Machine Learning for Condition Monitoring

Johnathan DiMatteo
School of Computer Science
University of Waterloo
Waterloo, ON, N2L 3G1
jdimatteo@uwaterloo.ca

Abstract

The following is a report for a graduate research project for the University of Waterloo Computer Science "CS 680: Introduction to Machine Learning". The goal is to use machine learning to estimate the operating condition of an asset. In particular, the algorithm will be implemented and evaluated on an industrial furnace fan critical to a steel plant. This will allow operators in the steel mill to monitor the asset schedule efficient maintenance tasks, reducing unnecessary maintenance and unexpected failures. A proposed solution, using self-organizing maps, is evaluated on real data.

Motivation

An often overlooked part of an asset's expenses is maintenance. A popular maintenance strategy used in several industries is known as Preventative Maintenance (PvM), where maintenance is regularly performed on an asset while it is still in good condition to prevent it from breaking down unexpectedly. Over $ 200 billion is spent on such maintenance every year in the United States and one-third is wasted on improper or unnecessary maintenance [1]. Even worse, no maintenance at all can lead to unexpected failures which in turn can cause serious economic consequences or injury. There exists a significant need to modernize maintenance techniques around the world to ensure safety, reliability, and efficiency.

During the Second World War, a British scientist named Conrad Waddington made a fascinating discovery about the maintenance of aircraft while working for the Royal Air Force (RAF). Previously, aircraft bombers had a notorious problem of breaking down - in fact the ideal serviceability in a squadron of bombers was only around 70-75% [2]. What he discovered was that preventative maintenance methods actually increased the rate of unexpected failure. The process of more maintenance leading to more failures became known as the Waddington Effect as a result. By increasing the interval between maintenance cycles and eliminating all maintenance deemed unnecessary, Waddington was able to increase the effective flight hours of the RAF bomber fleet by 60% [2].

After this discovery, asset owners around the world tried to find the optimal time to repair an asset. This led to the invention of Predictive Maintenance (PdM), a philosophy that uses the actual operating condition of assets to optimize operations [1]. For PdM to be effective, the asset's operating condition must be estimated. Estimating the asset's operating condition is the focus of the paper, which is also referred to as the *health score*.

1 Background

1.1 Why Machine Learning?

One of the most common reasons PdM methods fail is a lack of continuous improvement and a lack of repeatability [3]. Additionally, equipment monitoring is a time consuming process, requires experts to identify failure patterns, and is expensive. Machine learning provides an automated approach that requires minimal asset knowledge, is inexpensive, can be trained on many assets, and can be re-trained as operating conditions change.

Machine learning techniques for predictive maintenance were considered not practical, too complex, or too time consuming. In particular, plant managers did not want to change their existing infrastructure (the software that handles data acquisition and analyzes it) to adopt the technology. But now Asset Performance Management (APM) software providers are growing and condition based maintenance is at the forefront. As they team up with cloud based data solutions, it becomes easy for asset operators to implement machine learning in their existing data infrastructures via a simple call to the cloud. Manufacturers around the world use APM technology from Bentley Systems, a global leader in APM capabilities according to a recent Gartner report [4]. The proposed solution will be deployed and maintained using APM software from Bentley Systems.

1.2 ArcelorMittal Dofasco

ArcelorMittal Dofasco is a steel company located in Hamilton, Ontario. They use Bentley's APM software and are eager for a machine learning solution to detect the operating conditions of various assets. In particular, they have offered a real data set of several industrial level furnace fans located in the Hamilton plant. Specifically, the data is composed of several smaller data sets, each representing various hours of operation. In a steel making plant, called a steel mill, operations run almost 24/7 except when the mill is shut down once a month for repairs and maintenance. A failure of an asset leading to a shutdown at any other time results in severe costs. If the operating condition of the asset is known, then operators can determine whether or not it should not be repaired during that scheduled downtime, thus avoiding costly unexpected failures and the Waddington Effect.

