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Prognostic Approaches Using Transient Monitoring Methods

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I am submitting herewith a dissertation written by Michael Eric Sharp entitled "Prognostic Approaches Using Transient Monitoring Methods." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Nuclear Engineering.

J W. Hines, Major Professor

We have read this dissertation and recommend its acceptance:

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Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)
Prognostic Approaches Using Transient Monitoring Methods

A Dissertation Presented for
the Doctor of Philosophy Degree
The University of Tennessee, Knoxville

Michael Eric Sharp
August 2012
Abstract

The utilization of steady state monitoring techniques has become an established means of providing diagnostic and prognostic information regarding both systems and equipment. This is mainly driven by both the wealth of available analysis techniques and the comparatively larger amount of data. However, steady state data is not the only, or in some cases, even the best source of information regarding the health and state of a system. Transient data has largely been overlooked as a source of system information due to the additional complexity in analyzing these types of signals. The development for algorithms and techniques to quickly, and intuitively develop generic quantification of deviations a transient signal towards the goal of prognostic predictions has until now, largely been overlooked. By quantifying and trending these shifts, an accurate measure of system health can be established and utilized by prognostic algorithms. In fact, for some systems the elevated stress levels during transients can provide better, more clear indications of system health than those derived from steady state monitoring.

This research is based on the hypothesis that equipment health signals for some failure modes are stronger during transient conditions than during steady-state operations because transient conditions (e.g. start-up) place greater stress on the equipment for these failure modes. From this it follows that these signals related to the system or equipment health would display more prominent indications of abnormality if one were to know the proper means to identify them. This project seeks to develop methods and conceptual models to monitor transient signals for equipment health. The purpose of this research is to confirm that transient signal monitoring can in some systems provide alternate or better indicators of incipient equipment failure prior to steady state signals. The research also identifies methods, both traditional and novel, suitable to implement and test transient model monitoring in both a useful and intuitive way. By means of these techniques, it is shown that the additional information gathered during transient portions of life can be used to either to augment existing steady-state information, or in cases where such information is unavailable, be used exclusively for developing prognostic models.
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<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Amps</td>
</tr>
<tr>
<td>AAKR</td>
<td>Auto Associative Kernel Regression</td>
</tr>
<tr>
<td>AANN</td>
<td>Auto Associative Neural Network</td>
</tr>
<tr>
<td>ACT</td>
<td>Absolute Correlation with Time</td>
</tr>
<tr>
<td>APS</td>
<td>Average Prognostic Suitability</td>
</tr>
<tr>
<td>AR</td>
<td>Auto Regressive</td>
</tr>
<tr>
<td>ATFD</td>
<td>Adaptive Time–Frequency Decomposition</td>
</tr>
<tr>
<td>BLDC</td>
<td>Brushless Direct Current</td>
</tr>
<tr>
<td>CBO&amp;M</td>
<td>Condition-Based Operations and Maintenance</td>
</tr>
<tr>
<td>CCDF</td>
<td>Cohen’s Class Distribution Function</td>
</tr>
<tr>
<td>CLC</td>
<td>Current Life Consumption</td>
</tr>
<tr>
<td>CPM</td>
<td>Cycles Per Minute</td>
</tr>
<tr>
<td>CST</td>
<td>Control Switch Trip</td>
</tr>
<tr>
<td>DWT</td>
<td>Discrete Wavelet Transform</td>
</tr>
<tr>
<td>EHC</td>
<td>Electrical Hydraulic Control</td>
</tr>
<tr>
<td>EMF</td>
<td>Empirical Mode Function</td>
</tr>
<tr>
<td>EMI</td>
<td>Electro-Magnetic Interference</td>
</tr>
<tr>
<td>FBG</td>
<td>Fiber Bragg Gratings</td>
</tr>
<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
</tr>
<tr>
<td>FPGA</td>
<td>Field Programmable Gate Array</td>
</tr>
<tr>
<td>GPM</td>
<td>General Path Model</td>
</tr>
<tr>
<td>HP</td>
<td>Horse Power</td>
</tr>
<tr>
<td>HT</td>
<td>Hilbert Transform</td>
</tr>
<tr>
<td>HHT</td>
<td>Hilbert-Huang Transform</td>
</tr>
<tr>
<td>IMF</td>
<td>Intrinsic Mode Function</td>
</tr>
<tr>
<td>JTFA</td>
<td>Joint Time Frequency Analysis</td>
</tr>
<tr>
<td>JTFS</td>
<td>Joint Time Frequency Spectrum</td>
</tr>
<tr>
<td>KR</td>
<td>Kernel Regression</td>
</tr>
<tr>
<td>LTC</td>
<td>Load Tap Charger</td>
</tr>
<tr>
<td>MAPE</td>
<td>Mean Absolute Percent Error</td>
</tr>
</tbody>
</table>
MCSA  Motor Current Signature Analysis
MHC   Mechanical Hydraulic Control
MOV   Motor Operated Valve
MTPV  Motor Torque Periodic Verification
MTTF  Mean Time to Failure
NPP   Nuclear Power Plant
O&M   Operations and Maintenance
OLM   Online Monitoring
PCB   Printed Circuit Board
PD    Partial Discharge
PEM   Process and Equipment Monitoring
PEP   Process and Equipment Prognostics
PHM   Proportional Hazards Model
PI    Plant Information
PLP   Pseudo-Linear Prognosability
PNNL  Pacific Northwest National Lab
RBC   Roll Bowl COP
RCP   Reactor Coolant Pump
RF    Radio Frequency
RFI   Radio Frequency Interference
RMS   Root Mean Square
RMSE  Root Mean Square Error
RPM   Revolutions Per Minute
RUL   Remaining Useful Life
SDMS  Self-Diagnostic Monitoring System
SPRT  Sequential Probability Ratio Test
STFT  Short-Time Fourier Transform
SVAF  Space Vector Angular Fluctuations
TFDA  Time-Frequency Domain Averaging
TSA   Time Synchronous Averaging
TOF   Time Of Failure
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOP</td>
<td>Transient Operations Prognostic</td>
</tr>
<tr>
<td>WD</td>
<td>Wigner-Ville Distribution</td>
</tr>
<tr>
<td>WT</td>
<td>Wavelet Transform</td>
</tr>
<tr>
<td>ZAM</td>
<td>Zhao-Atlas-Marks distribution</td>
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</table>
1 Introduction

Steady-state condition monitoring is a well-known and often used online evaluation technique to appraise the state of modern equipment and systems. More recent research and applications focus on the use of steady state operational data for equipment and system prognostics, which is the estimation of remaining useful life (RUL). While this proven concept of using steady state data continues to be a valuable asset in a complete reliability management regime, the eventual goal of this proposed dissertation is to extend these methods with additional information that can be gained through the monitoring of transient phases within a component or system’s lifetime in which the system may be at higher stress levels. This research intends to not only assess the feasibility of using transient signals to provide alternate or potentially faster and/or more accurate indicators of equipment condition that can be used to perform prognostics, but also provide a generic framework for identification of and model construction with these indicators.

Within the industrial community, the science of prognostics revolves around the estimation RUL for both systems and equipment. Although occasionally overlooked, prognostics represents a primary aspect of a complete reliability regiment, and should be thought of as the culmination of information gathered at each step in the chain before it. By utilizing the full spectra of reliability information and especially that developed through prognostic algorithms, project leaders are able to provide more informed and valuable decisions concerning the current operational tasks, or duty cycle of the equipment. Decisions regarding when best to shut down for maintenance, or whether to expect a system to perform through the upcoming duty cycle, can be made with much more precision and foundation than a simple regularly scheduled maintenance program.

This dissertation will identify, examine, and extend the current state of the art technologies used in power plant equipment prognostics, and more specifically, transient analysis for condition based monitoring. Often in the power industry, and the nuclear power industry specifically, the word transient is used to refer to an abnormal or faulted condition, such as the plant experienced a rod drop transient. This is not the definition used for this work. Instead, the word transient is used to denote any shift in conditions that results from the normal operations of the system in question. Such shifts or transients include but are not strictly limited to: system start-ups,
shutdowns, changes in workload, or operating conditions. A less rigid definition is any dynamic shift in the system not resulting directly from any developed or incipient fault, or in other words, any non-steady-state operations.

Nearly all systems and equipment experience some form of transient conditions during their lifetime. In some systems these conditions are commonplace, shifting in workload, startups, or similar situations. For these systems, utilization of information gathered during these shifts could be integral in providing the most accurate and timely system degradation information. In general, any system undergoing additional stress during transient operations would benefit provided a proper algorithm could be constructed to detect incipient faults or determine a measure of system degradation, and especially if this can be done prior or more accurately than by similar steady state monitoring methods. Some equipment experiences transient conditions which are environmentally driven, and while this research does not focus on these, there is no reason that any conclusions or algorithms developed from this work would not directly translate to that class of external transients as well.

1.1 Problem Statement

Traditional equipment and system monitoring techniques focus on steady-state operations due to the fact that most analytical means require fulfillment of the assumption of a near stationary signal in order to return logically meaningful results. However, even personal experience can tell us that for many systems the signals of incipient equipment damage can be stronger during a transient such as the start-up or shut-down, or even a state change. One everyday example of this could be the length of time a fluorescent light bulb flickers prior to full illumination after supplying power. While there is not an obvious shift in the steady state illumination from the bulb, flickering during the ‘warm up’ time increases over the lifetime of the bulb. If this were this monitored, it could provide a direct indication of how soon the bulb will need to be replaced. Another simple example might be the vibration and maximum displacement of a water pump during start-up due to the priming and in-rush of water. Monitoring such features and comparing them to similar features to known ‘healthy’ equipment, potentially allows for a prognostic indication of Remaining Useful Life (RUL) or the Current Life Consumption (CLC) to be made.
Based on the hypothesis that equipment health signals for some failure modes are stronger during transient conditions than during steady-state, this research examines and illuminates methods for quantifying, extracting, and modeling system information from transient conditions (e.g. start-up) due to the greater stress placed on the equipment for these failure modes. Cases cited in this work show that these signals related to the system or equipment health can display more prominent indications of abnormality if one were to know the proper means to identify them. This project seeks to develop methods and conceptual models to monitor transient signals for equipment health. The purpose of this research is to assess if monitoring transient signals could provide alternate or better indicators of incipient equipment failure prior to steady state signals and to provide a generic framework for identifying proper algorithms to utilize this information.

1.2 Original Contributions

1. Development of Prognostic algorithms tailored to utilize information in transient signals.
3. Validation of developed methods using several data sets including data collected from the accelerated degradation of electrical motors.

1.3 Organization of the Document

Chapter 2 reviews the relevant literature in transient analysis as well as prognostics algorithms, techniques, and applications. The development of a generic methodology for describing, analyzing, and modeling transient operation signals is presented. The methodology describes the use of both traditional and novel analysis and feature extraction techniques. Chapters 4 and 5 detail multiple case studies applying said techniques and algorithms. These pilot applications include the analysis of motor aging data taken from a previously performed experiment as well as data from an accelerated motor aging experiment tailored to provide transient information for this project. The startups of degraded impellers are also examined. After detailing the results of these applications, there are some concluding remarks as well as proposed areas of future work that do not fall under the scope of this dissertation, are given in Chapter 6.
2 Background and Literature Survey

In this research, the current state of the art technologies used in power plant equipment
prognostics and transient analysis for condition monitoring will be both examined and identified
in order to verify the novelty of the work. As mentioned above, in the power industry and the
nuclear power industry specifically, the word transient is used to refer to an abnormal or faulted
condition. To prevent any confusion it bears repeating that this is not the primary meaning used
in this research, but the term transient is instead used to denote any shift in conditions that results
from the normal operation of the system in question. As an example, lowered water flow through
a pump due to a controlled shift in pump speed would be considered an operational transient.
Lowered flow due to an impeller breaking off would not.

In order to better understand the current developments in both transient monitoring and system
prognostics, a literature survey was performed to guide this research and to verify that similar
work has not been completed in the past. The state of the art of the acquisition, analysis, and
treatment of transients and dynamic processes was surveyed; these techniques are summarized in
the following sections. A brief review of prognostic techniques is also provided, including
model classification, development, and evaluation.

2.1 Review of Transient Analysis Techniques

There are many different mathematical methods and algorithms currently in use for the analysis
of system transients. Understanding and extracting information from any non-stationary signal is
considered one of the more difficult tasks in monitoring and diagnostics because many
traditional signal features and statistics such as mean, variance, or frequency spectra can lose
meaning and violate underling assumptions when applied to non-stationary signals. This is why
common traditional signal analysis relies on the processing of stationary, or steady state, signals.
Some of the more popular methods for analysis of transient signals are wavelet analysis, joint
time-frequency analysis (JTFA), Hilbert Huang transformation, and variations of these
algorithms.
Understanding the nature of a given transient and the time scale on which it operates, can and should greatly affect an informed decision regarding the type of analysis method used. Methods such as vibration analysis or motor current signature analysis, which require data to be sampled at high rates compared to the speed of the transient, are often more complicated and are expected to yield more precise information about the monitored system. However, in some cases this ‘high frequency’ information is not available or simply not necessary because other ‘low-frequency’ techniques can obtain enough useful information to perform the analysis. ‘Low-frequency’ monitoring of tracked variables such as maximum/minimum signal values or length of the transient may also yield valuable and accurate information about the condition of the system. The following sections briefly describe an alphabetical list of the current state of the art transient data analysis techniques.

2.1.1 **Adaptive Time-Frequency Decomposition**

According to work presented by Shi [Shi 2004], the core of adaptive time–frequency decomposition (ATFD) is to compute a linear combination of the original signal over a set of redundant elementary atoms, or base wave signals. These atoms are derived from a collection of different waves, whose selection should reflect the form of the signal being analyzed, as shown by McClure [McClure 1997]. In order to match the original signal $s_0$, the following equation must be satisfied:

$$\min \left\| s_0 - \sum_{n=0} c_n g_n \right\|$$

where $c_n$ is the $n$th matching value and $g_n$ is the $n$th elementary atom. The signal is then decomposed into an inner product between $g_0$ and the approximation of $s_0$ and a residual. This decomposition approach is an iterative algorithm that sub-decomposes the residual $R_s$ by projecting it on an optimized elementary atom selected from an atom dictionary that matches $R_s$, as it was done for $s_0$. This approach provides a precise interpretation of complex signals that consist of various time–frequency structures. By decomposing the signal into parametric, redundant and well-localized components in the time–frequency plane, information about the signal can be gathered with high time–frequency resolution and no interference terms. ATFD provides a more compact and adaptive representation in comparison with wavelet transform
(WT) and the Short Time Fourier Transform (STFT), both of which are discussed in later sections. ATFD possesses the same time and frequency resolution as Wigner-Ville distribution (WD), which is much higher than either STFT or WT. Another advantage of this technique is that ATFD has no interference, which can pose severe problems in WD type algorithms. Thus ATFD can easily be used to monitor the transient vibration of rotating machinery and can be used to specify the critical speed and accelerating rate in the run up or shut down stage [Shi 2004]. Shi demonstrated this through experimental validation on an electric motor test rig.

2.1.2 Cohen’s Class Distribution Function

Cohen’s Class Distribution Function (CCDF) utilizes bilinear transformations through kernel functions to perform time-frequency analysis [Cohen 1995]. The general form of a CCDF for a signal \( f(t) \) is given by:

\[
D(t, \omega, \phi) = \int \int \int e^{i(\xi \mu - \tau \xi t)} \phi(\xi, t) \, d\mu d\tau d\xi.
\]

where \( \phi(\xi, \tau) \) is the transformation’s kernel that defines the transformation. CCDF analysis methods can inherently be applied to non-stationary signals and data collected during transients due to the non-linearity of the kernel functions. These methods have also been shown by Cohen [Cohen 1995] to have good resolution in both the time and frequency domains. Perhaps the only major drawback of these techniques is the appearance of cross term artifacts which are caused by a linear combination of both auto- and cross-terms that result in increased signal redundancy; this may obscure some frequencies necessary for fault identification. Cohen also identifies methods to mitigate the obscuring effects of these artifacts including: changing parameters of the kernel, utilizing different kernels, applying a filter, and using the analytic signal [Cohen 1995].

One particular study showed that the use of the Zhao-Atlas-Marks (ZAM) distribution (a particular CCDF) to provide a time-frequency spectrum allows for the detection of dynamic
eccentricity in Brushless Direct Current (BLDC) motors [Rajagopalan 2006]. This algorithm begins by filtering the stator current adaptively to remove the fundamental frequency and other inverter harmonics, thereby preventing any cross-terms at the frequencies of interest. The filtered stator current is then converted into an analytic signal using a Hilbert Transform (HT) before the fault frequencies are extracted from this analytic signal by computing the ZAM distribution. The root mean squared (RMS) value of the instantaneous amplitudes of the extracted fault frequencies is then used to indicate a developing rotor fault. The author submits that the method could be extended to detect other faults such as bearing faults, or gear faults, or applied to faults in other kinds of motors such as broken rotor bar detection in induction motors.

2.1.3 Joint Time-Frequency Analysis and the Short Time Fourier Transform

The Short-Time Fourier Transform (STFT) is one of the most common frequency analysis techniques used to create a joint time-frequency spectrum (JTFS). Time-frequency spectrums are useful in observing how frequency components of a signal evolve through time, unlike traditional Fourier spectra, which ignore any time dependency. Gabor [Gabor 1946] proposed a kernel weighted window approach to this process, which has become a common method. By splitting a time domain signal into small, overlapping segments, the traditional algorithm applies the Fourier Transform to each of these segments to obtain an estimate of the signal's frequency as it evolves through time.

\begin{equation}
G_x(t, f) = \int_{-\infty}^{\infty} e^{-\pi(\tau-t)^2} e^{-j2\pi f \tau} x(\tau) \, d\tau
\end{equation}

\begin{align*}
x & = \text{signal} \\
f & = \text{frequency} \\
\tau & = \text{transform parameter}
\end{align*}

The above equation shows the mathematical form of the Gabor Transform. It is functionally similar to the Fourier Transform (FT) with a time based offset and decay term used to isolate specific regions of the signal. Since this approach is still based on the FT, it works best if the segments are sufficiently small that the signal appears stationary in each segment. There is also an inherent trade off between frequency and time resolution with this algorithm. The smaller
each of the segments, the more precise the time resolution the spectrum will show. Unfortunately, this also means fewer samples for the STFT, resulting in lower frequency resolution. More information about this can be found in Gabor's original work [Gabor 1946].

By decomposing a single signal into an overlapping series of Fourier transforms, the Gabor transform allows the evolution of frequencies over time to be more directly analyzed. As shown in Figure 1 below, the Gabor Transform is able to capture the shifts in frequency as a signal progresses through time. A more traditional Fourier Transform would lose this time dependence, making direct analysis more difficult.

As an example, Figure 1 shows the STFT applied to the sound of a bird chirping to create a JTFS. Notice that both the frequency and amplitude of each of the bird’s chirps are important in the full analysis of the characteristics of the signal. From the top chart, each individual ‘chirp’ can be seen to grow and diminish in volume, while the bottom chart also makes it easy to discern that each chirp also starts out at a high frequency, and quickly falls off. The use of a JTFS makes frequency drifts become readily apparent. More importantly for this work, any frequency shift patterns arising from transient operations can be much more easily identified and compared than with more traditional Fourier Transform analysis. Without this deconstruction, a single Fourier transform will likely lose any subtle, yet important, frequency spikes or shifts that occur during transient phases.

