CURTISS-WRIGHT

StressWave Analysis and Predictive Pattern Recognition In Wind Turbines

Condition Based Monitoring and Predictive Maintenance Solutions

Abstract

Ultrasonic data analysis as a method of early-stage machine fault detection has been successfully utilized in the Predictive Maintenance (PdM) industry for over 25 years. The challenge with this type of machine health monitoring is the collected data's sensitivity to the changes in machine operational condition, such as load, speed, and/or pressure. Typically, any alarm or fault criteria threshold based on ultrasonic data would need to be sufficiently elevated in order to accommodate the machine's variable operational conditions, or else the monitoring system would generate excessive false alarms due to, for example, a high load condition. However, a sufficiently high alarm level results in a reduced response accuracy in the ultrasonic monitoring system to specific machine fault conditions. A proposed solution to the high sensitivity of the ultrasonic monitoring system is an integrated solution with a predictive pattern recognition system that would predict the ultrasonic data level based on machine operational conditions. Based on the ultrasonic data analysis, the pattern recognition algorithm is able to create dynamic or variable alarm conditions to improve the accuracy of determining machine health and/or the presence of mechanical faults.

INTRODUCTION

Machine health monitoring and fault detection techniques have typically been accomplished via of traditional monitoring, such as vibration analysis, thermography, or oil analysis. But the Predictive Maintenance (PdM) industry is shifting towards incorporating advanced analysis technologies such as Artificial Intelligence (AI) and Machine Learning (ML) algorithms due to the potential advantages of these technologies over the challenges of traditional machine health monitoring. As Hosanagar explains:

> AI involves enabling computers to do all the things that typically require human intelligence, including reasoning, understanding language, navigating the visual world, and manipulating objects. Machine learning is a subfield of AI that gives machines the ability to learn (progressively improve their performance on a specific task) from experience – the aptitude that underlies all other aspects of intelligence. As modern algorithms have incorporated more AI and machine learning, their capabilities and their footprint have expanded.[1]

Traditional predictive maintenance (PdM) techniques for machine fault diagnosis have typically comprised of one or more of the following: (1) Manual interpretation of traditional monitoring data using historical data charts and/or FFT analysis; (2) Incorporating advanced machine monitoring data collection techniques, such as ultrasonic acoustic sensors, motor current signature analysis (MCSA), infrared thermography, and/or online oil debris detection; and (3) custom designed software for identifying specific machine defects. The PdM industry as a whole has been slow to incorporate advanced technologies to automate some of the manual data analysis required to determine machine fault issues, but as ML and AI systems have advanced, the PdM industry has begun to utilize some of these systems in the areas of machine fault diagnosis.

For example, vibration monitoring typically requires an experienced analyst to interpret the data and make informed conclusions about the machine's health and/or the presence of specific faults. With the vast amounts of data being generated by typical machine monitoring systems, this type of fault detection analysis can be extremely time consuming, and can result in a specific fault being missed due to data overburden strain. A system that can scrutinize the vast amount of machine operational data for anomalous behavior will be advantageous to generating prompt and accurate machine fault identifications. Per Goodfellow, Bengio, and Courville, "Machine learning enables us to tackle tasks that are too difficult to solve with fixed programs written and designed by human beings."[2]

While predictive pattern recognition can routinely detect anomalous behavior from the collection of condition monitoring sensors associated with an asset, due to the nature of the measurements typically available from traditional monitoring it is a challenge to

1 Kartik Hosanagar, A Human's Guide to Machine Intelligence: How Algorithms are Shaping Our Lives and How We Can Stay in Control, (New York: Penguin Random House LLC, 2019), 6.

