Anomaly Detection Techniques for the Condition Monitoring of Tidal Turbines

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Abstract

Harnessing the power of currents from the sea bed, tidal power has great potential to provide a means of renewable energy generation more predictable than similar technologies such as wind power. However, the nature of the operating environment provides challenges, with maintenance requiring a lift operation to gain access to the turbine above water. Failures of system components can therefore result in prolonged periods of downtime while repairs are completed on the surface, removing the system's ability to produce electricity and damaging revenues. The utilization of effective condition monitoring systems can therefore prove particularly beneficial to this industry.

This paper explores the use of the CRISP-DM data mining process model for identifying key trends within turbine sensor data, to define the expected response of a tidal turbine. Condition data from an operational 1 MW turbine, installed off the coast of Orkney, Scotland, was used for this study. The effectiveness of modeling techniques, including curve fitting, Gaussian mixture modeling, and density estimation are explored, using tidal turbine data in the absence of faults. The paper shows how these models can be used for anomaly detection of live turbine data, with anomalies indicating the possible onset of a fault within the system.

1. Introduction

Tidal power has great potential worldwide to be a major contributing source of renewable energy. It is a European target for 20% of energy generation to come from renewable resources by 2020, as stated in the European Union Committee 27th Report of Session 2007-08. Within the UK alone, tidal stream generation could potentially supply over 4 TWh per year within the next 5 to 10 years, with the potential to reach up to 94 TWh per year with an installed capacity of 36 GW (King & Tryfonas, 2009), around 26% of the total electricity generated within the UK in 2013 (UK Government electricity statistics). It is therefore clear that tidal energy has the potential to provide a major contribution to renewable sources of energy.

However, tidal power technology is in its infancy, and no clear tidal turbine design has emerged as an industry standard for extracting energy from tidal flow. The state of the art in turbine design includes many horizontal and vertical axis solutions, some with major structural and operational variations (Aly & El-Hawary, 2011). However, a common focus is the horizontal axis design, holding many similarities with a standard wind turbine.

Maintenance on tidal turbines requires a lift operation to access the turbine above sea-level. This can be a costly and lengthy procedure, resulting in prolonged periods of downtime. An effective condition monitoring system would therefore be of great benefit to this industry, allowing the health state of system components to be known, and allowing maintenance to be scheduled efficiently.

Condition monitoring has already been well established for the wind industry. However, despite similarities between tidal and wind power turbine design, the operating environment is vastly different. Water is over 800 times denser than air and, despite slower flow rates (around 3 m/s compared to around 15 m/s for offshore wind), tidal flow has a much higher kinetic energy compared to wind flow (Winter, 2011). This causes tidal turbines to operate with higher torque and thrust loading, inducing increased stress on the machine, particularly on the low speed stages of the drive train. Additionally, the marine environment provides other complications, such as corrosion and interaction with plant and animal life. Furthermore, there is limited historical data of failures from tidal turbines required to implement condition monitoring techniques used as standard in the wind industry.

This paper focuses on using anomaly detection techniques for identifying developing faults within tidal turbines with limited historical data. Using the CRISP-DM data mining methodology (Wirth & Hipp, 2000), key relationships between sensor data parameters from an operational tidal turbine were identified, describing the normal response of the turbine over variable operating conditions. These trends were then defined using several modeling techniques, allowing for deviations from expected data patterns to be detected from live turbine data, alerting the operator to the possible onset of a fault. The implementation of an intelligent condition monitoring system is also discussed, to integrate a number of seperate models together through a decision system to assess the state of the turbine and its components.

1.1. HS1000 Turbine

The data examined within this paper was sourced from the Andritz Hydro Hammerfest HS1000 turbine (Figure 1). The HS1000 is an operational tidal turbine with a rated power of 1 MW, deployed off the coast of Orkney, Scotland, as part of the European Marine Energy Centre (EMEC).

Figure 1. The Andritz Hydro Hammerfest HS1000 tidal turbine

The turbine has an open-blade horizontal axis design, fixed to the seabed. Similar to a wind turbine, its drive train consists of a gearbox connected to an induction generator, translating tidal speeds of around 3.5 m/s to rotations exceeding 1000 RPM within the generator. The turbine has no yaw, with blades rotating in opposite directions in response to upstream and downstream tides. Pitch control of the blades is used to control the output power produced.

This paper will focus on data from the following sources:

- Tri-axial generator vibration velocity
- Gearbox vibration velocity
- Bearing vibration velocity
- Bearing displacement
- Bearing temperature
- Generator rotor speed
- Output power

1.2. Data Mining

Data mining is the analysis of large data sets for knowledge discovery. It involves the use of processing techniques, involving statistical, machine learning and visualization methods, to extract patterns and relationships hidden within data parameters (Olson & Delen, 2008). Data mining has been commonly used by banking and marketing firms, and also within the medical field applied to vast amounts of patient records for improved diagnosis and prediction (Maimon & Rokach, 2005).

Within this study, data mining was used to discover trends and relationships between parameters within initial datasets from the HS1000 tidal turbine. A modeling stage then defines the expected response of the turbine over its typical range of operating conditions. By comparing live turbine data to these models, anomaly detection is used to indicate a change in the response of the system, indicating the possible onset of a fault.

