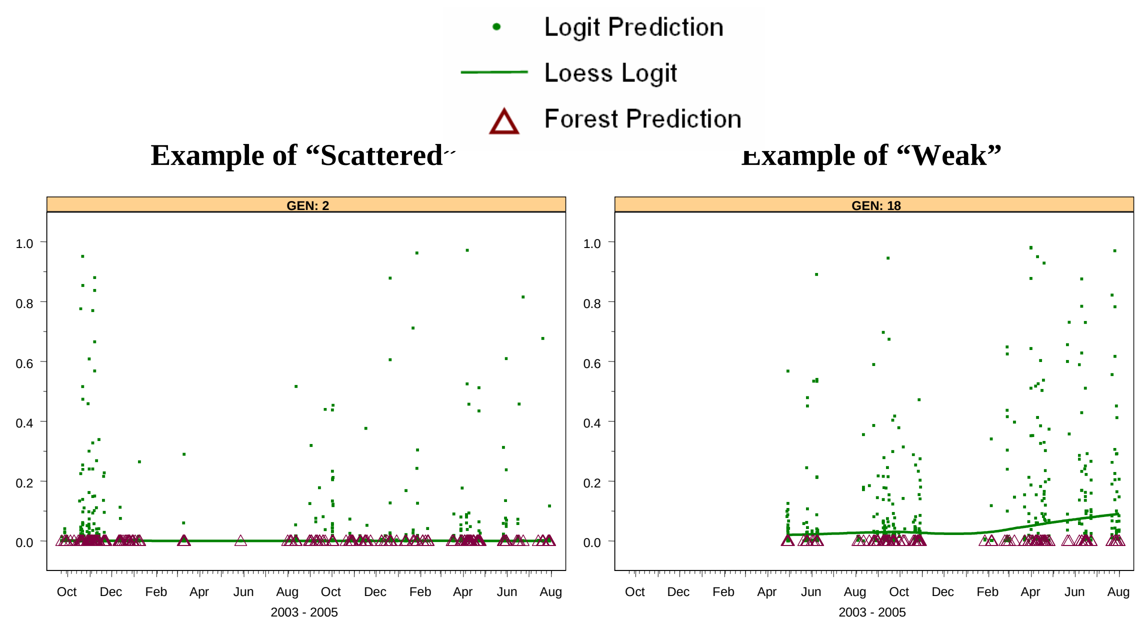

Figure 18. Generators Numbers 2 and 18: Examples of "Scattered" and "Weak" Logit Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

5. Good Generators

There are only three classified good generators with any bad (1) forest of trees predictions (numbers 10, 39, 65). These few bad predictions are sporadic and each time they are accompanied by weak or scattered logit predictions as depicted in Figure 19. However, with the loess smoother applied the logistic regression model classifies these three generators strictly as good.

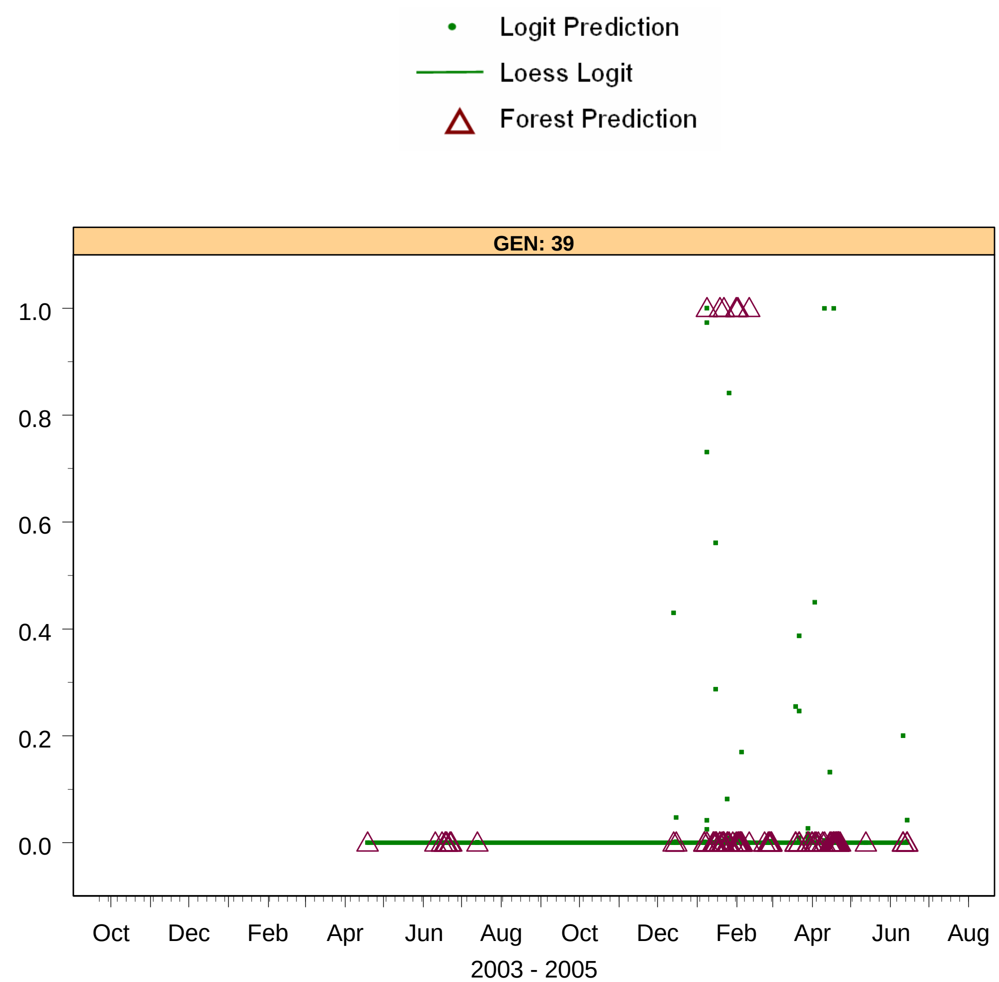

Figure 19. Generator Number 39: Example of Sporadic Forest of Trees Predictions, Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

B. RESULTS FOR GENERATORS IN THE EXPERIMENTAL SET

With generator number 7 reclassified as bad prior to its maintenance and with both models refit with this reclassification the logistic regression and forest of trees models are applied to the experimental set. A summary of the logit results is given in Table 10.

Table 10. Classification of Experimental Set Generators Based On the Logistic Regression Fit. (>.66 - 1.0 Strong, >.33 - .66 Moderate, >0.0 - .33 Weak, 0.0 Good)

Prior Classification	Logit Predictions				
	Good	Weak	Moderate	Strong	Total
Good	4	0	0	1	5
Bad	1*	0	0	0	1
Watch List	2	2	1	1	6
*generator #33 removed due to generator caution light no IMD-HUMS indications or model predictions of being bad					12

1. Classified Generators

The lone experimental generator classified as bad, number 33, taken off the aircraft due to a generator caution light has no logistic regression or forest of trees predictions of bad condition as well as no HI warnings (Appendix C). Thus evidence points to the cause of failure to be strictly electrical, such as a short-circuit.

Of the five generators classified as good (numbers 15, 40, 58, 64, 66) in the experimental data set, four show no bad predictions made by either the logistic regression or forest of trees models. Generator number 15 shows a highly unusual and fairly strong logistic regression result comparable to generator number 30 of the experimental data set and generator number 9 of the training set. However, those generators also show bad predictions with forest of trees and at least some HI warnings. Generator number 15 has no bad predictions from the forest of trees model. (Figure 20).

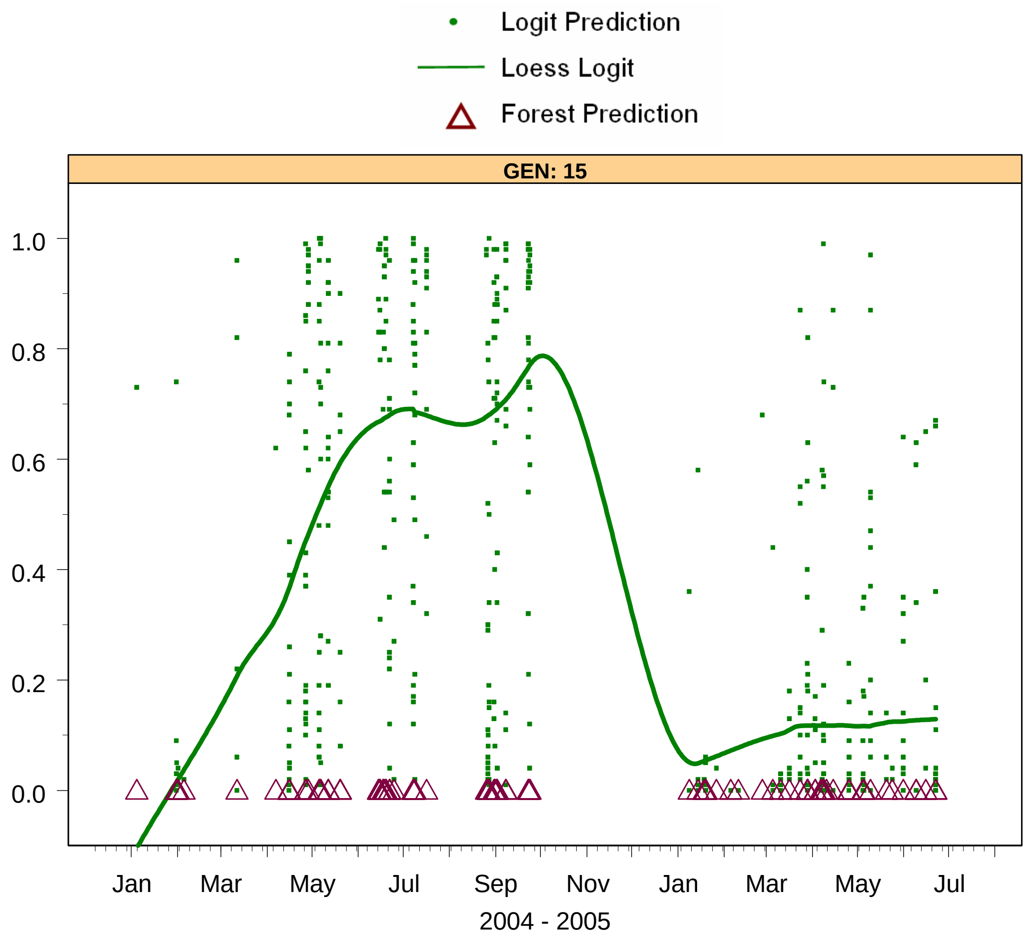

Figure 20. Generator Number 15 (Aircraft 9326493, Left): Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

A request was sent to the users for additional information concerning the current state of this generator and whether any maintenance had been performed. A detailed inspection of maintenance records indicates that indeed the generator had been replaced during a major maintenance reset in October 2004. This coincides directly with the drop from strong to weak logit prediction. The logit model has again properly identified a generator in bad condition.

2. Unclassified "Watch List" Generators

The logistic regression and forest of trees models are then used to predict the status of the generators of questionable status (watch list) in the experimental data set. The summary table and a complete set of result graphs are given in Appendix C.

Generator Number 30, which has shaft HI alarms, is predicted as bad fairly strongly by both the logistic regression and forest of trees models. This generator is unusual due to the sharp increase in both the predicted probability of bad and the number of instances of bad classification that occurs while shifting into alarm status (Figure 21).

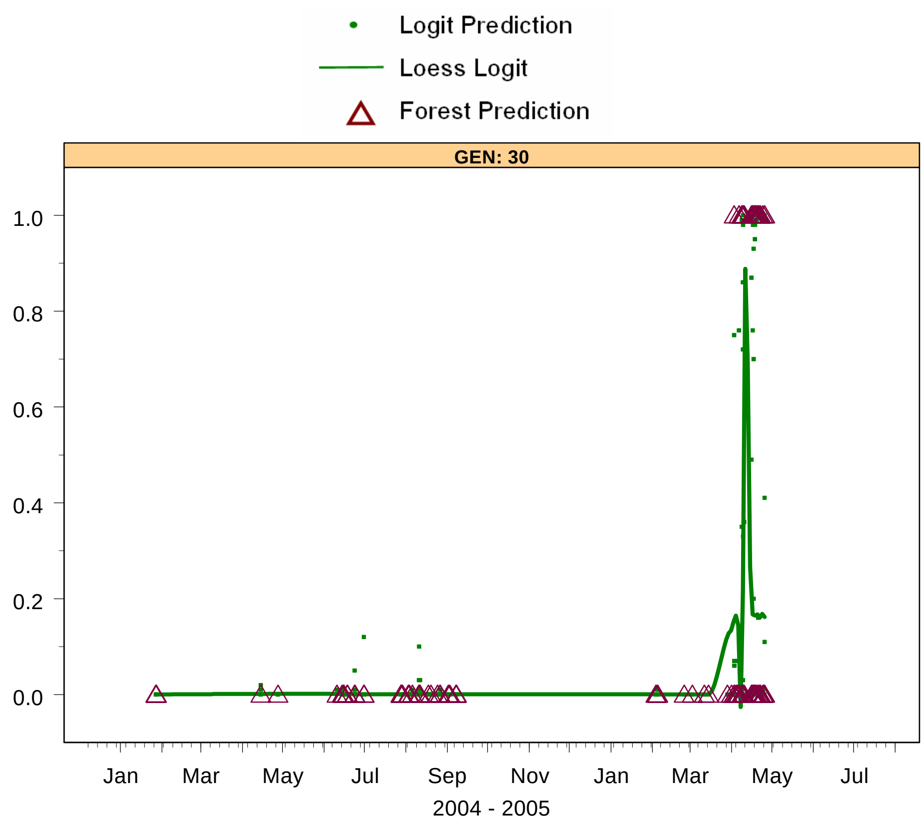

Figure 21. Generator Number 30 (Aircraft 9426545, Left): Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

Generators Numbers 21 and 48 have shaft HI alarms predicted fairly strongly with the forest of trees model and weakly with the loess smoothed logistic regression model (Figure 22). The high variability of these generators keeps the loess curve from climbing, but such high variance can be a symptom of impending failure. Therefore the subjective assessment is made that these are indeed bad generators.