2 Ian Goodfellow, Yoshua Bengio, and Aaron Courville, *Deep Learning*, (Cambridge, MA: MIT Press, 2016).

identify specific failure mechanisms before any damage has started to occur. For example, by the time a vibration or temperature monitor detects anomalous behavior, the damage to the machine asset may be beyond a simple repair. The ideal situation is to have the monitoring system identify anomalous machine behavior before the damage to the asset is severe. By using ultrasonic detection to monitor the machine's frictional behavior, the system is able to detect the anomalous behavior at a very early stage, and by applying that data to an AI/ML system, such as predictive pattern recognition, the integrated solution can predict anomalous behavior at a higher level of accuracy than traditional manual data analysis techniques.

METHODOLOGY

PREDICTIVE PATTERN RECOGNITION

Predictive pattern recognition is a real-time, continuous, on-line monitoring system that utilizes existing data signals available through installed DCS systems, historians, and other monitoring systems for anomaly detection. While predictive pattern recognition has features common to other advanced pattern recognition applications, there are some unique capabilities included in predictive pattern recognition that differentiate this application from other technologies.

The underlying algorithm embodied in predictive pattern recognition is the System State Analyzer (SSA). As Mott, Radtke, and King state, "The SSA is a software-based pattern-recognition system that uses previously established relationships of signals from the plant data acquisition system to compare with relationships of current signals"[3]. Just as a human is able to recognize that the behavior of a system "looks right" from past experience, the SSA can assess a system based on patterns it discerns from numeric data. The SSA predictive engine is capable of interpreting data in ways that are currently impractical by any other means; it functions by learning and discerning data patterns associated with normal system operation and then comparing the learned reference characteristics with subsequent monitored system behavior. The SSA performs its analysis by:

- Learning the patterns associated with normal system operation from archived numeric data values to establish a reference for the model
- Monitoring the numeric data from continued process operation
- Identifying discrepancies between the learned patterns and the monitored data
- Presenting results graphically
- Alarming detected anomalies

When the SSA analyzes a system, a value is predicted for every signal in the system. Comparison of the monitored signal value with the SSA's predicted value can provide a fault detection or validation capability for each signal in the system – the SSA can detect or validate these changes even if a particular signal is drifting or has failed altogether. If a signal is missing, the SSA provides an accurate replacement for the missing value in a process known as "synthetic variable generation"; even when many signal values are missing or incorrect in the monitored data, the SSA's pattern recognition algorithm will continue to provide accurate predictions.

The SSA performs analysis by "learning" the characteristics of normal system operation and using those characteristics to evaluate the current status of the overall system, its individual components, and each input signal. The "learning" process involves loading sets of data into a reference library (i.e., system states) that represent good operating practices and well-calibrated instrumentation; subsequent monitored data sets are then compared with those in the reference library for similarity. A group of the most similar reference states that bound the monitored state are stored in the learned domain, completing the "learning" process. The learned domain is then manipulated to develop a mathematical representation of the system given the current operating conditions.

When this mathematical representation is combined with the monitored state, a prediction for each signal is calculated. The predicted state is then compared to the monitored state to evaluate overall system operation. Additionally, the value for each signal in the monitored state is compared to its corresponding predicted value to identify signal failure, calibration drift, and/or component performance changes and degradation. Figure 1 shows an example of predicted dynamic alarming's advantages versus a fixed alarm threshold criteria.

3 J. E. Mott, W.H. Radtke and R.W.King, *EBR-II System Surveillance Using Pattern-Recognition Software*, CONF-880748--6, (Idaho Falls, Idaho: EBR-II Division, Argonne National Labratory, July 31-August 3, 1988).