1.2.1. CRISP-DM

The CRISP-DM (Cross-Industry Standard Process for Data Mining) process model was utilized for this study. This model manages the data mining process as six key stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment (Wirth & Hipp, 2000). These stages are shown in figure 2.

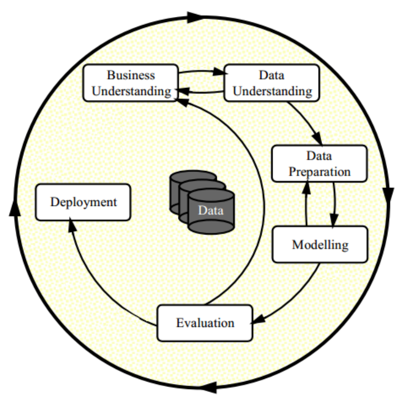


Figure 2. The CRISP-DM process model for data mining (Wirth & Hipp, 2000)

Each stage of the CRISP-DM process model was employed as follows:

- Business Understanding – Understand the operating environment of the turbine and how condition monitoring may be used to assess turbine health.
- Data Understanding – Use statistical analysis to identify key parameters, relationships, and trends to learn the

response of sensor data over standard operating conditions.

- Data Preparation – Organize sensor data before modeling, trending data and grouping by tidal cycle and operating state of the turbine.
- Modeling – Model key trends and relationships using curve fitting, Gaussian mixture modeling and kernel density estimation to define the response of data parameters over varying operating conditions.
- Evaluation – Evaluate the performance of each model, using past operational data to train and test models for anomaly detection.
- Deployment – Compare live data to models and identify deviations from expected behavior, integrating multiple models together through an intelligent condition monitoring system.

2. BUSINESS UNDERSTANDING

The business understanding phase of the CRISP-DM process model involved an appreciation of the operating environment and its effect on the expected response of the turbine. The role of condition monitoring within the field was also considered.

2.1. Condition Monitoring

The use of sensor data from turbine components (such as the gearbox, generator, bearings, blades, etc) can allow the onset of faults to be detected before they cause failure. This enables an efficient maintenance strategy to be employed, as maintenance can be scheduled to reflect to the known health of system components.

Examples of previous research on condition monitoring for tidal turbines includes:

- A review of condition monitoring and prognostic techniques applicable to tidal turbines (Wald, Khoshgoftaar, Beaujean & Sloan, 2010).
- Use of Failure Modes and Effects Analysis (FMEA) to detect faults and failures within tidal turbines (Prickett, Grosvenor, Byrne, Jones, Morris, O'Doherty & O'Doherty, 2011).
- Design of a dynamometer for simulating tidal turbine bearing faults, and application of wavelet based monitoring (Duhaney, Khoshgaftaar, Sloan, Alhalibi & Beaujean, 2011).
- Fatigue analysis of tidal turbine blades (Mahfuz & Akram, 2011).

However, since tidal turbines have limited deployment, there are few examples of condition monitoring systems implemented in practice reported in the literature.

2.2. Turbine Operation

The EMEC test site in Orkney experiences a semi-diurnal tide, with corresponding high and low tides each day. Upstream and downstream tidal flow is experienced by the HS1000 turbine in cycles between each high and low tide.

Figures 3 and 4 demonstrate the response of the turbine to a single tidal flow cycle, detailing generator rotor speed and output power. The rotation of the turbine is controlled through a combination of blade pitching and torque control through a frequency convertor. Generator rotor speed is held at approximately 800 RPM at low tidal flow rates, increasing to a value of over 1000 RPM as the flow rate increases. Output power varies more gradually with tidal flow rate, reaching a maximum of around 1 MW.

It is expected that these parameters will be most indicative of turbine operation, driving relationships with other data parameters as turbine components respond to changes in loading due to variation of tidal flow.

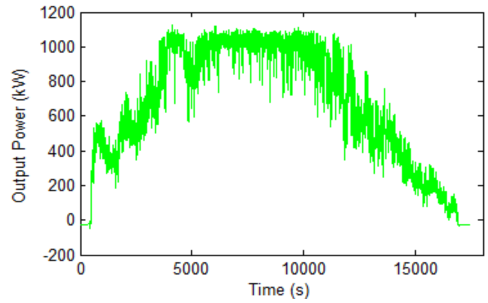


Figure 3. Trend of output power against time for a single tidal cycle.

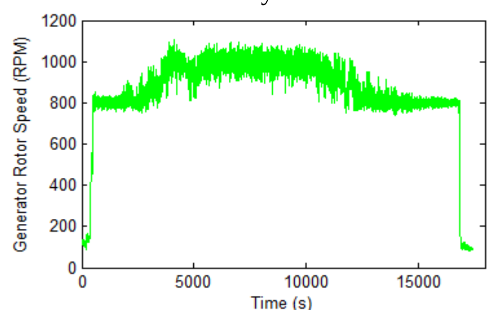


Figure 4. Trend of generator rotor speed against time for a single tidal cycle.