One example of the JTFS used in motor monitoring is termed a "sensorless" method for measuring induction motor speed during start-up [Wang 2008]. The method is based on high-resolution spectral analysis of space vector angular fluctuations (SVAF) using the STFT. Due to the eccentricity and supply current unbalance present even in healthy induction motors, spectral components whose frequency varies with motor speed can be monitored. The method has proved to have excellent agreement between the estimated speed and the measured speed of an induction motor using an actual speed sensor.
2.1.4 Hilbert-Huang Transform

The Hilbert-Huang transform (HHT) is a method used to decompose a signal into successive intrinsic mode functions (IMFs) based exclusively on the signal values. The Hilbert transform (HT) is then applied to these IMFs to obtain instantaneous frequency and amplitude information for each IMF [Huang 1998]. Each IMF is defined by the criteria that, in the whole data set, the number of extrema and the number of zero-crossings must differ by no more than one, and, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. After finding the IMFs from the signal, the instantaneous frequency can be found by applying the Hilbert transform shown in the equation below on each IMF.
Equation 3 - Hilbert Transform

\[ X(t) = \text{Re} \left\{ \sum_{j=1}^{n} a_j(t) e^{i \int \omega_j(t) dt} \right\} \]

Equation 4 - Single Integral Form of Hilbert Transform

\[ Y(t) = H(x(t)) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \]

\[ Z(t) = X(t) + jY(t) = A(t) \exp(j \theta(t)) \]

\[ \omega(t) = 2\pi f(t) = \frac{d}{dt} \theta(t) \]

Whereas more traditional forms of analysis and decomposition rely on deconstructing the signal into functional forms of known parametric equations, such as a sinusoid for the FT, the HHT assumes no such functional form. Transient or non-stationary signals are ideally analyzed with this algorithm as it can be used to provide instantaneous frequency information and has been shown to give much better resolution than the more traditional time-frequency decompositions.

Another advantage of signal analysis derived from the HHT is that, unlike processes like wavelet transform which have a fixed-scale frequency resolution; the HHT provides multi-resolution in various frequency scales and takes the signal's frequency content and variation into consideration. The two primary features extracted from the HHT are both the analytic amplitude and the instantaneous frequency of each IMF. While the first is simply the absolute value of each IMF from the HHT, the instantaneous frequency is calculated by looking at the first derivative of the phase angle for each IMF.

One interesting study develops a methodology for analyzing the stator current demanded by an induction motor during the startup transient using the HHT [Antonino-Daviu 2009]. This methodology is based on extracting the characteristic transient evolution of harmonic components created by corresponding faults. This evolution is also dependant on the motor slip as it varies during startup. Tests show that a major advantage of using the HHT for motor monitoring, as opposed to other decomposition techniques, is the ability to easily discriminate
between rotor bar breakages and mixed eccentricities. In addition, the second IMF arising from
the HHT shows great potential for quantifying the severity of the identified fault. This is an
important point if prognostic prediction is to be performed using the startup signal.

Another paper presents a methodology for discovering bearing failures using the Fast Fourier
Transform of the IMFs developed from the HHT [Rai 2007]. Applying this methodology to
bearing vibration data avoids the subjective error in the calculation of characteristic defect
frequencies of rolling element bearings that is associated with the HT-based time domain
approach in the HHT.

2.1.5 Time-Frequency Domain Averaging

Time-frequency domain averaging (TFDA) is a method by which a signal from rotating
equipment is divided into time segments equal to one rotation, and then corresponding data are
averaged according to the position of the rotation. This averaging allows for noise reduction as
well as direct comparisons between shaft locations. This method can also accommodate variable
rotation speeds through proper applications of interpolation or down sampling. The frequency
deconstruction of the segments can be performed either post or prior to averaging the signals.
Each processing method will have variations on the type and amount of noise removed, as well
as different sensitivities to shifts in load.

In his paper on integrated prognostics and health management in advanced aircraft, Watson
[Watson 2010] gives a description of one such TFDA algorithm. A time waveform contains P
equally sized blocks (B₁…Bₚ) and P×N samples, where each block of the time waveform
represents a period of sampled signal (or one complete rotation) with N samples. A wavelet
transform of the time waveform is then applied to generate wavelet coefficients (P×N by m) at
different scales (a₁…aₘ). Each column of this matrix represents the wavelet coefficients
corresponding to each block of the time waveform (e.g., V₁ to B₁). The next steps are to segment
the columns (V₁…Vₚ) of the wavelet coefficients, add up all of the segments, and then divide the
summed column by the number of columns (P). The resulting column represents the averaged
wavelet coefficients, and each row contains one complete rotation of samples (N) at different scales.

Using the features such as energy cumulant extracted from vibration data with this algorithm, Watson [Watson 2010] was able to detect broken teeth in a gear box despite induced torque oscillations, creating transient load conditions. Where the more traditional gearbox features become unstable during these oscillations, the TFDA extracted features do not. Watson was also applied this technique to various gas turbine propeller gearboxes and found that the RMS of the TFDA was able to detect fretting and corrosion on the rear planet carrier with a 98% probability through realistic load cycling and that the many features formed through this algorithm remain constant, independent of load or speed shifts.

2.1.6 Wavelet Analysis

Wavelet analysis is another form of monitoring, similar to time-frequency monitoring, but with the major advantages of allowing the use of long time intervals in areas needing more precise low-frequency information and shorter intervals where high-frequency information becomes important. Though the concepts are similar and similar information can be gleaned from both methods, it is more correct to call wavelet analysis a time-scale representation as opposed to a time-frequency one, as the coefficients in wavelet analysis do not directly relate to the traditional concept of frequency. Wavelet analysis reveals aspects of data often missed by other signal analysis techniques, such as certain trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Most pertinent to this research is that wavelet analysis can be used to capture subtle shifts in a signal around a more dominant transient mode without losing significant temporal information. This time scale decomposition is similar to a JTFS created via a STFT or the Gabor Transform, but seeks to overcome the trade off in resolution between time and frequency that commonly plagues those methods. A brief description of wavelets is presented next, for a more complete guide, see "Introduction to Wavelets and Wavelet Transforms: A Primer" by Burrus, Gopinath, and Guo.
The discrete wavelet transform (DWT) utilizes an algorithm of computation from successive low-pass and high-pass filtering of the discrete time-domain signal. Its significance is in the manner it connects the continuous-time multi-resolution discrete-time filters. In Figure 2, let \( X[n] \) denote the signal, where \( n \) is an integer, \( G_0 \) denote the low-pass filter, and \( H_0 \) denote the high-pass filter. At each level, the high pass filter produces detail information, \( d[n] \), while the low pass filter associated with scaling function produces coarse approximations, \( a[n] \). At each decomposition level, the half band filters produce signals spanning only half the frequency band, doubling the frequency resolution as the uncertainty in frequency is halved.

Some research has focused on the development of OLM systems of induction motor failures by analyzing the transient signals during start-up with a DWT. One paper focused on the implementation processing spectral frequency shifts in vibration startup signals with an embedded system of field programmable gate arrays (FPGAs) [Rodriguez-Donate 2008]. In order to detect this frequency shift, the authors decomposed the original signal with Daubechies 40 DWT to obtain the detail levels of interest. Next, the time-domain of each detail level was reconstructed with the Inverse DWT. By then calculating the variance of these pertinent decomposed modes, an estimate of motor health was obtained. Another application of the wavelet decomposition is fault detection in induction motors. Rotor bar breakages are associated with a left sideband harmonic created within the stator current.

A method has been developed to detect these rotor bar breakages through the study of an approximation signal resulting from the wavelet decomposition of the startup stator current [Riera-Guasp 2008]. Using a physics-based numerical model as comparison, a detailed description of the evolution of the left sideband harmonic during the startup transient is compared against the DWT to diagnose motor health.
Another paper highlights an algorithm that first finds a least squares fitting of a sinusoidal function with a variable phase angle, amplitude, and frequency of the inrush current signal, and then applies a DWT to the residuals between the fitted function and the inrush current [Douglas 2004]. This algorithm has the advantage of removing a modulated primary signal, which, assuming this is the fundamental mode of the startup transient leaves the remainder to account for the variations within the transient. After allowing for natural signal and processing noise, these variations should contain any available information related to the system health.

The methods listed above as well as others are integral to feature extraction and information processing to find degradation trends in a signal. This degradation information is integral to making prognostic estimates, as described in the following sections.

### 2.2 Equipment Prognostics

The ability to accurately and efficiently determine the RUL of a system can be invaluable when making maintenance and operation decisions, such as when to shut down a system or whether the operation can be altered to allow for successful mission completion. Prognostic models are traditionally created from an analysis of past failure and/or lifetime data and generally fall into two broad categories: physics of failure models and empirical models. Models based entirely on physics of failure without past observational data are possible, but these models are difficult to derive and become impossible for failure mechanisms that are not well understood.
Even in cases where no failures have been explicitly documented or observed, if system lifetime data exists, a prognostic methodology for RUL predictions may be implemented, by creating either a probabilistic, or simulated progression to a prescribed “failure point” (condition when equipment no longer performs within acceptable criteria).

Figure 3 exemplifies a typical hierarchy of reliability monitoring information and the degrees to which it can be utilized. The path of optimal utilization of data is highlighted with the larger arrows. Each progressively larger arrow represents further utilization of available information. Data collected from an individual or group of systems must first be monitored to determine the presence of any faults or anomalies.

Collecting data but not monitoring it is as useful as not taking data at all. Likewise, if detecting these faults and anomalies is all that is done, a complete picture of system health and reliability is not obtained. To better characterize the health of the system, these faults can be diagnosed and categorized, determining exactly what type of failure mode has occurred, the location of the failure mode, and, in some cases, the severity. This information can then be delivered to a prognostic routine, which in turn delivers a complete and accurate estimation of RUL.
Alternatively, the fault and anomaly information can be delivered directly into a prognostic algorithm without first classifying the type of fault. While this method is generally considered suboptimal and could provide less accurate results, it is a simpler method and is, upon occasion, all that is necessary, or even all that can be accomplished due to lack of information regarding the fundamental failure modes. The totality of this information can be used to form a complete picture of a system's overall condition and predict its future reliability. This knowledge is invaluable for answering questions dealing with future mission length and load, and maintenance scheduling. Based on this complete picture of system health, O&M decisions can be made to provide a potential means to prolong system life while compensating for the fault.

Traditional prognostic methodologies and algorithms can be classified into three primary categories, as shown in Figure 4 based on the current and historical data available for analysis [Hines 2010]. Type I, or reliability-based, prognostics are those routines built exclusively upon historical Time of Failure (TOF) data. These methods include distribution-fitting routines such as Weibull analysis, making use of both censored and uncensored TOF data [Weibull 1951]. Type II, or stressor-based, prognostic models use additional environmental stressor data such as operational load, operational temperatures, or other environmental conditions that are related to a component failure mode, in order to adjust the Type I failure distributions accordingly. These more sophisticated models types include the proportional hazards model, Markov chain models, shock models, and several methods of regression. Type II prognostics characterize the RUL of the average system under specific conditions, whereas Type I prognostics predict the RUL of the average system under average conditions. The most case-specific and accurate form of prognostics is Type III, or degradation-based, which characterizes an individual component’s response to its actual operating and environmental conditions. For Type III prognostics, data related to how the system is responding to the operating environment and how it is degrading is acquired and fused into a degradation parameter, a parameter that can be used as a measure of damage. This degradation parameter is then used to construct a degradation model, such as the general path model (GPM) [Lu 1993]. Models are built using past failure data from either a measured, inferred, or simulated degradation parameter. In the case of Type III prognostics, an accurate estimate of RUL can be obtained for an individual component.
2.2.1 Type I: Reliability Data Based Prognostics

Prognostic methodologies which fall within this category are used to estimate and model failure density functions. These models can be either parametric or non-parametric and are based on a monitored population of systems or components which have known running and/or failure times. Although known failure times for units are preferable, un-failed units can be treated as censored data and the known running time can still be used to provide useful information.

The typical methodology for developing a Type I prognostic model involves parametrically fitting a common probability distribution function to the collected set of failure times. This can then be translated into a probability of failure at any given query time. The simplest distribution to model is a constant failure rate, which is applicable to systems and components that are assumed to not degrade over time. Effectively they are subject only to random failures. Electronic systems are often treated this way. Models of this nature require only a single parameter and use an exponential functional form to describe the failure probability over time. While this simplistic model has many applications, often a more complex distribution is required to more accurately describe different failure distributions. Weibull distributions, alternatively, have two parameters, giving the large flexibility that makes this distribution one of the most common and preferable distributions used for failure analysis.
Equation 5 - Weibull Distribution

\[ \lambda(t) = \frac{\beta}{\theta} \left( \frac{t}{\theta} \right)^{\beta-1} \]

As can be inferred from the above equation and is shown in Figure 5 Weibull distributions can describe components exhibiting an increasing failure rate (\( B>1 \)), a constant failure rate (\( B=1 \)), and a decreasing failure rate (\( B<1 \)). The second parameter (\( \theta \)) describes the characteristic life of the distribution, giving the time when 63.2% of all units in a population have failed. With the proper choice of shape parameter (\( B \)), the Weibull distribution does a good job of modeling the exponential, normal, or Rayleigh distributions. Additional information on Weibull modeling can be found in a multitude of texts, such as the New Weibull Handbook [Abernethy 1996]. Unfortunately, there are many cases where the uncertainty associated with calculating the average lifetime of the average unit is unacceptable. The need for more accurate information leads to the incorporation of further information, such as environmental factors.

### 2.2.2 Type II: Stress Based Prognostics

Where Type I prognostics predict the failure distribution for an average component operating under average conditions, Type II prognostics are able to account for additional useful information about the operating condition or environment of the system in question.

![Figure 5 - Weibull Failure Distributions with Different Shape Parameters b](Hines 2008)
This can provide a more accurate estimate of RUL, assuming that units operating under more harsh conditions would be expected to fail more quickly than those units operating under milder conditions.

The most straightforward class of Type II prognostics uses an ordinary least squares regression model to predict failure time, as in the Figure 6. By using information such as component load, temperature or other working conditions in addition to the time to failure data, a multivariate regression can be performed to predict the expected failure time. In this model the slope is related to the stress caused by operating condition. Another approach to Type II prognostics uses multiple Type I models which account for different working conditions, or in special cases a single Type I model with a correction factor which accounts for stress based information.

A technique often used to combine failure data with stress data is the proportional hazards model (PHM) [Cox 1984]. This model uses stress data as covariates to modify a baseline hazard rate function.

Figure 6 - Linear Path Model Example [Hines 2009]
Equation 6 - Cox Proportional Hazards Model

\[ \lambda(t; z) = \lambda_0(t) \exp\left( \sum_{j=1}^{q} \beta_j z_j \right) \]

\( \lambda_0 = \) Baseline hazard rate \qquad \beta_j = \) Covariate weights \qquad \( z_j = \) Covariate parameters

The covariate parameters (\( B_j \)) are found using ordinary least squares regression against the stress based data. The basic assumption of the PHM is that the covariates (temperature, load, speed, etc.) are multiplicative, meaning that when the ratio of two historical cases is evaluated at some time, their hazard rates are proportional. The baseline hazard is the hazard rate when covariates have little or no influence on the failure rate.

2.2.3 Type III: Effects Based Prognostics

Type III, or effects based, prognostics result in an individualized prognostic model. They require and are able to utilize a myriad of information related to unit degradation and failure. Effects based prognostics model the degradation of a specific unit from fault to failure. The degradation parameter is either directly measured from the system, such as tread depth, or is derived from several measured parameters, such as tire pressure, operating temperature, etc. The degradation model can then be used to predict the RUL of that unit. Type III prognostic model development must also take into consideration the method by which degradation is accumulated. A common assumption is that made by a cumulative damage model [Ramakrishnan 2003], which assumes that all damage incurred remains until some external source actively repairs the system. One consequence of this assumption is the additional assumption that the degradation parameter cannot spontaneously move towards a less degraded state; that is, systems do not self-heal, and any indication of such is due strictly to measurement error. In other words, all damage incurred by a unit is cumulative and builds toward some threshold beyond which the unit will no longer meet its design specifications to some prescribed confidence. This assumption does not hold true in every case. Indeed, some systems, such as batteries given periods of rest, do experience a form of self-healing. However, this is a minority of cases and unless specific reason not to, the apparent ‘self healing’ is assumed to be an incomplete understanding /analysis or even incomplete information contained in the of the inferred degradation signal. Beyond this assumption of no self-healing, another common assumption is that of a common failure.
threshold. One source of both difficulty and uncertainty is the definition of this failure threshold. Systems rarely have a hard failure threshold which holds for each unit; more often there is an associated failure distribution which must be taken into account when estimating RUL and its uncertainty.

These assumptions may not strictly hold in every case, but are often made to simplify the degradation model and RUL estimation. Another difficulty, and perhaps the greatest obstacle associated with Type III prognostics, is obtaining the degradation parameter for the system. Often, obtaining this parameter is neither simple nor direct. Only in rare cases can an explicit degradation parameter be measured. More often the degradation incurred by a system must be inferred from one or more monitored system parameters. Identification of this degradation parameter requires engineering judgment, expert opinion, multivariate analysis or a first principle model. The degradation measure could be a function of several measured parameters which are used to infer a quantitative measure of degradation. For example, pipe wall thickness may be an appropriate degradation parameter but there may not be an unobtrusive method to directly measure it. However, there may be related measurable variables that can be used to predict the wall thickness, such as temperature, pressure, and flow rate. These related and measurable parameters can be used to predict the wall thickness and create estimates of RUL through prognostic modeling. Both the general path model and Markov chain based models are common methods used to predict such cumulative damage degradation pathways.

General path models (GPM) were first proposed by Lu and Meeker [Lu 1993] to predict future degradation as a function of time or duty cycles using measurable degradation data. Upadhyaya et al. [Upadhyaya 1994] used extrapolation of this degradation function for RUL estimation using both linear regression models and neural networks. The model complexity and number of parameters required to describe the relationships in the data vary greatly. Model parameters must be estimated from historical data or from high fidelity simulations of physics of failure models. By measuring the current degradation trend, an RUL estimate can be calculated extrapolating the current degradation parameter to the critical failure threshold.
Confidence intervals on RUL estimates and other uncertainty measures can also be calculated using traditional techniques [Usynin 2007].

Prognostic model parameter estimation is often updated during unit operation. As the unit is monitored and new information becomes available, it is often advantageous to incorporate this new information into the historical information database. As discussed in Carlin and Louis [Carlin 200], a common method for integrating prior population-based historical data with current individual data is Bayesian updating. As described in Figure 7, historical data is used to estimate the model parameter. As new data are collected, they are used to update the model fit resulting in a new posterior distribution of the model parameters. This posterior is then used as the new prior distribution for further updates. When new data are collected, they are used to update the parameter distribution again.

Another common modeling technique is the use of Markov chains and Markovian transition probabilities to predict damage pathways (Figure 8). The most common form of Markov chain prognostic modeling simulates possible degradation pathways using distributions which are discrete in both time and degradation. In other words, Markov chain based models are formulated as a probabilistic simulation of the degradation of the component. If the degradation is directly measurable or inferable, then the simulation is only performed as an extrapolation,
estimating the damage pathway from the current degradation measure to the failure threshold. This modeling technique uses historical degradation pathways to estimate the probability of incurring damage during a duty cycle, the magnitude of the damage incurred, and the critical failure threshold at which incurred damage results in component failure. Typically, each of these parameters is considered a discrete value, or a distribution of discrete values; however, fitted continuous distributions may also be easily substituted for both time and degradation, commonly known as a shock model [Esary 1973] [Mallor 2003] [Gut 1990]. Much like the GPM approach, Markov chain models can simulate cumulative damage pathways, but, unlike GPM, the probabilistic repair of damage can also easily be accounted for. This form of model is useful for modeling systems which may undergo self-healing, such as batteries experience during periods of rest. Markov chain and shock models are highly versatile and can be used in conjunction with Monte Carlo simulation techniques in order to simulate possible future damage pathways and, by extension, RUL estimates.

