Trends in Research Techniques of Prognostics for Gas Turbines and Diesel Engines

Joseph T. Bernardo[1], Karl M. Reichard[2]

[1,2]*The Pennsylvania State University Applied Research Laboratory, P.O. Box 30, State College, PA 16804-0030, USA*

jtb17@psu.edu
kmr5@psu.edu

ABSTRACT

Research techniques of prognostics for gas turbines and diesel engines have advanced in recent years. An analysis of trends in these techniques would benefit researchers assessing growth in the field and planning future research efforts. Prognostics research techniques were identified in 1,734 published papers dated 1997-2016 from both the Prognostics and Health Management (PHM) Society and papers identified by CiteSeer^x that were published at venues other than the PHM Society. In order to categorize papers by research technique, a taxonomy of prognostics was created. Additionally, the papers were categorized into two topics: gas turbines and diesel engines. In a large proportion of papers, trends in research techniques of prognostics for gas turbines and diesel engines reflected improvements in the speed of multi-core computer processors, the development of optimized learning methods, and the availability of large training sets. The variety of prognostics research techniques that were identified in this review demonstrated the growth in prognostics research and increased use of this knowledge in the field. This systematic analysis of trends in research techniques of prognostics for gas turbines and diesel engines is useful to assess growth and utilization of knowledge in the larger field, and to provide a rationale (i.e., strategy, basis, structure) for planning the most effective use of limited research resources and funding.

1. INTRODUCTION

The field of prognostics is a discipline that seeks to estimate the impact and predict the trajectory of the state of incipient faults (Bernardo, 2014). The study of prognostics is complicated by the diversity of applicable techniques, which are a collection of mathematical and heuristic techniques from the disciplines of statistics, signal processing, computer science, operations research, and decision theory (Hall & McMullen, 2004). Additionally, it involves multiple challenges in understanding and processing sensor data. Consequently, it is difficult for researchers and engineers to understand, choose, and apply the appropriate techniques to address a problem at hand from the growing number of research techniques available.

While not intended to be mathematically rigorous, the objective of this paper is to assist researchers and engineers in understanding trends in research techniques of prognostics for gas turbines and diesel engines. This understanding will help them plan the most effective use of limited research resources and funding.

In Section 2, a taxonomy is extended to highlight the interrelationships among the diverse set of prognostics techniques. In Section 3, the methodology for the analysis of trends is explained. Section 4 provides the results of the analysis of trends. In Section 5, trends are discussed, suggestions for further research are offered, and references are provided for the more fundamental texts. Finally, Section 6 draws conclusions.

2. TAXONOMY

In Section 1, the problem of assessing trends in prognostics research was introduced. The authors surveyed the corpus described in Section 3 of 1,734 titles and abstracts on prognostics from the last twenty years (1997-2016); they identified 144 individual techniques. To characterize these techniques, the taxonomy developed by Hall and McMullen (2004) was extended to partition additional techniques and algorithms into specific categories.

The taxonomy defines conceptual categories of techniques and groups specific techniques into those categories. As such, they are conceptual and not mathematically rigorous. Figure 1 shows the overview of the prognostics taxonomy, which identifies three categories: model-based methods, data-driven methods, and ancillary support algorithms.

While shown as logically distinct, individual techniques in a functioning prognostics system would be integrated.

Additionally, some individual techniques have characteristics of more than one category. For example, neuro-fuzzy models could be grouped with neural networks or with fuzzy set theory. The trend analysis on individual techniques in Section 4 would not change if a technique were moved to a different category.

Model-based techniques, the first category shown in Figure 1, seek to estimate impact and predict the trajectory of the state of incipient faults using physics-based, cognitive-based, or process models. Cognitive-based models are grouped into the subcategories of knowledge-based, event-based, and possibilistic models. Techniques utilized for model-based methods tend to be probabilistic (e.g. least squares optimization), heuristic (e.g., templates, frames, scripts), or possibilistic (e.g., fuzzy set theory)

The second category shown in Figure 1 is comprised of data-driven techniques, which seek to estimate impact and predict the trajectory of the state of incipient faults by either characterizing the data (e.g., clustering) or by training a model on the appropriate data (e.g., k-nearest neighbor, kernel regression, Bayesian networks).

The third category shown in Figure 1 is comprised of ancillary algorithms that support prognostics. These include statistical techniques (e.g., regression), data transformation techniques (e.g., fast Fourier transform), and data processing techniques (e.g., complex event processing).