3. DATA EXPLORATION

Within this study, the data understanding stage of the CRISP-DM data mining process involved a statistic analysis of data parameters. Principal component analysis and correlation were used to reveal key relationships between parameters, indicative of normal operation of the HS1000 turbine over a range of operating conditions. This analysis also revealed differences in the response of the turbine to opposing tidal flow directions.

3.1. Principal Component Analysis

Principal component analysis (PCA) is a technique used to extract and remove linear correlations from a set of multivariate data (Pearson, 1901). This technique generates a set of principal components, which are the uncorrelated parameters underlying the observations within the data (Abdi & Williams, 2010).

Components are a list of coefficients, representing a weight for each input parameter, and an eigenvalue. Parameters with high weightings are the highest contributors to relationships within the data, and parameters with low weighting contribute the least. A component's eigenvalue is representative of the significance of a component to the data.

Results for this analysis returned components with high coefficient weightings for output power and generator rotation speed values, with high corresponding eigenvalues (in the range of $1x10^3$ to $1x10^5$). This confirmed these parameters were highly relevant within the data, driving relationships between other data parameters.

3.2. Correlation

Correlation describes the statistical relationship between two variables or data sets. This can be expressed via Pearson's correlation coefficient, which is a value describing the linear dependence of two parameters (Rodgers & Nicewander, 1988). This value ranges between +1 (an ideal increasing linear relationship) and -1 (an ideal decreasing linear relationship). Parameters with a correlation coefficient of zero have no association to each other.

Pearson's correlation coefficient was calculated for every pair of data parameters. High correlation was consistently seen in output power and generator rotor speed parameters, confirming these parameters are key to the response of other sensor data parameters (in particular gearbox and generator vibrations). Therefore, for the modeling stage of data mining, all other data parameters (including vibration, displacement and temperature readings from the gearbox, generator and bearings) were trended against output power and generator rotor speed. These relationships describe the response of turbine components over a range of varying operating conditions.

Comparison of these values also highlighted a change in system response between upstream and downstream tidal flows. This was expected as changes in tidal flow direction alter the direction of loads on the turbine. As a result, for the following stage of analysis, data was batched by tidal cycle and categorized by tidal flow direction. Separate models were then constructed to define the expected turbine response for both tidal flow directions.

3.3. Visual Analysis

Visual analysis confirmed meaningful relationships were generated by plotting data parameters against output power and generator rotor speed.

Trends against output power showed a spread of data across the full range of output power. This is expected, since the turbine generates at all tidal flow rates, and the output power is proportional to tidal flow. Figure 5 shows an example of gearbox vibration trended against output power for a single upstream tidal cycle.

Trends against generator rotor speed exhibited a less consistent spread of data, with points grouping in specific regions of the plot. This is because the generator rotor speed dictates the frequency of output power, which must be within defined limits to export power to the grid. Therefore, above the cut-in tidal flow rate, generator rotor speed increases immediately to approximately 800 RPM. Figure 6 shows an example of this trend, with generator vibration X-axis trended against generator rotor speed.

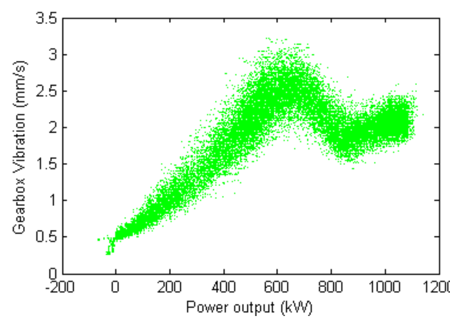


Figure 5. Trend of gearbox vibration against output power.

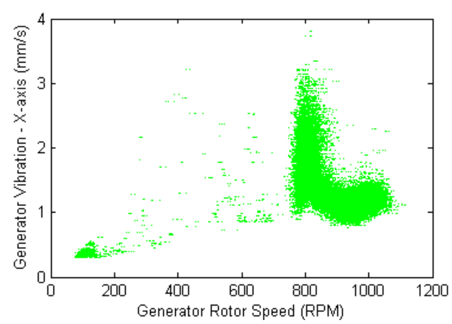


Figure 6. Trend of generator vibration X-axis against generator rotor speed.

4. DATA PREPARATION

The data preparation stage of the CRISP-DM model involved the organization of data before modeling, once key relationships had been identified.

Data was batched by tidal cycle, with upstream and downstream tidal flow data separated. Data parameters were then trended against output power and generator rotor speed.

Also at this stage, four key regions of data were defined, to further segment data before models were constructed. These regions were representative of the operating state of the turbine, and defined using change point analysis (Killick & Eckley, 2013) applied to the speed-power curve of the turbine.

4.1. Change Point Analysis

Change point analysis is a technique used to find a series of points within data parameters where changes in the data are most significant. Change points are determined by calculating a vector of the sum of differences between each data point and the mean of all data points. The maximum or minimum point on this vector will indicate the location of a change point (Killick & Eckley, 2013). This process can be repeated to find additional change points within each newly identified region.

Four regions of operation were visible from the speed-power curve (figure 7):

1. Start up and shut down region
2. Constant rotor speed region
3. Increasing rotor speed region
4. Turbine rotor speed and power limitation region

Figure 7 shows the result of change point analysis in defining these operating state regions. Separating these regions allowed the effects of the turbine's control scheme to be seen across other data parameters and was used to help partition data for use with anomaly detection techniques.