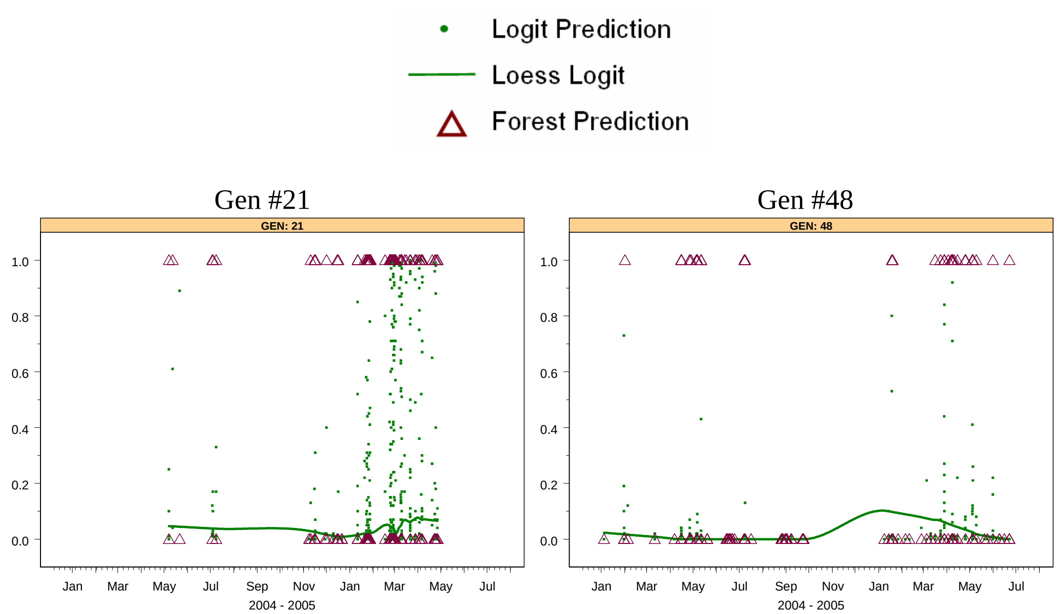

Figure 22. Generator Numbers 21 and 48: Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

Generator number 55 had medium predictions from both the logistic regression and the forest of trees models (Figure 23). Interestingly, the logistic regression model shows an improvement in the generator's state while the forest of trees model predicts a bad state only sporadically toward the latter portion of the acquisitions. This shows that the models indeed function differently, even though they tend to agree with each other.

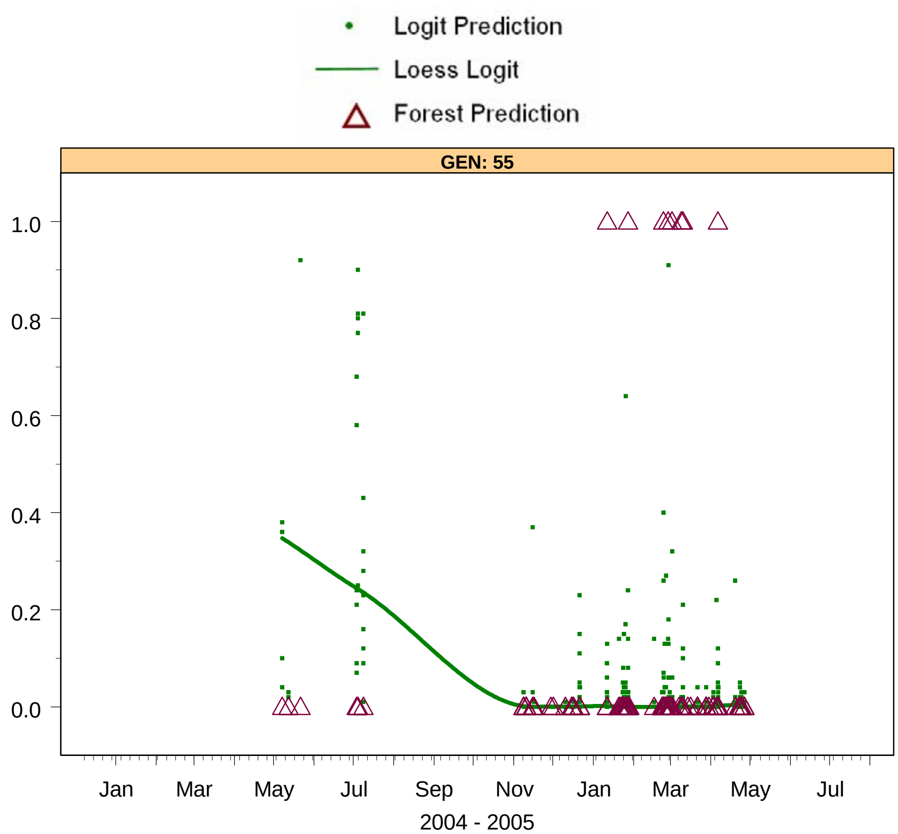

Figure 23. Generator Number 55: Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

Generator number 6 and generator 24 are on the watch list but are not predicted bad by the logistic regression or forest of trees models. Notably, generator number 24 does have some sporadic logit predictions as seen in Figure 24. The subjective assessment is that they are not bad enough to warrant replacement.

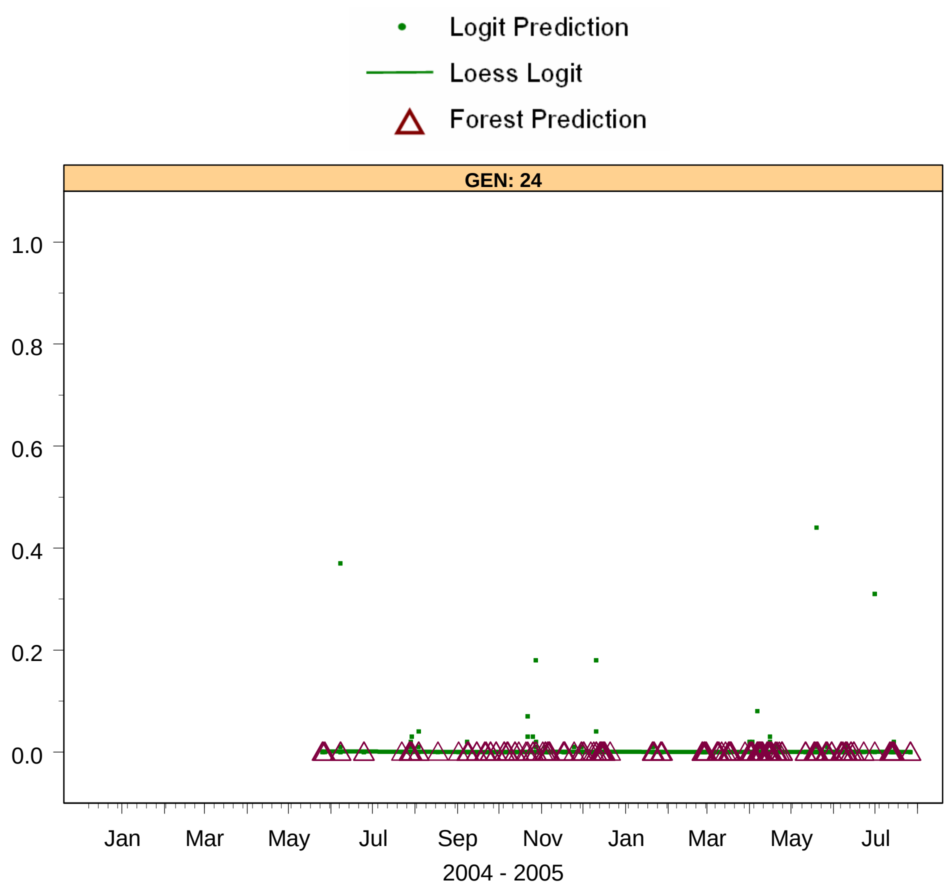

Figure 24. Generator Number 24: Plot of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

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V. CONCLUSION

This thesis demonstrates that a logistic regression model which predicts the overall state of a UH-60L electrical generator can be fit using IMD-HUMS data collected with known cases of failed generators and properly operating generators. Generator status serves as the dependent, binary response variable. The independent predictor variables can be chosen using correlation with the dependent variable, backwards elimination using p-values, and classification rates. The model is refined by incorporating new failures as they occur into the data set and refitting to produce a more sensitive and accurate prediction model. This results in an accurate picture of a "bad" generator and generators susceptible to failure.

A random forest of trees was also created as a nonparametric augmentation to the prediction effort. It serves to quickly and automatically sample combinations of the predictors, aggregating votes in order to make accurate predictions which are fairly robust to false alarms. A single classification or regression tree can be created as a parallel effort in understanding the important predictors, helping during variable selection for a logistic regression model.

A. APPLICATIONS

Due to the highly variable nature of the predictor values, this model has lower success predicting states with just one acquisition. In addition, this type of model may not be able to predict failures of types not included in the model building. As data is accrued, these previously unobserved failure modes should become increasingly rare. No effort is recommended to supplant any current algorithms currently on board the aircraft. Its greatest value may be in the picture it creates of how an at-risk mechanical component behaves. This technique is easily transferable to other components on the helicopter as well as to other, completely different, platforms. The beauty of these models and the process of deriving them is that the relatively accurate state pictures they produce are attained with minimal effort, time and expense. Requirements are only an understanding of the system and data set, off-the-shelf statistical software and a computer.

Concurrent with data collection, the development of component prediction models of importance, for example for transmissions or engines, could be initiated. The selection of pertinent CI predictors should start using not only an understanding of the system's mechanics and vibrations but also the incorporation of parametric and nonparametric statistical approaches. As more data, including component failures, is collected the models are refined. The use of Ggobi in detecting different failure modes is a particularly simple and quick way to investigate the IMD-HUMS data. These real-data based models, which are easily derived, are pertinent in the move toward Condition Based Maintenance.

For instance, periodically a serious defect is found on one or more single-type aircraft resulting in a grounding of the fleet. ASAM, SoFM and IRAC messages dictate specific inspections or corrective maintenance actions which must be accomplished on each aircraft prior to the resumption of flight operations. The time required to fulfill the requirements of these messages severely impacts both real-world and training operations. In the move toward CBM, this dual logistic regression and forest of trees process could be used to focus initial inspection efforts on only those aircraft whose "picture" resembles the problem aircraft. The other aircraft could continue operations and get inspected at the next convenient maintenance period.

Another practical application of this process is to reduce data collection requirements of the onboard system. Important predictor variables which continually show up in logistic regression and forest of trees models would be retained while variables which never show importance become candidates for removal. This would free up valuable memory space in the onboard system.

B. RECOMMENDATIONS FOR FURTHER STUDY

Aspects critical to the development of better component health prediction models are the incorporation of variance within the multiple CI, concise variable selection, and time-series trends.

It is known that an increase in CI variability overtime is an indication of deteriorating component health, but the thresholds between normality and abnormality of variance for the many CI has not yet been determined. The large data sets now being produced by IMD-HUMS can be used to estimate the variance of the CI.

Further analysis of variable selection in component health prediction models is also worthy of more attention. If the number of CI can be definitively limited to a few very effective predictors the "curse of multi-dimensionality" can be eliminated and component health distributions can be estimated accurately.

The multiple acquisitions over time for each CI can be used for trend analysis. Rates of change in the CI values incorporated in the prediction models could ultimately be used in accurately estimating available component lifetime. The loess smoothing used in the logistic regression model serves as a primitive attempt to account for trends. However, the data provides potential to use time series information in a much more effective manner. Further study of the time series relationships may illuminate factors which cause the seemingly random oscillations in CI.

The further study of variability and trends could help in addressing the great deal of noise present in the data. Random data spikes complicate the setting of thresholds and the development of accurate, real-time state prediction algorithms. In the logistic regression model, this created the need for loess smoothing. While the random forest of trees is more robust to false alarms caused by certain spikes, the Type II error rates are not known and the model may be too insensitive.