The three aforementioned categories are large and contain many individual techniques. Therefore, they are expanded in subsequent figures.

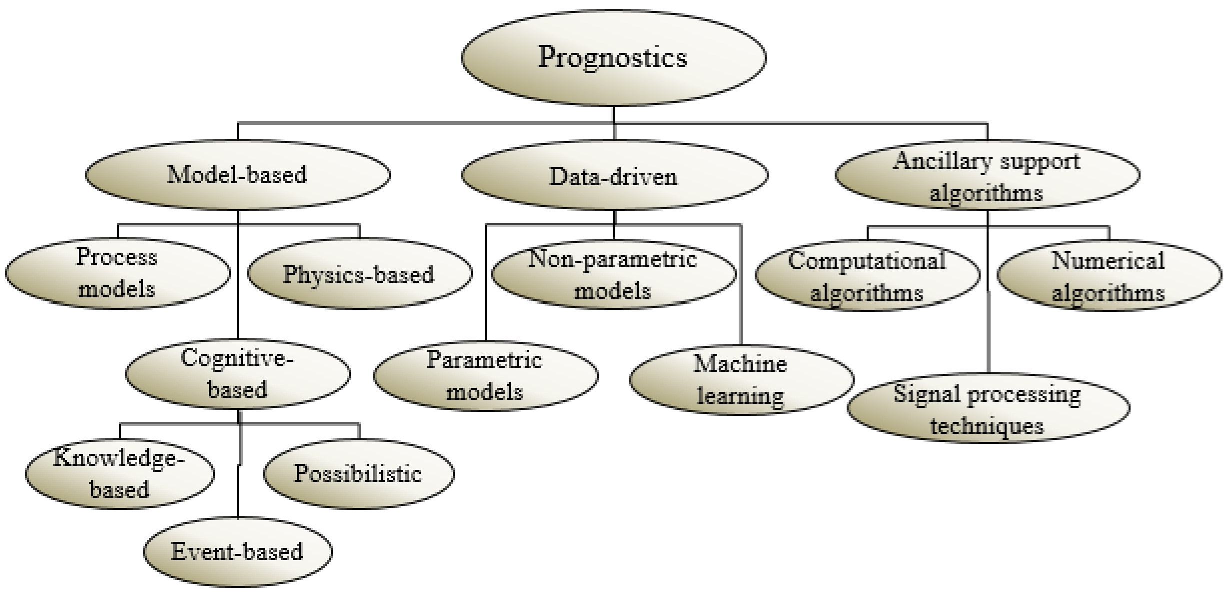

Figure 1. Overview of the prognostics taxonomy
Extended from Hall and McMullen (2004)

Model-based techniques seek to estimate impact and predict the trajectory of the state of incipient faults. As shown in Figure 2, there are three categories of model-based techniques: process models, physics-based models, and cognitive-based models.

First, process models seek to predict response variables from explanatory variables using a model that is not explicitly tied to the physical properties of materials or sensors. Techniques in this category include classical estimation methods and Kalman filtering.

Second, physics-based models attempt to model sensor-observable data (e.g., temperature, vibrational spectra) accurately and to estimate their impact by matching predicted states to the observable data. Techniques in this category include sensor models and grain boundary sliding.

Third, cognitive-based models seek to mimic the inference processes of human analysts in recognizing and predicting faults. Techniques in this category include rules, logical templates, and fuzzy set theory. In various ways, these methods are based on a perception of how people process observations to arrive at conclusions.