Figure 8 demonstrates how each operating region shapes the trend of gearbox vibration against output power. Changes in operating state can be clearly seen as maximum and minimum turning points in vibration level.

Figure 9 shows how groups of data are formed by the operating state of the turbine. Separating data points by operating regions allow these groups of data to be isolated and modeled separately.

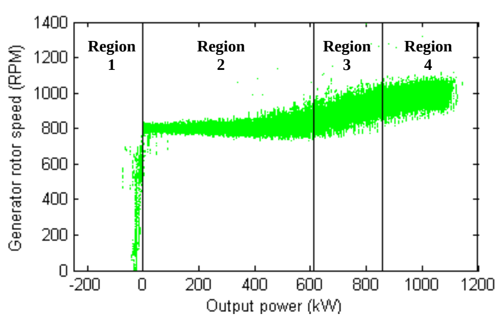


Figure 7. Turbine operating regions identified by change point analysis applied to speed-power curve.

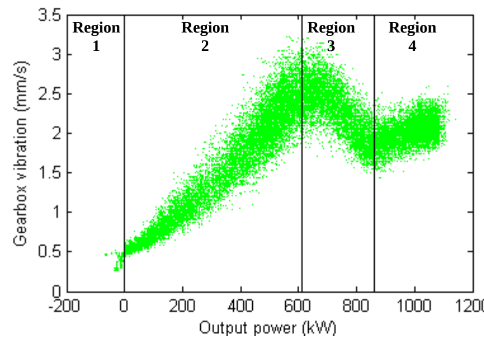


Figure 8. Turbine operating regions over gearbox vibration trended against output power.

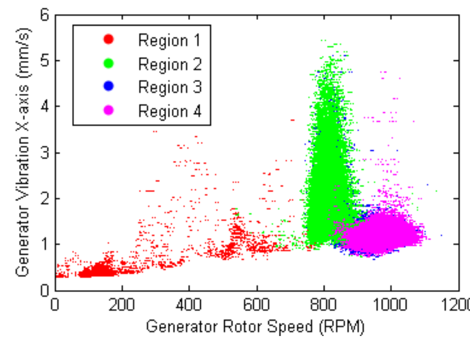


Figure 9. Generator vibration X-axis trended against generator rotor speed, separated by turbine operating region.

5. MODELING

With parameters trended against output power and generator rotor speed, a number of techniques were employed to best define the response of the system. Two types of relationships were observed between parameters: those where data was evenly spread throughout the trend, exhibiting patterns that could be modeled by an individual function; and those where data points tended to cluster within specific areas of a plot.

Curve fitting was used to define even spreads of data, fitting a function to the envelope of the trend or the entire trend itself. Within the data, this was applicable for vibration data trended against output power.

Gaussian mixture modeling and kernel density estimation techniques were used for defining relationships where data points clustered within specific areas. Clusters of data were separated by operating region (as in section 4.1), with areas defined probabilistically. This applied to parameters trended against generator rotor speed.

The output of this stage is a set of models that define the expected response of each turbine component. These models can then be used for anomaly detection, where live turbine data is compared to these models, and deviations represent the potential development of a fault within the system.

5.1. Curve Fitting

Curve fitting was applied to data parameters trended against output power, where relationships displayed an even spread of data across the trend. Initially, this technique was applied to the envelope of these trends, as maximum levels of vibration varied with output power. Anomalies would be detected in this case by data points exceeding maximum expected levels of vibration, lying about a curve fitted to the envelope.

Curve fitting was also applied to describe the trend between gearbox vibration and output power as a whole. This would enable additional metrics, such as variance, to be measured, with anomalies detected where data points exceeded a threshold of distance from the fitted curve.

Within this study, curve fitting was implemented in MATLAB using the 'Trust-Region-Reflective Least Squares' algorithm. This is an iterative method that tunes parameters $(\gamma_1, \gamma_2, \ldots, \gamma_n)$ of the chosen function $f(\boldsymbol{x}, \boldsymbol{\gamma})$ to minimize the squared error between each data point (x_i, y_i) and the function itself, equation (1) (Hung, 2012).

$$\min_{\gamma} \sum_{i=1}^{m} \left(y_i - f(x_i, \boldsymbol{\gamma})\right)^2 \qquad (1)$$