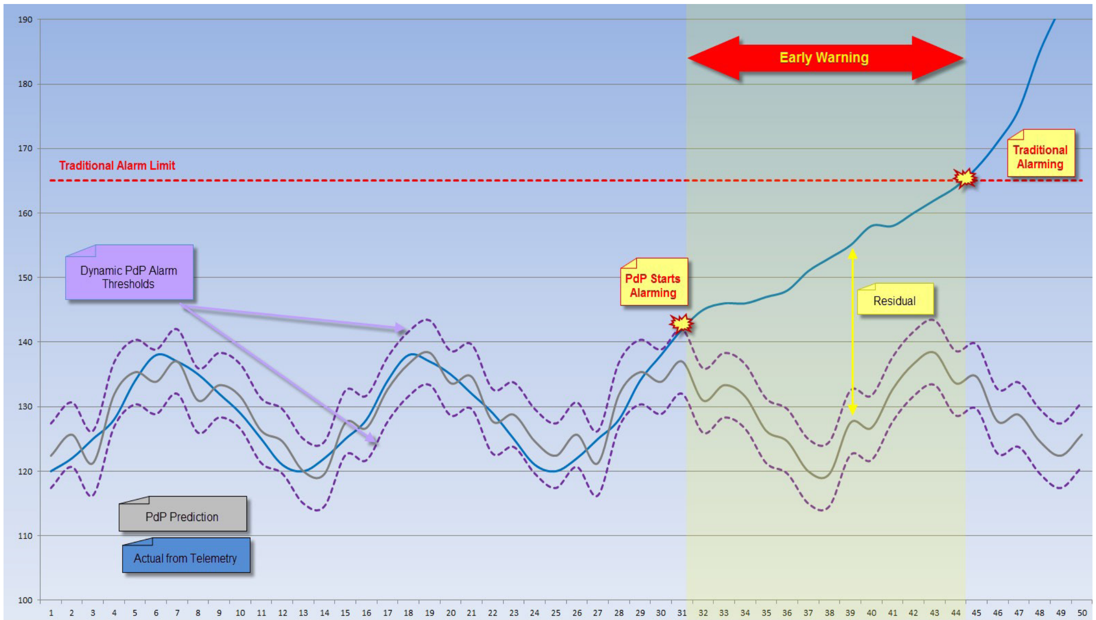

Figure 1: Predictive Pattern Recognition Dynamic Alarming vs. Traditional Fixed Alarm Limit

ULTRASONIC CONDITION MONITORING

Utilizing ultrasonic condition monitoring provides superior accuracy in the early detection of machine damage and faults. Per Shaw:

> It has been determined, through many years of field and laboratory research, that base friction and friction events, generate high frequency (ultrasonic) sound emissions that can travel through the machine's structure and be detected by a suitably designed sensory apparatus."[4]

The ultrasonic detection system typically employs distributed data acquisition units and sensors that monitor high frequency sound generated by friction that naturally occurs between the moving parts of a machine. This technique provides a higher degree of dynamic resolution and more failure lead-time than traditional diagnostic methods. As Board adds:

> It is superior to vibration analysis for detecting and quantifying discrepant conditions that generate friction and shock. This includes not only localized fatigue damage to bearings and gears, but also includes lubrication problems, abnormal dynamic loading, and foreign object damage."[5]

Ultrasonic acoustic emission is defined as the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from a localized source or sources within a material; an example would be the progression of a crack in a solid, due to inter-granular plastic deformation. Ultrasonic acoustic emissions are also continuously generated from contact stresses between two surfaces with relative motion. An important distinction of ultrasonic acoustic emissions is that they typically have higher energy content, and will propagate further through solid structures as well as across material interfaces, such as bolted flanges, mating gear teeth, and antifriction bearing rolling elements/races. This structure-borne ultrasound is caused by friction and shock events between the moving parts of a machine. An externally mounted sensor on the machine's housing detects the ultrasonic acoustic emissions transmitted through the machine's structure. As the high frequency emissions propagate into the sensor, a piezoelectric crystal resonates at a central ultrasonic frequency and is converted into an electrical signal, which is then amplified, band pass filtered, and demodulated to remove unwanted low frequency sound and vibration energy. The output of the signal conditioner represents a time history of individual shock and friction events in the machine based on this ultrasonic data.