One of the most costly failures occurs when the fans for the reheating furnace fail. A reheating furnace is used to raise the internal temperature of steel, so that it can be shaped into a final product. Setting the correct temperature is one of the most essential factors of product quality in the plant. In fact, the temperature is so high that if the furnace must be inspected, the entire line must be shut down for days to allow the furnace to cool. A subject matter expert from the steel manufacturer suggests this could cost millions of dollars in lost production.

1.3 Self Organizing Maps

A Self-Organizing Map (SOM) is a type of neural network that is often used as a dimensionality reduction technique as it produces a low dimensional representation of the training samples [5]. A SOM consists of a number of neurons, each represented by a weight vector. They are different from other neural networks because they employ competitive learning. The basic idea behind competitive learning is to have the neurons compete with each other to see who is the most similar to the input vector, 'winner takes all' style. The similarity is usually defined as the Euclidean distance (Eq. 1) between the input vector and the weight vectors of each neuron.

$$\|\boldsymbol{x} - \boldsymbol{w}\|_2 \tag{1}$$

To create a SOM, the size of the map is set to be approximately $5 * \sqrt{n}$, where n is number of data points [6]. The input data is normalized for each variable and the number of neurons are set. The weights of the closest neurons are updated for each instance in the input data. Once training is complete, the SOM can be used again to measure the similarity between a test point and the learned mapping.

2 Previous Work

Using machine learning for condition monitoring is not new. There are typically three approaches:

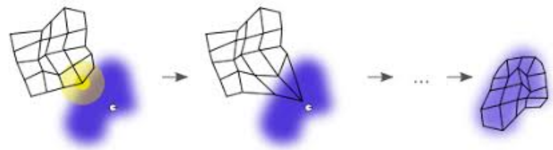

Figure 1: A SOM mapping the training data to a two dimensional grid.

1. Supervised algorithms using sensor data and maintenance data.
2. Unsupervised algorithms using only sensor data.
3. Semi-supervised algorithms using only *healthy* sensor data.

Supervised methods require labelled data. Labelling is the process of associating an output with a set of variable values at a certain point in time. For example, if there is knowledge to when the failures occurred and there are sufficient failures, the data can be labelled as healthy or not. Unfortunately, there is just not enough failure data in practice to make this feasible. Failure data can be estimated and artificially generated but even then the algorithms are limited to a binary outputs [7].

Using k-nearest neighbours (kNN) to estimate asset condition directly is difficult due to noise, and requires domain specific knowledge to choose appropriate variables. One paper improves on kNN methods for detecting the levels of severity for cracks in gears [8]. The disadvantage in these approaches is that it requires significant data in a variety of conditions, and it uses classification to identify a severity level instead of a numerical value.

Researchers in [9] train an autoencoder on healthy imaging data to get a feature representation in a smaller number of dimensions. Utilizing the Support Vector Machine (SVM), they learn a decision boundary to identify anomalies. This approach is interesting for high dimensional data but focuses on point anomalies, where as we are interested in projecting asset health over time.

SOMs have been used in condition maintenance as visualization tools for aircraft engines and ball bearings [10]. By mapping the input data to a two dimensional grid researchers can identify failures trends. Alternatively, Huang et al. were able to use the minimum quantization error (Eq. 2) between a test point and the closest neuron of the SOM as the health indicator for ball bearings [11].

$$Q = \min_{k} \|D - B_k\| \tag{2}$$

Where Q is the minimum quantization error, D is a test set observation, and B_k is the weight vector of the k^{th} closest neuron of the SOM. But, using quantization error can be improved as it is sensitive to noise. Researchers Tian et al. use a SOM and a k-nearest neighbours algorithm in combination with the Euclidean distance between the test data and the healthy data to develop a more robust health score [6].

3 Implementation

3.1 Overview

The project will solve PdM hurdles for operators in modernized workplaces by providing an accurate estimate of asset health. The proposed method is to replicate the results achieved by other papers using SOMs for condition monitoring. Specifically, to train a SOM and get a health score by calculating how much a test data point deviates from normal operation. The higher the health score, the lower the operating condition of the asset. As discussed, this has been done before but is rarely seen in industry today and the use of these algorithms on real and significant data is challenging and relevant. For example, the data will be provided in hourly chunks throughout the year (instead of one continuous data set). Furthermore, feature engineering techniques are be explored to improve performance, use-ability and interpretability.