2.2.4 Combined Prognostic Model Types

Some prognostic model architectures can make use of a combination of historical failure data, environmental data, and effects based data. Often the modeling techniques discussed above can be used in conjunction with other techniques to improve performance. For example, a Markov Chain model can be based strictly on environmental information to construct a Type II prognostic model, or it can use this information in conjunction with effects based data to create a more accurate combined model.

![Figure 8 - Markov Chain Prognostic Model Example [Hines 2009]](image)
Prognostic information can be incorporated into a control algorithm. Explicit knowledge of the upcoming stress level need not be required; in fact, a correctly constructed model can be used in the operations decision making process. Given the current state of a component, the future life of this unit can be simulated under different stress level in order to find what work load will optimize the usage and lifetime of the unit. A highly degraded unit might not be expected to operate another full duty cycle under a high stress level, but under a lower level of stress, the unit may be expected to complete the duty cycle. The use of the prognostic information for intelligent reconfiguration of the system or for changing operational stresses is commonly called prognostics for control.

2.3 Survey of Potential Areas of Application for Transient Prognostics

Transient analysis is proposed as an enabling technology for improved accuracy of prognostic estimates. However, not all components and systems will benefit from such an analysis. Of the components which do experience operational transients, some would not benefit from transient analysis for several reasons: they may not experience increased stresses during transients, their transients may be too brief to glean any useful information, or the necessary transient data may be difficult or impossible to collect. In this research, key components of power plants were analyzed to determine the expected usefulness of transient monitoring. The following sections report the results of the review of power plants themselves, then several components and systems found within power plants. This selection of components and systems is by no means an all-encompassing list of structures and processes that can be affected by transients or dynamic processes; instead, it is merely a sampling of those expected to be most affected. The systems and components reviewed include in order:

- Nuclear and Other Power Plants:
- Coal Pulverizers
- Electric Circuit Cards
- Electric Motors
- High Voltage Transformers
• Motor Operated Valves
• Pumps and Related Systems
• Steam Turbine Generators

2.3.1 Nuclear and Other Power Plants

Transient monitoring in NPPs is crucial to early warnings and anomaly detections. Many systems within a power plant are affected by operational transients. According to one EPRI report, temperature differences in evaporators during initial startup between tubes are one of the top ten fatigue failure degradation modes [Dooley 2009]. Boilers are another example of a system that is affected this way, with fluctuating stresses such as temperature pressure transients causing increased degradation and damage [McQueen 2009]. Several approaches and benefits of periodic condition monitoring regimes have been suggested. One such program includes measures to monitor and detect a variety of information, such as metallic loose parts, rotating machinery faults, reactor upper block leakage, and possible coolant flow asymmetries in the reactor core, by using transient signals analysis on vibration and acoustic data and process noise signals of detectors [Kiss 2005]. The program is applicable to the reactor vessel and primary coolant systems in pressurized water reactors. The data collection sensors and monitoring computers from several stations within the plants, as well as several different plants, can all be evaluated from a centralized computer and software package by sending the information over Ethernet and/or internet lines. This lowers the number of employees needed to observe and maintain the online monitoring models. This centralized monitoring facility is responsible for the in depth analysis of the data, including more detailed and tuned event analysis based on Sequential Probability Ratio Testing (SPRT), spectrum estimation, and Auto Regressive (AR) modeling, allowing the expert to readily find the time block where anomalous events take place.

Crucial to any plant wide OLM system is the data collection process. Most current methods for OLM are based on the addition of sensors to existing systems and equipment. While this approach has been proven effective, some systems may actually benefit from the incorporation of the sensors directly into the development of the equipment itself. Some of the systems that have
been suggested would benefit from this smart component development are boiler feed pumps and the medium-voltage motor train [Rosen 2009].

One important development in plant wide OLM is the development of the on-line intelligent self-diagnostic monitoring system (SDMS). Using an array of integrated active and passive sensors, there has been work showing a proof of principle demonstration on a pilot plant service water system [Bond 2000]. Wireless radio frequency (RF) smart modules were designed and utilized in the test setup allowing for ease of communication, both locally at the sensor with an electronic display and remotely at a computer monitoring station, with minimal wiring. Not only did the setup include wireless sensors, but it also employed smart sensors that began the basic preprocessing of data before transmitting the information to be further processed at a computer workstation. This effectively gets data management down to the lowest possible level so that the processing is unaffected by a higher level system wide failure. This process loop was able to successfully demonstrate data collection for diagnostic and prognostic monitoring of nuclear components.

Such a complex system as that of a power plant would present unique issues in regards to the building of any transient operations prognostic model. While many systems within the plant undergo higher levels of stress during these times, any prognostic model that attempts to relate plant health as a whole might be less useful to operators than models tracking individual components or systems within the plant. Unless the transient operations prognostic model for a power plant is able to distinguish where and what is causing the registered anomaly, its value to operators is severely limited. Incorporating the results of component-level prognostic models into one measure of system health is a key area of future research; however, it necessitates that accurate component-level models are first available.

Some key systems that could potentially benefit from the addition on transient operations prognostic analysis are those that undergo rudimentary pass/fail startup testing, such as backup diesel generators. Transient prognostic modeling could reduce the number of these tests needed,
as well as provide more accurate information regarding these systems. Other similar emergency and high-risk equipment could also benefit, such as high pressure injection systems, main steam isolation systems etc.

2.3.2 Coal Pulverizers

A high value component found in coal-fired power plants is the coal pulverizer. OLM technology can provide real time information concerning the grinding elements operation and material condition of coal pulverizers. In fact, past work has shown that the addition of vibration sensors to traditional process signals can greatly improve the effectiveness of any OLM analysis of this equipment [Wolosewicz 2003]. Building on this, one form of OLM that has been shown effective in the preventive/predictive maintenance area of coal pulverizers is the "Roll Bowl COP "(RBC) technology [Santucci 2008]. Using non-intrusive, externally located instruments, the RBC technology allows for analysis and an in-depth engineering evaluation with minimal operations involvement. Each of the grinding rolls is equipped with a displacement transducer and an accelerometer. Additional accelerometers are integrated into the system and placed on the worm gear, vertical shaft thrust bearing, and outboard drive motor bearing. This is a total of 3 displacement transducers and 6 accelerometers on each pulverizer. RBC technology creates reports on system health using these instruments. These analyses can be cataloged and used for reference when prioritizing plant resources for maintenance.

While the data is commonly reviewed in both the frequency and time domains, the time domain is especially informative during the initial introduction of the coal to an empty pulverizer. During this transient, the relative position of respective journal traces provides indications of conditions in the journal assembly regarding poor equipment settings as well as indications such as wear or the spring constant. Time domain information is also invaluable at discovering short-term events such as such as tramp material or pluggage, which may require prompt attention to avoid consequential damage and maintain operations.

The analysis also examines the data in the frequency domain, primarily in the lower frequency spectrum (~40-600 cycles per minute (CPM)), which provides characteristics distinctive of the
bowl and each of the journal rolls. This allows for detection of such events as spalling of weld overlay, mechanical looseness, and relative roll diameters. Conversely, higher frequency can be used to detect faults like bearing degradation.

After accessing the data and analyses through the plant information (PI) system, data trending can be used to identify gradual degradation of bearings, early detection of roll weld overlay issues, abrupt changes in cyclic fatigue stress, and coal hardness variations. These RBC online capabilities allow plant engineering staff to be proactive, enabling maintenance on an as-needed basis, and to avoid pulverizer-related unscheduled derates.

Pulverizers experience much higher levels of stress during transient operations that could presumably lead to valuable monitorable indicators of system health, which could be used in the development of transient prognostic models. However, the scope and scale required for the data collection process and model development on these systems suggests this is a focus of large-scale future work.

2.3.3 Electric Circuit Cards

While circuit cards are quite prevalent throughout the industrial and civilian worlds, their primary modes of degradation are external variables that are very difficult to measure. Many reports point to external environmental factors such as vibration and external thermal cycling as the degradation accelerating factors [Bingham 2009]. There have even been extensive studies into methods for accelerated and validation testing of these cards through means such as the use of multi-directional “shakers” [Habtour 2010]. Prognostic routines have been developed to predict the physical weakening of solder joints due to these stressors [Oja 2007]. This is not to say that internal electrical load cannot affect the breakdown of these joints; in fact, some work indicates that transients such as powering up/down of the card can cause thermal stresses [Drake 2010]. Some circuits have even been shown to suffer from intermittent faults caused by manufacturing residuals, oxide degradation, process variations and crosstalk induced delays. These intermittent faults are activated and deactivated by voltage, frequency, and operating temperature variations [Constantinescu 2008]. One method of diagnostic monitoring shown to be
useful is the boundary scan, which, under computer control and without the aid of external testing equipment, allows an entire series of boards to be monitored to a desired degree. In several industries, prognostics algorithms are used to calculate the RUL of a printed circuit board (PCB), based on stressor service conditions to which the board is subjected [Butt 2009]. Some research indicates that electromagnetic interference (EMI) and radio frequency interference (RFI) are the most significant degradation and failure stressors in some digital systems with printed circuit cards and are used in a wide variety of environments [Messman 2006]. This would indicate that any internal workload transient would be unlikely to be the best source of early prognostic information for circuit cards and electrical processing equipment, except in the special cases where the external environment is carefully controlled to be nearly static, such as in a on-site server room. Using internal load shifts as the sole basis for prognostic modeling of circuit cards would in most cases give an incomplete set of information. Unless the circuit cards were also equipped with some device to monitor the external factors most likely to dominate the failure probability (i.e., accelerometers, thermocouples, etc.) or some other way to infer these factors, then any estimate made would have such uncertainty associated with it as to be effectively useless.

2.3.4 Electric Motors

Electric motors are used in a wide variety of industrial applications. Given this wide applicability, it is not surprising that there has been much work and effort dedicated to the monitoring and health prediction of electric motors. The University of Tennessee has performed work in the past on diagnostics and prognostics with induction motors [Erbay 1999]. Accelerated ageing testing was performed according to IEEE Standard-117 and UL 1446 [IEEE Std 117-1974/ANSI C50.32-1976]. During start-up and other severe transient operations, induction motors draw large amounts of current, produce voltage dips and oscillatory torques, and can generate harmonics in the power systems. Much work has been applied to developing methods for analyzing these transients. One suggested methodology suggests using dq axis based modeling (an arbitrary reference frame imposed on a rotor based on the relative positions of coils used to simplify modeling of an electric motor) in three different reference frames: stationary reference frame, rotor reference frame, and the synchronous reference frame [Pahwa 2009]. Another developed methodology consists of analyzing the stator current demanded by the
machine during the connection process (startup transient) [Antonino-Daviu 2009]. Due to the varying dependence on slip during a direct startup in many components, a Hilbert-Huang transform is able to extract and discriminate the characteristic transient evolution created by various faults such as rotor bar breakages and mixed eccentricities. The IMF of the HHT provides a reliable indicator of the presence of each fault by examining the appearance of characteristic waveforms during startup. Additionally this signal can be used to evaluate the severity of the fault, as this corresponds to higher amplitude and energy of the signal. This methodology has been shown to be quite useful in detecting and diagnosing electromechanical faults [Antonino-Daviu 2009].

Another algorithm specifically developed for the analysis of motor currents in induction machines operating during transients extracts the amplitude, phase and frequency of a single sinusoid embedded in a non-stationary waveform [Rai 2007]. An analysis of the residual current during startup processes using a wavelet-based approach is able to detect broken rotor bars without the need for parameters such as speed or number of rotor bars. In fact, the algorithm is not load dependant and thus would also make it suitable for motors that operate continuously in the transient mode, e.g., wind generators or motor-operated valves. This algorithm is able to detect faults that may be invisible or require a priori knowledge with more traditional approaches using the transient in-rush current.

It has also been shown that the monitoring of three axis vibration during a startup transient can detect broken rotor bars in induction motors [Rodriguez-Donate 2008]. Using low cost FPGAs to implement an embedded wavelet analysis allowed for rapid online monitoring and base level diagnostics to be performed autonomously at the sensor site. The results of this analysis can then be transmitted to a centralized processing unit for large scale decision making.

It has been suggested that mathematical models are mostly inadequate for predicting precise signal behavior during electric motor transients because of the nonlinear relationships that occur [Mugford 2006]. Knowing that the motor magnetic circuits operate at the knee of the curve (in
saturation), the hysteresis loop illustrates the nonlinear relationship between volts and amps. Mathematical analyses tend to assume linearity in order to simplify calculations; however, this is known to introduce errors in the analysis. With proper testing and data acquisition techniques, empirically based models may provide a much more accurate model with which to perform any analysis.

One effective form of such analysis is Motor Current Signature Analysis (MCSA). MCSA provides a non-intrusive method for detecting mechanical and electrical problems in motor driven rotating equipment. Since an electric motor driving a mechanical load acts as an efficient, continuously available transducer, it is able to sense mechanical load variations and convert them into electric current variations that are transmitted along the motor power cables. Monitoring and analysis of these current variations can provide an indication of machine condition, which may be trended over time to provide an early warning of machine deterioration or process alteration [IAEA-TECDoc-1551]. Another test similar to MCSA is electro-magnetic interference (EMI) analysis; this form of testing is correlated with PD events and is similar to other PD monitoring technologies for identifying changes in the activity [Leonard 2008].

Electric motors show great promise for the development of transient prognostic models. There are many well understood methods for monitoring these devices during transient operations, the results of which indicate that there is a greater level of stress during these times. Using MCSA as well as other techniques, such as acoustic and vibration monitoring, on a large sample set of test motors monitored through transient operations, can result in an accurate transient prognostic model.

2.3.5 High Voltage Transformers

High voltage transformers undergo strong transient conditions during a loading and discharge cycle. Typically monitored parameters on transformers and their components include such parameters as dissolved gases and moisture content in oil, partial discharge, and temperature, and other data such as load, operating events, and alarms. Two of the main modes of degradation for these devices involve localized ‘hot-spots’ within the device and partial discharge (PD) events,
both of which lead to the break down of insulation. The detection of PD is important in
determining the condition of transformers. Acoustical detection is not as sensitive as electrical
detection in factory settings but when used in-situ it has better sensitivity than electrical methods
and is sufficient to detect some PD sources in power transformers [Ward 2010]. During the
development of prognostic tools for transformers, some researchers discovered that sensors
would often provide anomalous readings and give indications of faults when there are none
[Ward 2010]. In order to better detect and diagnose true degradation events, there has been
research [Wang 2006] designed to develop an integrated fiber optic sensor system with
multiplexed PD sensors and temperature sensors for the on-line detection of electrical faults and
thermal faults at multiple points inside a high voltage transformer. In order to detect these two
major fault types, the integrated fiber optic sensor system can be divided into two sub-systems: a
multipoint temperature measurement sub-system using wavelength division multiplexed fiber
Bragg gratings (FBG), and a PD detection subsystem, using diaphragm-based extrinsic Fabry-
Perot interferometric fiber optic sensors. This sensor is small enough that it can be placed inside
the transformer where the acoustic waves from PD events are stronger, giving a more accurate
reading.

Other research has focused on the detection of winding deformation and insulation degradation
on energized power transformers. It was shown that online quantification of these values can be
accomplished through frequency response analysis [EPRI 1013929]. In addition a diagnostic
model built on a large database of load tap charger (LTC), dissolved gas analyses was developed.
This model utilized an online monitor capable of specifically detecting two key LTC gases.

Power quality and power disturbances have become an increasingly important factor throughout
electrical networks. Ferroresonance events are one of the disturbances that can occur on
distribution systems, causing quality and security problems. These phenomena appear after
transient disturbances (transient overvoltage, lightning overvoltage or temporary fault) or
switching operations (transformer energizing or fault clearing) [Valverde 2007]. Sustained high
overvoltages and overcurrents with maintained levels of current and voltage waveform distortion
produce extremely dangerous consequences. Even though the events themselves may be difficult
to predict, other related events such as partial discharges can help to identify a ferroresonant situation. The analysis methods are typically based on three different methods: spectral density, phase plane, and Poincaré map.

Operational prognostics could be applied to high voltage transformers. Past research indicates that the reliability of prognostic models can be greatly affected by the types and quality of sensors used in the transformer [Wang 2006], so the sensors must be chosen to be sensitive to the faults of interest. Most transformer monitoring currently focuses on post-event monitoring may provide some warning before catastrophic failure. Using the presence of the fault events to develop a model for RUL may be possible, but models giving warnings of impending events may be more difficult to develop. In other words, faults provide indications (such as gassing) of transformer degradation which may be used to predict RUL, but the prediction of the occurrence of faults is very difficult. Transformers are a collection of components of considerable complexity (fans, cores, oil, wire, etc.), and may be a fertile area for future research.

2.3.6 Motor Operated Valves

Motor operated valve (MOVs) operations can be classified as transient processes. The dynamic act of opening or closing the valve will periodically stress the system between the normally longer periods of inactivity. This situation demands specialized analysis techniques when performing any form of diagnostics or health monitoring on an MOV, because it does not operate under traditional steady-state conditions.

One evaluation method of motor control center (MCC)-based test data presented in the literature is called the motor torque periodic verification (MTPV) method [EPRI. 1013929]. This method begins with the development of baseline test data for a given MOV, which can be used as comparison as long as there are no significant changes to the setup. The initial baseline test is designed to obtain key parameters needed to establish the minimum and maximum MTPV limits. These factors include: MOV factor, a ratio of measured motor torque (above hotel load) to measured stem thrust; motor torque hotel load, the motor torque required to engage the actuator
gearing and stem nut without any load on the stem; and inertial thrust component, the additional stem thrust developed after control switch trip (CST) due to the inertia of moving parts. After determining the baseline parameters, these can be used to confirm that the setup and operation of an MOV is within acceptable limits as determined by the baseline test data. Periodic static performance testing is not intended to re-affirm the acceptance criteria, but simply the existence of an acceptable margin [IAEA-TECDOC-1551]. The measurement of supply current, supply voltage and switch actuation times at the MCC should be used to create meaningful measurement parameters.

Research indicates that motor current is not a sensitive indicator of motor torque due to the effect of bus voltage on motor current demand; in general bus voltage is inversely proportional to motor current [Hosler 2004]. This leads to higher bus voltages causing lower motor current for a given motor torque. During transient loading, motor current can actually decrease in response to increased motor torque output. Motor power measurement is a more robust indicator of motor torque output, as it is unaffected by changes in bus voltage. However, there are limitations since motor efficiency can also be affected by such changes, although to a lesser degree than motor current measurements. Motor current signature analysis (MCSA) is also employed by many utilities in monitoring MOVs by analyzing data in the frequency domain.