PROPOSED DESIGN FOR PREDICTIVE PATTERN RECOGNITION / ULTRASONIC INTEGRATED SOLUTION

The typical alarm functionality of a machine monitoring system is to establish a list of major parameter values, with upper and lower limits as appropriate, for each mode of operation or each state of

4 William T. Shaw, PhD, CISSP, *Continous stress wave monitoring for failure progression analysis*, (Fort Lauderdale, Florida: SWANTECH, LLC, 2006).
5 David B. Board, *Stress Wave Analysis of Turbine Engine Faults*, (Fort Lauderdale, Florida: SWANTECH, LLC, 2004).

the machine. These parameters are examined on a regular basis and checked against their limits in a process referred to as a polling technique. The problem with this solution is that it is not very accurate in a dynamic sense. Because the system is closed and many of the parameters are coupled or correlated with each other, if some parameters change, then other parameters also change. Moreover, the movement of some variables is often a precursor to component or system failure.

An example would be the case of a pump motor beginning to draw too much power; if the pump power increase is not correlated with a flow increase or a coolant temperature change and corresponding density change, then it may indicate that the shaft is beginning to bind because of foreign material intrusion or that the bearings are beginning to fail. In any case, the vast number of correlations are difficult to anticipate and recognize on a timely basis using a polling technique.

Alternatively, by utilizing a predictive pattern recognition system based on the learning process of the System State Analyzer (SSA), the methodology is able to simultaneously validate hundreds of signal values and replace many failed signal values with estimates that depend only on a dynamic estimate of the state of the system, with both signal validation and replacement occurring in near-real-time.

To improve machine fault detection and diagnosis, the proposed solution utilizes ultrasonic signals as a data source basis for the predictive pattern recognition system. As shown in Figure 2, the typical plant monitoring layout is utilized, with the addition of a connection between the ultrasonic monitoring hardware and the predictive pattern recognition system. Therefore, due to the familiarity of existing condition monitoring applications that utilize this type of on-line data collection, the proposed integration is not a complicated endeavor. The integration of ultrasonic and predictive pattern recognition involves specific data transfers via industry standard protocols such as Modbus TCP/IP and OPC – the predictive pattern recognition database can be easily configured to accept the ultrasonic data as a signal source for the SSA engine from these methods.

Data collected using ultrasonic techniques benefits from the advantage of utilizing a proven system that allows the system to predict the machine fault issue at a much earlier stage in the fault progression than traditional monitoring techniques such as