3.2 Feature Engineering

There are vibration signals used for the following: the interior bearing of the fan, the outer bearing of the fan, the interior bearing of the motor, and the outer bearing of the motor (Figure 3). The

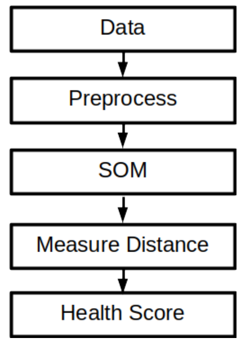

Figure 2: Implementation steps from Data.

mean, standard deviation, skewness, kurtosis, and peak to peak were calculated every five minutes for each of the variables. These five time domain features are commonly used to describe a signal [6]. Additionally, the correlation between the signal and the other three was added as it increased the performance of the SOM.

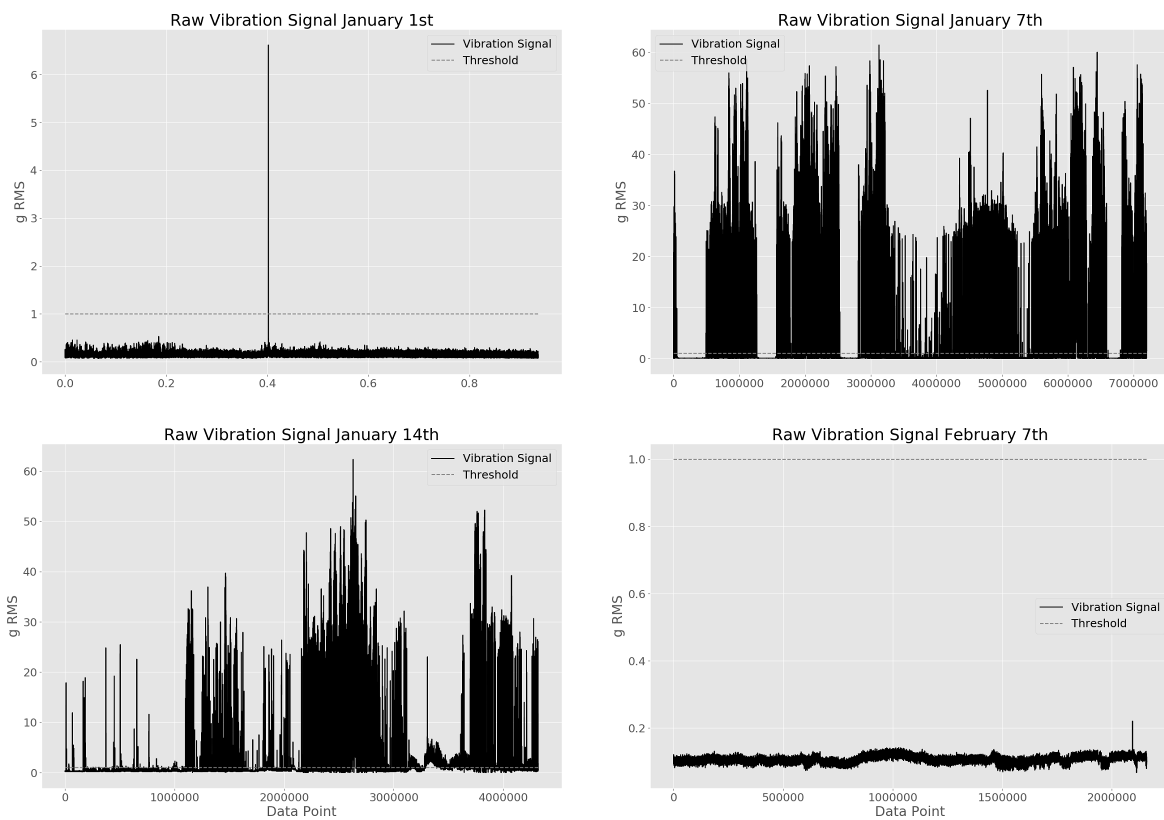

Figure 3: Raw vibration signals.