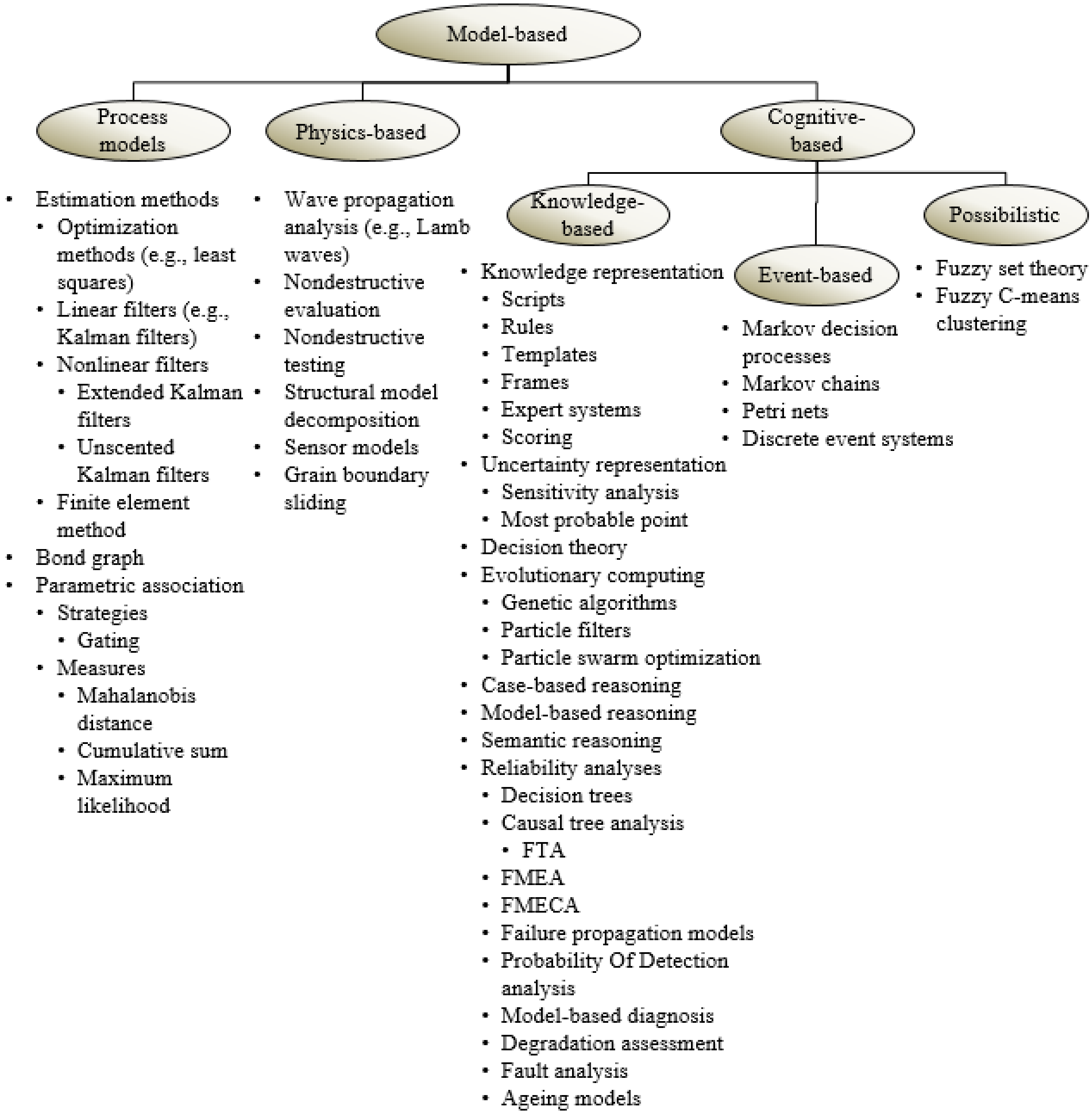

Figure 2. Model-based techniques for prognostics
Extended from Hall and McMullen (2004)

Data-driven techniques seek to make inferences based on data without utilizing physical models. As shown in Figure 3, there are three categories of data-driven techniques: parametric, non-parametric, and machine learning. First, parametric techniques are probabilistic, which require a priori assumptions about the statistical properties (e.g., probability distributions) of the data.

Second, non-parametric techniques do not require a priori statistical information. Examples are voting methods and entropic techniques.

Third, machine learning techniques are used to make inferences by either characterizing the data (e.g., clustering) or by training a model on the appropriate data (e.g., k-nearest neighbor, kernel regression, Bayesian networks).