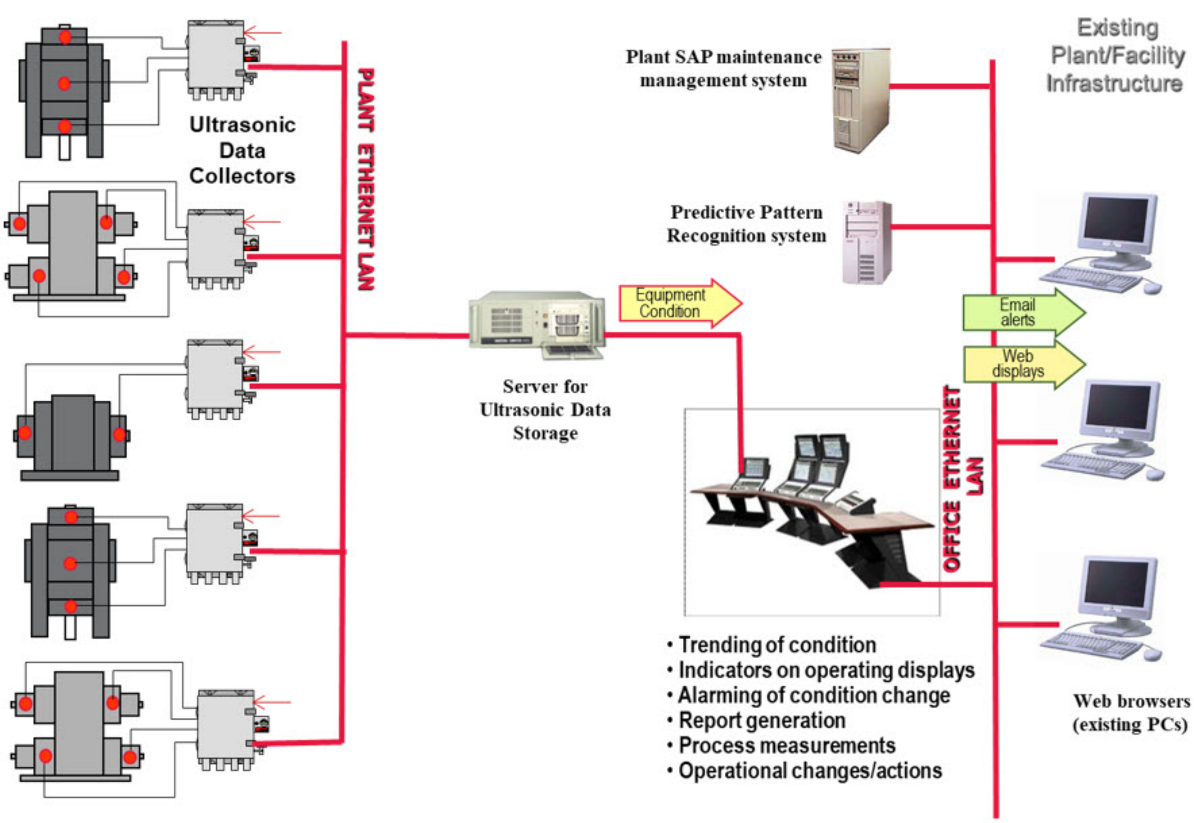

Figure 2: Overall System Diagram Implementing Predictive Pattern Recognition with Ultrasonic Data Collection

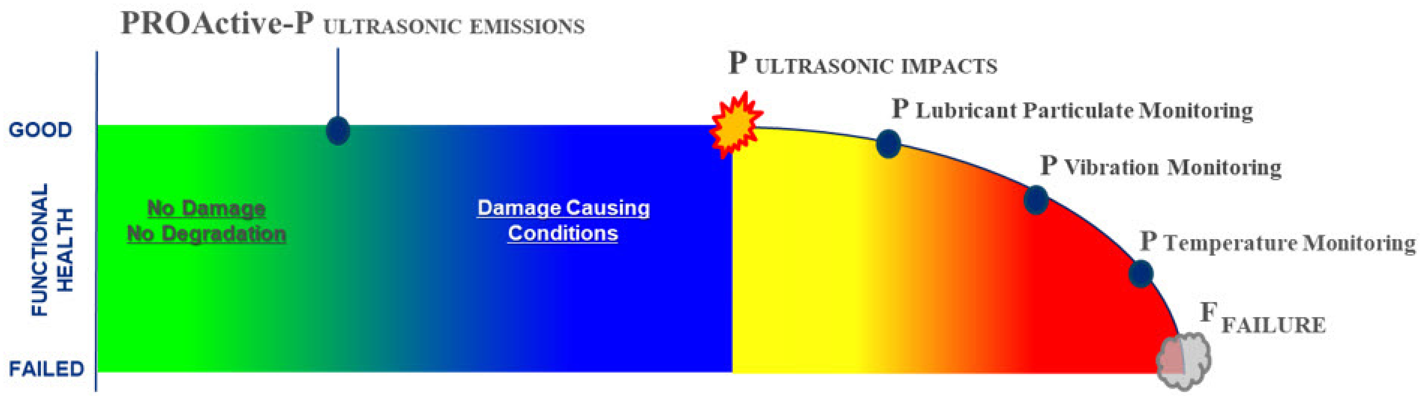

Figure 3: Relative Placement of Monitoring Technologies along the P-F Curve

vibration or infrared monitoring. By measuring shock and friction events, the ultrasonic technique is able to detect wear and damage at the earliest stages, and track the progression of a defect throughout the failure process. This tracking is possible because as the damage progresses, the energy content of friction and shock events increases.