4 Validation and Application

4.1 Setup

Four data sets were received representing two weeks, one week, the day of, and three weeks after a bearing failure occurred 4. Each data set has data sampled at an interval of 0.2 milliseconds, although data values are only updated every two milliseconds or so. After talking to a subject matter expert, it was determined that the data one week and the day of should be considered as failing. The

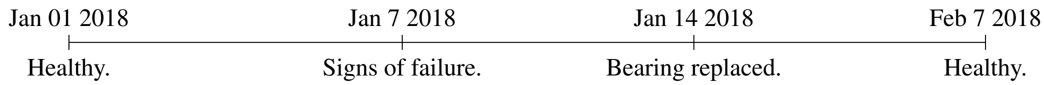

Figure 4: Time Line

data two weeks before and three weeks after represent healthy data. Therefore the experiment setup is as follows:

1. the SOM will be trained on data from February 7th.
2. validation on January 1st data should not show signs of failure, otherwise the model failed to generalize.
3. evaluation on January 7th and 14th should show signs of failure.

The size of the map was set to be 64, representing a 2D grid 8 by 8 grid of neurons. Figure 5 shows the SOM after training the map on data from February 7th, where each square represents a neuron. The colour indicates how similar neighbouring neurons are, and the number of times a neuron has won a competition is labelled on each neuron. Neurons with less than two wins are determined to be too noisy for use in the evaluation [11]. These neurons are ignored. To calculate the health score, the minimum quantization error is averaged over the three closest neurons. This is analogous to the 3-NN method used by [6].

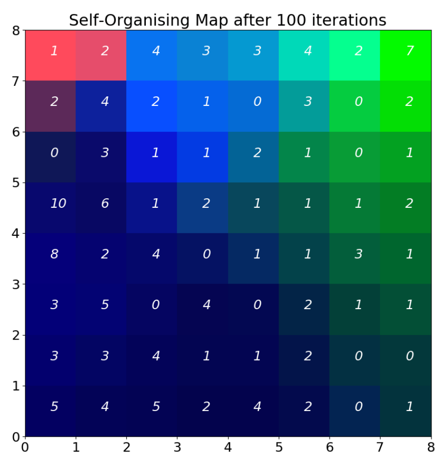

Figure 5: SOM colour map showing the number of hits for each neuron in the map on the training data.

4.2 Results

Operators currently analyze the vibration signals manually. A vibration expert spends time looking at the raw vibration signals to determine a threshold. If the threshold is crossed, an alarm is generated. Operators must manually determine when to replace the bearing based the percentage of time spent above the threshold. This is a common technique used in a multitude of industries. The moving average or the standard deviation of the raw signal can also be used. This method is compared with the SOM and the results are summarized in Table 1. For all methods the threshold was optimized to get the best results. Another significant metric to compare the practicality of all methods is the number of alarms generated (see Table 2). Ideally, an alarm should trigger only once to indicate failure.

The results of the health score are shown in Figure 6. The health score given by the SOM was significantly higher when operators said the bearing was failing. Upon examination the health scores seemed to act as a smoothing mechanism for the raw vibration signal. This makes sense intuitively as the primary determinant for a bearing's health should be the vibration signal itself.

