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GAS TURBINE MACHINERY DIAGNOSTICS: A BRIEF REVIEW AND A SAMPLE APPLICATION

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The intersection of machine learning methods and gas turbine sensor data has expanded rapidly in the last decade to include numerous applications of regression, clustering, and even neural network algorithms. Learning algorithms have pushed traditional engine health management into the realm of prognostic health management. This paper starts with a review of several common computational methods used to monitor the condition of gas turbines currently employed by both industry and academia. Sources of application of machine learning algorithms from outside the gas turbine industry are also brought in. Focus is generally placed on industrial gas turbines with an industry standard monitoring system. The authors explore beyond gas path analysis with a novel use of machine learning algorithms to engine component classification. The paper concludes with a case study of applying learning algorithms to machine data to identify different fuel valves.

INTRODUCTION

Engine diagnostic monitoring and health management for gas turbines has been implemented, starting in the mid-1970s, in various forms. Algorithms and implementation have evolved significantly as both engines and computational capabilities have become more efficient, complex and powerful. Much of the early development of such methods was born out of the aerospace industry's engine's safety requirements [1]; however, recent years have seen significant contributions from industrial applications. Recent advances in technology have enabled a proliferation of smaller, cheaper and more accurate sensors that are capable of generating a wealth of data for the analysis of the engine condition and overall health. This increase in engine data has lent itself to analysis by algorithms ever-increasing in sophistication.

The definition of "Equipment Health Management" (EHM) has many subtle variations one can find when surveying the field of definitions; however, these can usually be distilled into three primary components: monitoring, diagnostics and recommendations [1]. The first component, *monitoring*, is the act of periodically observing the machine state while keeping a record of the observations. Monitoring can be done at the machine or remotely, depending on the machine setup. The current industry standard is to have the capability of remote monitoring, in which sensor values are captured at a given sampling frequency and then bundled, sent to a remote source and stored [2]. Typically, monitoring is done with intent to determine if the currently observed machine state is at a nominal state or close to nominal state. This introduces the second component of engine health management, *diagnostics*. Diagnostics, according to Merriam-Webster [3], can be defined generally as "investigation or analysis of the cause or nature of a condition, situation or problem." Thus, by definition, diagnostics can only take place after a problem or condition has been observed. Observation of a state that departs from the specified nominal state requires the observer to determine or classify what "departure" actually entails. Further, the granularity of detail in the investigation of the cause of the observed departure depends at least in part, on the sophistication of the monitoring system, as well as the experience of the

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engineer performing the investigation [4]. Naturally, the final piece is the *result/recommendation* of (or based on) the diagnosis of the equipment's departure from a nominal operating state. This final piece is when value is added from the standpoint of the equipment owner [5]. The equipment owner, armed with the result and/or recommendation, is then able to make an educated decision on what action to take next, as it relates to the afflicted equipment, in order to satisfy business requirements.

With the above definition of EHM in place, it is easy to see how various algorithms can be used to aid in this process. In last year's ASME Turbo Expo, a new, vogue term called the "digital twin" emerged in keynote addresses. This term refers to the application of algorithms which simulates the processes of the gas turbine system to a high degree of accuracy. In fact, there are many applications of generalized modelling and simulation of gas turbines [6] [7] [8]. Delving further into the analysis of the gas turbine as it relates to EHM, one finds more direct applications of algorithms to specific sections of the gas turbine or degradation detection. Indeed, neither degradation and anomaly detection nor gas path analysis are new topics for algorithmic based anslysis. [9] [10]. There are numerous mathematical tools that can be employed with computers to aid in the analyzing of the monitored machinery, many of which can be found in Lee, Wu et all [11]. In much of the literature on EHM, application of such algorithms are used directly to ascertain the state of the machine [11] [12] [13] [14]. However, a critical step that is often overlooked or under emphasized in application of these methods is understanding the source of the measurements and how changes to this source can change the measurements and ultimately, the conclusions drawn. For example, many authors state that fuel flow is a critical parameter in gas path analysis [10] [7]. When looking at typical fuel flow time series data, it is easy to fall prey to the idea that the measurement has a great deal of noise in it. However, this idea can be misleading. As will be seen later in this paper, different fuel valves have subtly different flow characteristics, which can lead an engineer to make incorrect conclusions about degradation when looking at data from a fleet of engines. Therefore, it is easy to see that a gas path analysis across a certain set of engines for EHM purposes could be misleading without a proper understanding of which components were installed on the machine.