Experienced reliability engineers will recognize Figure 3 as a stylized version of the typical P-F curve. The unit is in good condition until, at some point in time, damage begins and its condition starts to degrade. Point P on the curve identifies where an observation or dedicated condition monitoring measurement would first recognize the fact that the condition has started to degrade. This point represents the first time that the Potential for failure not only exists, but it can be objectively acknowledged to exist. Point F is the point where the Failure occurs.

When examined with this graph, the advantages of monitoring ultrasonic emissions over more traditional condition monitoring technologies appear:

- Point P for ultrasound is exactly the point where damage, manifested by impact pulses, begins, and
- A PROActive Point P exists, prior to actual damage occurring, where ultrasound can identify that conditions are right for damage to occur even though it hasn't actually started.

Traditional condition monitoring methods and technologies are only effective after the initial damage has occurred and progressed to the point where it can be recognized over its routine measurement background levels. They merely identify the fact that significant damage has already occurred and progressed to their respective Point P's, and without intervention, failure is inevitable. Additionally, it is expected that the predictive pattern recognition/ultrasonic integrated system will predict normal ultrasonic levels as they vary with typical operation, allowing a dynamic alarm band that could provide earlier warning than a fixed threshold alarm or criteria.

Thus, by combining the advantages of a "rules-based" algorithm, such as predictive pattern recognition, with the early-warning benefit of ultrasonic monitoring, the combined system is proposed to be a very effective technique, producing effective and reliable results in machine fault diagnosis and the PdM industry as a whole.

EXPERIMENTAL RESULTS AND ANALYSIS

WIND TURBINE DATASET

Wind turbine monitoring has proven to be a challenging environment for traditional data collection to produce accurate fault detection due to factors inherent in wind turbine design and operation, including: (1) variable speed and power conditions, (2) high levels of integral structural vibration, (3) low speed conditions of the main shaft bearing, (4) extreme environmental conditions, and (5) high stress levels applied to drivetrain mechanical components during shutdown operations. These factors have created demanding operational conditions for traditional monitoring technologies and have resulted in the industry's momentum shifting towards using cutting-edge condition monitoring techniques for wind turbines.

The numerous advantages of ultrasonic technology can produce a positive outcome when applied to wind turbine monitoring. These advantages include: (1) shaft rotation speed does not affect ultrasonic signal production, (2) inherent wind turbine vibration is filtered out by the sensors, (3) the frictional detection capability of ultrasonic is useful in determining oil effectiveness during extreme temperature fluctuations, and (4) the short duration, high level mechanical forces applied to wind turbines can be effectively monitored and time-stamped for future mitigation.

In this analysis, a wind turbine's dataset of ultrasonic values is applied to the predictive pattern recognition system to determine if the combination of the two technologies is an effective system for determining anomalous behavior. The investigation will determine the effectiveness of the predictive pattern recognition system to identify anomalous conditions when compared to using the ultrasonic technology unassisted.

ASSESSMENT OF FAULT DETECTION CRITERIA

The primary advantage of the predictive pattern recognition system, as applied to wind turbine monitoring, is its capability to determine predicted values based on power output conditions. This allows the predictive pattern recognition system have a variable alarm structure, which is constructed on the difference between actual and predicted values. If the difference, or residual, exceeds a defined value, the system can trigger an alarm output. In contrast, the ultrasonic system has fixed alarm thresholds, and in order to accommodate the high values of wind turbine power output, the alarm levels need to be established at a sufficiently high level to minimize the occurrence of false triggers.

RESULTS

The wind turbine data set is analyzed by two methodologies: (1) ultrasonic only data and (2) predictive pattern recognition applied to the ultrasonic data. This analysis contrasts the ability of the predictive pattern recognition system to determine a wind turbine's overall health condition via the predicted System State Analyzer (SSA) versus the ultrasonic data collected via the ultrasonic signal generation functionality.