While diagnostic methods for MOVs have come a long way in development, the large level and sources of variability could make development of a generalized transient prognostic model difficult. This is not to say impossible, and in fact the development of such a technology could prove to be rather fruitful. Use of MCSA and other MCC monitoring techniques could possibly be used in the development of an operational transient prognostic model, but at least some up front ‘nominal’ data collection from the unit in question would most likely be required before any real confidence could be placed in the model’s RUL estimates. In other words, sources of variability due to different operational conditions may require models specifically designed for each individual valve.
2.3.7 Pumps & Related Systems

The data analysis leading to feature extraction for the centrifugal charging pump gearbox shows promise for future analysis of similar rotating machinery, such as the pump unit themselves. One particularly interesting approach is time synchronous averaging (TSA) [Lebold 2003]. This process divides data into segments equal to one shaft rotation then identifies the points corresponding to given locations along the axle and averages these corresponding points. In order to accommodate for variable speeds, which would create different numbers of data points during a single shaft rotation during the data collection process, either down-sampling or interpolation for the creation of additional points may be necessary. In this way, operational shifts in speed can be manipulated and compared against slightly different operational shifts or even steady state conditions by relating them back to the point on the shaft during its passage. Speed shifts that have different accelerations may still be compared to one another to look for anomalous readings in the shaft. In this fashion transients of different magnitude may be recorded and compared expanding the usefulness of transient monitoring be reducing the potential need for separate models to be made for each different load shift.

Data collection is crucial for degradation monitoring, but the exact level of degradation is not always directly measureable. Research from Pacific Northwest National Lab (PNNL) on condition-based operations and maintenance (CBO&M) focuses on trending the stressor characteristics to determine a precursive relationship that will allow a more accurate projection of the RUL [Jarrell SA-36771]. This research centered on development of models for the two most predominant mechanisms that result in centrifugal pump failure: cavitation and vibration. Data analysis from this work showed a clear correspondence between the motor position indication, the vibration response, and the dynamic force loading on the bearings. Another validation experiment utilized accelerometers to monitor pump cavitation and relate this to metal removal rate of the pump impeller. These, as well as other research, lead to the development of first principles based prognostic algorithms that allow for accurate predictions of RUL. One of the primary authors of this work obtained a patent based on the ideas of measuring and quantifying stressors that are responsible for the activation of degradation mechanisms in order to identify the degradation and failure of mechanical systems [Jarrell 2005].
For loose parts monitoring of main coolant pumps in nuclear power plants (NPPs), the most interesting effects can be typically found during the start-up period of the unit [Kiss 2005]. A program has been developed that includes measures to monitor and detect metallic loose parts by using transient signals analysis on acoustic data generated due to loose parts impact. The detection and monitoring system includes a set of 6 accelerometers installed in the vicinity of regions where loose parts impact is likely to occur. This is a clear indication that the main coolant pumps experience higher levels of stress during start up, giving further support to the hypothesis that prognostic algorithms focusing on transient operational conditions may be able to detect anomalies sooner than those that utilize only steady state data.

Other work has shown that, during the start phase of a new turbo compressor, repeated damage of the mechanical seal system occurred, indicating great potential for the application of transient prognostics for this type of fault [Lenz 2007]. Analysis showed high axial vibrations of the pinion shaft and also of the mechanical seal in the rotation frequency of the bull gear shaft, along with casing vibration in the horizontal direction, which, if properly monitored, could be used to detect or predict these types of failures. As these machines are somewhat analogous to pumping systems, this again provides a clear example that these types of equipment experience greater levels of stress and degradation during operational transients.

Vibration analyses can also be used to detect crack propagation in the rotary shaft. Using finite element modeling, the torsional natural frequencies of the pump can be identified a priori and suitable locations for optimal sensor placement can easily be identified [Trethewey 2006]. These analyses also lead to the development of a torsional vibration system monitoring method to identify any characteristic changes in the torsional vibration associated with a propagating crack. This method, which is near insensitive to changes in the pump rotor setup and condition (e.g., seals, oil film, and supports), can provide a robust measure of the shaft structural integrity. Tracking these torsional vibration features can lead to accurate diagnostic and prognostic modeling.
Many univariate algorithms can also be applied to the system signals. Techniques such as the sequential probability ratio test (SPRT) [Wald 1945] and autoregressive (AR) modeling have been used to successfully model shifts in vibration on reactor coolant pumps (RCPs) [Lu 2007]. Use of AR algorithms, along with feature extraction and analysis from the signals, allowed for accurate fault detection on archived plant data, discriminating process dynamics and transients from shifts due to faults and anomalies.

Both prognostics and transient monitoring on pump systems have developed to the point where combining the two is the next logical step. As mentioned above, much research suggests that these pump systems experience large levels of stress during operational transients, leading one to suspect that early indications of the onset of damage and degradation would be discernable from transient analysis. Pump systems appear to be an excellent candidate for research combining these transient monitoring analyses with state of the art prognostic routines.

2.3.8 Steam Turbine Generator System

Steam turbines are often subjugated to both system and process transients due to the overall change in plant load or demand. Traditional approaches to steam turbine condition assessment rely heavily on expert judgment, review of plant maintenance data, physical walk downs, and trended supervisory instrumentation. Online monitoring (OLM) can expand this capability by automatically processing significantly more sensor data. Unfortunately, many turbine components and systems are typically not sufficiently instrumented for use in a continuous OLM approach. Therefore, in order to maximize nuclear steam turbine availability, the focus should be placed on three primary subsystems: the mechanical hydraulic control system (MHC), the electrical hydraulic control system (EHC), and the overspeed protection system. By doing so, and incorporating a more inclusive OLM regimen, the system is expected to see a reduction in vibration-related problems, the need for inspections, and other valve-related problems.
There are examples of commercially available products which monitor and diagnose turbine systems during transient phases such as start up. One such system uses National Instruments-based commercially available software which to successfully monitor a 600 MW steam turbine for vibration analysis during start up [Weiss]. That work experimentally confirmed the system’s natural frequencies, identified shaft rubs and quantified their severity, and confirmed good alignment and consistent thermal growth. Information gathered with this technology allowed the contractor to safely complete start-up tests and ultimately deliver base-load power to the grid.

Another commercially available product is a suite of intelligent software tools integrated with a diagnostic monitoring platform developed as a team effort by EPRI, Impact Technologies, Boyce Engineering, and Progress Energy [Angello 2005]. This software-based diagnostic system can monitor the health of a combustion turbine in real time and provide valuable information on the machine’s performance to its owner/operators. The *Combustion Turbine Health Management System* interprets data from existing monitoring instrumentation to assess the “total health” of combustion turbines. Included in the diagnostic monitoring platform is a start-up diagnostics model that focuses exclusively on monitoring the system during this transient phase.

Another proposed and tested OLM scheme opted for data driven model development as the basis for monitoring steam turbine health [EPRI – 1004963]. The data driven model relies on obtaining past operational data; in order to maintain a high applicability of the model, this historical data should be updated at regular intervals throughout the life of the turbine generator. Using the results derived from this model, another diagnostic model can then be constructed based on an expert rules-based system, which must be largely user defined. The complex nature of these models and the desire to keep them updated would greatly benefit from the assignment of an asset manager whose sole job is to maintain and oversee these models. However, due to the data transmission capabilities, a single manager would be able to oversee the OLM for several plants from a centralized location and from there delegate physical inspections or maintenance as needed. The model development should include identification of correlated signals which can be used as mutual references to check each other. Table 1 lists some potential signals that may be useful for fault detection and prognostics.
Table 1 - Possible Sensor Selection for Condition Monitoring of Turbine Generators [EPRI – 1004963]

<table>
<thead>
<tr>
<th>Sensor Description</th>
<th>Used To Indicate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross generation</td>
<td>Load level of turbine</td>
</tr>
<tr>
<td>Turbine first stage pressure</td>
<td>Load level of turbine</td>
</tr>
<tr>
<td>Turbine bearing oil drain temperature (bearings 1–6)</td>
<td>Damaged/wiped bearing</td>
</tr>
<tr>
<td>Turbine bearing metal temperature (bearings 1–6)</td>
<td>Damaged/wiped bearing</td>
</tr>
<tr>
<td>Turbine bearing vibration (bearings 1–6)</td>
<td>Seal rubbing or balance problem</td>
</tr>
<tr>
<td>Turbine thrust bearing drain oil temperature (front and rear bearings)</td>
<td>Damaged bearing</td>
</tr>
<tr>
<td>Turbine thrust bearing metal temperature (front and rear bearings)</td>
<td>Damaged bearing</td>
</tr>
<tr>
<td>Turbine oil from cooler temperature</td>
<td>Inadequate cooling-fouled heat exchanger</td>
</tr>
</tbody>
</table>

Another signal that has been proven useful to monitor is the shaft voltage-current; this has been useful in revealing shorted stator laminations [EPRI – 1004963]. Once the sensors have been selected for monitoring based on availability and correlations between signals, a sufficiently large bank of historical data needs to be collected in order to form any data driven models. The author is unspecific as to what form of data driven technique is best suited for turbine generator monitoring, but he appears to be setting a small windowed linear regression type model and checking for a nominal upper and lower limit on the statistical deviations from this range based on the historical observations. These limits can be highly sensitive to a few “bad” data points. Verifying the quality of the data and checking for outliers is of paramount importance before accepting any model developed based purely on data driven techniques [NUREG/CR-6895].

Power plant steam turbines could greatly benefit from the development of transient prognostic model development. There is a wealth of signals and stressors that can be monitored, and greater stress is induced during some operational transients. The difficulty in this line of research arises from the fact that along with the wealth of sensors, there are a multitude of fault modes adding to the complexity of the problem. The data collection and model development time would be extensive, but this would be a potentially strong area of future research.
2.4 Summary

A sample of the sophisticated transient analysis techniques currently in use within various areas of signal analysis and modeling are reviewed and presented in this section. Other more classical statistical methods are often inadequate to fully develop an analysis of a non-stationary, or transient signal. These classical statistics such as mean, standard deviation, kurtosis, etc. may still provide valuable information about a signal and should not be completely discounted. But due to nature of these statistics and their assumption of stationary signals, they often work best when coupled with some of the more sophisticated feature extraction techniques.

The basic ideas of prognostic analysis and techniques for making predictions of RUL are also reviewed. By utilizing a quantifiable and trendable parameter that can be related back to the system health or degradation within equipment, extrapolation models can be used to make predictions of RUL. These parameters may present themselves directly from the data, or more often must be extracted using sophisticated algorithms or modeling techniques. Other, more general and often less accurate techniques for RUL estimation rely on simple run time and failure time distributions. These distributions can also be modified with environmental or workload information to help modify the distribution, making their predictions more accurate.

Presented is an analysis of the applicability of transient prognostics to various key components in power plants. Several identified active components could potentially benefit from the application of transient prognostics systems, including electric motors, pumps, steam generators, and coal pulverizers. Two of these components lend themselves to small-scale experimentation and degradation testing: electric motors and pumps. These two components are suggested as candidates for the focus of future work in developing transient prognostic methods.
3 Methodology

3.1 Failure Modes and Stressors Effected by Transients

Both electric motors and impeller driven pumps can be considered as types of rotating machinery. Much work has gone into the understanding of these types of equipment, and many failure modes have been shown to overlap different systems. This turns out to be especially true with regards to electric motors and impeller pumps, as many of the pumps are actually driven by electric motors. The remainder of this section will focus on this type of pumps, as well as separate electric motors. Except where explicitly noted, failure modes (if not the actual percentages) of electric motors and expected stressors from electric motors are also relevant to electric motor driven impeller pumps.

3.1.1 Electric Motor Failure Modes

IEEE lists that bearing failures are the primary cause of failure in electric motors, with 41% of failures [Culbert 2000]. Often bearing failures have been known to contribute to collateral damage such as stator and or rotor rub, seal wear, or shaft damage. Stator and rotor failures are the next most dominate, with 36% and 9% respectively; all other failure modes account for only 14% of total failures in the system. Each of these may have any number of independent failure modes leading the component towards failure. Figure 9 below shows a detailed breakdown of these failure modes. Faults of a mechanical, thermal, or electrical nature are the typical causes of bearing failures in descending order according to an IEEE study. According to EPRI’s PM Basis Database, inadequate lubrication, soft foot, misalignment, excessive loading, and other environmental or operational conditions such as temperature or debris precipitate mechanical bearing failures. Excessive vibration, heat, and friction are the common factors in all these degradation influences.
The traditional means of discovering these mechanical failures, short of manual inspection, all revolve around either an online thermographic or vibration analysis. Data analysis from work performed by Jarrell showed that there is a clear correspondence between the motor position indication, the vibration response, and the dynamic force loading on the bearings [Jarrell SA-36771].

Load shifts, and especially startup transients may exacerbate fault related vibration features. Although vibration levels may be expected to increase during transients, it is unlikely that transients will cause increased signatures that would provide earlier detection than current steady state analysis. Bearing faults have been studied to a great degree and have specifically had much research dedicated to their steady state detection. Steady state analysis such as provided by FFTs is fairly simple to implement while transient analysis techniques utilize advanced signal processing strategies that are much more complex. It is unlikely that transient analysis will provide significant advantages in bearing fault detection; however, formal comparisons between steady state and transient techniques have not been made.
Rotor failures account for significant percentage of motor failure, albeit not the most common cause. Poor casting, such as a blowhole or porosity in the aluminum, is a possible cause of rotor-winding defects. However, more pertinent to this research is the fact that according to an EPRI report [Culbert 2000] rotors can also be damaged by excessive starts without allowing time for the rotor to cool between start attempts. Excessive starting and motor overloading can cause rotor bar cracking and/or warping of rotor components. In addition to the vibration and thermographic analysis which were discussed above, one of the more common ways to detect rotor degradation is through Motor Current Analysis. Again, this is a currently utilized online monitoring technique that would be ideal for a pilot transient prognostics application and may be couples with vibration analysis.

Stator failures can have several underlying causes: some from manufacturing defects, others from general wear and degradation, but ultimately most of them evolve through the movement of the wires, high temperatures, and the erosion of insulation. Most stator windings are sensitive to high temperature, such that for every 10°C increase in operating temperature above rated temperature, the winding life is halved [Culbert 2000]. While there can arise conditions where the stator temperature can be raised above that for which it is rated, such as environmental conditions, excessive workload, improper ventilation, etc., this is not typically a condition that is planned to occur. None the less, it is important to note because monitoring of the stator temperature can give an early indication of any incipient anomalies. Vibration also degrades the wiring as it accelerates rubbing and movement between the wires. Another accelerator is the magnetic forces created during startup when commonly ~6x steady-state current flows through the coils. These magnetic forces try to push the coils apart and the differential motion can cause rubbing between conductors that will contribute to eventual winding failure. Like the failures mentioned above, stator failures typically rely on vibration and motor current analysis for detection. Some research also looks at electromagnetic field analysis [Balamurugan 2004] for the analysis of stator failures.

The known relationship between multiple degradation mechanisms and motor startup give credibility to the postulate that transient monitoring may provide earlier, more accurate
predictions of remaining useful life when used in conjunction with advanced signal processing and properly constructed prognostic models. Utilizing vibration and motor current monitoring, both of which can be continuously monitored in many industrial settings, a model could be developed to monitor for all three of the major failure types seen in induction motors. This information could be supplemented with thermographic and or electromagnetic field information, but as these are less frequently utilized in an online monitoring situation, it is unlikely that existing data containing these signals would be easily found. Therefore, these should not be the focus of any pilot applications.

Electric Motor startup analysis has several advantages over steady state monitoring. First is the identification of a spectral component, which is present when the rotor bars become broken within the motor. Antonino-Daviu’s paper and several others mentioned above agree that these spectral locations are determined by the supply frequency, and the slip. During steady state conditions, the slip is small, making the frequency of the broken rotor bar very near that of the supply frequency. This makes them difficult to detect. Conversely, during a startup transient the slip will cycle down from its maximum value before arriving at its steady state value. Thus as the slip is at its maximum, the distance between the broken bar frequency and the supply frequency will also be at a maximum, making it easier to detect. In addition, magnitudes of startup transients have the useful quality of being independent of load. Load only affects the time required for a startup transient, implying that fault detection analysis can be performed equally well at low loads and heavy loads, unlike steady state analysis.

3.1.2 Pump Failure Modes
Many failures found to occur in pumps are those common to any piece of rotating machinery. Particularly, electric motor driven pumps will have failures overlapping those mentioned in the section above, and so will not be repeated here. In fact nearly all of the failures that would typically be monitored for, in an online fashion, could utilize the same techniques of vibration, motor current, and thermographic analysis described above. Some of the more common pump problems that may be found this way include pump cavitation, misalignment issues, and out of balance issues. Vibration or acoustic monitoring are often used for monitoring these types of faults and are ideally suited for the development of pilot applications for this project. Losing
suction and output head issues are traditionally discovered through pressure or flow monitoring. Again pressure monitoring can be performed in an online method. Startup transients are known as a highly stressful time for a pump from both a water pressure and priming standpoint, which can be detected through vibration and acoustic emission signatures. This makes pumps ideal for testing transient prognostic applications. There are other failures that can arise in a pump systems related to loss of suction, improper fluid or system setup, and while these are sometimes detectable from these signals, this study will largely ignore these types of failures for simplicity.

3.2 Generic Algorithm for Prognostic Extraction and Utilization of Information from Transient Signals

Many of the traditional methods and algorithms for the analysis of transient signals, such as those discussed above, are particularly suited for a specific type of signal or application. In general it is best not to rule out any possible means of analysis without specific reason to do so. The basic process of sorting through and gauging the usefulness of data signals for prognostic purposes is shown here. A more detailed example, which follows a case study, is provided in the next chapter.

A good basic outline for the analysis of any signal, transient or otherwise, with the explicit goal of prognostic parameter generation starts with the most basic of steps: look at the data. Visually inspect all signals within the data, and look for any obvious trends that may occur. To aid in this process, look at some basic features of the signals as they evolve through the life of the historical cases. Some of the more telling features include simple calculations such as the first four statistical moments (mean, standard deviation, skewness, and kurtosis), amplitude or power of the signals, or even something as mundane as the maximum and minimum of the signal. While at this point such prognostic metrics as those described in the previous section can be applied to help clarify and validate findings, what is more important at this step is the identification of clear evolutions through signals. This shows the potential for pertinent health related information within that signal. Further combination, manipulation, and feature extraction of additional signals later on will help to improve prognostic parameter performance prior to any General Path Model (GPM) development.
Another simple and powerful tool, particularly in the case of oscillatory signals, is the Fourier transform. This method, coupled with the Gabor Transform, can be used to identify evolutionary frequency shifts that can provide more or better health and degradation information about a system even when the more basic statistics described above may not. Unfortunately when using frequency analysis, it is not always easy to discover and isolate the minute changes that may be significant but over shadowed by less important but more constant frequencies. This is doubly true for Joint Time Frequency Spectra (JTFS) because the pertinent change may need to not only be located in frequency, but in time as well. Physics models of the system can help to overcome this by providing a guide to the expected dominate degradation modes. When this type of physics model, or related information is not available however, the use of the Hilbert Huang Transform (HHT) can serve to help identify this same type of information.

The HHT excels at highlighting the instantaneous dominant frequencies of a signal at any given point in time. By examining the multiple layers of Intrinsic Mode Functions (IMFs) and the instantaneous frequency of each, subtle frequency shifts which may evolve over time stand out, both in time and frequency over larger more dominate frequencies. These can be used is the form of the HHT, or as a guide to go back and reevaluated the simpler to calculate JTFS. Not only can the HHT provide frequency information, but information regarding power and amplitude as well. Though the HHT is typically computationally costly to calculate, the information it provides can be invaluable in the prognostic analysis, either from direct use or as a guide to identifying more simple trackable features.