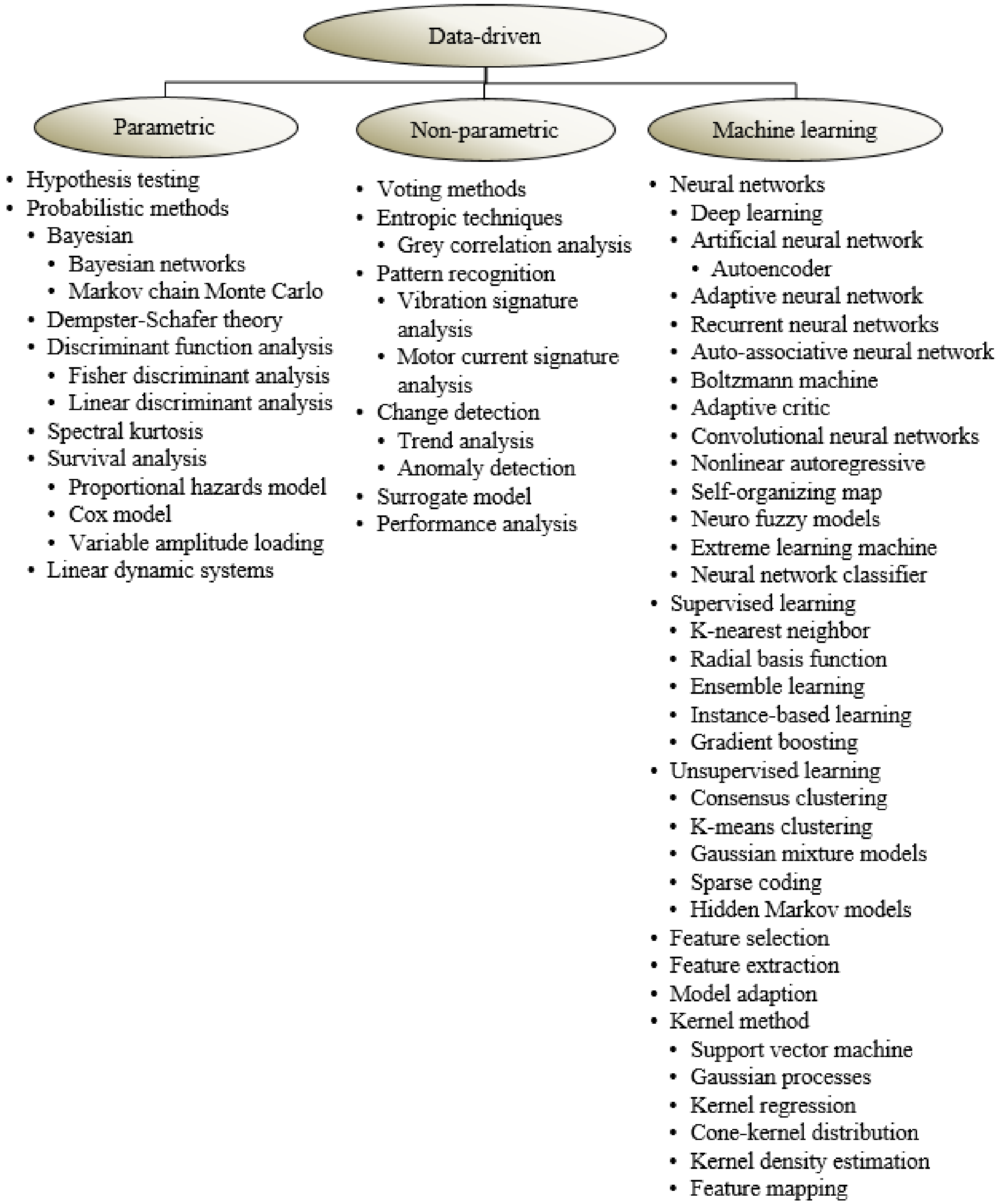

Figure 3. Data-driven techniques for prognostics
Extended from Hall and McMullen (2004)

Ancillary support algorithms are required to support prognostics. As shown in Figure 4, there are three categories of ancillary support algorithms: computational algorithms, signal processing techniques, and numerical algorithms.

First, computational algorithms process the input data. Second, signal processing techniques offer data transformations that help satisfy the linearity requirement of many models. Third, statistical techniques are utilized to form predictive models, increase accuracy, and eliminate outliers.