Three wind turbines are selected for data analysis: T1 has no mechanical issues; T2 has a minor level of unspecified mechanical issues in the generator; and T3 has a major level of unspecified mechanical issues in the gearbox. Since this analysis is focusing on determining the accuracy of the overall health indicator between the two solutions, i.e. ultrasonic alone versus predictive pattern recognition of the data, the specific mechanical issues do not need to be identified.

The results in Table 1 indicate that the ultrasonic data shows zero criteria excursions for the wind turbine with no issues, but that only 1% of samples exceeded the criteria for the turbine with issues present. In contrast, the predictive pattern recognition system had a very low excursion rate for the good wind turbine, but had a much higher level of samples that exceeded the criteria for the wind turbine with issues. Most systems have some level of alarm filtering, and a high level of sample excursions will permit a stronger presence of an issue within the alarming system. It is therefore shown that the predictive pattern recognition/ultrasonic integrated solution is able to generate a more accurate response to the wind turbine's mechanical condition.

The results in Table 2 indicate that for the wind turbine with no issues, T1, both the ultrasonic only system and predictive pattern recognition system show a very low number of samples that exceed each system's criteria. But when contrasting the wind turbine with gearbox issues, T3, the ultrasonic system has a 54% criteria excursion rate, while the predictive pattern recognition system

GENERATOR DRIVE END SENSOR	ULTRASONIC DATA				PREDICTIVE PATTERN RECOGNITION/ULTRASONIC			
	# of Samples	Criteria	# that exceed criteria	% of samples that exceed	# of Samples	Residual Criteria	# that exceed criteria	% of samples that exceed
T1 – No Issues	10666	2000	0	0%	10666	200	47	0.44%
T2 – Issues Present	28030	2000	284	1.0%	28030	200	2547	9.1%

Table 1: Generator Data from T1 and T2: Comparison of Ultrasonic vs Predictive Pattern Recognition/Ultrasonic Data Analysis

GEARBOX HELICAL SENSOR	ULTRASONIC DATA				PREDICTIVE PATTERN RECOGNITION/ULTRASONIC			
	# of Samples	Criteria	# that exceed criteria	% of samples that exceed	# of Samples	Residual Criteria	# that exceed criteria	% of samples that exceed
T1 – No Issues	29256	3000	6	0%	29256	200	660	2.3%
T3 – Issues Present	26557	3000	14331	54%	26557	200	26557	100%

Table 2: Gearbox Data from T1 and T3: Comparison of Ultrasonic vs Predictive Pattern Recognition/Ultrasonic Data Analysis

has a 100% criteria excursion rate. This analysis indicates that the predictive pattern recognition system is more effective at identifying wind turbines will issues present.

Figure 4 is a sample of wind turbine data from the Generator Drive-End sensor that indicates the difference between actual versus predicated ultrasonic data. The power output of the wind turbine shows how the ultrasonic data is influenced by the increased load, and thus friction, being applied to the wind turbine. The predictive pattern recognition system indicates that it can track or predict the increase in ultrasonic level with good accuracy as the wind turbine power output increases.