Ideally, the best of models would determine from a single acquisition a component's state and the remaining lifetime of use. The development of such models require further study in understanding the distribution of failures for each component, variability within and among CI, and trending of CI over time.

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APPENDIX A IMD-HUMS SHAFT, GEAR AND BEARING CI

Each IMD-HUMS acquisition concerning the shaft, spur gear and bearings of a generator results in the reading of the 169 variables listed here. The response variables and the generator number are added for this study. The subset of 65 potential predictors remaining after initial variable elimination are highlighted in grey.

RESPONSE
status
status binary

SHAFT CI
Component Name- shaft
Date_Time
ah.Tail
GEN Number
Torque
Airspeed
Main Rotor Speed
OAT
MGBTEMP
Regime
OpIdx
OpRTR
OpNPH
RTRUSG
NPH
Health
PriRAW
SecRAW
COMP
SENS
Eng1Torque
Eng2Torque
DQ
XAXIS
Shaft Order 1 (IPS)
Shaft Order 2 (IPS)
Shaft Order 3 (IPS)
Half Shaft Order (IPS)
Shaft Order 1 (OBS)
Shaft Order 2 (OBS)
Shaft Order 3 (OBS)
RecomputedHealthIndicator
Shaft Order 1 (g)
Shaft Order 2 (g)
Shaft Order 3 (g)
Half Shaft Order (g)
Half Shaft Order (OBS)
Sig Avg Peak to Peak
Sig Avg RMS
Health Indicator
Sig Avg Crest Factor
Sig Avg Skewness
Sig Avg Kurtosis
Sig Avg Fifth Moment
Sig Avg Sixth Moment
Residual Peak to Peak
Residual RMS
Residual Crest Factor
Residual Skewness
Residual Kurtosis
Residual Fifth Moment
Residual Sixth Moment
Sig Avg L1
EO Peak to Peak
EO RMS
EO Crest Factor
EO Skewness
EO Kurtosis

EO Fifth Moment
EO Sixth Moment
Gear Distributed Fault
Resample Rate
MeasuredShaft Speed Phase Kurtosis
EO L1
Total Torque
Airspeed
Main Rotor Speed
Engine1GasTurbineSpeed
Engine1PowerTurbineSpeed
Engine1Torque
Engine2GasTurbineSpeed
Engine2PowerTurbineSpeed
Engine2Torque

GEAR CI

Date_Time
Tail
Name-gear
Health
PriRAW
SecRAW
COMP
SENS
DQ
XAXIS
Residual Kurtosis
Residual RMS
Sideband Mod 1
Narrowband CrestFactor
Gear Distributed Fault
G2-1
Residual Peak to Peak
RecomputedHealthIndicator
Sig Avg Peak to Peak
Sig Avg Kurtosis
Sig Avg RMS
Residual Skewness
Residual Crest Factor
Residual Fifth Moment
Residual Sixth Moment
Gear Misalignment 1
Sideband Mod 2
sm_3 AS Sideband Mod 3
Health Indicator
Gear Misalignment 2
Gear Misalignment 3
Narrowband RMS
Narrowband Peak to Peak
Narrowband Skewness
Narrowband Kurtosis
Narrowband FifthMoment
Narrowband Sixth Moment
Instantaneous Frequency
CSM
AM Kurtosis
Derivative AM Kurtosis
FM Kurtosis
Derivative FM Kurtosis
FM Peak to Peak
G2-2
G2-3

BEARING CI

Date.Time
ah.Tail
BearingName
BearingPart
Health
PriRAW
SecRAW
COMP
brg.Priority
DQ
XAXIS
Ball Energy (Norm)
Cage Energy (Norm)
Inner Race Energy (Norm)
Outer Race Energy (Norm)
Bearing Energy 15k-20k
Total Bearing Energy (Norm)
Envelope RMS
Recomputed Health Indicator
Ball Energy
Cage Energy
Inner Race Energy
Outer Race Energy
Total Bearing Energy
Envelope Peak to Peak

Envelope Crest Factor
Envelope Skewness
Envelope Kurtosis
Envelope Fifth Moment
Envelope Sixth Moment
Health Indicator
Envelope Distributed Fault
Tone Energy
Base Energy
Ball Mod Cage
Inner Race Mod Ball
Inner Race Mod Cage
Inner Race Mod Outer

Outer Race Mod Ball
Outer Race Mod Cage
TotalBearingCoupling Energy
Ball Mod Shaft
Cage Mod Shaft
Inner Race Mod Shaft
Outer Race Mod Shaft
TotalShaft-Bearing Coupling
Ball Spin Ratio
Cage Ratio
Inner Race Ratio
Outer Race Ratio

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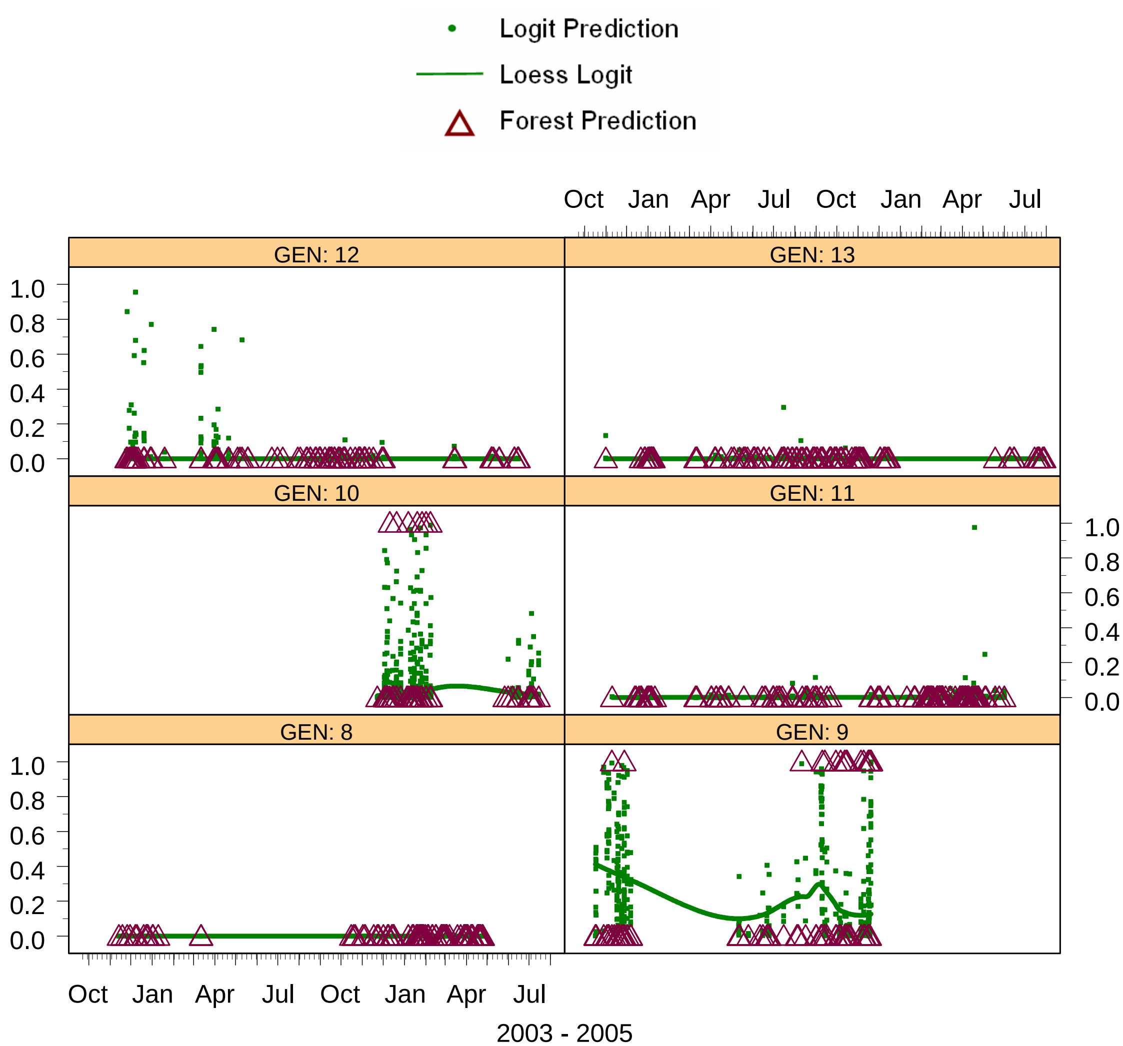
APPENDIX B TRAINING SET RESULTS SUMMARY

Appendices B and C give the complete logistic regression and Random Forest of Classification Trees results. Appendices D and E give a complete set of IMD-HUMS HI for comparison. Note the change in the method of shaft HI computation around October 2004.

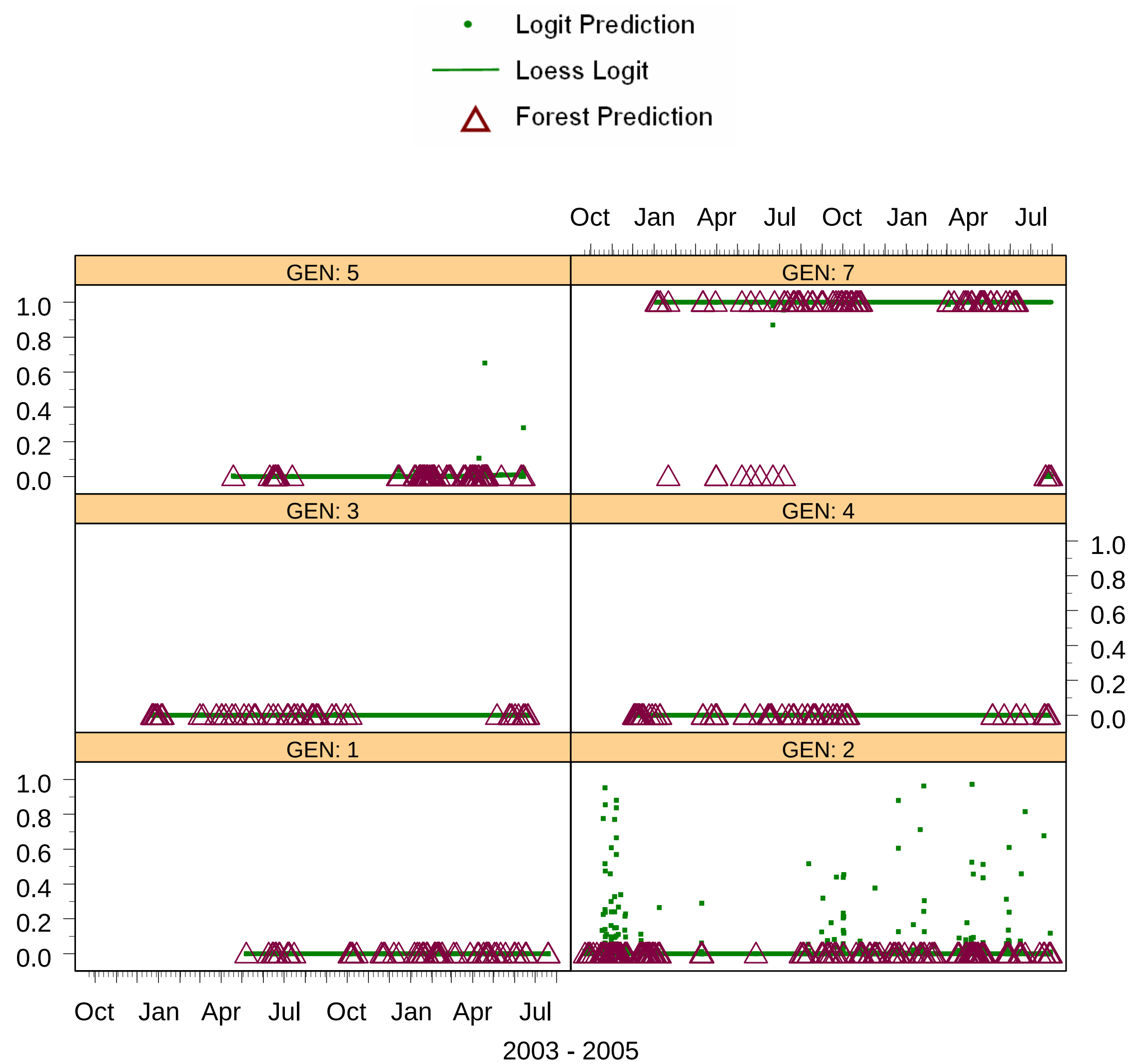
status binary	
Bd	denotes generators with proven faults (bad)
Gd	denotes generators without proven faults (good)
HI : Health Indication provided by IMD-HUMS on-board algorithms	
S	shaft warning (**SS** denotes alarm status)
G	gear warning
B	bearing warning (**BB** denotes alarm status)
Logit	
strong	loess smoothed values over 0.66
moderate	loess smoothed values over 0.33
weak	loess smoothed values between 0 and 0.33
scattered	logit spikes of 1.0 that do not pull loess curve above 0
Forest	
strong	majority of classifications are 1.0 (bad)
moderate	minority of classifications are 1.0 (bad)