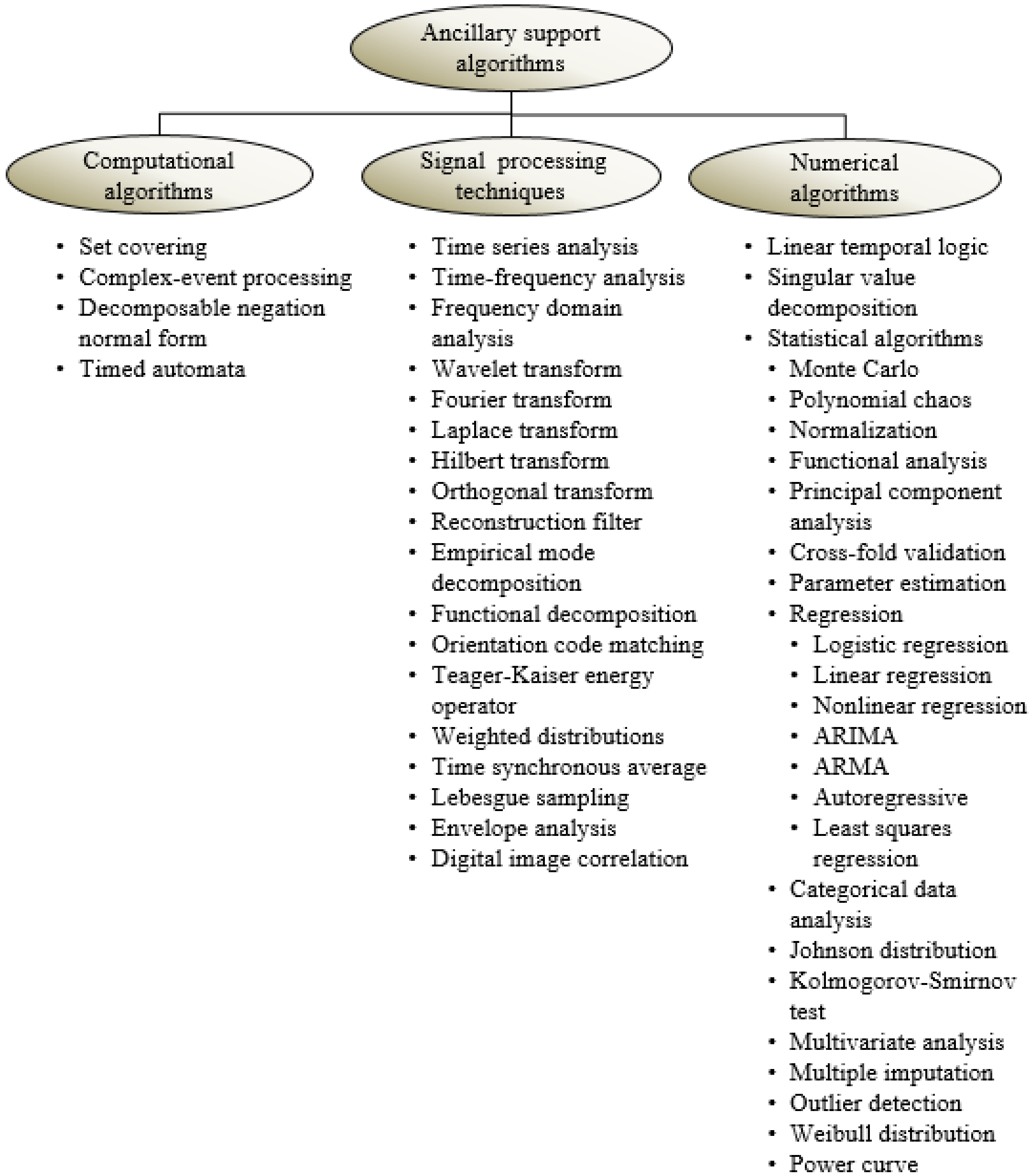

Figure 4. Ancillary support algorithms for prognostics
Extended from Hall and McMullen (2004)

3. METHODOLOGY

The authors obtained titles and abstracts of all 891 scholarly papers published in the International Journal of the Prognostics and Health Management (PHM) Society and in all PHM Society conferences from their start in 2009 through 2016. Using commercially available text mining software (RapidMiner), the authors removed stop words from the set of PHM Society titles and abstracts; converted the words to lower case; stemmed words; and generated 1-, 2-, and 3-grams.

To identify scholarly papers on prognostics from venues other than the PHM Society, the authors leveraged PHM Society titles and abstracts as a training set for a binary classifier: prognostics or not. However, classification accuracy suffers in such high dimensional problems (Friedman, 1997); therefore, to increase accuracy, the authors reduced dimensionality by forming a word vector of n-grams that occurred in at least 10% of the PHM Society titles and abstracts. This word vector of the key n-grams represented the cluster of prognostics papers to be used two steps later—binary classification.