While gas path analysis is a wonderful use of numerical algorithms, this paper proposes a different application of machine learning based algorithms. Specifically, this paper proposes using machine learning algorithms in the identification of specific components of the gas turbine system. The utility of such an application is evident in instances when an operator or owner is trying to monitor the health of many of the same line of turbines in his or her fleet, and needs to know which turbines have which specific parts. A service provider of EHM falls into this category. Note that EHM providers can be both Original Equipment Manufacturers (OEM)s and non OEM's. In the case of the OEM, original engineering documents should be available in any analysis. However, it is possible that such information is incorrect or that parts have been replaced without all documentation being updated. Such a case arises when a customer has monitored the health of their turbine on their own for the first part of the turbine's life and then for the second part elected to have the OEM takeover monitoring responsibility. In these circumstances, not all of the applicable maintenance records are readily available. In the case of non OEM's, the EHM provider may not even have access to engineering documents. In either case, it can be difficult or impossible to ascertain specific component information.

This paper seeks to highlight the importance of understanding the source of measurement data to be used in EHM algorithms. First, the paper tours the space of mathematical algorithms commonly used in industry for the monitoring of mechanical systems and in particular, rotating machines and gas turbines. The remainder of this paper is a more in depth look at three 'classification type', machine learning algorithms which will be utilized in a case study that follows. The final portion of the paper expands upon the case study and subsequent results. In the case study, a subset of 25 gas turbines is selected, in which each fuel valve installed on each machine is known. Machine learning techniques are implemented in order to classify which fuel valves are installed on which engines, and results are examined and analyzed. The paper concludes with ideas to extend the accuracy of these methods as well as future research areas for such applications of machine learning methods.

NOTATION

ML	Machine Learning
FT	Fourier Transform
WT	Wavelet Transform
AR	Autoregression
ARMA	Autoregressive Moving Average
NN	Neural Network
HMM	Hidden Markov Modeling
SVM	Support Vector Machine
LR	Logistic Regression
DT	Decision Tree
KF	Kalman Filter
IoT	Internet of Things
OEM	Original Equipment Manufacturer
EHM	Equipment Health Monitoring

MACHINE LEARNING ALGORITHMS FOR EQUIPMENT HEALTH MANAGEMENT

Statistical Learning refers to a vast set of tools for understanding data [15]. A direct definition of machine learning comes from Murphy: "Machine Learning is a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty." [16]. Broadly speaking, ML methods fall within two broad categories: *supervised* or *unsupervised* learning. Supervised learning refers to situations in which there are data consisting of inputs and output(s). In this case, information is obtained by relating the inputs to the corresponding outputs, where the relation is generated by the particular ML algorithm chosen. In the unsupervised case, the data only contain inputs. The association between inputs and outputs cannot be directly inferred, and instead, relations about the inputs are created.

Machine Learning as defined above is not a novel idea; in previous decades, the process of identifying relationships between inputs and outputs of a system has been called system identification, artificial intelligence, and pattern classification [17]. In the remainder of this section, some common algorithms for machine monitoring applied to rotary machinery systems are discussed. This section ends with a brief review of some standard classification algorithms that will be used in the presented case study.

Lee, Wu, et al present a summary table of so called "Prognostic Health Management" tools that relate common learning/identification algorithms to typical rotating machinery components. The following sets of machine components and their common failures, algorithms for detection come primarily from the exquisite work of Lee, Wu et al [11]. The addition of a valve section seeks to keep the structure of Lee, Wu et al. The technical details of the algorithms listed in each of the following subsections can be found in textbooks on machine learning and/or frequency domain analysis [17] [18] [16] [19]:

Bearings: Typical issues and failures include the outer-race, inner-race, roller or cage. Common measures include vibration signals, oil contaminant inspection and, less commonly, acoustic signals. Common features seen in data are vibration characteristic frequencies, metallic debris and sharp pulses of high intensity. Common detection algorithms include Fourier Transforms (FT), Wavelet Transforms (WT), Autoregression (AR) Frequency Spectrum, Neural Networks (NN), Hidden Markov Modeling (HMM), Support Vector Machines (SVM) and Principle Component Analysis (PCA).