Helicopter Tail Number	Generator Side	Status	Generator Number		HI S,G,B	Logit	Forest
9126351	Left	Gd	**1**		**G**		
9226432	Left	Gd	**2**		**BB**		
9226435	Left	Gd	**3**				
9226438	Left	Gd	**4**				
9226439	Left	Gd	**5**				
9226443	Left	Gd,Bd	**7**		**G,B**	**strong**	**strong**
9226446	Left	Gd	**8**				
9226450	Left	Gd	**10**		**B**	**weak**	**moderate**
9226453	Left	Gd	**11**		**S**		
9226455	Left	Gd	**12**		**G,B**		
9326477	Left	Gd	**13**				
9326485	Left	Gd	**14**		**G**		
9326500	Left	Gd	**16**				
9326506	Left	Gd	**17**		**B**		
9326507	Left	Gd	**18**		**S,B**	**weak**	
9326509	Left	Gd	**19**			**weak**	
9326515	Left	Gd	**20**				
9326524	Left	Gd	**25**		**B**		
9326530	Left	Gd	**26**				
9426533	Left	Gd	**27**		**B**		
9426534	Left	Gd	**28**		**S,G,B**	**weak**	
9426537	Left	Gd	**29**		**G,B**	**weak**	
9426549	Left	Gd	**32**		**G**		
9126351	Right	Gd	**35**				
9226432	Right	Gd	**36**				
9226435	Right	Gd	**37**		**S**		

Helicopter Tail Number	Generator Side	Status	Generator Number	HI S,G,B	Logit	Forest
9226438	Right	Gd	**38**			
9226439	Right	Gd	**39**	**SS,G,B**	*scattered*	**moderate**
9226443	Right	Gd	**41**	**G,B**	*scattered*	
9226446	Right	Gd	**42**			
9226450	Right	Gd	**43**	**G,BB**		
9226453	Right	Gd	**44**	**B**		
9226455	Right	Gd	**45**	**G,B**		
9326477	Right	Gd	**46**			
9326485	Right	Gd	**47**	**G,BB**		
9326500	Right	Gd	**49**	**S,G**		
9326506	Right	Gd	**50**	**G**		
9326507	Right	Gd	**51**	**B**		
9326509	Right	Gd	**52**	**G**		
9326515	Right	Gd	**54**	**G**		
9326518	Right	Gd	**57**			
9326524	Right	Gd	**59**	**S,G,B**		
9326530	Right	Gd	**60**	**G**		
9426533	Right	Gd	**61**	**G**		
9426534	Right	Gd	**62**		**weak**	
9426537	Right	Gd	**63**	**S,G**		
9426549	Right	Gd	**65**	**SS,G**	*scattered*	**moderate**
9226450	Left	Bd	**9**	**B**	**moderate**	**moderate**
9326518	Left	Bd	**22**	**SS**	**strong**	**strong**
9426549	Left	Bd	**31**	**SS**	**strong**	**strong**
9326515	Right	Bd	**53**	**SS**	**strong**	**strong**
9326518	Right	Bd	**56**	**SS**	**strong**	**strong**



Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period



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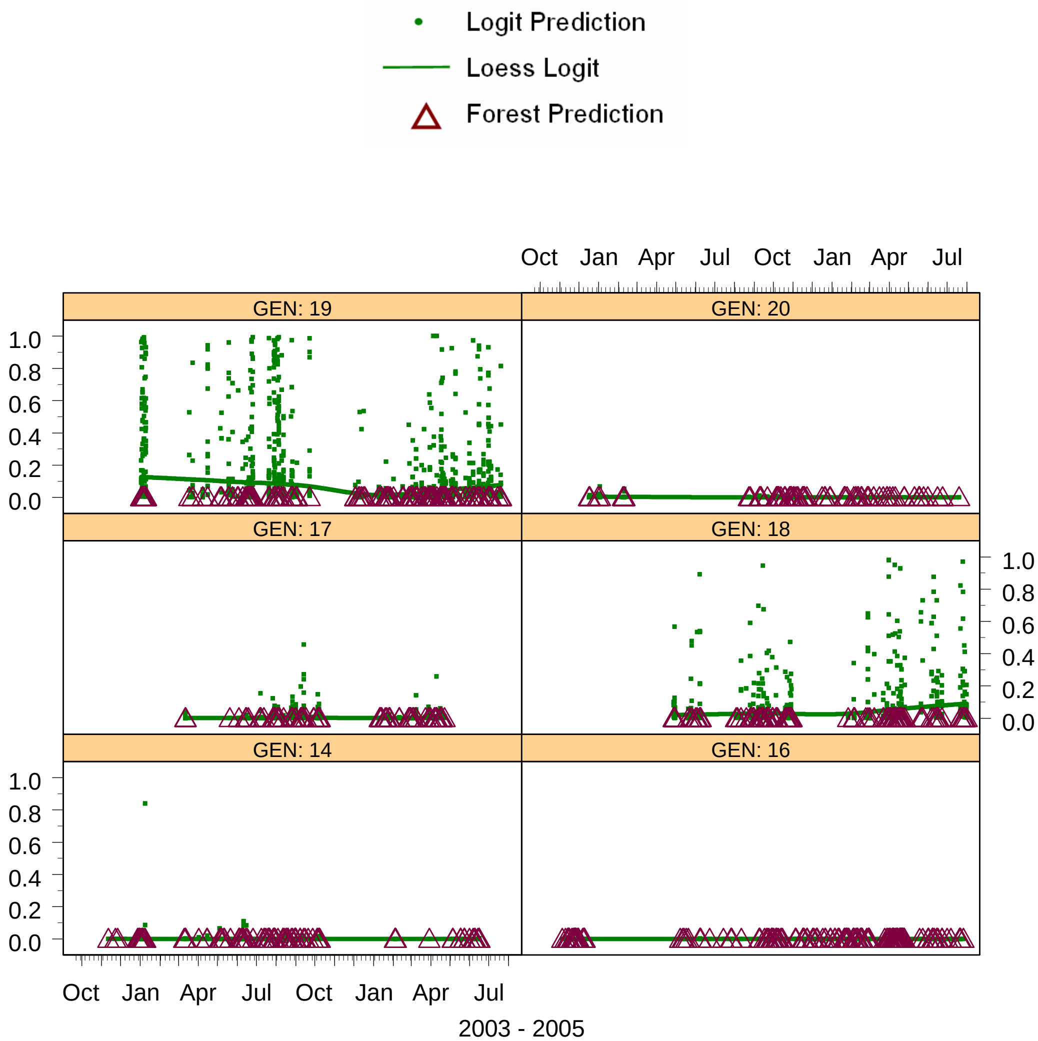

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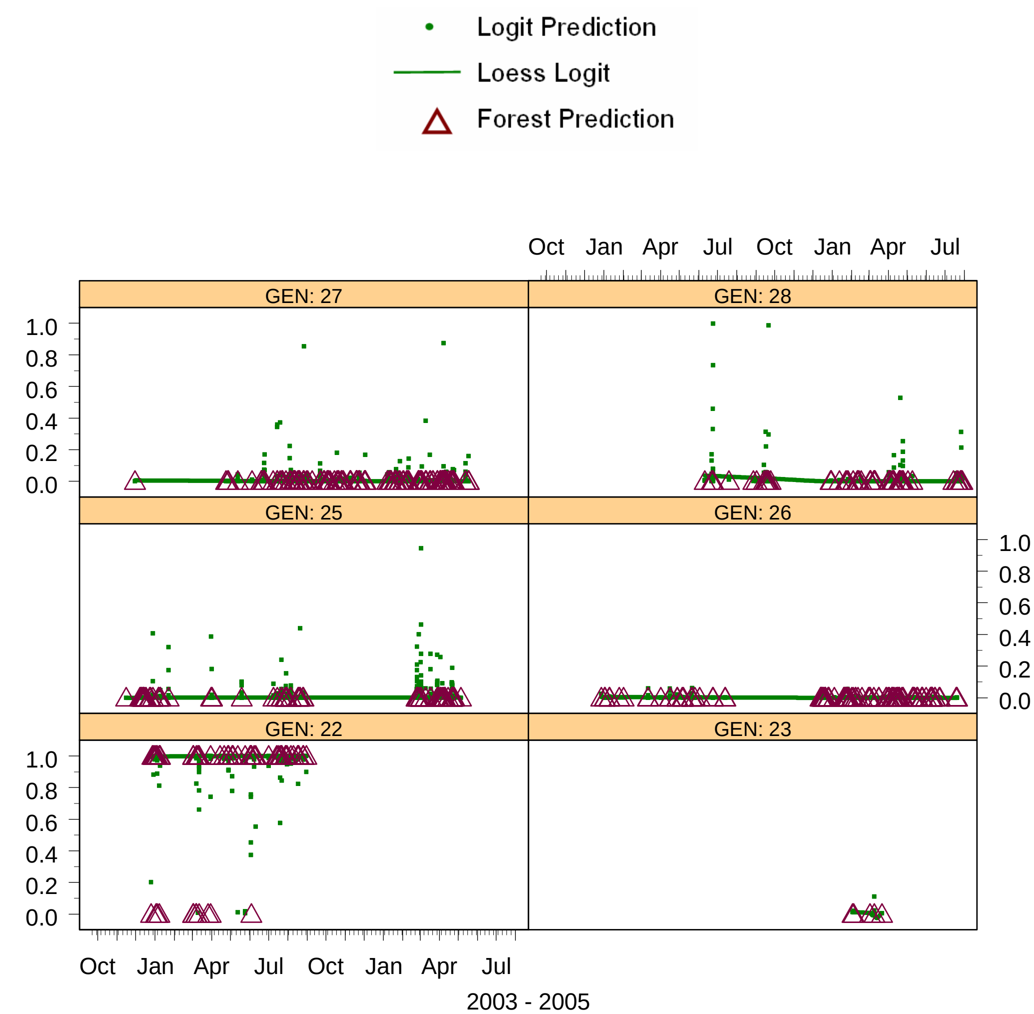

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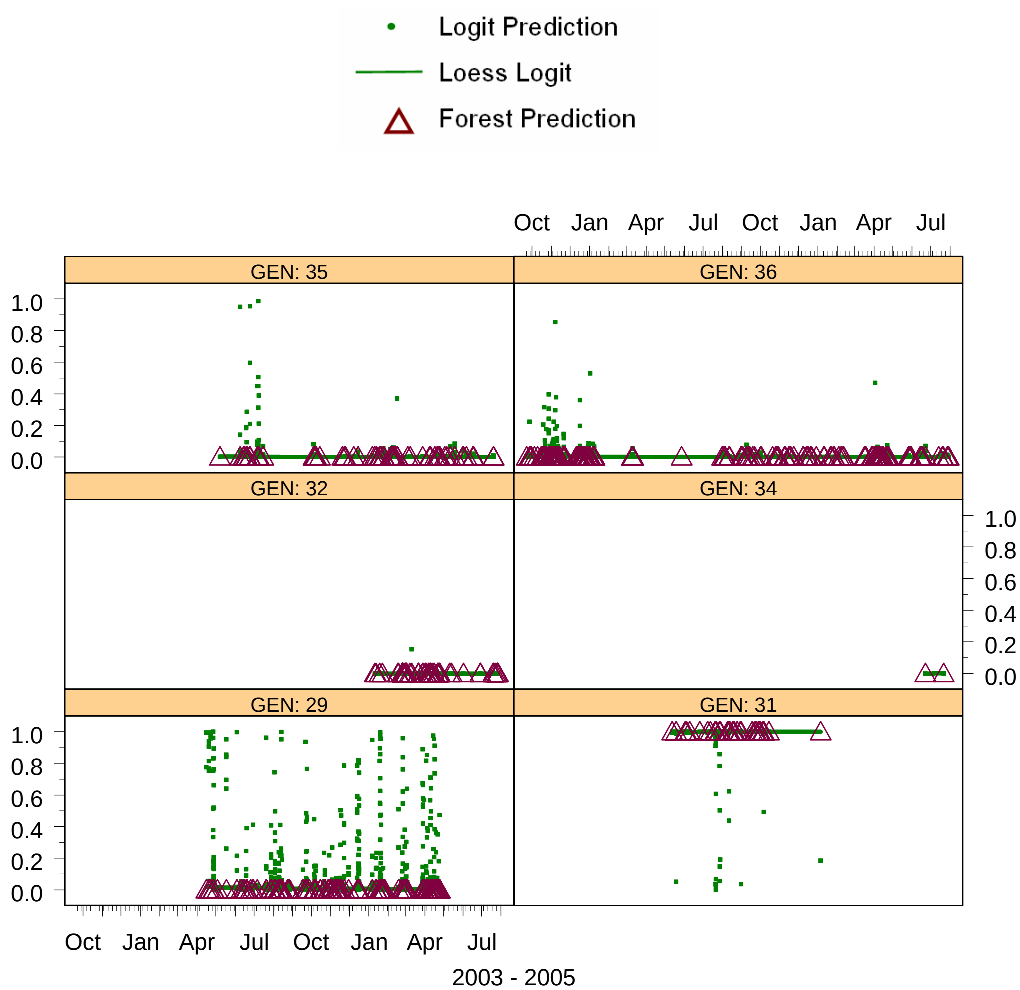