Subsequently, the authors obtained titles and abstracts of scholarly papers found in CiteSeer^x (Li, Councill, Lee, & Giles, 2006) on prognostics published during the last twenty years (1997-2016) at venues other than the PHM Society. Similar to what they performed on the PHM Society titles and abstracts, the authors removed stop words; converted the words to lower case; stemmed words; and generated 1-, 2-, and 3-grams. Additionally, they formed word vectors from the n-grams.

Binary classification was performed using cosine similarity and a fixed decision boundary to identify prognostics papers, of which there were 843. Together, the two collections of titles and abstracts form a corpus of 1,734 titles and abstracts on prognostics from the last twenty years (1997-2016).

To categorize the set of papers, the authors removed stop words from the titles and abstracts; converted them to lower case; and stemmed them. Using the taxonomy described in Section 2, the authors categorized each paper of the corpus by matching the stemmed techniques in the taxonomy to the stemmed titles and abstracts.

The goal of this study was to identify trends in prognostics in two specific application areas: gas turbines and diesel engines. Papers on gas turbines were identified by querying the stemmed titles and abstracts for the terms "turbin", "turbofan", "turbojet", "combust turbin", "turboprop", "turbin engin", and "apu". Papers on diesel engines were identified by querying stemmed titles and abstracts for the terms "diesel", "reciproc engin", and "automot engin". Of the 1,734 papers, 41 were on diesel engines and 98 were on gas turbines.

The authors drew line charts showing relative incidence of individual and rolled-up techniques by topic and by five-year intervals. Similarly, they drew corresponding line charts for gas turbines and diesel engines. The line charts were examined for trends.

4. RESULTS

Three trends in the relative incidence of prognostics techniques emerged: a recent upward trend in deep learning, an established upward trend in particle filters, and an established downward trend in neuro-fuzzy models.

As Figure 5 shows, the corpus contained no incidences of deep learning in the first fifteen years (1997-2011). However, the most recent five years (2012-2016) showed that 2% of papers on all topics and 5% of the papers on gas turbines used deep learning. Therefore, the most recent trend for prognostics is an upward trend in deep learning. Section 5 contains takes a deeper look at the factors affecting this trend.

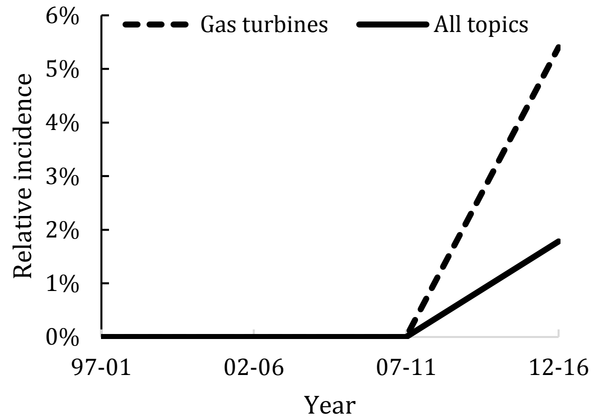

Figure 5. Trend in papers referencing deep learning

From 1997-2001, the corpus contained no incidences of particle filters. Then, in the period of 2002-2006, 3% of papers on all topics used particle filters, but none on diesel engines used particle filters. Next, from 2007-2011, 5% of papers on all topics used particle filters, but none for diesel engines were found. Recently (2012-2016), the relative incidence for particle filters has increased, when 7% of papers on all topics and 11% of the papers on diesel engines used particle filters. Figure 6 shows the established upward trend of particle filters for prognostics.