5.1.1. Envelope Fitting

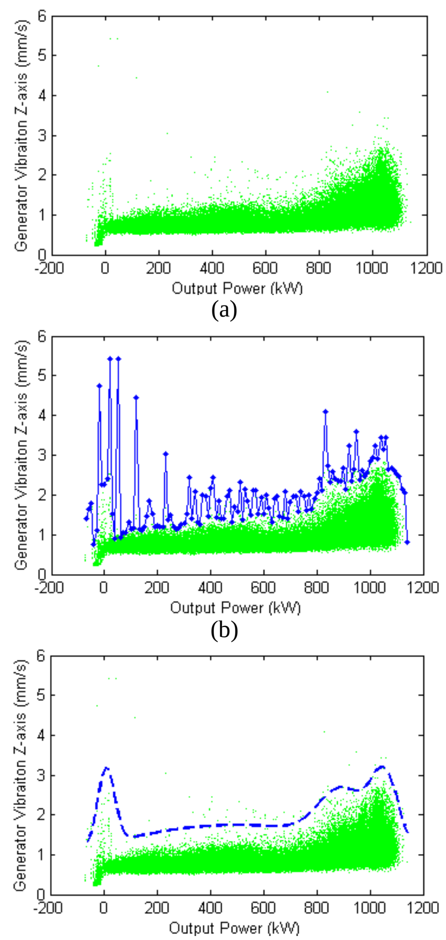
Within the data from the HS1000 turbine, parameters trended against output power displayed varying levels of maximum vibration across their envelopes. Curves fitted to these envelopes will therefore describe a threshold of maximum expected vibration levels over the full range of turbine operation for each parameter, with anomalies detected above this threshold.

An envelope was determined by sampling maximum values of output power across a trend. A curve was then fitted to this envelope, describing the expected boundary of a data parameter. Each stage of this process is outlined in figure 10.

Functions were chosen to model each parameter trended against output power that minimized the root mean squared error (RMSE) between the function and the envelope. Table 1 summarizes the RMSE values for Gaussian and Polynomial functions of increasing orders fitted to the envelope of generator vibration Z-axis trended against output power. Gaussian functions of varying order were found to best fit the envelopes of all parameters trended against output power, with the order number representative of the number of peaks across the envelope.

Table 1. Summary of RMSE values for curve fitting applied to envelope of generator vibration Z-axis trended against output power.

Function	RMSE
6th order Polynomial	0.732
7th order Polynomial	0.727
8th order Polynomial	0.719
9th order Polynomial	0.722
3rd order Gaussian	0.761
4th order Gaussian	**0.709**
5th order Gaussian	0.782



(a) (b) (c)

Figure 10. Curve fitting applied to the envelope of a generator vibration Z-axis trended against output power. (a) Data parameter trended against output power. (b) Sampled envelope across trend. (c) 4th order Gaussian function fitted to envelope.

5.1.2. Gearbox Vibration Curve Fitting

Gearbox vibration parameters trended against output power displayed all data points varying across the relationship (figure 5). Fitting a curve to describe the relationship as a whole would allow for additional measures to be determined, such as variance, to reveal additional information about the response of the system. Anomalies would be detected in this case by data points exceeding a certain distance from the fitted function.

A number of different functions were fitted to this relationship, observed by three seperate vibration sensors. Table 2 summarizes the results, including Gaussian and polynomial functions, as well as a piecewise linear fit within each defined operational region (i.e. four sequential linear fits). The accuracy of each function was compared using the RMSE value between the function and all data points used to generate the model.

Table 2. Summary of RMSE values for curve fitting applied to the trend of gearbox vibration against output power

Function	RMSE		
	Gearbox vibration sensor 1	Gearbox vibration sensor 2	Gearbox vibration sensor 1
Linear fit between operating regions	0.204	0.209	0.243
6^{th} order Polynomial	0.221	0.218	0.238
3^{rd} order Gaussian	**0.203**	**0.205**	**0.237**

The Gaussian function was found to best describe this relationship returning the lowest RMSE. This is shown in figure 11.

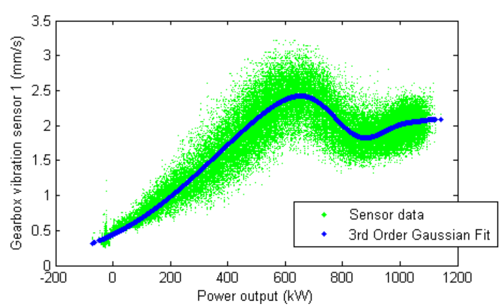


Figure 11. 3^{rd} order Gaussian function fitted to gearbox vibration sensor 1 trended against output power.

5.2. Gaussian Mixture Modeling

Since the generator rotor speed does not behave as a continuous variable (unlike output power), curve fitting approaches are less appropriate. Two techniques were employed to define the operational groups of data against generator rotor speed: Gaussian mixture modeling and kernel density estimation. Each technique defined regions of data by probability. Deviations from expected response of the turbine can be identified as live turbine data occurring with low values of probability when compared to these models.

Gaussian mixture modeling is a method used to fit a combination of n-dimensional Gaussian distributions, each with a given weighting, to an n-dimensional data set (Dempster, Laird & Rubin, 1977). This was performed in MATLAB through the Expectation Maximisation algorithm (Bilmes, 1998). This method involves making an initial 'guess' (randomly generated within a given range) of Gaussian parameters, and calculating the probability of the data points within this model. The model parameters are then updated iteratively to maximize the likelihood of each data point. This process is stopped once a threshold of convergence is reached.

Figure 12 details the result of Gaussian mixture modeling within a contour plot for the Z-axis component from the generator vibration sensor trended against generator rotor speed, separated into the four operating regions. Within this plot, outwardly lines represent areas of decreasing probability. These plots revealed this method works well for regions 2, 3 and 4, where contour lines fit tightly around clear groups of data. However, this technique is not as effective for region 1, where data points are spread more sparsely throughout the plot.