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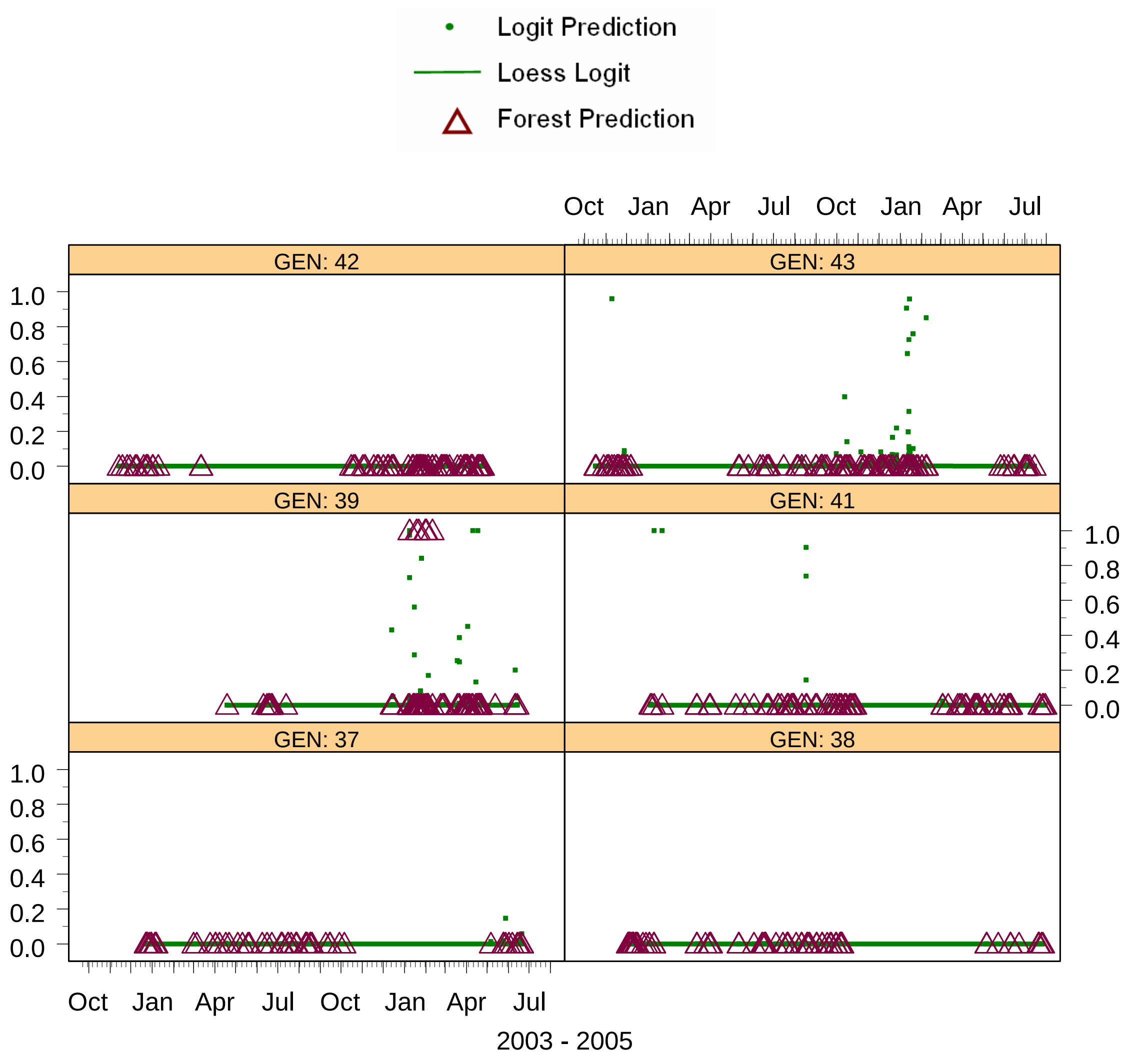
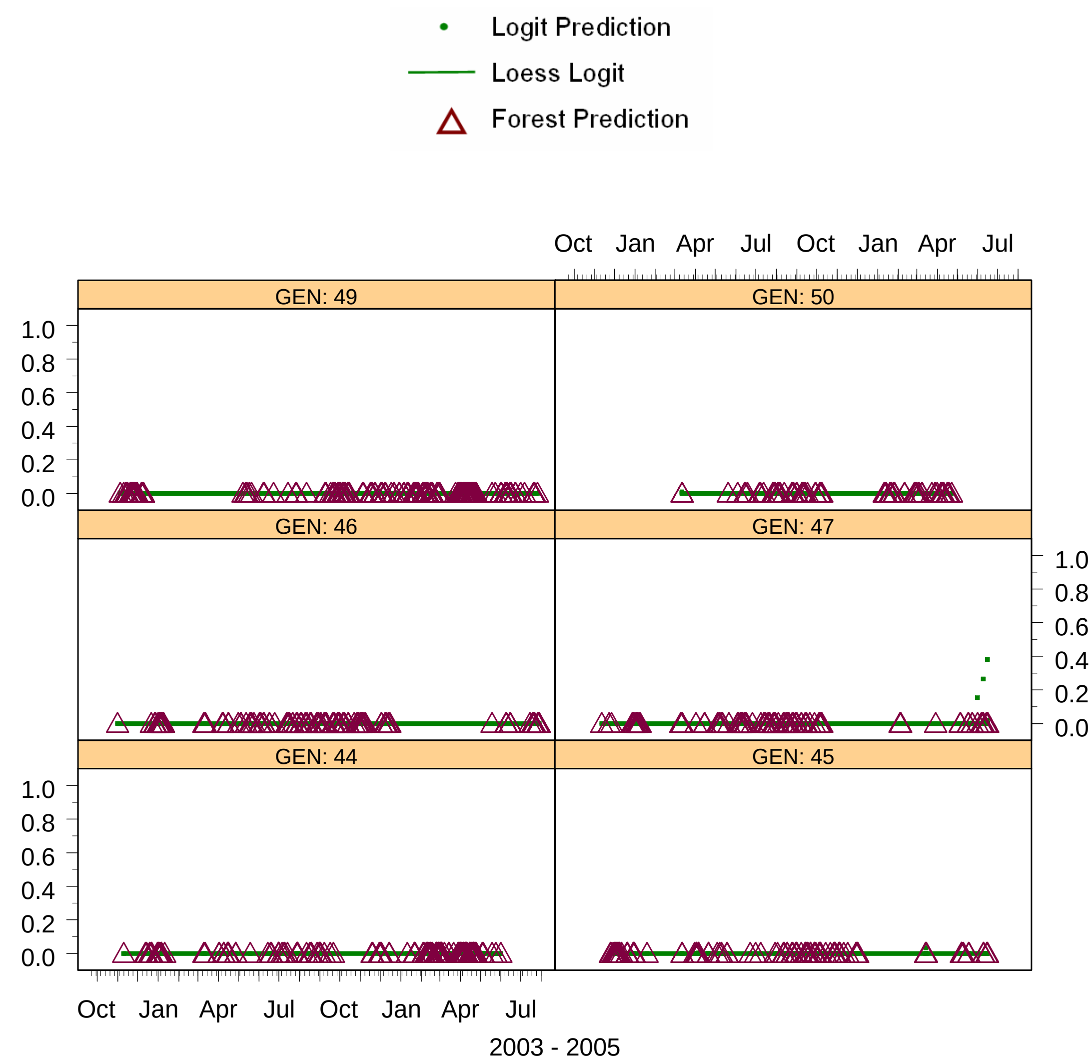
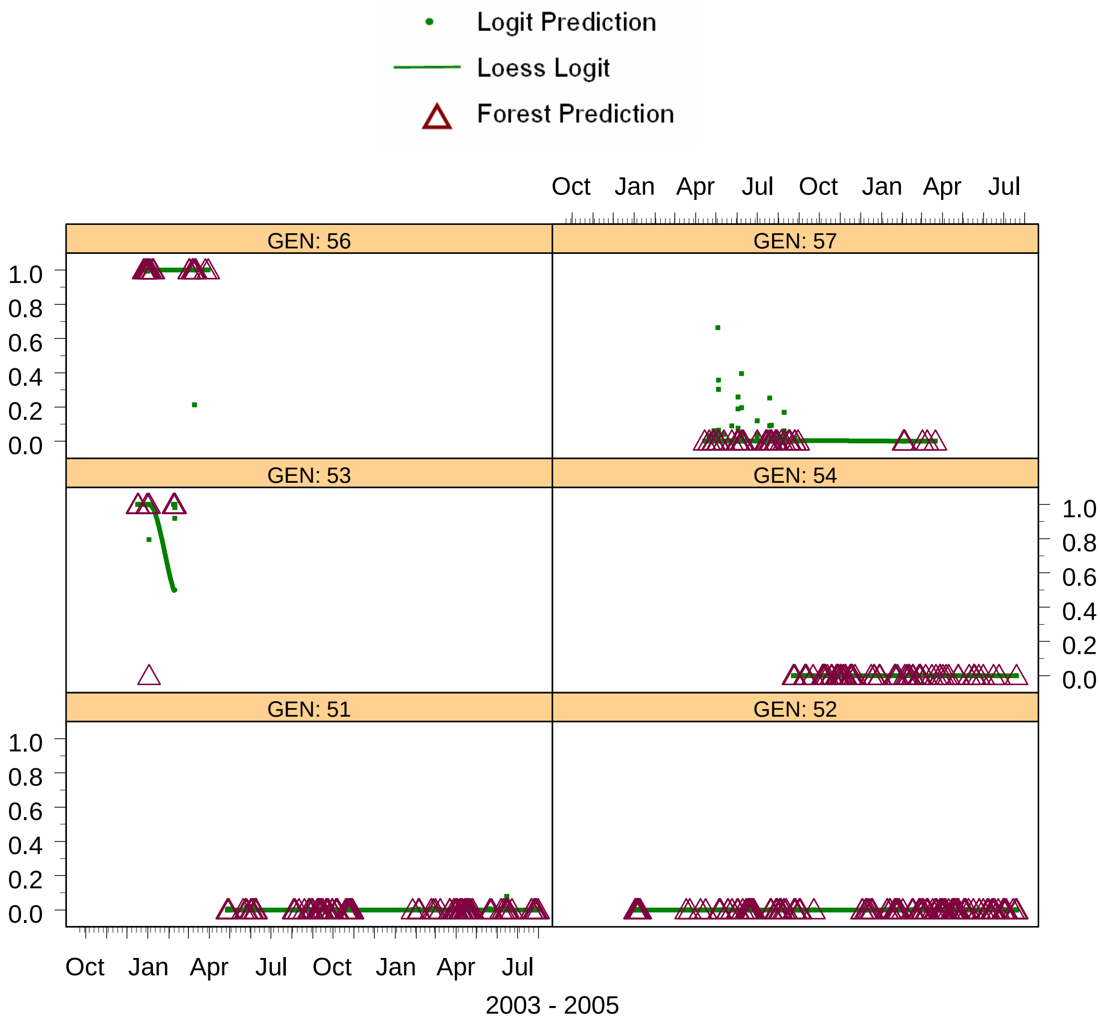


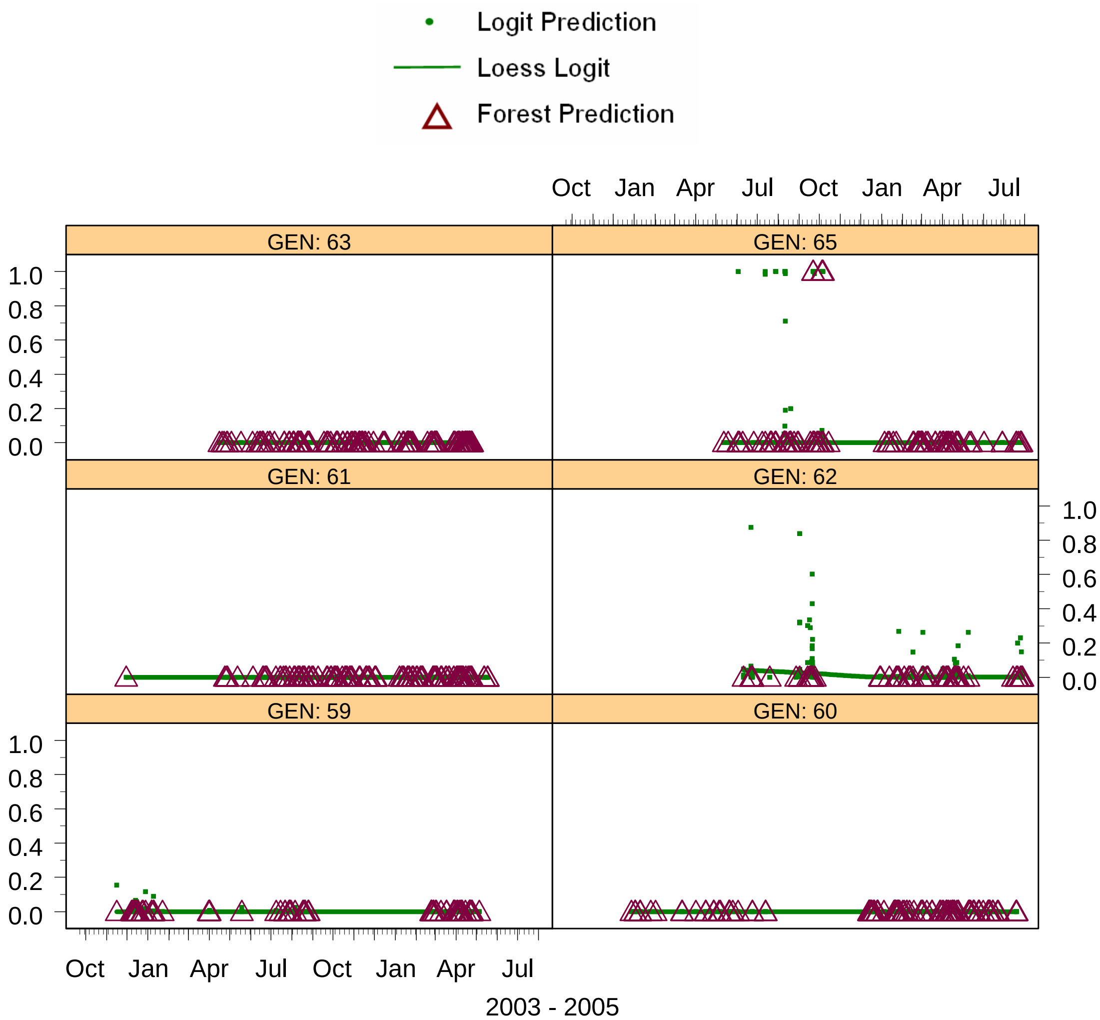
Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period



Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period



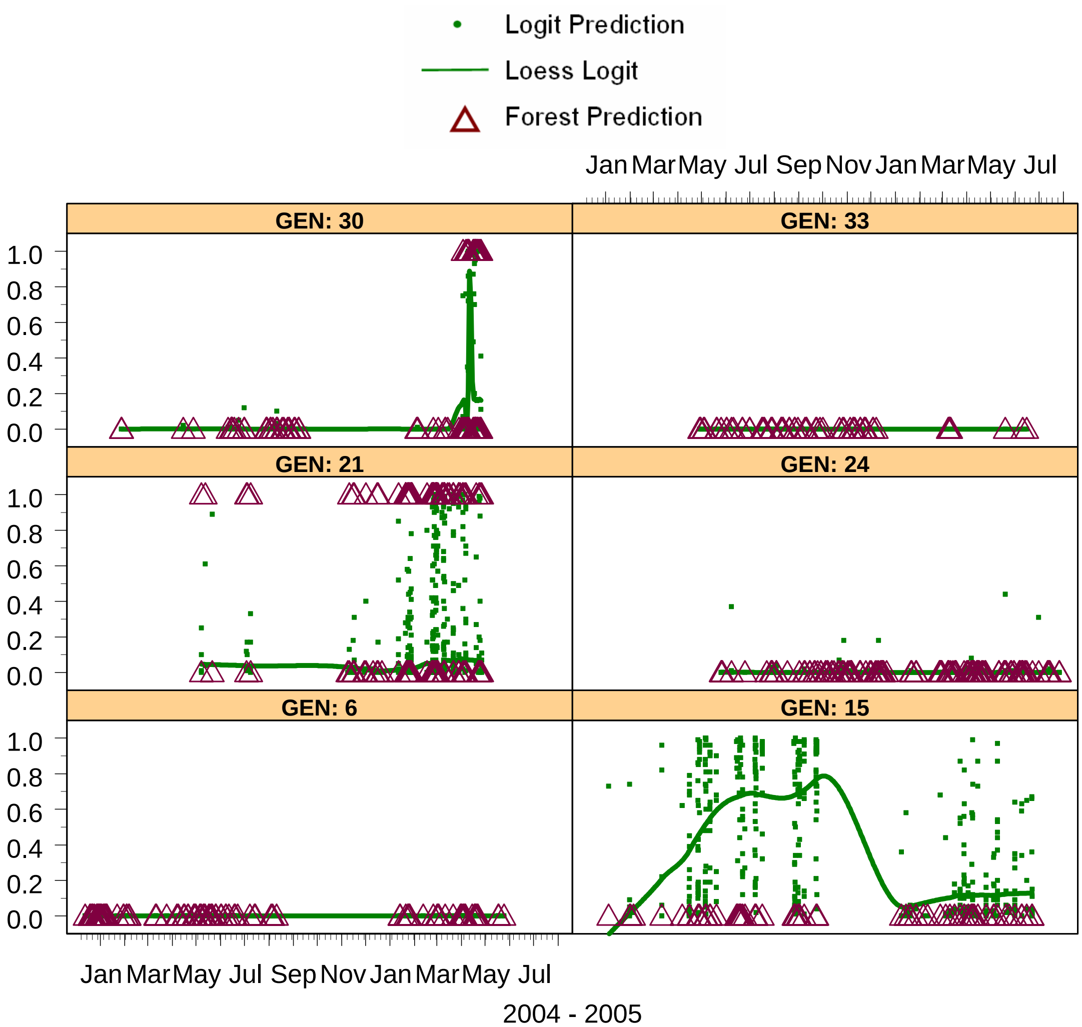
Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period



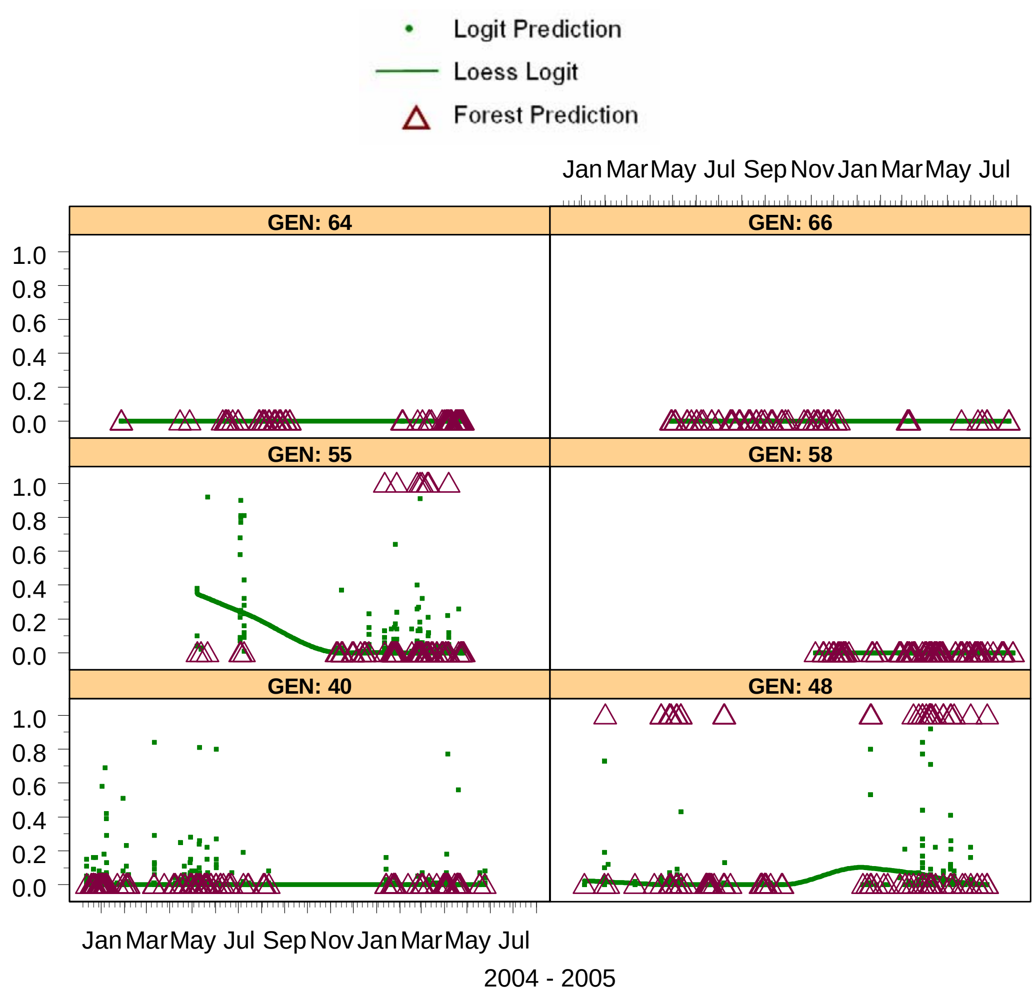
Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

APPENDIX C EXPERIMENTAL SET RESULTS SUMMARY

Helicopter Tail Number	Generator Side	Status	Generator Number	HI S,G,B	Logit	Forest
9226441	Left	watchlist	**6**	**G**		
9326493	Left	Gd	**15**		**strong**	
9326516	Left	watchlist	**21**	**SS**	**weak**	**strong**
9326519	Left	watchlist	**24**	**S**		
9426545	Left	watchlist	**30**	**SS**	**strong**	**strong**
9926829	Left	Bd	**33**			
9926441	Right	Gd	**40**	**S**		
9326493	Right	watchlist	**48**	**SS,G**	**weak**	**strong**
9326516	Right	watchlist	**55**	**S,G**	**moderate**	**moderate**
9326519	Right	Gd	**58**	**B**		
9426545	Right	Gd	**64**	**S**		
9926829	Right	Gd	**66**	**G**		



Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period



Plots of Estimated Probability of Bad from the Logistic Regression Model with Smoothing and the Classification of Being Good (0) or Bad (1) from the Forest of Trees Model for the Entire Two-Year Acquisition Period