Gears: Typical issues and failures include manufacturing error, teeth missing or teeth erosion, and gear cracks. Common measures include vibration signals and oil contaminant inspection. Common features seen in data are vibration characteristic frequencies and metallic debris quantity. Common detection algorithms include Fourier Transforms (FT), Wavelet Transforms (WT), Autoregression (AR) Frequency Spectrum, Neural Networks (NN), Hidden Markov Modeling (HMM), Support Vector Machines (SVM) and Kalman Filters (KF).

Shaft(s): Typical issues and failures include unbalance, bends, cracks and misalignment resulting in rub. Common measures include vibration signals and harmonic frequency components. Common features seen in data are vibration characteristic frequencies and system modal characteristics. Common detection algorithms include Fourier Transforms (FT), Autoregressive Moving Averages (AR)MA, Neural Networks (NN), and Support Vector Machines (SVM).

Lastly, we introduce a mechanical element that does not rotate, and so does not generate waveform data as the other elements do. This inclusion serves two purposes: (1) to show that algorithms and machine learning can be applied to non-rotating machinery data, and (2) to show that many of the same algorithms are used regardless of the dynamics of the system.

Valves: Typical issues and failures include deadband, hysteresis and stiction (sticking due to friction) [9]. Common measures include upstream/downstream pressures, temperatures, command and position feedback signals. Common features seen in data are response frequency shifts and time domain statistical characteristics. Common detection algorithms include Neural Networks (NN), Support Vector Machines (SVM), and various Regression applications.

ALGORITHMS

As seen by the definitions stated at the beginning of this section, ML algorithms are also supposed to make decisions as well as recognize patterns. Loosely speaking, this describes *classification* algorithms. These algorithms classify data sets (or rather, partition data in parameter space and associate the various partitions with some type of identifier) and can be both supervised or unsupervised algorithms. In the table below, a summary of algorithms available in the MATLAB® classification learner is presented. We discuss briefly the mechanics of the three chosen algorithms which will be presented in the case study later in this paper. The three algorithms were chosen on the following basis: they needed to be available in the Matlab machine learning library and there needed to be both linear boundaries and non-linear boundaries.

Algorithms In MATLAB® Classification GUI
Decision Trees (CART)
Discriminant Analysis
Logistic Regression
Support Vector Machines
Nearest Neighbor
Ensemble Methods

Decision Trees: Decision trees are a way of stratifying the predictor space into n non-overlapping, exhaustive regions , $\mathcal{R}_k$, such that $\cup_{k=1}^{n}\mathcal{R}_k = \mathcal{R}$, where $\mathcal{R}$ is the entire predictor space. Classification decision trees can be used to predict a qualitative or discrete response. In implementation, after the tree algorithm has been trained, an observation is assigned the value of the most commonly occurring class of training observations in the region to which it belongs [15]. To "grow" or train a classification tree, recursive binary splitting is used. To perform recursive binary splitting, all predictors $X_1,...X_q$ and all possible division points for each predictor are considered. Choice of the predictor and division point are determined based on some form of minimized error. The most popular choice of error function for classification trees is the *Gini Index*, $G = \sum_{k=1}^{W} 2p_{wk}(1-p_{wk})$ where W is the number of classes in the response and p_{wk} is the proportion of training observations in the w^{th} region, from the kth class. Here, $2p_{wk}(1-p_{wk})$ can be seen to be the variance of a binomial random variable [20], so the Gini Index method seeks to minimize total variance across the k classes. Another relatively popular choice for minimizing error is the *Cross-Entropy* function; see [16].