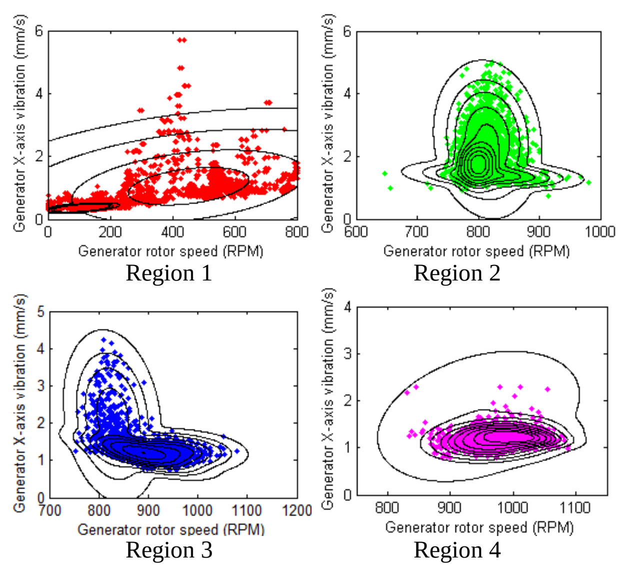


Figure 12. Contour plot of Gaussian mixture modeling applied to the trend between generator vibration X-axis and generator rotor speed.

5.3. Kernel Density Estimation

Gaussian kernel density estimation is a technique similar to Gaussian mixture modeling, used to the same effect within this study to define regions of probability between parameters. However, this technique differs as it aims to approximate the true probability density function (PDF) of the data.

The true distribution is estimated by computing the sum of small individual PDFs at each observed data point (Zucchi, 2003). In this case, the Gaussian distribution was used as the individual (kernel) PDF. This method will generate a more accurate model, however it is a lot more computationally intensive. This was implemented in MATLAB by adapting a method by Cao (2013).

Figure 13 shows a contour plot describing Gaussian kernel density estimation applied to the Z-axis component from the generator vibration sensor trended against generator rotor speed, separated into the four operating regions. In comparison to Gaussian mixture modeling (figure 12), this technique provides a much closer fit to the data, particularly within region 1.

Although this model was more accurate, it produces a less general model, treating individual data points lying outside the main group of data as separate regions of data. This model can be improved by training with as many datasets as possible. It is expected that additional data points will fill in some of the spaces between separately defined regions. Alternatively, smaller groups of data could be removed in pre-processing, and the resultant model could be smoothed over a larger area.

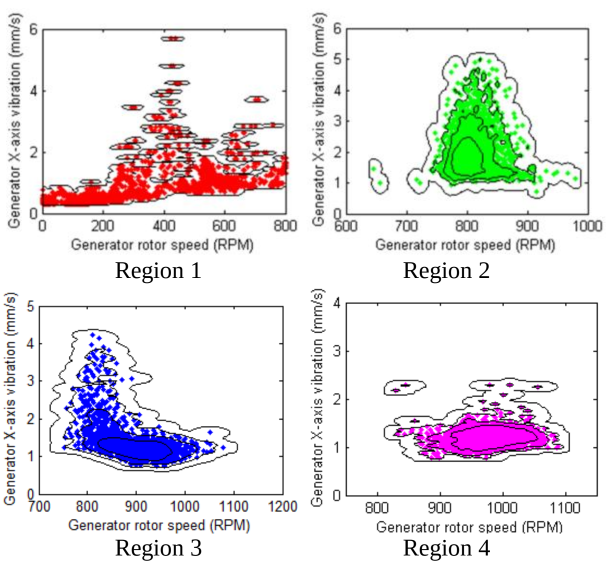


Figure 13. Contour plot of Gaussian kernel density estimation applied to the trend between generator vibration X-axis and generator rotor speed.

6. EVALUATION

Using the techniques described above, models were constructed using training data from October 2013, and tested using data from subsequent December, January and February. Appropriate metrics were then extracted to detect anomalies and measure the severity of deviations from training data. Although no fault data was available, results showed the effectiveness of each technique in defining system behavior and observing changes over time.

6.1. Envelope Fitting

Envelope fitted models, describing parameters trended against output power (as in section 5.1.1.) were tested, where anomalies were detected as data points exceeding the Gaussian function used to describe the envelope of training data.

Some anomalies were detected as crossing the boundary, shown in figure 14. Using this technique a number of metrics can be extracted, including number of anomalies, percentage of anomalies and average distance from the boundary, to indicate the severity of a deviation from normal behavior.

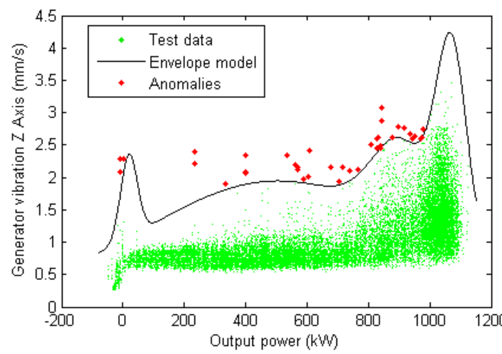


Figure 14. Envelope fitting anomaly detection applied to December 2013 test dataset.