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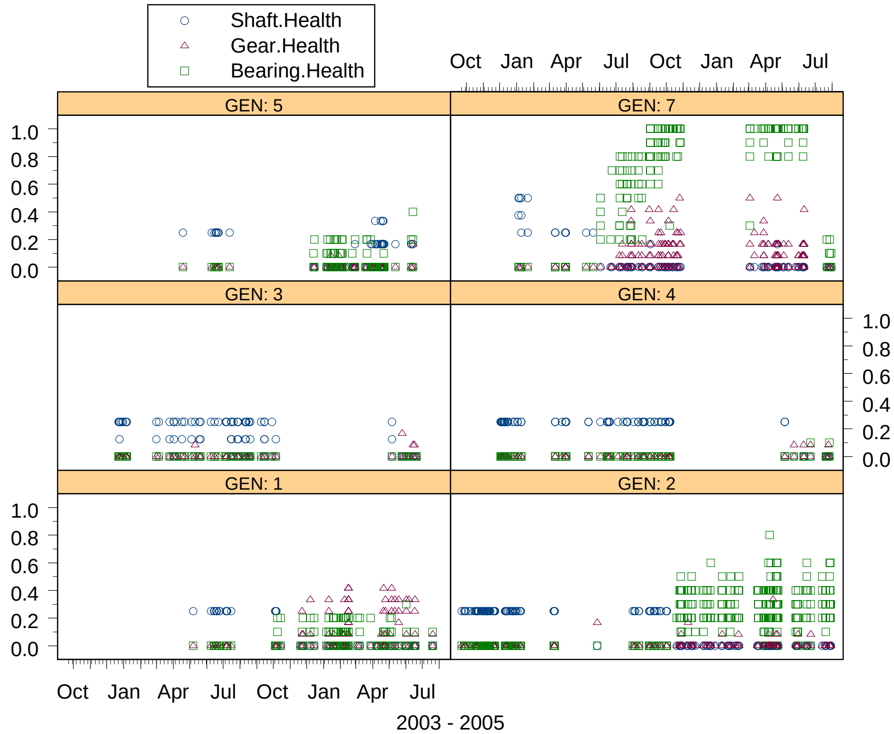
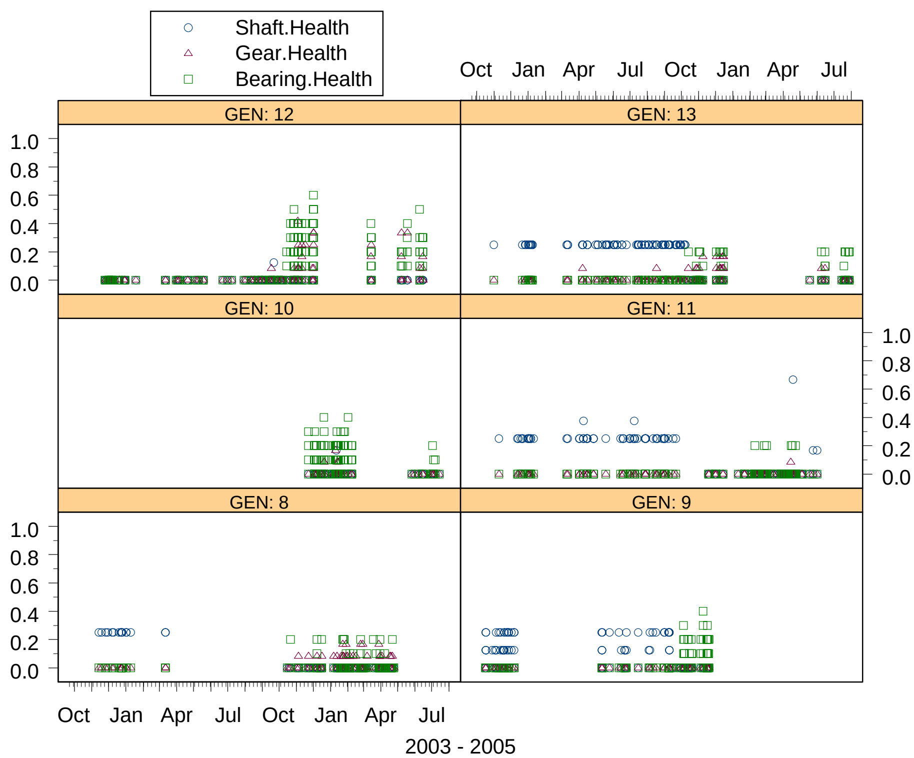
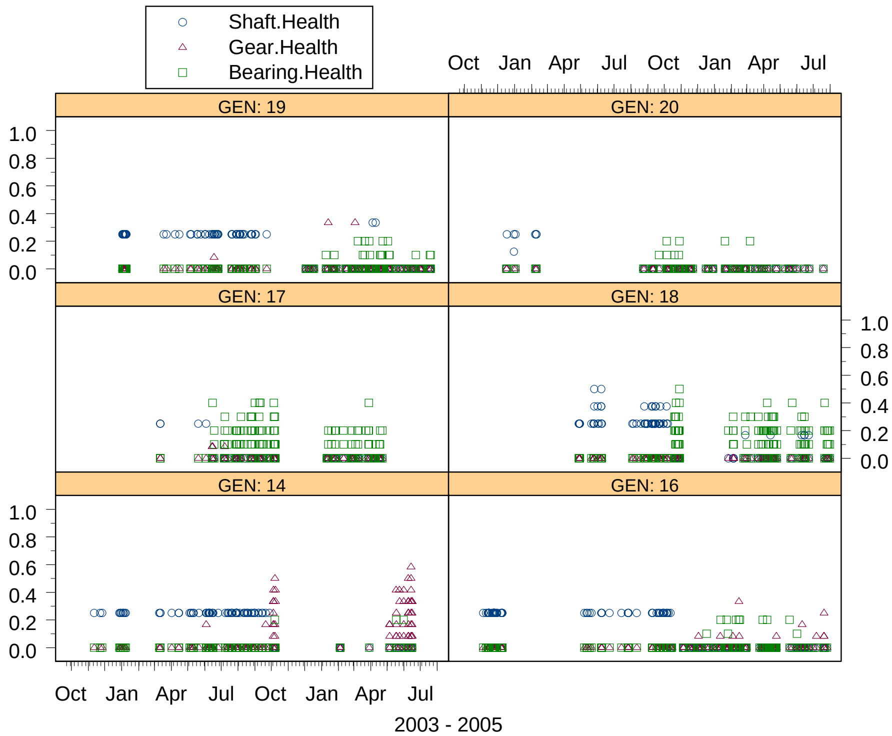
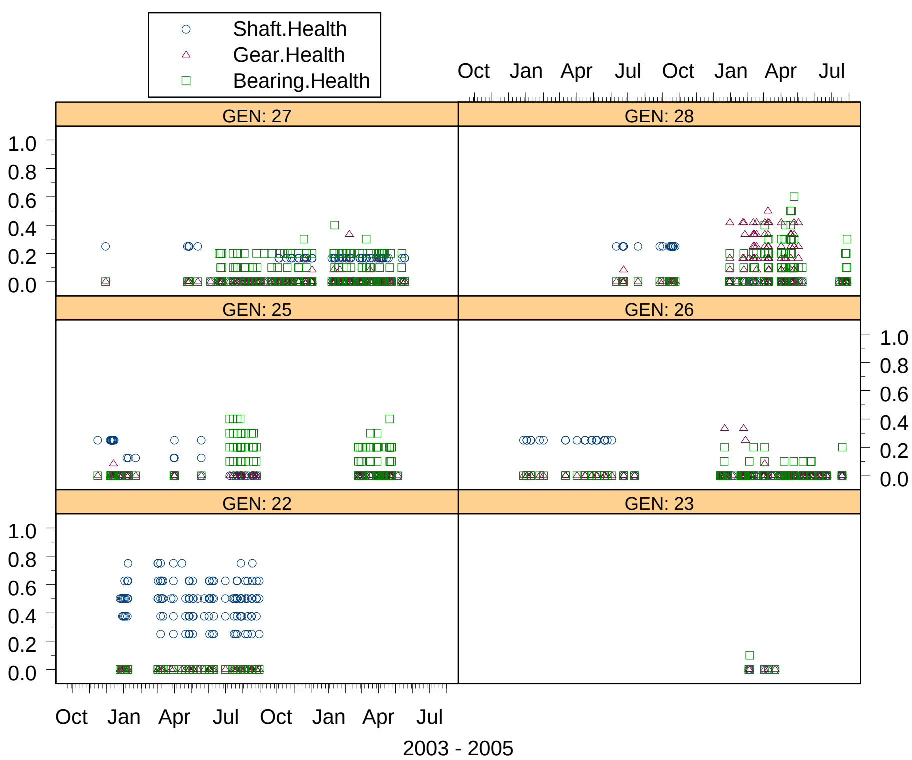
APPENDIX D TRAINING SET HI



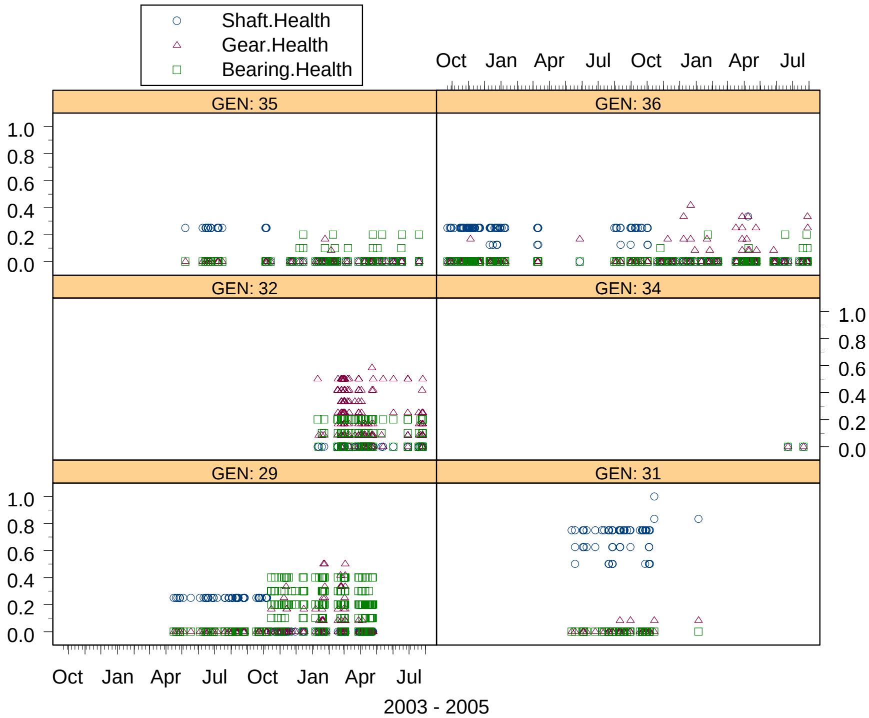


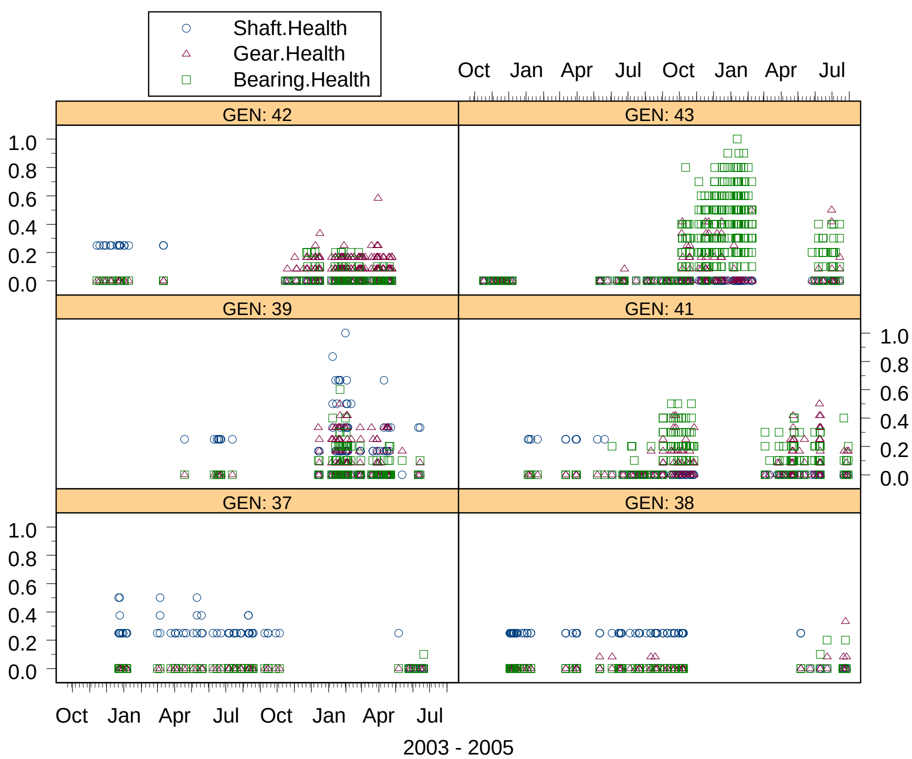


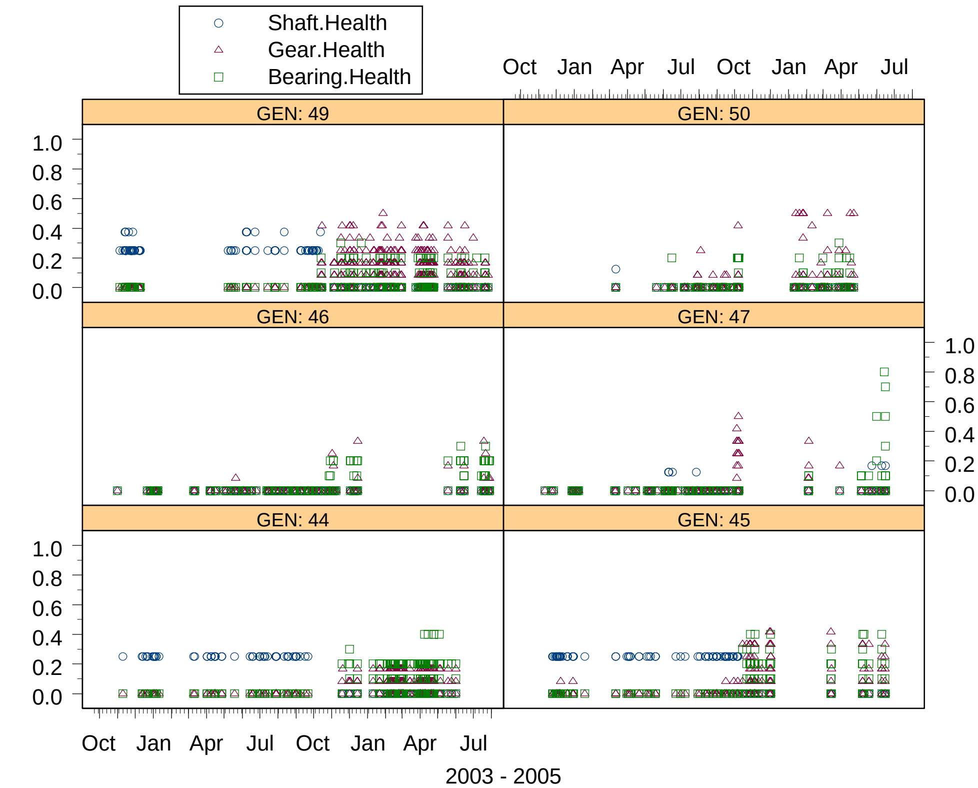
Shaft.Health
Gear.Health
Bearing.Health
GEN: 19
GEN: 20
GEN: 17
GEN: 18
GEN: 14
GEN: 16
Oct Jan Apr Jul Oct Jan Apr Jul
1.0
0.8
0.6
0.4
0.2
0.0
2003 - 2005