Logistic Regression: Logistic regression gets its name from the underlying function that generates the classifications, the *logistic function*, $\hat{y} = \frac{e^{a_0+a_1x_1+\cdots+a_px_p}}{1+e^{b_0+b_1x_1+\cdots+b_px_p}}$, where x_k is the kth predictor and $0 < \hat{y} < 1$. To make a classification, a threshold value T is chosen, where $0 < T < 1$, such that if $0 < \hat{y} < T$, $\hat{y} = 0$, otherwise $\hat{y} = 1$. By construction, this function is a binary classifier, although there are ways to use it for more than two classes [15]. Since the function is nonlinear, finding the coefficients a_k, b_j is typically done by using a numerical minimization technique on the objective function, $\underset{a_k,b_j}{\arg\min} f(y-\hat{y})$, with $f = \|\cdot\|_l$, some specified l-norm. Popular optimization algorithms include but are not limited to 'Newton - conjugate gradient', 'Levenberg Marquardt', 'Iteratively reweighted least squares' and the 'BFGS' methods. These methods and more can be found in [21].

Support Vector Machines: The support vector machine algorithm is a variant of the support vector classifier, which is the implementation of the *soft margin classifier algorithm*. Specifically, the soft margin classifier satisfies an optimization on M:

$$\max_{\beta_0,\beta_1,\ldots,\beta_p,\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_p} M$$
$$\text{subject to } \sum_{j=1}^{p} \beta_j^2 = 1,$$
$$y_i(\beta_0 + \beta 1x_{i1} + \beta 2x_{i2} + \ldots + \beta p x_{ip}) \geq M(1-\varepsilon_i),$$
$$\varepsilon_i \geq 0, \sum_{i=1}^{n} \varepsilon_i \leq C$$

The support vector machine brings in *kernel* functions, $f(x) = \beta_0 + \sum_{i=1}^{n} \alpha_i K(x,x_i)$, where $K(x,x_i)$ represents the kernel function. The constraints must be adjusted accordingly; for example, $y_i(f(x)) > M(1-\varepsilon_i)$. Popular kernels are the *polynomial kernel* $K(x_i,x_i') = (1+\sum_{j=1}^{p} x_{ij}x_{i'j})^d$ and the *radial kernel* $K(x_i,x_i') = exp(-\gamma \sum_{j=1}^{p}(x_{ij}-x_{i'j})^2)$. For a more technical review of SVMs, see [18].

CASE STUDY: GAS VALVE CLASSIFICATION

In this section, we present a case study: the classification of the type of fuel valve in use in an industrial gas turbine, based only on standard signals measured on a gas turbine. A priori knowledge is used that the population of data has only two possible valve types, and so an individual set of data points at time t, is categorized as *valve 1* or *valve 2*.

This case study and the motivation for this paper come from real life lessons learned from attempting to jump from raw machine output data to engine condition monitoring [22]. In this previous study, uncertainty in the fuel flow measurements was attributed to insufficient knowledge about the engine systems under investigation, specifically that there were different fuel valves present in the same fleet. Recognizing that the crucial step of understanding how the data was generated had been overlooked, we sought to classify the fuel valves present in the fleet in question.

The choice of the fuel valve classification to illustrate the proposed machine learning algorithms is indeed a practical one. From the perspective of the OEM, maintenance records are not always available. Customers can and do replace hardware on their own without leaving a sufficient paper trail. An example being a customer who has monitored the health of their turbine on their own for the first part of the machine's life and then for the second part elected to have the OEM monitor the machine. In this case, it is often found that not all maintenance records are available. Furthermore, even when knowledge of the valve part is available, it is still useful to classify the operation of the valve as healthy or unhealthy. Such a classification can be done using the same techniques as proposed in the two-valve case study. These realizations provide the current problem statement. **Can specific components of a gas turbine be predicted using machine learning techniques?**.

This case study attempts to provide an initial answer to this question. A fleet of 25 similar turbines is analyzed, where it is known that each turbine has one of two possible fuel valves installed. The fuel used in the sample fleet is known to be of similar composition but time varying. Using measurements of the pressures and temperatures of the gas, command of the fuel valve and standard operating parameters like shaft speed, power and ambient conditions, three separate types of ML models are trained and used to classify a given engine's fuel valve as "valve 1" or "valve 2". The first classification approach uses data from a high fidelity engine simulation, in which site conditions and engine setpoints were assumed. The second classification approach uses actual field engine data from the fleet of engines. In both cases, the three chosen ML algorithms are trained and then applied to the fleet. Lastly, results and conclusions are discussed.