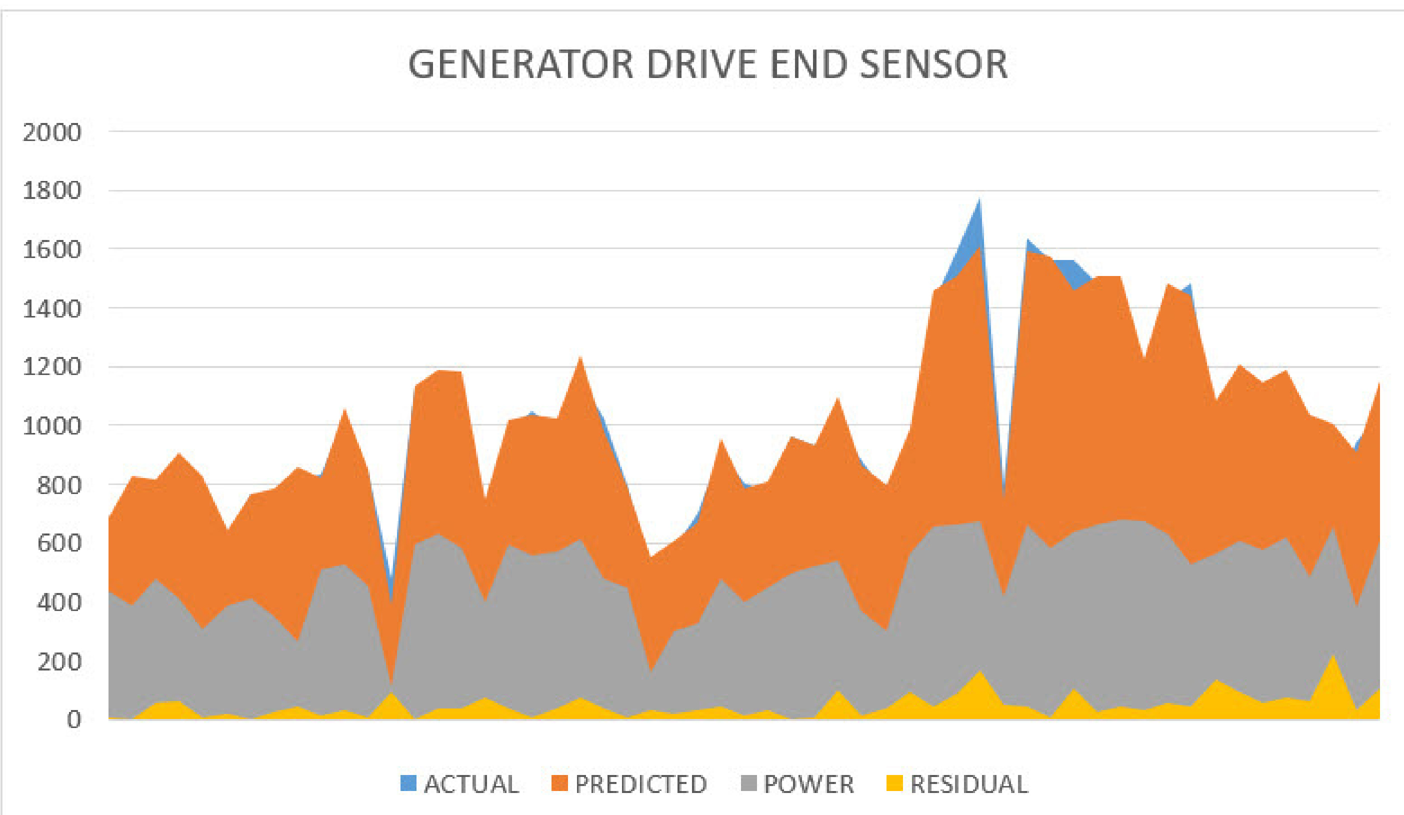

Figure 4: Comparison of Predictive Pattern Recognition Data – Actual vs PredictedAnalysis

CONCLUSION AND FUTURE WORK

The analysis performed in this paper indicates that the application of ultrasonic data into the predictive pattern recognition system improves the sensitivity of signaling the presence of mechanical defects within the mechanical components of a wind turbine. This result can be translated into the monitoring of other mechanical systems where the speed, load, or power output varies during the machine's operation. Due to varying degrees of machine operation, it can be difficult to accurately define a machine's overall health condition based on the ultrasonic data analyzed on its own because of the effect of increased frictional energy on the ultrasonic signal. But by applying the predictive pattern recognition predicted value structure to the ultrasonic data, the variable machine operation can be minimized and the quantity of accurate criteria alarms is increased.

The next step in this evaluation is to apply advanced ultrasonic data structures, such as energy distribution skewness and machine defect frequency analysis, to the predicted value data analysis in predictive pattern recognition. Further data points can allow the system to pinpoint the presence of specific mechanical defects, such as poor oil lubrication and bearing defects, within the predictive pattern recognition system.

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