Table 3 summarizes the results of testing this technique, with each metric measured for each test dataset. No significant deviations were detected in the test datasets, with the total number of anomalies being minimal and average distances not being significantly large. This correctly suggests normal behavior.

Table 3. Envelope fitting test results

Testing dataset	Number of anomalies	Percentage of anomalies	Average distance (mm/s)
December 2013	156	0.1718 %	0.226
January 2014	36	0.0361 %	0.388
February 2014	69	0.0418 %	0.355

6.2. Curve Fitting

The curve fitting modeling technique was tested on the relationship between gearbox vibration and output power, using a 3rd order Gaussian curve (as in section 5.1.2.).

Figure 15 shows the December 2013 testing data compared against a trained model constructed from October 2013 data. In contrast to envelope model fitting, no set boundary is used to indicate anomalous data points. Instead, metrics such as maximum error and RMSE can be used to measure the severity of any deviation from normal system response.

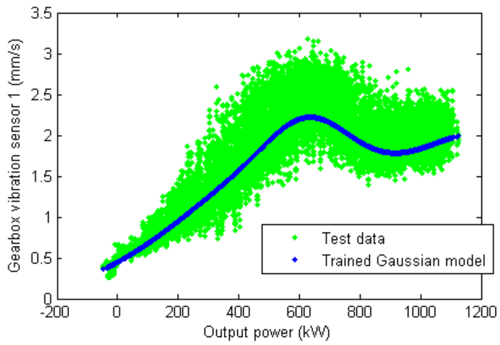


Figure 15. Curve fitting anomaly detection applied to December 2013 test data.

Table 4 summarizes testing results using these metrics. An increase in RMSE is seen in both December and February where more data points are lying above the Gaussian function, indicating an overall increase in vibration across the full operating range. This was attributed to seasonal changes in tidal flow affecting the test data, and not component wear or damage.

Table 4. Curve fitting test results

Training dataset	**Max Error (mm/s)**	**RMSE (mm/s)**
October 2013	1.45	0.203
Testing dataset	**Max Error (mm/s)**	**RMSE (mm/s)**
December 2013	1.26	0.251
January 2014	0.93	0.202
February 2014	1.04	0.235

6.3. Gaussian Mixture Modeling

Gaussian mixture modeling was tested on clusters of generator vibration data trended against generator rotor speed, separated by operational regions, as described in sections 4.1. and 5.2. Results detailed in this section were recorded from the generator X-axis vibration parameter.

Anomalies were considered to be data points lying outside the 95% confidence interval. The percentage of anomalies lying outside the 95% confidence interval (CI) was used as a metric. A value exceeding 5% was considered to indicate that the model was not a good fit to the test data and a change in system response may have occurred.

Table 5 and figure 16 show the results of testing. A number of clusters were identified to have a significant number of anomalies, with percentages exceeding 5%. These results indicate a deviation in system response over time, however, the variations were due to seasonal changes in tidal flow. The significant number of anomalies is therefore not representative of the relatively small variation in data, and it was concluded that Gaussian mixture modeling provided a poor representation of training data distributions.

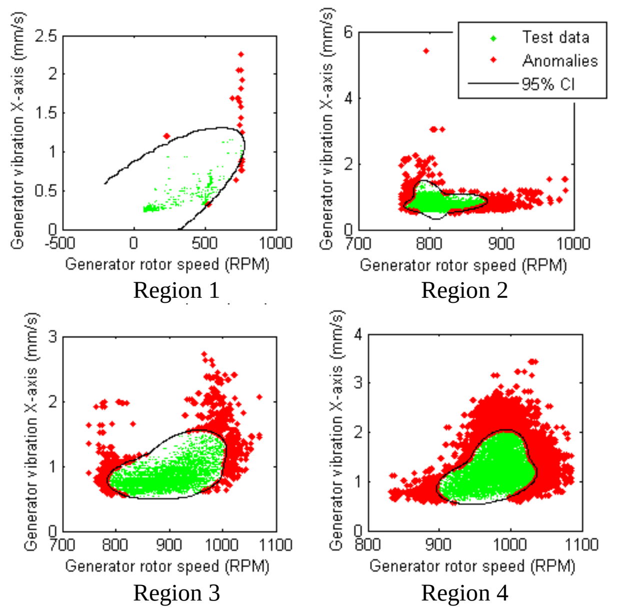


Figure 16. Gaussian mixture modeling anomaly detection applied to December 2013 test data.