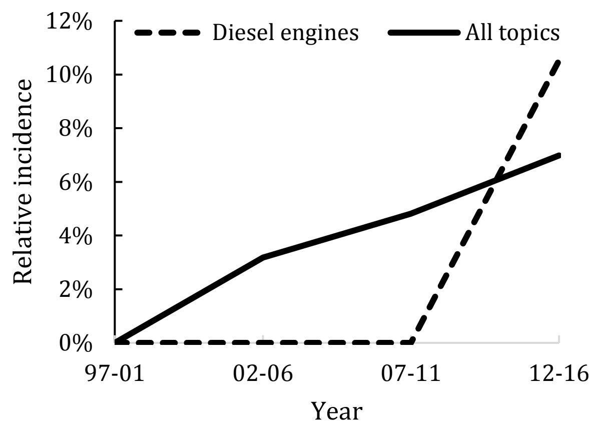

Figure 6. Trend in papers referencing particle filters

The relative incidence of neuro-fuzzy models is shown in Figure 7. In 1997-2001, 3% of papers on all topics used neuro-fuzzy models, followed by 2% in 2002-2006, 3% in 2007-2011, and 1% in recent years (2012-2016). The number of papers on gas turbines using neuro-fuzzy models drops from 25% in 1997-2001 to zero in 2002-2016. Therefore, neuro-fuzzy models in prognostics established downward trend.

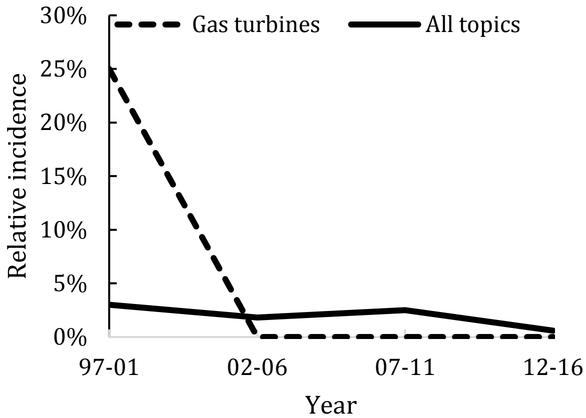

Figure 7. Trend in papers referencing neuro-fuzzy models

5. DISCUSSION

An important step toward deep learning was the neural network research that began in the late 1950s and 1960s with the development of perceptrons (Rosenblatt, 1961) and the use of multiple layers of perceptrons (Widrow, Groner, Hu, & Smith, 1963) to form neural networks. The application of multi-layer perceptrons was advanced by the development of backpropagation algorithms (Hecht-Nielsen, 1989) to train the weights connecting the perceptrons from one layer to the next. Lecun, Bottou, Bengio, & Haffner (1998) successfully applied multi-layer perceptrons to optical character recognition.

Neural networks have been applied in pattern recognition and object classification problems since the development of the backpropagation algorithm provided an efficient method for supervised training of the neural networks. Neural networks have also been used as nonlinear filters and have been trained to synthesize the response of nonlinear systems (Nerrand, Roussel-Ragot, Personnaz, Dreyfus, & Marcos, 1993). Traditional neural networks, however, worked well with static data, but were cumbersome for dealing with temporal data. Recurrent neural networks introduced the ability to add time (Funahashi & Nakamura, 1993) as a variable into the classification process, but most neural network based fault classifiers still relied on the use of traditional signal processing techniques (ancillary support algorithms, Figure 4) to extract features that could then be used as inputs to the neural network.

Despite their success in in pattern recognition and fault classification, neural networks still suffered from several shortcomings. A general lack of computer processing power made it difficult to quickly train neural networks, while a lack of large training sets with metadata describing operating conditions and the occurrence of faults or failures made it difficult to automate training. Finally, because of the lack of large data sets, neural network classifiers tended to be easily over trained. Unlike competing approaches such as Bayesian classifiers and nearest neighbor techniques, which have mathematically describable class boundaries in their N-dimensional feature spaces, neural networks can learn a complicated nonlinear boundary between class members within the feature space leading to a trained classifier that does not generalize well.

Hinton, Osindero, & Teh (2006) introduced deep learning techniques that changed the way neural networks are structured and trained. Further advancements were made in the late 2000s (Deng et al., 2009) with significant demonstrations and applications beginning to appear in 2011. Perhaps the most visible early application of deep learning was the introduction of IBM's Watson computer on the TV show Jeopardy in 2011. Applications of deep learning in prognostics is following a general trend of more numerous and more accurate applications of deep learning in many scientific and engineering disciplines.

The upward trend in applications of deep learning in prognostics since 2011 (see Figure 5) and the overall increase in the use deep learning techniques in general are the result of several factors. First is the development of faster and more powerful multi-core computer processors. While Watson ran on a super computer, deep learning neural networks today run on the processing equivalent of laptops or desktop computers, with the next frontier being implementation on embedded devices and the Internet of Things. A second reason is development of optimized architectures and learning methods, improving the efficiency of training algorithms. Finally, another very significant development is the availability of large training sets, i.e. big data.