A more generically applicable form of feature extraction is discussed and developed in the following section. The Sharp Transform expands a single, or multiple signals into a non-uniform, empirically determined bin space, or cross density space. This higher dimensional space can effectively be used to implicitly capture and subsequently extract changes in the overall distribution of a function. These include, but are not limited to shits in mean, variance, or even gross scale frequency shifts. Using the generic method developed in the next section, extraction and quantification of deviations within a transient signal becomes a trivial task. These extracted residuals or features can then be directly utilized with subsequent steps of prognostic modeling.
After suitable features have been identified, the next step is to manipulate and combine these features into a single prognostic parameter. This can include filtering, and averaging of the signals together to help suppress inconsistencies in the information. One method of finding the optimal combination of the found parameters is to use genetic algorithms to maximize the pertinent prognostic metrics as described by Coble [Coble 2011]. When the optimal prognostic parameter for the given case has been found, it becomes an intuitive task to then translate that into a working GPM type prognostic model as described in earlier sections.

3.3 Developed of Methods: Generic Transient Monitoring Techniques

The major drawback to all the previously discussed methods of transient signal analysis is the lack of widespread instant applicability. In other words, most techniques do not generalize across different systems or equipment without some additional knowledge and research into understanding the system. For example, although the Hilbert Huang Transform is highly adaptive and able to pick out subtle features in a given signal, there is no assurance in which level, and at what point in the decomposition an important feature will surface. With understanding of a system, one may infer, or expect to find features of interest at certain points, but these points will change between systems. What this research seeks to provide and examine broadly generic processes for modeling and monitoring transient signals with the explicit goal of extracting a useable prognostic parameter.

Two such algorithms for generic feature extraction are detailed in the sections below. The Sharp Transform (TS) developed in this work provides a novel method for expanding single or multiple signals into a non-uniform matrix space, or a similar cross-pattern. Similarly, by adding a temporal dependence to the traditional kernel regression, predictions of an evolving signal can be quantified based on a historical memory matrix and used to create a prognostic parameter. Both of these algorithms can then create residuals based on the expected output that are then transferable to further prognostic algorithms. These residual errors calculated can be used individually as prognostic parameters, or combined using genetic algorithms to create a more suitable GPM prognostic parameter [Coble 2011].
3.3.1 The Sharp Transform: Time Distribution Mapping

One generically applicable algorithm for the monitoring of transients developed during this research is known as Sharp Time Distribution Mapping (STDM) or the Sharp Transform (ST). The Sharp Transform is a dimensional expansion into non-uniform, empirically based, temporally dependent signal or cross signal density space. In less rigorous terms, this algorithm refers to taking successive measures of the empirical distribution of a signal throughout time and storing them in a serial temporally ordered fashion, thus creating a map of how the distribution of a signal evolves through time. Detailed below is the algorithm for developing models based on a series of single variable processing for STDM, but there is no reason that cross signal interactions could not also utilize this exact same algorithm, and cross density mapping. Unfortunately, adding cross signal mapping, and especially cross mappings of greater than two signals, becomes cumbersome to visualize, so for the illustration purposes of this document, it will be left out.

An empirical measure of a signal’s distribution over any given interval can easily be calculated by taking a simple histogram of the signal over that window. In order to become a true probability distribution, scaling based on the window size must be enforced, but as will be shown later, provided the window size remains unaltered, this scaling becomes unnecessary. All necessary processing can be accomplished with the un-scaled discrete distribution provided by the histogram. Unfortunately, the full complexities of a transient signal cannot be expressed with a single distribution.

![Example Transient Signal](image)

Figure 10 - Oscillatory Transient Signal
Consider the transient signal in Figure 10: this oscillatory signal exhibits many shifts in amplitude and variance over the observed span. If one were to perform standard a series of tests on this data one could estimate that it has a mean of -0.028, a standard deviation of 0.059 and upper and lower limits at 0.081 and -0.288 respectively. While most of this can be seen or estimated from a typical histogram, shown in Figure 11, none of this captures any of the highly temporal aspects of this signal.

However, if one were to take successive histograms of the signal through time and over smaller windows these temporal aspects are easily captured. Shown in Figure 12 is a series of histograms, each with ten bins with varying bin locations based on the amplitude of the signal over twenty observation windows. The selection of the number of bins as well as the window size is case dependent, but in general a window size of greater than twice the number of bins is desirable and can also be set as function of percentage of the lengths of the transient.

This ST map is able to capture both implicitly and explicitly many aspects of the signal as they evolve through time. Aspects regarding the mean, variance, and skewness as they evolve in time are all embedded within this ST map. Even gross changes in frequency are implicitly captured in the displayed information of this map.
That is not to say that by looking at this map a non-dominate frequency shift of five Hertz in one of the upper peaks would be observable in this figure, but a frequency shift significant enough to change the distribution on the scale of the observable window could be detected. In fact, the most obvious, simplest, and yet most all encompassing statement that can be made is that any alterations in the localized distributions through time are captured with this method. It is this ability to implicitly monitor multiple aspects or implied features of the signal at once that sets it apart and increases the general applicability from traditional techniques such as the Gabor Transform of windowed statistical moment monitoring.

Once the concept of STDM has been established, it is next important to explain how these can be used to develop prognostic parameters to be used in the creation of Remaining Useful Life (RUL) estimations. The first information required is multiple “good” or nominal transients recorded from the equipment. Between three and ten of these exemplars make a good base for developing the ideal reference case. Development of this reference ST map does assume that the transients in question exhibit similar behavior. If they do not, then multiple reference ST maps should be developed for each category or pattern of transient. For example, load shifts from half to full load may not be the same as those from one quarter to full load, but all startups from zero to full load may be expected to look the same. In fact, in order to shift between continuous environmental or state conditions, provided a representative series of transients has been collected, a weighted combination of these transients can be used to create a suitable ST map using a nearest neighbor method such as kernel regression.
After the nominal transients are collected and appropriately grouped, they need to be divided into equally spaced segment based on the chosen window size. The selection of both the number of bins and the window size is highly dependent on the observed length of the transient, the sample rate, and the level of detail desired versus the robustness of the distributions. While it is intuitive that greater number of bins provides greater detail in the map itself, greater numbers of bins also require larger windows to develop full distributions, losing some of the time resolution of the map. In practice segmenting the transient signal into between approximately 30 and 100 windows and choosing a bin number about one tenth the window size seems to produce reliable results. Of course this is dependent on the available data and can be tailored to suit any needs. Also, in this discussion the windows are treated as discrete and wholly separate from each other, there is no reason that the windows could not overlap or even “scroll”, over each observation in time. It is simply ignored for this discussion to simplify both computations and explanations.

Once the window size and number of bins has been determined a “master” bin map can be created. The maximum and minimum values inside each window observed over all the exemplar cases define the range of the bins for that time window. Unless there is special reason not to, the bin edges can then easily be defined as linearly spaced points between these ranges. This master bin map will now be the bin edges that will be used to make all the ST maps used from this point forward. ST maps of each of the exemplar cases based on these bin locations will then be averaged together to create the reference ST map. With this reference ST map, and the master bin map, it is possible to create progressive ST maps throughout the lifetime of the equipment, which can then be compared to create a measure of change that is relatable to degradation. By monitoring the summed square of the residuals between any given ST map and the reference STDM, a quantitative value that can be related to the overall health of the system based on that signal can be made. This value and its progression through time are then directly usable as a prognostic parameter in models for estimating RUL.

It is possible for the prognostic parameter developed by this method to saturate if a signal experiences a mean shift greater than the span of the reference ST map, but this is easily overcome by simply developing a new reference ST and master bin map based on these new
levels of degradation. In order to compare separate units, the residuals from the reference ST may need to be scaled by the residuals associated with the exemplar cases used to create it, but this is a trivial task and should not impair the results of the analysis.

This generic idea of mapping the progressive aspects of a signal over time through windowing and comparing them to a reference signal is the most widely applicable method of monitoring transients for degradation. Similar mappings of Joint Time Frequency Spectra (JTFS) or similar statistical evolutions can also use this methodology. ST mapping is presented as the best generic test that with the broadest number of implicit anomaly detections possible. This is not to say it is the best for a given application, but it will be applicable in most cases. Case studies of the development and use of this STDM modeling technique are provided in subsequent sections.

3.3.2 Temporally Dependent Kernel Regression

Kernel Regression (KR) is a non-parametric, non-linear universal function approximator that has been well established as useful for a large variety of application. First proposed in 1964, KR is a modeling technique which estimates a response parameter value by comparing a query vector to a matrix of historical input memory vectors with then taking a weighted average of the corresponding output vectors [Nadaraya 1964]. Typically this comparison is done with a traditional Euclidian distance, but other distance metrics can be equally valid for a given application. Using a kernel operator, typically Gaussian, the distance metric is translated into a normalized kernel weighting based on the equation below.

\[ W_i = \frac{K(d_i, h)}{\sum_{i=1}^{N} K(d_i, h)} = \frac{\exp\left(-\frac{d_i^2}{h^2}\right)}{\sum_{i=1}^{N} \exp\left(-\frac{d_i^2}{h^2}\right)} \]

Note that in this equation, the kernel operator, K, is described as a Gaussian kernel with bandwidth h. From this we can see how an individual kernel weight, \( W_i \), is equal to a corresponding distance metric, \( d_i \), passed through the kernel operator normalized by the sum of all distance metrics passed through the same kernel operator. By this method the weights are
insured to have a sum one, which is crucial for creating the weighted output estimate. This estimate is created using the simple equation,

\[ \hat{Y}_{est} = \hat{W}^T \hat{Y} \]

where the product of the transposed vector of kernel weights, \( W \), and \( Y \), the historical output memory vectors creates a model output \( Y_{est} \).

Though powerful and versatile as this memory-based algorithm is, one major shortcoming is the complete lack of any temporal information. In that respect KR can be thought of as similar to a Markovian process, only the current query vector has any effect on the model. Any information in points leading to the current vector is ignored. For many applications this is not only acceptable, it is in fact actually preferred. However, especially when dealing with transient signals in which the leading information directly affects the ranges and effects of the next points, this is not the case. Thus it is a natural extension to add some form of temporal dependence to the basic KR model.

There are possibly an infinite number of processes and algorithms to incorporate temporally dependant information into the traditional KR model, what is described below is but one method which focuses on transient signals of a known finite length which would be expected to behave in regular fashion. Given this, instead of incorporating information from previous input vectors into the model inputs via derivatives, averages, or direct insertion, a new “time” input is created which represents the point within the finite transient the current query vector is located (ex. 5 seconds from initiation). This new vector, as detailed below, forms the basis for adaptively updating and weighting the basic input and output memory matrices to incorporate only information close to the relative position of the query vector. In this way we allow for accurate, temporally dependant output estimations to be produced.

For a finite length transient (single or multiple input signals), the time vector \( T \) can be thought of as having regular increments and representing the percent completion of the transient. Though
the scale of $T$ is not incredibly important, it will be the basis for the rest of the process, so unless you have explicit reason to do so, it is important not to change the scale after it has been established. In other words, if the transient in question is known to have varying length of time but otherwise exhibits similar characteristics, it may be valid to scale each query vector $T$ to be between 0 and 100 percent. Conversely, if each transient is expected to have similar length, it may be better to scale $T$ according to the data sample rate (i.e. 0, 0.051, 0.102, …). As mentioned, regardless of which is chosen, it is important to remain consistent in both model creation and use.

After establishing the time vector $T$, the next step is to create a window of time weightings. The first step in creating this window is to pass $T$ through a kernel operator similar to the distance metric in traditional KR. In order to restrict the timeframe the KR will look at, a lower limit can be set for the time window, and all values below this limit set to zero. In practice, this can also be used to limit the number of memory vectors that a query will look at, thus speeding up computations. After enacting this limit, the time weighting window must be renormalized to one.

Beyond this, temporal KR is identical to traditional KR with the exception that the time weighting window must be first applied to the distance based kernel weights. This gives the basic KR equation the form shown below.

\begin{equation}
\hat{Y}_{est} = \left( \frac{W_k + W_T}{2} \right)^T \bar{Y}
\end{equation}

In this equation, $W_k$ represents the distance based kernel weights, and $W_t$ represents the time based window weights. This added time vector allows for the traditional KR algorithm to be quickly and easily adapted for use with highly time dependent signals.

4 Proof of Concept Experiments

Though many of the techniques and algorithms presented above have been established as useful tools for the analysis of transient signals, their use and application directly towards prognostic
modeling is still in the infantile stage. The following sections provides two separate proof on concept experiments that solidify the hypothesis that not only are these techniques valid in processing transients with the goal of prognostic modeling, but that transients in general are valid and reliable sources of degradation and system health information. These experiments also seek to compare and validate some of the novel techniques for transient analysis presented in this paper, such as the Sharp Transform (ST).

4.1 Previously Performed Accelerated Motor Degradation Experiment

In 1997 a research team lead by Dr. Bell Upadhyaya performed an accelerated aging study of induction motors [Upadhyaya 1997]. Though originally intended for steady state analysis, the data collected during this research contains information in both steady state and transient conditions, which makes it ideal for use in this work. This accelerated aging data contains sensor readings for nine 5-horsepower (HP) motors.

4.1.1 Experimental Setup

The research performed under Upadhyaya at the University of Tennessee used 5-HP, three phase, 220 volt squirrel cage motors. These 1800-RPM motors were supplied by the U.S. Electrical Motors Division of Emerson Electric Company to be used as subjects for the accelerated aging experiment. Each motor was rated as 15 amps max inrush current and 12 amps continuous running.

<table>
<thead>
<tr>
<th>Motor Numbers</th>
<th>Test Performed</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1 - M3</td>
<td>Insulation Aging</td>
</tr>
<tr>
<td>M4 – M6</td>
<td>Thermal Bearing Aging</td>
</tr>
<tr>
<td>M7 – M9</td>
<td>Bearing Fluting</td>
</tr>
</tbody>
</table>

Each motor was subjected to one of three forms of accelerated aging: on-off testing and high temperatures to produce stator insulation aging, heating and quenching to induce both bearing corrosion and thermal aging, and produce bearing fluting through induced current. Three motors
were subjected to each form of aging. This form of testing has become the accepted standard developed in “IEEE P117 Standard Test Procedure for Evaluation of Systems of Insulation Materials for Random-Wound AC Electric Machinery” and “Standards for System of Insulation Materials”. As indicated in Table 2 - List of Motor Aging Tests, motors 1-3 received insulation aging, motors 4-6 received thermal bearing aging, and the final three, motors numbered 7-9, were subjected to the current induced bearing fluting.

The collected signals from each motor during the startup transient include the 3 phases of both voltage and current, the speed, the torque, and various vibration signals. In order, the sixteen collected signals pertinent to this research are:

1) Voltage $xy$ (Volts)
2) Current $x$ (Amperes)
3) Voltage $yz$ (Volts)
4) Current $y$ (Amperes)
5) Voltage $zx$ (Volts)
6) Current $z$ (Amperes)
7) Voltage $\text{load}$ (Volts)
8) Current $\text{load}$ (Amperes)
9) Speed (RPM)
10) Torque (Lb-ft)
11) Cover Vibration (g)
12) Short End Axial Vibration (g)
13) Short End Horizontal Vibration (g)
14) Short End Vertical Vibration (g)
15) Pulley End 45 Degrees Left of Vertical Vibration (g)
16) Pulley End 45 Degrees Right of Vertical Vibration (g)
In this list the subscripts x, y, and z denote the three electrical phases respectively, while the subscript 'load' indicates that the signal comes from the loading dynamometer. The high frequency data was collected for 10 seconds at 12 kHz during each startup. Other signals relating to temperature and some low frequency data were also collected, but these were ignored during this research, as they were not sensitive enough to show startup transient effects. Unfortunately, many of the vibration signals also had to be ignored due to the fact that the startup vibration exhibited greater force than the DAQ setup could handle. This resulted in the signal saturation or value clipping as shown in Error! Reference source not found.. Readjusting the gain or sensor span could fix this in future experiments.

4.1.2 Data Analysis

Many methods for feature and parameter extraction were investigated, including but not limited to:

- Statistical moments of collected signals, their derivatives, and other calculated metrics (i.e. current magnitude, power level, phase angle, etc.)
- Extreme Value Monitoring
- Traditional frequency analysis and peak monitoring
- Qualitative and quantitative assessments of time-frequency information with both the Gabor and Hilbert Huang Transforms
- Noise analysis
Each progressive step into the analysis of this data was precipitated by either the previous step, or some review of past work. Statistical moments are generally considered to be the first place to start any analysis. From there, it is a short extension to apply these same statistics to signals derived from the directly collected signals. In this case, many of these derived signals, such as phase angle, stem from standard electrical analysis. Other work, mainly discussed in the literature review, lead on to the more sophisticated time frequency analysis of the data. Other investigations, such as noise analysis are generally good practice, and the fact that it lead to a trendable parameter was quite a boon. Ultimately the models and methods described above were best suited to the data set available for this analysis. Additional methods and work could make more accurate models of data from a similar test set up which overcomes the problems listed earlier for this data set. The methods and results given here validate the hypothesis that the more stressful transient operation data signals can provide useful and more accurate information regarding RUL and system health. As the number of methods to analyze and identify features in a non-stationary signal grows, the list of methodologies identified in the literature survey as well as those identified and implemented here represent some of the most promising methodologies for TOP modeling.

![Figure 14 - Startup Electrical Signals](image)

Figure 14 - Startup Electrical Signals

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One possible degrading factor in the motor data is the large inrush current values during startup. This inrush current, shown in Figure 14, is expected to exhibit indications of incipient faults and anomalies. As noted above, and according to the past reports, these motors were rated at 12 amps (A) for steady state. From the top graph of this figure, one can see that the inrush current has an RMS value of about 75 A and the steady state value was found to be approximately 8 A. Since inrush is expected to be 7-10 times the steady state, this fits the expectations. It is during this high stress inrush time period that degradation is expected to be detectable. A full analysis of the data signals was conducted and proved to be useful for the understanding of the system and the development of prognostic models.

The stresses, both electrical and mechanical, are much more severe during startup than any other time of operations for these electrical motors as indicated by the inrush current and radial vibration. When compared to similar signals at both steady state and spin down (turning the system off), these higher stress signals appear intuitively more likely to reveal any underlying faults more rapidly than those during other operations. Figure 16 shows the tail end of some exemplar signals at steady state leading through the spin down, or powering down, process. None of these exemplar signals exhibit greater values in the steady state portion of this figure (before 0.04 sec) or the spin down phase (everything after 0.04 sec) than those experienced in the startup transient. The startup data can further be broken down into loaded and unloaded startups. Although both were run without the steady state testing load, those referred to as unloaded did not have the dynamometer connected while those referred to as loaded did. This difference does affect the expected shapes and patterns of various signals during startup. Since the full effects of loaded versus unloaded startups in regards to prognostic monitoring are not completely intuitive, both subgroups were investigated together and separately for identification and development of possible prognostic parameters to be used in model development.
Figure 15 - Motor Startup Radial Vibration Exemplar Data Run

Figure 16 - Exemplar Signals During Powering Down Transient

Figure 17 - Average Value of the Relative Voltage Angle for Each Motor Over Time
From Figure 15, it appears that the vibration signatures may hold vital information about the state of the motor; however, an analysis of their information content did not show additional information beyond that extracted during steady state and therefore they were not used for prognostic model development. An additional reason for this is that most of the vibration signals collected on various motors during the experiment were corrupted and unusable due to signal saturation. Most likely this was due to improper gain settings during the data collection process causing an amplitude input higher than the data acquisition card was specified to acquire. While a more involved model development project may still be able to incorporate and accommodate the varying useful signal inputs, that would require work not fitting into the scope and time scale of this project, leading to the decision to omit the vibration data from the bulk of the analysis and model development. In future work vibration may provide additional, and possibly vital, information regarding system health, with appropriate data acquisition.