Table 1: Percentage of Time Spent Above Threshold for Each Score

	% of Time Above Threshold		
Method	January 1st	January 7th	January 14th
Raw Vibration	0 %	31.3 %	34.7 %
Moving. Avg.	0 %	50.7 %	47.2 %
Moving Std. Dev.	0 %	57.5 %	38 %
SOM	3.5 %	100 %	100 %

Table 2: Number of Times the Threshold is Crossed for Each Score

	(No. of Alarms)		
Method	January 1st	January 7th	January 14th
Raw Vibration	1	5630	5975
Moving Avg.	1	380	204
Moving Std. Dev.	1	370	206
SOM	1	1	1

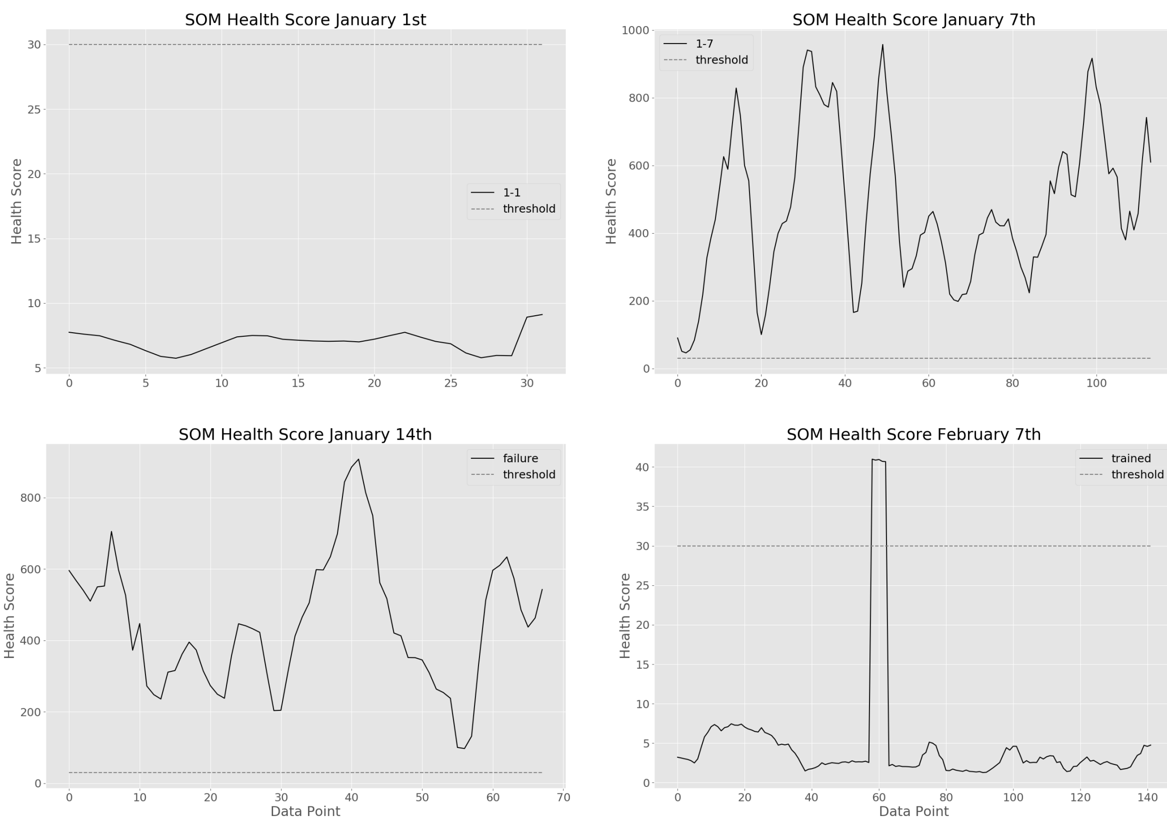

Figure 6: Bearing health scores for each data set. The threshold is set to 30. The SOM map is able to smooth the raw vibration signal to provide a robustness health metric.

5 Conclusion

The raw vibration signal itself is too noisy and thresholds will result in too many alarms. To alleviate this, using features such as the moving average or the standard deviation of the signal can help. Still, these methods only analyze one signal at a time and lack robustness. A SOM factors multiple variables into one metric and eliminates the need for manual signal analysis or thresholds. It also beats traditional methods in terms of number of alarms and percentage of time above threshold. There was no opportunity to compare methods in terms of early prediction because all of the data sets provided to us were binary (a data set was either 'healthy' or 'unhealthy'). Despite this, there is evidence suggesting SOMs can in fact give early prediction of bearing failures [6] [11]. This should be the focus on future work, because the ultimate goal is to predict failure, not just detect it while it is happening. One way to achieve this would be to forecast the health score. Another way could be to try supervised methods such as logistic regression. Still, this application proved SOMs can be used on real data from industry for condition maintenance. Dealing with real industry data can be challenging due to noise and countless other factors. For example, operators at the steel mill may have lubricated the bearing resulting in temporary health improvement.