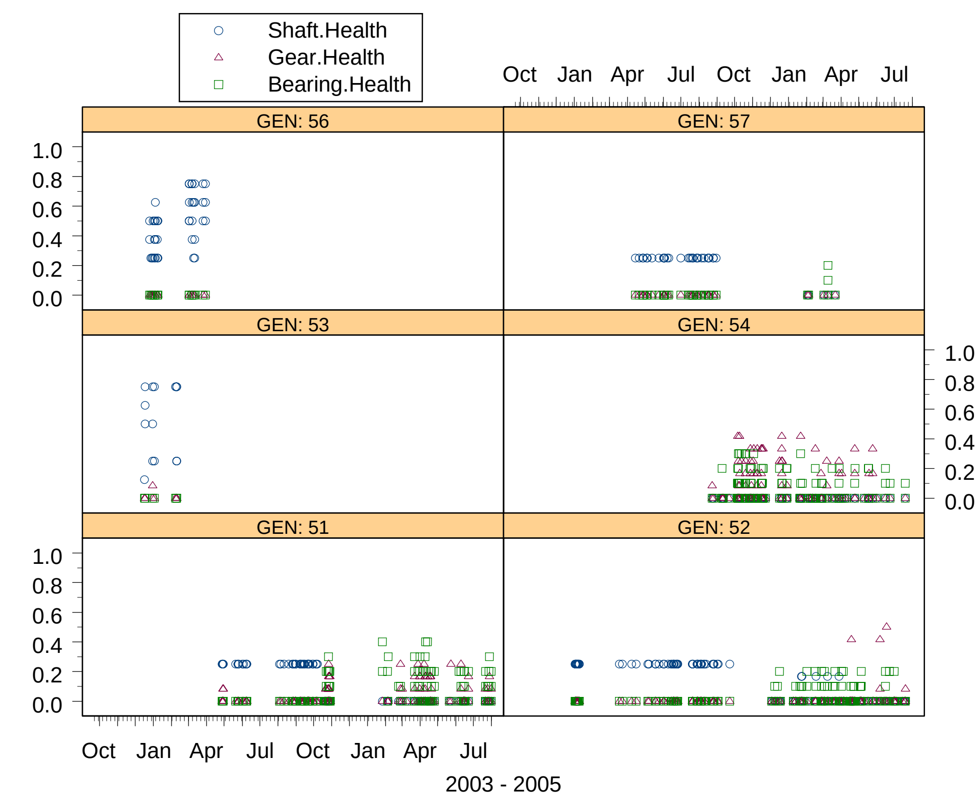


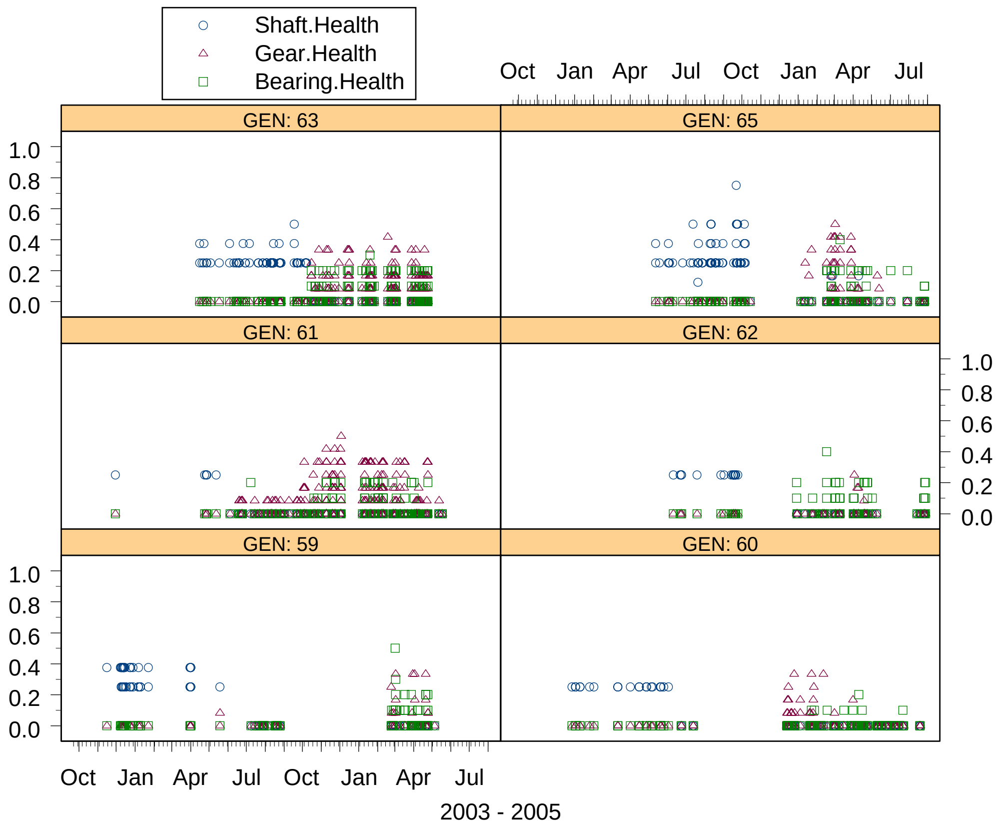
Shaft.Health
Gear.Health
Bearing.Health
GEN: 27
GEN: 28
GEN: 25
GEN: 26
GEN: 22
GEN: 23
Oct Jan Apr Jul Oct Jan Apr Jul
1.0
0.8
0.6
0.4
0.2
0.0
2003 - 2005


Shaft.Health
Gear.Health
Bearing.Health
GEN: 35
GEN: 36
GEN: 32
GEN: 34
GEN: 29
GEN: 31
1.0
0.8
0.6
0.4
0.2
0.0
Oct Jan Apr Jul Oct Jan Apr Jul
2003 - 2005


Shaft.Health
Gear.Health
Bearing.Health
GEN: 42
GEN: 43
GEN: 39
GEN: 41
GEN: 37
GEN: 38
1.0
0.8
0.6
0.4
0.2
0.0
Oct Jan Apr Jul Oct Jan Apr Jul
2003 - 2005


Shaft.Health
Gear.Health
Bearing.Health
GEN: 49
GEN: 50
GEN: 46
GEN: 47
GEN: 44
GEN: 45
Oct Jan Apr Jul Oct Jan Apr Jul
2003 - 2005


Shaft.Health
Gear.Health
Bearing.Health
GEN: 56
GEN: 57
GEN: 53
GEN: 54
GEN: 51
GEN: 52
Oct Jan Apr Jul Oct Jan Apr Jul
2003 - 2005



Shaft.Health
Gear.Health
Bearing.Health
GEN: 63
GEN: 65
GEN: 61
GEN: 62
GEN: 59
GEN: 60
Oct Jan Apr Jul Oct Jan Apr Jul
1.0 0.8 0.6 0.4 0.2 0.0
2003 - 2005

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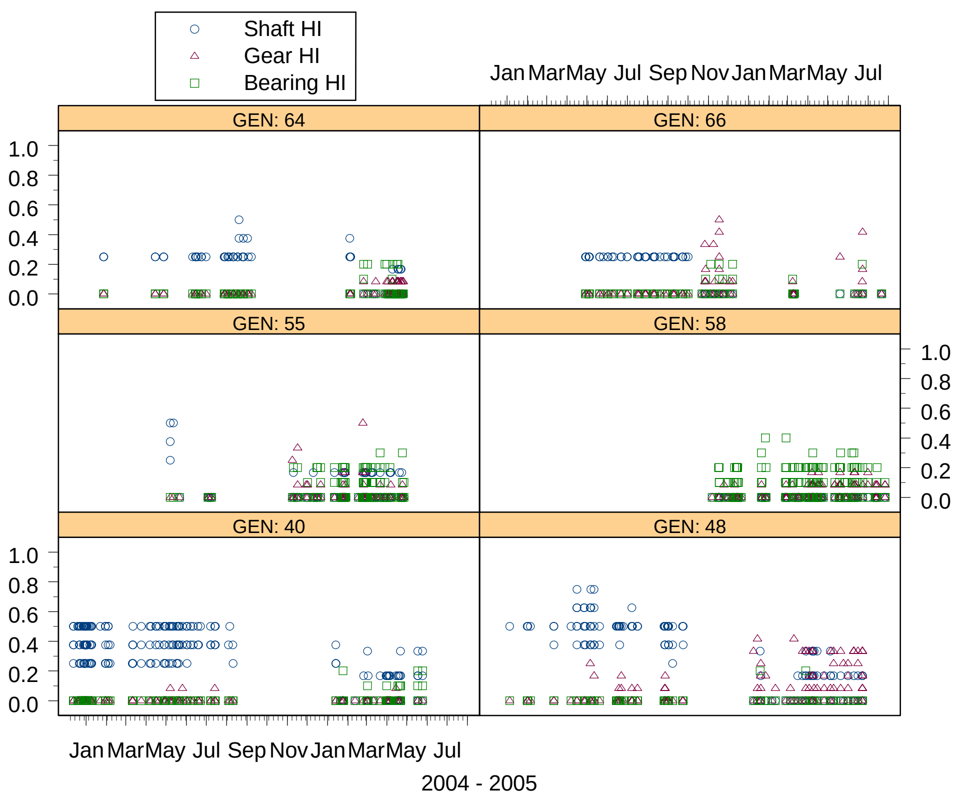
APPENDIX E EXPERIMENTAL SET HI



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APPENDIX F TRAINING SET CLASSIFICATION TREE

```
*** Tree Model ***

Classification tree:
tree(formula = status ~ Shaft.Order.1..IPS. + Shaft.Order.2..IPS. +
       Shaft.Order.3..IPS. + Half.Shaft.Order..IPS. + Gear.Distributed.Fault +
       Residual.Kurtosis + Residual.RMS + Sideband.Mod.1 +
       Narrowband.CrestFactor + G2.1 + Residual.Peak.to.Peak +
       Sig.Avg.Peak.to.Peak + Sig.Avg.Kurtosis + Sig.Avg.RMS +
       Residual.Skewness + Residual.Crest.Factor + Residual.Fifth.Moment +
       Residual.Sixth.Moment + Gear.Misalignment.1 + sm.3.AS.Sideband.Mod.3 +
       Gear.Misalignment.2 + Gear.Misalignment.3 + Narrowband.RMS +
       Narrowband.Peak.to.Peak + Narrowband.Skewness + Narrowband.Kurtosis +
       Narrowband.FifthMoment + Narrowband.Sixth.Moment +
       Instantaneous.Frequency + CSM + AM.Kurtosis + Derivative.AM.Kurtosis +
       FM.Kurtosis + Derivative.FM.Kurtosis + FM.Peak.to.Peak + G2.2 + G2.3 +
       Bearing.Energy.15k.20k + Envelope.RMS + Ball.Energy + Cage.Energy +
       Inner.Race.Energy + Outer.Race.Energy + Total.Bearing.Energy +
       Envelope.Peak.to.Peak + Envelope.Crest.Factor + Envelope.Skewness +
       Envelope.Kurtosis + Envelope.Fifth.Moment + Envelope.Sixth.Moment +
       Envelope.Distributed.Fault + Tone.Energy + Base.Energy +
       Ball.Mod.Cage. + Inner.Race.Mod.Ball + Inner.Race.Mod.Cage +
       Inner.Race.Mod.Outer + Outer.Race.Mod.Ball + Outer.Race.Mod.Cage +
       Total.Bearing.Coupling.Energy + Ball.Mod.Shaft + Cage.Mod.Shaft. +
       Inner.Race.Mod.Shaft + Outer.Race.Mod.Shaft +
       Total.Shaft.Bearing.Coupling, data = CGDNtrainingCUT.65, na.action =
       na.exclude, mincut = 5, minsize = 10, mindev = 0.01)
Variables actually used in tree construction:
[1] "Shaft.Order.1..IPS."    "G2.1"                  "Base.Energy"
[4] "Gear.Misalignment.3"    "G2.3"                  "Half.Shaft.Order..IPS."
Number of terminal nodes:  7
Residual mean deviance:  0.01577 = 16.29 / 1033
Misclassification error rate: 0.004808 = 5 / 1040
node), split, n, deviance, yval, (yprob)
      * denotes terminal node

 1) root 1040 658.400 G ( 0.09615 0.90380 )
   2) Shaft.Order.1..IPS.<1.72485 970 281.300 G ( 0.03299 0.96700 )
     4) G2.1<38.5724 200 175.900 G ( 0.16000 0.84000 )
       8) Base.Energy<0.655714 154   0.000 G ( 0.00000 1.00000 ) *
       9) Base.Energy>0.655714 46  56.530 B ( 0.69570 0.30430 )
        18) Gear.Misalignment.3<-41.7041 11   0.000 G ( 0.00000 1.00000 ) *
        19) Gear.Misalignment.3>-41.7041 35  20.480 B ( 0.91430 0.08571 )
          38) G2.3<65.3999 7   9.561 B ( 0.57140 0.42860 ) *
          39) G2.3>65.3999 28   0.000 B ( 1.00000 0.00000 ) *
     5) G2.1>38.5724 770   0.000 G ( 0.00000 1.00000 ) *
   3) Shaft.Order.1..IPS.>1.72485 70  18.160 B ( 0.97140 0.02857 )
     6) Half.Shaft.Order..IPS.<0.284577 65   0.000 B ( 1.00000 0.00000 ) *
     7) Half.Shaft.Order..IPS.>0.284577 5   6.730 B ( 0.60000 0.40000 ) *
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