As established, much of the work focused on the electrical signals from the motors, and features derived from them. The natural extension of this was to investigate other similar combinations of these signals. From this analysis, one particular signal arose to exhibit good prognostic suitability metrics: the relative angle between the 3-phases of voltage and the 3-dimensional unit vector, which is an arbitrary vector in 3 dimensional space with a magnitude of 1. Shown in Figure 17, the individual pathways shown between the green arrow at start of life and the red square at the end of life show a fairly strong APS of 0.66. Unfortunately this parameter does not show a consistent failure threshold in comparison to range, thus giving it a PLP of 0.50 and an ACT of 0.81.

![Figure 18 - Voltage Angle Relative to Arbitrary Unit Vector During Startup](image-url)
In regards to this research, the voltage angle holds another shortcoming; it appears to be unaffected in any meaningful way by the startup transient of the motors. This can clearly be seen in Figure 18, which shows this parameter during a startup sequence. The startup transient begins at approximately 0.024 seconds and continues to be viewable in the magnitude of the voltage signals until some time after 0.7 seconds. Clearly, this signal does not exhibit a similar pattern shift during startup. Though anomalous spikes do occur at random points during the startup, no pattern could be identified with respect to timing, magnitude, or frequency that had any correlation with the degradation of the motor. This may be a desirable feature for an overall prognostic system, but as this research is focused on the transient conditions, this actually makes it less desirable. However, this parameter provides a good point of comparison for signals affected by transient operation.

There was a concern that this signal may be related to the incoming power voltage and may be correlated with time rather than motor degradation. To investigate that notion, the signal was generated for the time period just after the motor was de-energized and after it coasted down.

Figure 19 presents the results. Investigation of Figure 19 shows that there is no discernable pattern that can be identified from these pathways, so the degradation is indeed responsible for the changes noted. Additionally, it would not be useful as a prognostic parameter because its APS is -0.17 which is to be expected since it is collected when the motor is disconnected. This is evidence that, despite its non-traditional nature, the relative voltage angle is in fact related to the degradation of the motor in question. By virtue of powering the operating motor, one or more of the voltage phases are undergoing a subtle shift or delay in frequency relative to one another in order to produce this effect. Future work may focus on directly monitoring for this shift in frequency. While the reason for this shift is still unclear, the fact that similar trends do not appear in the line after powering down indicates that this is unlikely to be some artifact of the supply line voltage. Further investigation as to exactly what why this effect occurs is difficult as this is old data, and not all the information regarding it is available.
Next the search for prognostic parameters expanded beyond the most basic statistical testing to include some more sophisticated techniques specifically suited for analysis of non-stationary, or transient signals. The most commonly used of these techniques was the use of the Gabor Transform or STFT to create a Joint Time Frequency Spectrum (JTFS) of the data. This processing technique was applied to each electrical signal of the motor.

Not surprisingly, Figure 20 shows that both the current and voltage signals exhibit a dominating 60 Hz component. This dominating frequency makes finding anomalies or other significant features of the data difficult, much like standing in a valley and trying to count small boulders on the mountaintops. Though ways to account for this exist, the first method used in this research was to examine the magnitude of the electrical signals. Shown in Figure 20, this provided more discernable patterns. Both the voltage and current magnitude show faint but discernable rise in frequency which seems to correspond to the motor speed starting at approximately 1000 observation points (0.01 seconds) and continuing till it reaches steady state at around 7000 observation points (0.58 seconds).
Although these small features are not directly useful as a prognostic parameter, they show that indirect information about the system can be gained from these techniques. While it is true that looking at the second derivative removes the primary mode of the current, analysis proved that this also did not yield a quantifiable metric suitable for prognostics. One interesting relationship was found however, between the 2\textsuperscript{nd} derivative of the current and the first IMF of the same signal. This relationship is examined in more detail later in this section.

Other investigated signals for this method included a summation of the three phases of voltage and current respectively. For the summed voltage signal shown in Figure 21, there did not appear to be any obvious features or recognizable patterns in the data. However, the JTFS of the summed current signal exhibited another notable frequency artifact that arises during the startup transient. This feature, which occurs in the current between 3500 observations and 6000 observations (0.29 seconds and 0.50 seconds), appeared similar to features discussed in previously performed research [Antonino-Daviu 2009] that arose from the application of a JTFS of the second imperial mode derived from a HHT of the current signature. Unfortunately, while several isolation and extraction methods were performed to capture this feature, no quantitative value was found that provided a viable prognostic parameter with an APS over $\sim$0.35.
The HHT is a mathematical method to successively derive empirical, non-parametric sinusoidal modes of a function, which are based on the outer envelope of each progressive layer of that function [Huang 1998]. In an attempt to repeat the success of a previous study analyzing the current of a motor with the HHT, an empirical mode extraction algorithm taken from the first steps of the HHT was implemented on this data. Though the previous research indicated that the second IMF (also called an empirical mode function (EMF)), was the one of interest, a full decomposition yielded over eleven IMFs for a given current signature. Depending on the exact form of the data, a given decomposition could lead to differing numbers of IMFs between runs. This difference usually was no more than one. An example of the first four modes of the current is given in Figure 22.

As mentioned earlier, there appears to be an interesting relationship between the first IMF of the current signal and that signal’s second derivative. As indicated in Figure 23, the joint time frequency information in both of these calculated signals is nearly the same. While the second derivative is far easier to compute, the fact that the frequency information in the IMF is cleaner
makes it a more desirable source of this information. As indicated by the previous work, when looking at the JTFS of the second IMF, a feature similar in shape to the one discussed above was found in the transient data. Unfortunately, though various automated and manual feature isolation techniques were applied to this feature, no quantifiable feature could be extracted that appeared to relate to system health. In fact, a visual inspection of the feature throughout the lifetime of any of the motors would also not indicate any noticeable progression of the feature, as shown in Figure 24. This figure gives the JTFS of the HHT of the summed current signal for a motor subjected to thermal and electrical aging at the beginning (top chart), middle (second chart) and end (bottom chart) of lifetime.

![Figure 22 - First Four Empirical Modes of The Summed Current Signal's Hilbert Huang Transform](image)

Figure 22 - First Four Empirical Modes of The Summed Current Signal's Hilbert Huang Transform
Figure 23 - Comparison Between 2nd Derivative and 1st IMF of Current During Startup

Figure 24 - Hilbert Huang Transform of Summed Current Signal At Various Lifetime Stages
Despite having identified a similar feature to that indicated in the previous research, no qualitative or quantitative aspect of this feature could be identified for this data set. A similar analysis was performed on various other IMFs and both current and voltage signals, but none showed promise as prognostic parameters across all motors. One reason for this could be the type of motor used in this analysis or the failure mode affected. Another likely explanation, and one of the major problems with multi-dimensional information like that in a JTFS, is that there are a seemingly endless number of features and methods for extraction that can be applied to them. Without knowing exactly how the research described in [Antonio-Daviu 2009] extracted and quantified these features, it is difficult to replicate their results.

Another shortcoming with regards to this data is that although the method of aging is known for each motor, a post mortem dissection and confirmation of failure mode is not available. While unlikely, it is possible that the true failure mode of these motors was one not detectable by the JTFS. If separate models and degradation parameters were built for each failure mode, this problem could be easily avoided. However, due to the constraints of the previously collected data, including the lack of large numbers of motor failures under similar conditions and definitive post-mortem analysis, this research opted to pursue a possibly less accurate, but more general model.

In regards to other non-traditional signals, this data set has the benefit of containing some signals not normally collected on industrial induction motors. With both due diligence and curiosity in mind, the analysis was expanded to include some of these signals as well. This yielded another promising prognostic parameter: the average value of the noise on the speed signal at the point during startup where the inrush current was at its highest. Signal noise has historically been proven to contain indications of system health. The noise level can be calculated in many ways; one of the more standard methods is to apply some smoothing filter to the data and then subtract this from the original signal to estimates the noise. Those values that deviate from the smoothed signal average can be defined as noise. This method was applied to the startup speed signal. Conveniently for this data, at the point of interest during startup, the recorded RPM was always some small variation around zero which produced a uniform zero mean. Shown in the top chart
of Figure 25, this is likely because the sensor required a set number of revolutions before outputting an average speed. Thus, an average is taken of all the recorded output values in the time from initially energizing the motors to when the inrush current reaches its highest value, and is logged and tracked as the pertinent portion of noise on this signal. Other recorded signals, such as the vibration shown in the lower chart of the figure above, verify that the motor was in fact moving at this time, the speed sensor was just unable to record it. This, however, does not really affect the usefulness of this signal in this case, as it was determined that the noise in the speed signal conveys the pertinent information. Figure 26 highlights the portion of the voltage output of the speed signal and the current corresponding to metric used as a prognostic parameter. Once again, after investigation, utilizing only the loaded startup group proved more effective than the unloaded subgroup, indicating that the additional stress on the system does indeed have a factor in determining the system health. This yielded a parameter much more suited to prognostics than the previously found relative voltage angle discussed above.
This noise level, as shown in Figure 27, exhibits a much more concise ending value threshold compared to its effective range (PLP of .85), and it also is highly trendable in its progression through time (ACT of .87), giving it an APS of .86.

This prognostic parameter based on noise level is highly transient dependent. For comparison in Figure 28, if the same metric is taken after the transient, it exhibits no significant trends of note and has an APS of 0.07. By looking at the same metric at steady state, all useful information regarding system health is completely lost, only the time between the initial charging and the maximum current magnitude show this useful metric.
Figure 27 - Average Noise Value From Speed Signals at Max Inrush Current for Each Motor

Figure 28 - Average Noise Value of Speed Signal During Steady State
A possible reason for the appearance of this metric may be increases in the shaft vibration during start up. However, once again due to data quality, this is difficult to confirm with this data. Work with more robust data presented later in this paper investigates specifically the vibration startup signature and confirms its usefulness in determining system health. Encouraged by the higher APS and the highly transient dependant nature of this noise signal, a rudimentary prognostic model prototype was created to verify and quantify the usefulness of this signal as a prognostic parameter. This model is build upon a non-parametric kernel regression (KR) [Nadaraya 1964] model optimized using the mean absolute percent error (MAPE) of the RUL of test cases selected in a leave one out cross validation method. MAPE, defined in the equation below, is an intuitive error metric that can give some sense of performance without knowledge of the time scales associated with a system as is required with some error metrics like root mean squared error (RMSE).

\[
\text{MAPE}_X = \frac{1}{N} \sum_{i=1}^{N} \frac{|\text{Prediction}_i - \text{Actual}_i|}{\text{Actual}_i}
\]

\(x = \) historical case number

This metric does have the shortcoming of exploding near RUL values of zero, which can easily be overcome by adjusting to be the percent of lifetime instead of percent of RUL, and later in this work will be presented as such.
**Figure 29** shows the individual mean RUL estimate errors over the second half of life for each of the motors using the prognostic model built upon the speed signal noise parameter. The overall average error for the second half of life is approximately 55%. This compares favorably to a similarly built model based on the transient independent relative voltage angle parameter which has an overall average error of 62.1% during the second half of life.

Additional work proved that a prognostic model utilizing a combination of both the transient dependant metric and the metric not dependant on the transient provided the most accurate RUL estimations. By simply including both metrics in the prognostic model during construction, the average percent error was reduced by ~8%. A comparison of the different models’ estimates over time for a single motor is shown in **Figure 30 - Comparison of RUL Model Predictions Over Time**. For this particular motor, the model built strictly on voltage, represented by the black line, has much greater swings in predictions and predicts failure a full cycle early. Conversely, the red line, indicating predictions from the model developed from the speed signal noise, stays much closer to the actual RUL values over the lifetime of the motor. Finally, the green line gives the results of the most accurate model, which utilizes both of these parameters and yields an overall average second half of life MAPE of 47.1%.
Table 3 - Prognostic Model Performance

<table>
<thead>
<tr>
<th>Predictor</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Voltage Angle</td>
<td>62.1%</td>
</tr>
<tr>
<td>Speed Signal Noise Features</td>
<td>55.8%</td>
</tr>
<tr>
<td>Both Features Use Together</td>
<td>47.1%</td>
</tr>
</tbody>
</table>

The error metrics shown in the table above give the MAPE during the second half of life. This is the time when demands on prognostic models are highest and so is the most important period. Larger errors early in life are far more acceptable than those later in life. And for a point of comparison, the 47.1% of the last model corresponds to an average of 1.16 motor aging and data collection cycles of these motors. During each cycle the motor is subjected to a full session of its respective aging mechanism, and then connected to the test setup and run at various conditions, collecting data at each. The practice of using multiple prognostic parameters often provides better results than either of the two parameters would be expected to separately. This is due primarily to increased robustness and “parameter noise” canceling effects. Assuming both can be treated as signals containing an indication of health with some uncorrelated noise added, it follows that by utilizing both signals, the effects of this uncorrelated noise are diminished.

4.2 Pump Impeller Degradation Experiment

In order to test the validity of the Sharp Time Distribution Map (STDM) modeling algorithm and the principle of transient monitoring for prognostic purposes, proof of concept experiments have been enacted. The first of these experiments involve the artificially induced degradation of neoprene horizontal pump impellers. The pumps were chosen to be analogous to the large pumps
found in many power plants, but on a much smaller scale. The focus of this experiment was to identify correlations between monitorable features found during startup and the amount of degradation found in the system.

Due to the lack of available comparison data regarding the true lifetime or rate of wear time of these impellers, direct estimation of Remaining Useful Life (RUL) could not be made, and it would be meaningless to attempt with this data. Instead a percentage of current life consumption (CLC) model is inferred such that with the addition of a known lifetime run, a RUL estimate model could be made.

4.2.1 Pump Setup and Data Collection

Data was collected using an accelerated degradation pump testing bed created for this experiment, which holds four fully instrumented self-priming pump flow loops. Seen in the picture below, each of these 4 GPM transfer pumps has been connected to a ~4.5ft draw, open air return flow loop.

Figure 31 - Flow Loop Setup
The open air return ensures that there is no additional forced suction from the returning water, and the 4.5ft distance was chosen to be a little under the maximum draw height for these pumps. The individual flow loops are each outfitted with a differential pressure gauge across the pump, as well as vibration sensors and current clamps attached to the pump motors themselves. Each AC motor, Jabsco pumps (Model No. 12310 Series), operates using Neoprene impellers with 6 flexible vanes. A full list of specifications is shown in Table 4.

The Data Acquisition System (DAQ) is a National Instruments based hardware setup connected to a LabView software interface inside the computer. This NI Compact DAQ (NI cDAQ-9178) is the housing for three input modules, a NI 9205 connecting the differential pressure data, and two NI 9234’s, which connect the current and vibration data and also provide anti-aliasing filters for that data. The data is collected at ~1.6kHz for slightly over two minutes after the startup of the pumps. The focus of this experiment is to capture the startup transient of these pumps. In order to accelerate the degradation process, and to precipitate impeller failures in a timely manner, increasingly large notches, such as those shown below, are cut into the center of the impeller vanes between each test run.
These notches are analogous to the type of degradation an impeller might suffer due to a spur or defect in the impeller housing. It is also thought to be able to be equated to more long term degradation due to impeller cracking due to age and fatigue. A full impeller failure has been defined as the inability of the pump to perform the ~4.5 ft draw necessary to self-prime.

4.2.2 Pump Data Analysis

During this data analysis, the increased stress levels associated with a pump startup were clearly seen in all three collected signals. The figure below exemplifies these elevated stress levels found in during such a transient. As is evident in the figure, both the vibration and inrush current exhibit greater amplitude during startup than that experienced at steady state. These are the primary regions of focus for this study.
The pressure signal shows a dramatic jump where the water actually hits the impeller during the transient. As this is not a typically sensed signal in most pumps, in this analysis the differential pressure is used mainly as verification that the pump has properly primed. While each signal shows obvious dependencies on the startup phase of the pump cycle, it is not until a comparison is made of the evolution of these transient signatures over time that a clear pattern related to degradation emerges.

Prior to performing the ST mapping analysis, a more traditional analysis was performed so as to have something to compare to. Blind application of most generic algorithms without special investigations in addition to them can produce results that though meaningful, may not have an obvious physical connection. During the proving phase of the development of any algorithm, this can be an issue. Therefore, in order to overcome this and confirm that the patterns and trends found using the ST modeling algorithm do in fact relate to some physical aspect of the impeller
degradation, a more traditional analysis of the signals is included below. While this is not meant to be an all-encompassing analysis, it is meant to identify and explain features in the startup transients that are relatable to degradation. If features found with the ST model follow the same basic pattern, this can be taken as confirmation that ST mapping can extract meaningful features from the data.

The first signal analyzed is the vibration. This signal contains much information regarding the state and operation of the pump system in question. Shown in the Figure 34, the bulk of the frequency content resides above 600 Hz. Because of this, and in order to strengthen the identification of instantaneous dominant frequencies, a post-production digital high pass filter was applied to the vibration signal cutting off all frequencies below 600 Hz. This is not to say that the lower frequency harmonics do not hold valuable information, but for the purposes of this analysis, they are not necessary. A more in depth study in the future may prove these to be quite valuable. By examining the Joint Time Frequency Spectrum (JTFS) of the vibration signal, it becomes obvious that the dominant frequency of the signal undergoes a shift during startup. Shown below, this simple JTFS created with the Gabor transform over 256 observation long windows clearly indicates that the most dominate vibration frequency briefly increases up to around 775Hz before slowly lowering back towards its steady state value.

![Vibration Frequency Spectrum](Figure 34 - Vibration Frequency Spectrum)
This corresponds to the brief time before the water hits the impeller, when the vane pass frequency is higher due to the lessened load on the motor. In other words, impeller vanes are moving across the pump housing faster without the weight of the water to slow them down. Thus by observing this feature, a direct calculation of priming time can easily be made. In order to extract this feature, a quantitative measure of the instantaneous dominate frequency must be made. The Hilbert-Huang Transform is ideal for this, but research shows that in this particular case the decomposition of the Intrinsic Mode Functions (IMFs) is not necessary for this signal. Thus the direct application of the Hilbert transform to the vibration signal and subsequent calculation of instantaneous frequency is able to cleanly extract this dominant frequency as shown in the Figure 36.

If you examine this dominant frequency signature as it evolves through the lifetime of the impeller, it becomes obvious that this heightened frequency increases in both amplitude and duration with increased degradation. Seen in the Figure 37, the time spent at a higher vane pass frequency, and thus the priming time of the pump increases by nearly a half second over the life time of the impeller.
Figure 36 - Hilbert Transform Instantaneous Frequency of Vibration Signal

Figure 37 - Instantaneous Vibration Frequency Signatures Progressing Through Life of Impeller

Figure 38 - Extracted Increased Vibration Frequency Feature Over Lifetime of Impeller
This dip in frequency relating to increased startup time can easily be extracted and modeled to find an approximate percent of Current Life Consumption (CLC). This extraction is shown in the Figure 38.

The strong correlation between this parameter and the system degradation makes it ideal for modeling the degradation and CLC of the pump in question. Yet this is not the only feature that can be extracted from the vibration signal that relates to the priming time of the system. In fact a second feature is much more intuitive to understand. Shown in Figure 39, the analytic amplitude of the vibration signal calculated via the Hilbert transform shows the there are increased levels of vibration during the priming sequence.