Overall, the use of this application at a steel manufacturer would give operators a sense of how necessary maintenance is at a particular time, encouraging only performing maintenance when the bearing is unhealthy. This would avoid unintended consequences such as the Waddington Effect. Even better, this could give operators the opportunity to change the bearing during a planned shutdown, avoiding a costly unplanned shutdown later on. This could save the plant millions of dollars in lost production.

References

[1] R.K. Mobley. *An Introduction to Predictive Maintenance*. Plant Engineering. Elsevier Science, 2002. ISBN 9780080478692. URL https://books.google.ca/books?id=SjqXzxpAzSQC.

[2] Philip M. Morse. OR in World War 2. Operational Research Against the U Boat. *Science*, 184(4144):1364–1365, 1974. ISSN 0036-8075. doi: 10.1126/science.184.4144.1364. URL http://science.sciencemag.org/content/184/4144/1364.

[3] Douglas Hart. Predictive Maintenance - Avoiding the Ten Most Common Pitfalls. Technical report, Emerson, 02 2017.

[4] Nicole Foust and Kristian Steenstrup. *Market Guide for Asset Performance Management Software*. Jun 2018.

[5] Teuvo Kohonen. Exploration of very large databases by self-organizing maps. In *Proceedings of International Conference on Neural Networks (ICNN'97)*, volume 1, pages PL1–PL6. IEEE, 1997.

[6] Jianrong Tian, Michael H. Azarian, and Michael Pecht. Anomaly detection using self-organizing maps-based k-nearest neighbor algorithm. 2014.

[7] Vasilis A. Sotiris, Peter W. Tse, and Michael G. Pecht. Anomaly detection through a bayesian support vector machine. *IEEE Transactions on Reliability*, 59:277–286, 2010.

[8] Yaguo Lei and Ming J Zuo. Gear crack level identification based on weighted k nearest neighbor classification algorithm. *Mechanical Systems and Signal Processing*, 23(5):1535–1547, 2009.

[9] Philipp Seebck, Sebastian Waldstein, Sophie Klimscha, Bianca Gerendas, Ren Donner, Thomas Schlegl, Ursula Schmidt-Erfurth, and Georg Langs. Identifying and categorizing anomalies in retinal imaging data. 12 2016.

[10] Etienne Côme, Marie Cottrell, Michel Verleysen, and Jérôme Lacaille. Aircraft engine health monitoring using self-organizing maps. In *Industrial Conference on Data Mining*, pages 405–417. Springer, 2010.

[11] Runqing Huang, Lifeng Xi, Xinglin Li, C Richard Liu, Hai Qiu, and Jay Lee. Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods. 21:193–207, 01 2007.

[12] Randy R Schoen, Thomas G Habetler, Farrukh Kamran, and RG Bartfield. Motor bearing damage detection using stator current monitoring. *IEEE transactions on industry applications*, 31(6):1274–1279, 1995.

[13] Shaojiang Dong, Shirong Yin, Baoping Tang, Lili Chen, and Tianhong Luo. Bearing degradation process prediction based on the support vector machine and markov model. *Shock and Vibration*, 2014, 2014.

[14] Teuvo Kohonen. Self-organizing map. *Proceedings of the IEEE*, 78:1464–1480, 1990.

[15] O. Geramifard, J. . Xu, C. K. Pang, J. H. Zhou, and X. Li. Data-driven approaches in health condition monitoring a comparative study. In *IEEE ICCA 2010*, pages 1618–1622, June 2010. doi: 10.1109/ICCA.2010.5524339.