Table 5. Gaussian mixture modeling test results

Testing dataset	**Region**	**No. of Anomalies outside 95% CI**	**Percentage of anomalies**
December 2013	1	59	1.006
	2	1532	4.454
	3	1425	9.799
	4	7180	19.928
January 2014	1	88	0.821
	2	347	1.998
	3	194	1.552
	4	10350	19.938
February 2014	1	2469	5.776
	2	6031	5.519
	3	1986	15.055
	4	19	52.777

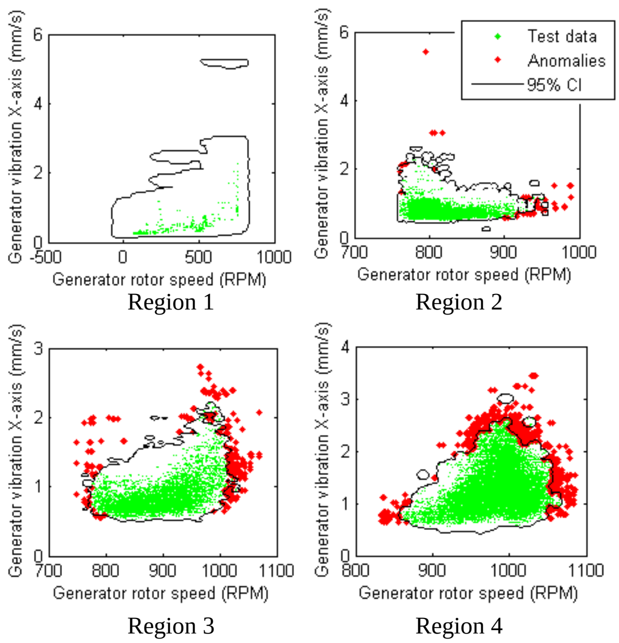


Figure 17. Kernel density estimation anomaly detection applied to December 2013 test data.

Table 6. Kernel density estimation test results

Testing dataset	Region	No. of Anomalies outside 95% CI	Percentage of anomalies
December 2013	1	0	0
	2	108	0.314
	3	499	3.441
	4	1085	3.011
January 2014	1	4	0.037
	2	6	0.025
	3	35	0.280
	4	1532	2.871
February 2014	1	0	0
	2	99	0.090
	3	777	5.894
	4	10	2.778

6.4. Kernel Density Estimation

Kernel density estimation was tested on clusters of data separated by operating regions as in 6.3. As with Gaussian mixture modeling, anomalies were detected as data points lying outside the 95% confidence interval (CI). Here, the confidence interval was calculated using bootstrap sampling, as by Chen, Goulding, Sandoz and Wynne (1998).

Table 6 and figure 17 show the results of testing. In contrast to results achieved through Gaussian mixture modeling, the number of detected anomalies is significantly less, and under 5% in the majority of cases. This suggests kernel density estimation provides a more accurate representation of the distribution of data points within each cluster and is therefore a more suitable technique for this application.

6.5. Summary of Results

Results were obtained to test the effectiveness of a number of modeling techniques, used to define the expected response of a tidal turbine under normal operating conditions.

Envelope and curve fitting techniques were observed to provide a good representation of expected turbine response, capable of detecting small seasonal deviations in data over time. Gaussian mixture modeling was seen to be less effective, detecting a large number of anomalies where little deviation occurred. Kernel density estimation was favored over this technique.

Each anomaly detection technique provides a seperate group of metrics to describe anomalous behavior, indicating the severity of deviations. Future work will involve the analysis of further metrics to support testing on additional data as it becomes available.

No significant changes in system response were observed within test data, with only small variations seen due to seasonal changes in tidal flow. It is therefore recommended that models are examined at regular monthly intervals with deviations matched against seasonal trends. Models can then be updated accordingly.

7. DEPLOYMENT

Since there is no single model which covers all parameter relationships, the deployment stage involves using each model of expected turbine response in parallel to perform anomaly detection of live turbine data. Each individual model can be integrated as part of an intelligent system, with seperate models implemented to process data from the turbine and output whether or not the data has deviated from expected trends. A decision system linked to these modules can then use these results to make assessments of turbine health.

Although anomaly detection is useful as an initial stage of condition monitoring, it is only suitable for indicating if a deviation from the defined normal behavior has occurred. Specific failure modes cannot be identified through this method. Further stages of condition monitoring include diagnosis and prognostics.

Diagnosis involves analysis of turbine component failure modes, and understanding how these will be represented within data parameters. Prognostics involve assessing the current state of the system and estimating the remaining useful life of individual components, or the system as a whole. Various algorithms can be used for these purposes, including those used within machine learning and artificial intelligence, such as neural networks or Bayesian classifiers. Future work will explore these algorithms in relation to the system, utilizing failure data as it becomes available. Diagnostics and prognostics can be implemented as additional modules in the intelligent system.

8. CONCLUSION

This paper outlined the use of data mining through the CRISP-DM process model to explore data from the HS1000 tidal turbine and define its expected operational behavior. The use of principal component analysis and correlation revealed key relationships within the data, relating parameters to output power and generator rotor speed.

Envelope and curve fitting techniques were found to provide accurate models of the response of system components to changes in output power. Kernel density estimation was also found to be an effective technique when used to model clusters of generator vibration data formed when trended against rotor speed. Gaussian mixture modeling was found to be less effective in this application.

Models were trained using past operational turbine sensor data, with anomaly detection performed using data from subsequent months. Small deviations in system response were detected, due to seasonal changes in tidal flow.

Future work will involve the analysis of further metrics to describe the severity of anomalous responses, using additional data as it becomes available. Once techniques are established, an intelligent condition monitoring system will be designed to integrate seperate modules together and assess the state of the turbine and its components. With further research, additional modules can be added to the intelligent system, to perform diagnosis and prognosis as failure data becomes available.

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