Again this makes intuitive sense as the water acts as a dampener to all vibration once it starts flowing through the system. Similar to the analysis above, a simple feature extraction and smoothing algorithm are employed to identify the time spent at this elevated stress level during priming. As shown in Figure 40, this feature also shows a strong correlation to the degradation incurred over the lifetime of the impeller.

Lastly, a reference ST map based on ten nominal startups using the algorithm detailed in the earlier section is created. Shown in the Figure 41, this reference ST map is then used as the basis for comparison for all of the collected startups. From this, the Root Mean Square Error (RMSE) between an individual startup and the reference ST map can be found and plotted over time. Shown in Figure 42, these errors show a trend which by casual inspection appears to be similar to both the vibration features mentioned above, and may in fact be some composite between them.
Figure 40 - Startup Vibration Amplitude Feature Extracted Over Lifetime of Impeller

Figure 41 - Pump Startup Vibration Reference ST Map

Figure 42 - Startup Vibration ST Map Residual Feature Extracted Over Lifetime of Impeller
In fact, comparing a ST map made using the master bin map for this unit from beginning of life with one made near end of life, and with the knowledge gathered from the earlier analysis, it becomes clear that this longer priming time is exactly what the ST map has extracted. Shown in Figure 43, the upper plot representing the beginning of life ST map exhibits a pattern very similar to the reference ST map. Conversely, there is a very clear lower edge skewing in the second plot. This corresponds to the prolonged greater amplitude and an apparent downward mean shift of the vibration signal over that time span.

However, the vibration signal is not the only one to hold information regarding the priming time of the pump. There is also a noticeable drop in amplitude in the current signal directly after the initial inrush current that if examined over the lifetime of the pump. As shown in Figure 44, this shows a clear correspondence to the system priming time and thus degradation as well. The reason for this lowered current draw is again directly related to the reduced load of the motor prior to the water arrival.

![Figure 43 - Comparison of Startup Vibration ST Maps at Beginning and End of Lifetime](image)
Figure 44 - Current Amplitude Signature Evolving Over Impeller Lifetime

Figure 45 - Lowered Current Draw Feature Extracted of Lifetime of Impeller

Figure 46 - Increased Frequency Echo As Found in JTFS of Hilbert-Huang IMF Wave Parameters
This feature can quickly be extracted through simple limit monitoring and used to model and estimate of CLC. **Figure 45** shows this extracted feature.

More surprising than this direct indication of system priming time is that an similar signature to that of the vibration frequency signature can be found in the JTFS of the current signal. It is much lower magnitude compared to the 60Hz carrier signal, but with careful filtering it can still be found and extracted. Another method of intensifying this redundant information is to look at the first IMF from the Hilbert-Huang Transform (HHT). Specifically this vibration frequency information is found in both the JTFS of the analytic amplitude and the JTFS of the instantaneous frequency as shown in **Figure 46**.

This powerful analysis technique allows for redundant verification of the information found within the vibration signal and may prove invaluable in cases where either vibration data is not available or needs to be verified. Again, a reference ST map is created for the current signal and the RMSE is extracted over all the startups. **Figure 47** shows this on the upper and lower plots respectively.

The results from this modeling are again able to capture a feature similar to the one developed in the more traditional analysis of the signal. Also similar to before, the prolonged lowered variance in the current signal due to a lower load is easily identified in the ST map from near the end of life. This can be seen in **Figure 48** as the longer dark region.

When compared against the standard training error, the region of shift becomes even clearer. In **Figure 49**, the red dashed line represents the standard deviation of the training error over time, and the blue line is the RMSE associated with the end of life run shown in the figure. From this figure, a clear and significant increase in error begins around the twentieth distribution window (~1.5 seconds) and continues until around the fifty-fifth distribution window (~4.2 seconds). This method of comparison helps to track down where exactly during the transient the increased error appears, aiding in the diagnosis of the fault.
Figure 47 - Results from Pump Startup Current ST Modeling

Figure 48 - Pump Startup Current ST Map from Near End of Lifetime

Figure 49 - Pump Startup Current ST Modeling Near End of Life RMSE VS Training Error
4.3 Accelerated Motor Aging Experiment
The study of electrical motors, and specifically their degradation through accelerated aging techniques, was selected as a pertinent and worthwhile case study to verify the use of information derived from the transient phases of their lifetime. Many systems using electrical induction motors are only started and/or tested on an infrequent basis. Systems such as backup pumps or generators are expected to have a high availability on demand, but their testing is sometimes limited to very brief pass/fail startup tests. These tests along with regular scheduled maintenance are expected to keep the system healthy. However, through the additional monitoring and prognostic techniques presented in this paper, a more accurate and reliable picture of those systems’ health can be constructed and used to fuel important decisions on the maintenance, reliability, and overall safety of the equipment and related systems.

4.3.1 Motor Experimental Setup and Data Collection
Electric Power Research Institute (EPRI) has funded the purchase and testing of ten 5hp (horsepower) electric motors. These U5P1G U.S. Electrical Motors/Emerson general-purpose industrial motors were chosen as low cost analogs to the high power induction motors found throughout industry. Below is listed the full nameplate specifications of the motors used.

- U5P1G U.S. Electrical Motors/Emerson Premium Efficient General Purpose Industrial Motor
  - 5 HP
  - 184T Frame
  - Three Phase
  - 3600 RPM
  - Volts - 575
  - "C" Dim -16.1
  - Frame - 184T
  - Full Load Amps - 4.9
  - Full Load Efficiency - 89.5
  - Apx. Wt. (lb) - 75
  - SF - 1.25
  - Motor Mount - Foot Mounted
Each of these 3-phase, 3600 RPM motors were subjected to a cyclic thermal aging process designed to induce accelerated insulation breakdown and corrosion within the motors. These fault modes have been selected as the most prominent and costly for inductions motors. The accelerated aging plan has been adapted from previous work performed by Upadhyaya [Upadhyaya 1997] and IEEE Standard 117, “IEEE Standard Test Procedure for Evaluation of Systems of Insulating Materials for Random-Wound AC Electric Machinery Degradation and Testing Plan.”

According to IEEE Standard 117, several testing procedures may be performed in order to perform accelerated degradation testing of motors. For Class F insulation (the type of insulation in the motors that will be tested during this project), the recommended testing time is 32 days at 170 degrees C. In this testing the motors have been divided into two groups, one which will be
heated to 160° C, and one with the temperature at a lower 140° C. This can provide two reference points for regression back to normal operation temperatures with any prognostic or diagnostic features extracted. The lower than IEEE standard temperature for the “hot group” provides a slower, more realistic evolution of any degradation mechanisms and related features of the motors. This also provides more data points, making a more accurate tracking and estimation of the degradation curve of the testing motors.

The IEEE Std 117 also recommends that the motors undergo moisture testing as well as thermal degradation to better simulate normal operating conditions. In order to achieve the moisture testing, the motors were recommended to be placed in a condensation chamber consisting of temperature-regulated coolant in a sealed container for a total of 48 hours at 100 percent humidity. The moisture should be uniform across the testing motor and no voltage should be applied at this time. After the condensation testing, the motors should be allowed to dry overnight.

During the previous testing by Dr. Upadhyaya, a condensation chamber was not used for moisture accumulation due to the difficult task of creating multiple condensation chambers for the motors being tested at the same time. In this previous experiment, the motors were instead quenched in a tub after being allowed to cool for six hours after the thermal degradation testing. After the quenching, the motors were allowed to dry overnight before beginning thermal degradation testing again. Since the primary focus of the experiment was on thermal degradation, this amount of moisture accumulation was sufficient for testing purposes, even though the motors did not use the procedure recommended by IEEE Std 117.

Each accelerated aging cycle has been designed to take just over one week, and performed in one of 3 identical EW-52402-91 Lab Companion Economy Mechanical Convection Oven. A detailed listing of the thermal aging cycle process is listed below.

- **Thermal Aging:**
  1. Heat motor in laboratory-grade oven at 140° C (or 160° C) for 72 hours
  2. Remove and allow to air cool for 6 hours.
3. Quench in enclosed shallow water pool for 15 minutes
   (this acts as the suggested replacement for the recommended humidity chamber)
4. Immediately place back in the oven and heat again for 72 hours.
5. Air cool for 18 hours before performing “Startup Testing”

**Figure 50** details the time requirements for both an individual thermal aging and data collection cycle in hours. This chart shows that each individual aging and data collection cycle will take just under a week of total time.

After undergoing each thermal aging cycle, the motor will be mounted on a test bed, connected through an elastomeric coupling to a Winco generator, and instrumented with a data collection system to collect various key signals from the motor during both the transient startup and periodically during the steady state operations. Because the primary focus of this project is the motor performance changes during the startup transients, several startups will be performed and recorded during each collection cycle. This will provide for statistically significant results. The full list and specification of sensors is shown below:

![Aging/Testing Cycle Timeline](image)

*Figure 50 - Time Requirements for Aging and Data Acquisition*
Data Collection System:

- Compact DAQ: NI cDAQ 9178 (8 slots)
  - 3x phases of current
    - Fluke i200s Current Clamps: Input/Output 600 V CAT
    - NI DAQ Module 9234
  - 3x phases of voltage
    - NI DAQ Module 9225
  - 2x accelerometers (90 degrees apart: vertical and horizontal from ground)
    - 0.0002 g resolution, +/- 50 g measurement range
    - NI DAQ Module 9234
  - Load current and voltage for the dynamometer
    - NI DAQ Module 9225
  - Motor speed from tachometer
    - ICP Laser Tachometer: Reads up to 30,000 RPMs
    - NI DAQ Module 9205
  - Thermocouple located in motor near the stator winding.
    - Omega K type 30 gauge Chromel Alumel surface mount thermocouple
    - Typical use range: 95°C – 1260°C
  - Acoustic sensor
    - PCB 130D20 ICP array microphone
    - Sensitivity 45 mV/Pa
    - Frequency Response (+/- 1 dB) 100 Hz to 4 kHz

The current and voltage from the connected output generator are also monitored, but are largely ignored for the work in this paper. A photo of the setup is show in Figure 51. The end sink for the supplied energy is a resistive load bank connected to the generator. Multiple startups are collected between aging cycles in order to help smooth trends and reduce measurement error in the analysis. The data is collected at just over 10kHz for slightly less than two seconds with a NI LabView interface. Figure 52 shows the LabView created user interface for the data collection. With this LabView VI, the collected data is stored on an external hard drive in an easily accessed and understandable file structure as shown below.
Figure 51 - Motor Testing Setup

Figure 52 - LabView Data Collection Interface
File Storage Structure:

<Testing Data>

<UnloadedStartups>

ULStartupTest_1.csv
ULStartupTest_2.csv
...

<Startups>

StartupTest_1.csv
StartupTest_2.csv
...

<SteadyState>

SteadyStateTest_1.csv
SteadyStateTest_2.csv
...

The LabView data acquisition software collects and manages all signals as double precision floating point values before all the collected data is stored in a comma delimited text file with seven digits of precision. This coupled with the convenient file storage system can serve to aid other researchers in as yet unknown, future uses of the data.

Figure 53 - Exemplar Collected Signals at Beginning of Life
An example of the collected data, both startup and steady state conditions is shown in Figure 53. This chart clearly shows the significant difference between startup and steady state. Nearly all of the signals undergo significantly higher magnitudes during startup than those experienced at steady state. This additional stress forms the basis for the hypothesis of this work that transient conditions can exacerbate fault indications and provide additional useful prognostic information regarding the system.

4.3.2 Generic Transient Monitoring Analysis

At the time of this paper, 8 of the ten motors failed beyond the capacity to start. Of the failed motors, two are ignored as an anomalous failure attributed to technical difficulties during testing. This figure below shows some typical startup signal signatures from an off-the-shelf motor, prior to any thermal aging.

Figure 54 - Exemplar Startup Signal Signatures
From these plots, it is clear that while current and vibration signals are highly transient during the motor startup, voltage undergoes comparatively little change. That is not to say that voltage does not undergo any change, but they do require specialized processing to properly observe. As expected, the acoustic signal exhibits a similar signature to the accelerometers, and the tachometer produces a steady increase in revolutions per minute (RPM). The thermocouple is largely ignored for this paper due to the slow reaction time compared to the timeframes in question.

In order to identify potential signals for prognostic monitoring and to validate the mythology presented above as well as previous work using the generic transient monitoring algorithm discussed previously in this paper, the signals from each motor were processed to develop a reference Sharp Time Distribution Map (STDM). This process has no preconceived parameters or inclinations towards the data, making it instantly applicable to the different signals without need of altering the algorithm.

Figure 55 - Reference Sharp Time Distribution (TD) Maps for Motor Startup (Log Intensity Scale)
Each map is constructed as previously discussed using 50 bins and a window size of 500 from the startup data collected prior to any thermal cycling. Figure 55 shows exemplar maps created for the similar signals to those shown above.

These ST maps have their relative bin value intensities shown in a log color scale for easier viewing. While the vibration is dominated by the center values, much like a Gaussian distribution, both the current and voltage are have more intensity near the extremes of the range due to the sinusoidal dominance of both signals. Another important piece of information that can be gleaned from these plots is that the startup voltage is not completely uniform. Near the time frame where the current begins to settle into its steady state value (0.65 – 1.0 sec) there are some fluctuations in the lower part map indicating that the signal did not reach its full span. As this map is created using multiple startups, those fluctuations could indicate a trend at that point in time.

From the creation of these ST reference maps, each new startup is then binned into this same reference space and residuals of the relative intensities are used to identify deviations from normality in the signals. Due to the temporal dependence of these maps, not only can specific signals be identified as containing anomalies, but also the time frame in which it occurs. Shown in Figure 56 below, each time bin contributes an associated error with that point in the startup transient, which can be mapped through time to pinpoint exactly when an anomaly occurs.

![Mean Absolute Residuals of Vertical Vibration](image)

Figure 56 – Signal Error Over Time
In this plot, the error associated with the start of the unit’s lifetime, and that of the end of life are shown with the blue and green lines respectively. Though the beginning of life error falls, as expected, within the error bounds associated with training, the error line associated with the end of life falls well outside nearly the entire transient. In fact, using the training error to normalize each residual signal over the lifetime of the unit, an evolution of these errors can be plotted.

A map of the vibration signal errors is shown in the Figure 57, with the horizontal axis of this figure shows the signal startup error over the motor’s lifetime, while the vertical axis is the time within individual startups. From this figure, it is apparent that the error of this signal grows significantly about midway through life, and starting at about 0.5 seconds into the startup. Though informative this figure may be, it is more convenient for both predictions and modeling to describe the errors as a sum over each run. This is shown in the upper plot of Figure 58, and further as show in the lower, in order to smooth the data and yield more consistent results, the errors between each of the four startups for a single aging cycle are averaged together.

As mentioned earlier, between each aging cycle a series of four startups are performed and recorded. As these are taken within a single day, it is assumed that the degradation incurred between these startups is negligible to that incurred during an aging cycle. As such, by averaging the errors obtained from each of these startups, a more robust measure of the overall degradation apparent in a signal can be made.

Of the eleven input signals collected from each motor during testing, all but the temperature reading are thought to hold information relating to the health of the system. Shown in Figure 59, their associated errors as created from the process detailed above, show the general increasing trend in overall system degradation. The reason temperature is being excluded is not because it has no bearing on the systems’ health, but because it responds too slowly compared to the time frame of the transient to get an accurate and consistent reading. In the time scales in question (~2 seconds) differences in the ambient air temperature could overshadow any significant changes in the motor temperature.
Figure 57 – Evolution of Signal Error Over Time

Figure 58 – Combined Summed Error Metric

Figure 59 – Errors Generated from Each Input Signal
The final step in creating a trendable prognostic parameter is to combine the errors from each of the other signals into a single value representative of the systems’ overall health. Though in some cases, trending each individual signal could be appropriate, in this case a combined weighting of the individual signal errors was chosen to create a more accurate, robust, and trendable parameter. Given that a good prognostic parameter should be generally monotonic, have a comparatively small spread the failure point values, and needs to follow generally the same trending function [Coble 2011], a genetic algorithm could be employed to optimize the error combination on these criteria. However, given the comparative speed and ease of finding an exact optimal weighting, an ordinary least squares algorithm was used to regress the “training” pathways to the most linear path. These regressions were all performed ignoring the current query path to insure the validation of the weighting. The combined prognostic parameter for the six motors that have currently failed is shown in Figure 60.

Using these parameters, preliminary estimates of remaining useful life can be calculated using simple linear regression techniques. However, to yield more accurate results and due to the high uncertainty associated with regressing low numbers of data points, a combination of Bayesian regression and locally weighted regression were used to improve the model estimates. This linear General Path Model [Lu 1993] is used to predict the RUL of these motors based on a hard threshold. A summary of the results is given in the results section.
4.3.3 Application of General Practice Data Driven Transient Analysis Methods

In addition to more generic analysis techniques, this proof of concept analysis examined some more traditional methods for analyzing the transient data in order to more accurately compare those techniques. This also serves to exhibit the general analysis methods that can be used on most given systems or equipment. This analysis started by identifying the most likely signals to contain pertinent information regarding the health of the particular system.

4.3.3.1 Simple Signal Features and Statistical Moments

One simple method of identifying these signals based strictly on the data, despite their shortcomings discussed earlier, is to calculate and track the evolution of some simple statistical properties or moments of the collected data throughout the life time of a historical unit, as shown in Figure 61. These figures represent the evolution of the first two statistical moments (Mean and Standard Deviation respectively) of some of the signals collected from the motors during the experiment. Each of these moments has been scaled such that the range is one, and the minimum value is zero. In as much as this is primarily a search, any significant progressive changes as oppose to the actual values of these moments, this scaling allows for a more direct comparison both between statistical moments and between signals.

![Figure 61 - First and Second Statistical Moments of Select Signals](image)
From these figures one can clearly identify possible trends in three of the four signals; an upward progression seems to occur in at least one of the two moments for each signal except voltage. From this we can that these signals (Input Current, Vibration, and Acoustic signals) are likely to be fertile grounds for prognostic parameter development. It is also important to note that the third and fourth moments, skewness and kurtosis, were also investigated for trends, but in this case addend no additional pertinent information, and were simply left out of the charts for readability.

It is in some cases possible to directly develop prognostic parameters from these statistical features of the data. The table below summarizes the Aggregate Prognostic Metric, APM, defined as the average of all pertinent prognostic parameter metrics discussed earlier in this paper. Notice that very few have a APM above 0.5, where above 0.7 is preferred for direct use in prognostic modeling. This does not negate the earlier assertion that certain signals are fertile grounds for development of prognostic parameters, it merely indicates that these statistical moments are not directly suited for development of a General Path Model (GPM) type prognostic model.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current 1</td>
<td>-0.13</td>
<td>0.27</td>
<td>0.08</td>
<td>0.40</td>
</tr>
<tr>
<td>Current 2</td>
<td>-0.11</td>
<td>-0.20</td>
<td>-0.22</td>
<td>0.46</td>
</tr>
<tr>
<td>Current 3</td>
<td>0.00</td>
<td>0.20</td>
<td>-0.21</td>
<td>0.40</td>
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<tr>
<td>Voltage 1</td>
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<td>0.18</td>
<td>-0.12</td>
<td>-0.03</td>
</tr>
<tr>
<td>Voltage 2</td>
<td>-0.12</td>
<td>0.02</td>
<td>-0.22</td>
<td>-0.14</td>
</tr>
<tr>
<td>Voltage 3</td>
<td>-0.13</td>
<td>-0.29</td>
<td>-0.46</td>
<td>-0.33</td>
</tr>
<tr>
<td>Vibration Hor</td>
<td>-0.19</td>
<td>0.08</td>
<td>0.04</td>
<td>0.42</td>
</tr>
<tr>
<td>Vibration Vert</td>
<td>0.54</td>
<td>0.69</td>
<td>0.51</td>
<td>0.53</td>
</tr>
<tr>
<td>Acoustic</td>
<td>0.24</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.36</td>
</tr>
<tr>
<td>Tachometer</td>
<td>-0.07</td>
<td>0.19</td>
<td>0.22</td>
<td>0.17</td>
</tr>
<tr>
<td>Temperature</td>
<td>-0.17</td>
<td>-0.07</td>
<td>-0.12</td>
<td>-0.34</td>
</tr>
</tbody>
</table>
Additional manipulation or combination of these features could possibly yield a suitable prognostic parameter. What this chart does indicate however, is that the vibration signal appears to have the highest APM across the board, and thus is a logical place to start with additional investigations.