Because of improvements in processor speed and algorithm efficiency, deep learning neural networks can be applied to problems with large amounts of data. Coincidentally, deep learning techniques yield results that are more generalizable when they are trained on large data sets. Initially, deep learning techniques were applied to problems such as facial recognition, by having the neural networks train on large libraries of images that were manually collected and categorized. By leveraging the ability to autonomously collect large amounts of data on which to train, such as through embedded sensors and the Internet of Things, deep learning techniques are increasingly being applied to new areas without the need for manual data collection.

One final trend in machinery condition monitoring and prognostics that is leading to more applications of deep learning is the emergence of large machinery health data sets. Many health monitoring applications have traditionally used snapshots of high sample rate data (e.g. vibration data) to determine the health of the system at a particular time. A recent trend has been to focus on the development of prognostic algorithms using low bandwidth sensor data (Grosvenor, Prickett, Frost, & Allmark, 2014), such as that available on vehicle control and sensor busses. Such data typically has a low acquisition or collection cost because it is already available on an existing platform bus and does not require the installation of sensors, wiring, and dedicated data acquisition electronics. Instead of small samples of high bandwidth data, the development is focused on using large sets of low bandwidth data collected across fleets of assets, resulting in big health data. Nevertheless, transmitting or collecting the data from the assets and connecting it to the computers hosting the machine learning programs is still a challenge in many application areas.

6. CONCLUSIONS

In the field of prognostics, it is increasingly difficult for researchers and engineers to understand, choose, and apply the appropriate techniques to address a problem at hand from the growing number of research techniques available. Therefore, a taxonomy was extended to highlight the interrelationships among the diverse set of prognostics techniques. The taxonomy is hierarchical, consisting of categories, subcategories, and 144 individual techniques.

A methodology was developed to analyze trends in research techniques in prognostics from a corpus consisting of 1,734 titles and abstracts on prognostics from the last twenty years (1997-2016) from both the PHM Society and from papers identified by CiteSeer^{x} that were published at venues other than the PHM Society. Papers in the corpus were categorized by research technique using the taxonomy. Additionally, the papers were categorized into two topics: gas turbine and diesel engine.

Three trends in the relative incidence of prognostics techniques in research emerged: a recent upward trend in deep learning, an established upward trend in particle filters and an established downward trend in neuro-fuzzy models.

In a large proportion of papers, trends in research techniques of prognostics for gas turbines and diesel engines reflected the improvements in the speed of multi-core computer processors, the development of optimized learning methods, and the availability of large training sets.

This systematic analysis of trends in research techniques of prognostics for gas turbines and diesel engines is useful to assess growth and utilization of knowledge in the field, and to provide a rationale (i.e., strategy, basis, structure) for planning the most effective use of limited research resources and funding.

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BIOGRAPHIES

Dr. Joseph T. Bernardo is a principal investigator at the Applied Research Laboratory at The Pennsylvania State University. He earned a Ph.D. in Information Sciences and Technology from The Pennsylvania State University in State College, Pennsylvania in 2014. He earned a M.S. and B.S. in Electrical Engineering from The Pennsylvania State University in 1988 and 1986 respectively. Dr. Bernardo has been leading research efforts in data fusion and information science since 1988. Prior to joining the Applied Research Laboratory at The Pennsylvania State University, he was employed at AT&T and Raytheon. Dr. Bernardo continues to publish at refereed conferences and in technical reports. He is a member of the Prognostics and Health Management Society and IEEE.

Dr. Karl M. Reichard is a Research Associate at the Applied Research Laboratory at The Pennsylvania State University and Head of the Embedded Hardware and Software Systems Department in the Systems and Operations Automation Division. He is also an Assistant Professor of Acoustics in the Penn State Graduate Program in Acoustics. He has more than 25 years of experience in the development of advanced sensors, measurement systems, and signal processing algorithms, for active noise and vibration control, system health monitoring, and robotic systems. Prior to joining Penn State ARL in 1991, he was employed by the U.S. Army Aberdeen Proving Grounds and Virginia Polytechnic Institute and State University, his alma mater. Dr. Reichard has published more than 25 papers in refereed journals, conference publications, and technical reports. Dr. Reichard serves as an Associate Editor of the International Journal on Prognostics and Health Management, and on the Board of Directors of the Prognostics and Health Management Society.