After identifying vertical vibration as a likely candidate for prognostic parameter development, the next step is to analyze this signal and it’s features for progressive evolutions that can be used in a GPM type model. Shown in Figure 62, the first, and some may argue, the most important form of analysis is to simply look at the data itself.

From this figure, one can clearly see that the vibration amplitude increases throughout the lifetime of the motor. This is somewhat expected given the previous analysis showing that both the average value and the standard deviation increased over this time frame throughout the motor’s lifetime. By looking at the overall vibration power over the first 0.59 seconds of runtime for each aging cycle and for each motor, as shown in Figure 63, though initially each motor appears to be increasing in vibration power until right before failure when there is a sharp decrease.
Investigations into this phenomenon would indicate that this trend is indicative of a bearing failure. In fact, the post mortem analysis provided in later sections of this report show that the bearings of these motors did degrade to the point where the inner ball were no longer performing their function, thus contributing to the apparent “self healing” trend. Knowing this, a simple manipulation could be used to transform this feature into a more GPM friendly parameter.

Another common signal to investigate for induction motors is the inrush current. This also showed the second best potential for prognostic parameter development based on the kurtosis from the simple statistical analysis. Directing looking at the signal, and the evolution of its’ amplitude over the lifetime of the motor, as was previously done for vibration, as can be see below in Figure 64 does not show as clear of trends.
This is mostly due to the 60Hz frequency component that drives many electrical signals. This does not mean that no meaningful useful information can be gained from this signal, far from it as was indicated by the kurtosis earlier. Such signals with dominate bystanders frequencies simply require more complex analysis to directly look at their pertinent features.

The power within the inrush current signal, for example, seems to hold degradation information similar to that in the vibration signal power. Shown below in Figure 65, this feature seems to progress sharply upward, mainly after the peak of the vibration power. These two features are perfect examples of degradation indicative features that could be used in conjunction with one another for a more complete estimate of overall health of the system.
It is also important to clarify that the feature represented in this figure is not electrical power exactly, but the signal power of an electrical signal.

4.3.3.2 Frequency Analysis

The next phase of analysis for any oscillatory signal should be in the frequency domain, either with a simple Fourier Transform, or a more complex Joint Time Frequency Spectrum (JTFS) using the Short Time Fourier or Gabor Transforms. Due to the known dominate 60 Hz component of the current signal, one might be inclined to begin a frequency analysis there. Unfortunately, as shown in the figure below, this self same component tends to overshadow any obvious frequency trends within the signal.
One good way of helping to isolate important frequencies within a signal is actually look at other related signals. As vertical vibration has already been established as a prime candidate for degradation information and is not expected to be modulated by any dominating frequency, it is intuitive to start such a frequency analysis there.

Unfortunately the primary problem with the typical Fourier Transform of a transient signal, shown below in Figure 67, is that any time dependant frequencies get smeared across a range of frequencies and become indistinct. Despite this, there is much knowledge to be gained in even this simple Fourier Transform. Most obvious from the lower chart of this figure is that later in life, there is significantly more power in the frequencies above 15kHz. In fact, it can be shown that this increase in power has a correlation coefficient of greater than 0.99 to the overall signal power in every failed test motor.
While this is interesting, it also shows that directly tracking the power in this range is an unnecessary convolution of the process needed to extract that information. Unlike with the current signal frequency, what is needed to better assess the vibration frequency information is a method of normalizing the power of the signal to help find the subtle shifts in frequency and power not related to the overall increase in signal power.

One method to accomplish this would be to simply normalize the frequency spectrum from each aging cycle such that the total power contained within it is one. Unfortunately this just serves to make the lower power spectra more prominent in comparison, and in this case gives no real benefit. A solution to this is to create a type of normalized JTFS with uneven segments based on pulses of the tachometer, and combines these into a single spectrum. Shown below in Figure 68, by normalizing the power in the spectra between each pulse to be one, this pulse modulated frequency spectrum helps comparison of the non-power dependant shifts.
Although, again due to the compression of data the direct temporal information is not represented in this analysis, this combination of modulated sub-spectra helps to mitigate the smearing effect of the transient “spin up” frequencies. Another similar method of mitigating this smearing effect is order analysis described later in this chapter.

To best fully visualize how these startup frequencies evolve over time a full JTFS must be examined. A traditional JTFS such as the ones shown in Figure 69 captures and displays any time-variant shifts in frequency.

![Figure 68: Pulse Modulated Vibration Spectrum Over Time](image1)

![Figure 69: Vibration Joint Time Frequency Spectra Through Life of Motor](image2)
The most obvious and notable feature which changes, looking at these vibration joint time frequency spectra, is how the rise in “spin up” frequency loses its’ distinctiveness over the life of the unit. In the upper chart representing start of life, there is a clean frequency ridge that rises from around 2000Hz to about 4500Hz over the time span of 0.2 to 0.45 seconds. At mid life this becomes less defined, and by end of life has completely lost its’ form.

This feature is easier to use as more of a qualitative measure of degradation. There are uncountable ways of quantifying this feature, or portions of it, but when doing so care must be taken to ensure it is the best aspect that can be modeled well across all motors. This can be a difficult task given to shear amount of information presented in each JTFS compounded by the total number of JTFS created over the lifetime of each motor. Most commonly, visual inspection and guess and check methods are used to extract and quantify useful features of a JTFS. This is typically a slow an often inconsistent task. Visual image processing algorithms could be employed to expedite and add consistency to this task, but to do so was beyond the scope of this project and would provide an excellent area for future research.

Figure 70 - Joint Time Frequency Spectra of Current Signal Over Life of Motor
Another interesting fact is that this same “spin up” frequency shift is echoed in the current signature JTFS. Unlike the vibration spectra, Figure 70 shows that this rise does not lose its’ distinctiveness over time in the current signature. This feature also is found at a much lower frequency that that found in the vibration signal. While this current frequency feature useful for monitoring the speed of the motor, no obvious and consistent evolutionary trends were found from it, making it not useful for prognostic modeling of this system.

Another useful method of narrowing down the search and focusing in on the most significant frequency shifts, either in the normal Fourier Transform, or some form of JTFS, is to perform a Hilbert Huang Transform (HHT) analysis. The HHT can provide additional and valuable insight into any frequency analysis.

4.3.3.3 Hilbert Huang Transform Analysis

The Hilbert Huang Transform (HHT) can provide information regarding both the analytic amplitude of a signal as well as the instantaneous frequency. Both of these aspects can give great insight into both the dominate, and as you continue to go down through the intrinsic Mode Functions (IMFs), more subtle effects and changes within a signal. In practice, most natural signals will have no more than 12 or fifteen IMFs. The deepest of these rarely hold any valuable information. Fortunately for this experiment, it was unnecessary to sift further than the third or fourth IMF to discover pertinent prognostic information, thus the IMFs presented here are not meant to show the full depth of the HHT, but merely highlight important features for this project.

Beginning the analysis by examining the HHT of the vibration signal, the figure below shows the analytic amplitude in the left column and the instantaneous frequency in the right. The first and most obvious feature that can be gleaned from these charts is a re-assertion that the amplitude and power of the signal increases with age. This comes from the fact that each of the top IMFs shows an increase of analytic amplitude over life, during a correspondingly high instantaneous frequency. This indicates that much more power is being put into those higher frequencies near end of life.
While this has already been discovered and discussed in the earlier statistical as well as Fourier analyses, the HHT provides and additional source of confirmation for these findings.

More notable and specific to the HHT is a dip in instantaneous frequency of the first several IMFs that occurs at about 0.2 seconds into each run. This dip corresponds to approximately 2500 Hz at start of life, and rises to closer to 3500 Hz near end of life. While this case study section is focused primarily on applying general practice, data driven techniques, it is interesting to note that the listed inner ball pass frequency for the bearing used on these motors is 2557 Hz; more information on the bearing frequencies is listed in the appendix. Purely data driven techniques are not meant to replace physics of failure models, but when such are not available, or need augmenting, data driven techniques can often lead to identical information.
This time frame for each IMF can be extracted and formed directly into pathways suitable for prognostic parameters as shown in Figure 72. These paths represent the average instantaneous frequency for each IMF between 0.2 and 0.3 seconds into the run, and each blue line is a separate motor. Individually, though each pathway shows a good linear evolution in time, Average Correlation to Time (ACT) of no less than 0.79 for each IMF, their spread of ending values is a bit large compared to the range lowering the Pseudo-Linear Prognosability (PLP). This extracted feature path from each of the three IMFs exhibits an Aggregate Prognostic Metric (APM) of 0.49, 0.53, and 0.41 respectively. Although, again with further manipulation and refinement these paths would be expected to yield better suitability metrics, such efforts may not be necessary. Calculating the HHT and extracting features from it on the fly is a computationally costly procedure. Using the information gained from the analysis, it is not possible to return to the simpler Fourier analysis with a focused direction and extract pertinent information from it. Namely, the power around the 2550 Hz range between 0.2 and 0.3 seconds.
Going back to the vibration frequency analysis and focusing on only the 0.2 to 0.3 second time frame a more easily computed feature can be extracted that, as shown in Figure 73, trends nearly equally as well as its’ HHT counterpart. This feature corresponding to the information found in the first IMF of the HHT exhibits an APM of 0.71 after filtering. The median filter was applied to remove noise and increase the accuracy of the pathways. This often helps strengthen potential prognostic parameters.

The HHT is also notable for being able to naturally sort through modulated signals such as the inrush current signal of the motor. Similarly looking at the first three levels of the HHT of the current signature, as shown in Figure 74, does not directly echo what was found in the statistical and frequency analyses. This is actually a desirable effect when dealing with modulated signals. The HHT allows for examination of the non-dominant signal modes, which in this case are the most interesting ones. Looking at the analytic amplitude for the second IMF, this particular motor shows an overall increase in the power of this IMF. All of the six analyzed motors show a similar trend in this feature. Indicated below in Figure 75, this upward trending feature may provide additional health information regarding the system.
Figure 74 - Hilbert Huang Transform of Current Signature Over Time

Figure 75 - Current Signature HHT Extracted Feature
Though noisy, combining this feature with others discussed as well as appropriate filtering could make this feature quiet useful in creating a prognostic parameter. While other features showing similar trends may be extracted, this one clearly demonstrates the availability of the information within the current signal and also requires comparatively less calculations than many others. Whenever applicable, the more simple calculations tend to deliver the better performance.

The Hilbert Huang Transform is both useful in directly creating and extracting features suitable for prognostic parameter development, as well as a means to drive more mundane ones during the analysis and formation of prognostic parameters. This powerful technique should not be overlooked in any in depth signal analysis.
5 Results

Often in the creation of a prognostic parameter, several separate measures of degradation will be combined together. This technique has can help to smooth small amounts of variance in the predictions allowing for a more robust and accurate measure of relative system health. These measures most often are all related to similar fault signatures in a system, but that does not always have to be true. In some cases, and depending on the implementation of the combination, it can also all allow for the signatures of different fault modes, which could be potentially found in different signals, to be combines together creating a more complete measure of overall health.

5.1 Pump Impeller Results

In the pump impeller degradation experiment, the separate measures relating to system priming time in the current as well as the vibration transient signatures were combined to create a more robust measure of system health. These separate features were passed through a median filter then summed together to create a parameter useable by prognostic algorithms. Figure 76 represents this combined feature for the exemplar case that was followed in earlier discussions.

This process was performed for each impeller in order to create estimations of their current state of health. Due to the artificial nature of the impeller degradation there was no reference time scale to relate the degradation parameters to. Therefore a current life consumption chart was created and utilized as the output from the prognostic model.
The current life consumption (CLC) of a unit, while not able to directly make estimations of Remaining Useful Life (RUL), can lead to these estimates as the rate of life consumption is discovered for a unit. CLC is a percentage measure of the amount of useful life a system or equipment has consumed over its lifetime workload, and by inference, the amount it still has available to it. Shown in Figure 77, indications of the measured prognostic parameter can be taken, and through the use of this chart, a percentage of the unit’s current life. The error bars on this chart represent the standard deviation in the values found at that percentage of life. For example, if a calculated degradation parameter is as 300, from this chart the indicated amount of life consumed would be approximately 60%, meaning there is 40% of the unit’s life still available for use.

![Current Life Consumption Chart](image)

**Figure 77 - Current Life Consumption Chart vs. Impeller Degradation Parameter**

5.2 **Accelerated Motor Aging Results**

The proof of concept accelerated motor aging experiment detailed in the previous section, focuses on utilizing a generic Sharp Time Distribution Mapping (STDM) mapping algorithm to process and monitor the startup transients of ten different induction motors. At the time of this paper, the experiment is ongoing with several of the motors not yet failed. Presented here are the preliminary results and estimations of Remaining Useful Life (RUL) for the motors that have failed to date. A Leave One Out Validation (LOOV) methodology is applied to create the
estimations and results presented here. The results are generated by creating multiple separate models without the benefit of a single test case, and then that test case is run as a known query case.

After using the residual error of the ST modeling to generate the prognostic parameter a weighed local regression is applied to trend the degradation of the motor and a prediction of the most probable remaining useful life is created. A graphic representation of this is shown in Figure 78. After regressing the current damage path it becomes a trivial task to predict the RUL based on the line crossing the failure threshold limit as well as a confidence base on the variance of the historical failure limits. In this fashion, an estimate of RUL can be created at each stage of life, Figure 79 shows one exemplar case.

![Figure 78 - Example of RUL Estimation](image1)

![Figure 79 - RUL Estimation over Motor Lifetime](image2)
Also as mentioned in the previous section, each estimate is also weighted against the mean time to failure based on cycle number to yield a more robust and reliable answer. Using this algorithm, the average Mean Absolute Percent Error (MAPE) over all the motors is approximately 7.8% of motor lifetime. This is calculated across the entire lifetime of each motor and if it is limited to the last 20% of life, the more critical region for RUL predictions, this drops to 4.5%. The Figure 80 shows this lifetime error for each motor.

In fact, the overall convergence of predictions and a notable decrease in their predictions trends towards the end of life. This is desirable and expected for a prognostic model as both the level of knowledge about a unit and the necessity to accurately predict failure increases with the life of the unit. This convergence for the developed model is illustrated in Figure 81.

This shows that during the last 20% of a unit’s lifetime, this model can predict the RUL of a given motor to within less than 1.5 aging cycles. This not only validates the generic transient modeling technique developed in this work, but also the usefulness of utilizing transient information in general to create prognostic predictions and further the overall condition and reliability knowledge base.


6 Conclusions

Prognostic estimations and predictions, which have been traditionally fed nearly exclusively from steady state monitoring techniques, can greatly benefit by the incorporation of information gathered during transients. In some cases that information can produce indications of incipient faults that are stronger than (or even unavailable) during steady state conditions. Towards this end, a generic algorithm to extract and utilize this transient based information to create prognostic models is developed in this work. This algorithm sets the framework by which a set of data gathered from any equipment undergoing an operational transient may be analyzed and for suitable prognostic features, and if found can then be utilized by any number of traditional prognostic modeling techniques. Most notably is the general path model, with its intuitive predictive capabilities, this is ideal for most feature based Remaining Useful Life (RUL) estimations.

To aid in implementing this developed algorithm, also developed and presented in this work is a list and review of suitable transient signal feature analysis and extraction techniques. Both traditional and novel, within the list of transient analysis techniques the most informative, and/or generically applicable have been highlighted and identified as the best candidates for the prognostic transient analysis algorithm. Specifically, the Gabor Transform for its’ intuitive frequency analysis capabilities, the Hilbert Huang transform for its ability to demodulate and
highlight subtle changes, and the newly developed method of time distribution mapping via a non-uniform empirically based high dimensional distribution space (the Sharp Transform) for its’ ability to capture a wide array of shifts in the signal without excessive optimization based on previous knowledge. These signal processing and feature extraction techniques have been identified as suitable for use in development of Transient Operations Prognostic (TOP) Models.

In order to validate the developed methods, three separate case studies are presented in this work. In each case the utilization of transient based information as well as the developed algorithms, was able to identify and extract usable features that could then be trended via prognostic modeling techniques. The work on Upadhyaya’s previously taken motor aging data was first able to show a clear link in the elevated stress levels of transient operations and exacerbated prognostic features which were not present during steady state. It also demonstrated the benefit of adding the prognostic information gathered during a transient to that gathered during steady state. Next, both the pump impeller degradation experiment and the more recent motor aging experiment, which was focused on startups, demonstrate the validity of the generic transient Sharp Time Distribution Mapping (STDM) modeling technique. The overall prognostic transient analysis algorithm is also demonstrated and validated through this experiment.

The clear link developed between operational transients and the indications of the amount of system degradation for all these cases prove the importance of monitoring these portions of system lifetime. Without that knowledge or the ability to analyze and understand it, valuable information would be lost. The broad range and styles of transient signatures make it nearly impossible to apply a single analysis technique to every case. However, the generic prognostic transient analysis algorithm developed as well as the STDM modeling technique was designed and implemented to accommodate the broadest number of transient signatures possible. With the development of this algorithm, any known transient can now be processed and modeled through the collection of historical cases.

Transient monitoring can be a valuable asset in the overall maintenance and reliability regime. The techniques and practices detailed in this paper have been shown to be able to make accurate and reliable prognostic predictions from signals gathered during often-unused transient portions
of equipment lifetime. An accelerated aging proof of concept experiments involving the analysis induction motor startups is ongoing, but has already yielded results showing that direct application of the STDM modeling technique can be used to create prognostic parameters suitable for use in traditional prognostic algorithms.

Transient processes are a fundamental part of a great number of systems and equipment. These portions of time represent a significant portion of the lifetime in many of these, and without proper techniques to observe and analyze these; the lost information associated with them could hinder the complete assessment of that system’s overall health.
7 Recommendations for Future Research

The results of this work provide clear indication of the usefulness of transient signals with regards to prognostic modeling. The author of this work recommend moving forward with implementation and field testing of the procedures developed within this paper. Either focused specific applications and algorithms, or more generally applicable transient analysis methods can be employed on high-risk low usage equipment to great effect. These methods can be used as a supplement to more standard steady state online analysis methods, or in cases of pass/fail startup testing such as backup generators, can provide stand-alone prognostic indications. Additional research areas should include focused work on identifying and collecting real world equipment signals applicable to these processes. Other areas of research include further development and refining of automated feature extraction and combination from multi-dimensional signal analysis techniques such as from the Joint Time Frequency Spectrum. Another area of potential future research is the theoretical study and development of the novel metrics presented in this research and their stability in providing consistent results. Optimization of the distance metric between successive equipment lifetime Time Distribution Maps has also been proposed.
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Vita
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