Eighth American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies
NPIC&HMIT 2012, San Diego, CA, July 22–26, 2012, on CD-ROM, American Nuclear Society, LaGrange Park, IL (2012)

INVESTIGATION OF GAS CIRCULATOR RESPONSE TO LOAD TRANSIENTS IN NUCLEAR POWER PLANT OPERATION

Jason J. A. Costello, Graeme M. West and Stephen D. J. McArthur
Institute for Energy and Environment
Department of Electronic and Electrical Engineering
University of Strathclyde
Glasgow, G1 1XW, United Kingdom
+44 (0) 141 548 2665
jjacostello@eee.strath.ac.uk

Graeme Campbell
EDF Energy UK
GSO Business Park
Glasgow, G74 5PG, United Kingdom

ABSTRACT

Gas circulator units are a critical component of the Advanced Gas-cooled Reactor (AGR), one of the nuclear power plant (NPP) designs in current use within the UK. The condition monitoring of these assets is central to the safe and economic operation of the AGRs and is achieved through analysis of vibration data. Due to the dynamic nature of reactor operation, each plant item is subject to a variety of system transients of which engineers are required to identify and reason about with regards to asset health. The AGR design enables low power refueling (LPR) which results in a change in operational state for the gas circulators, with the vibration profile of each unit reacting accordingly. The changing conditions subject to these items during LPR and other such events may impact on the assets. From these assumptions, it is proposed that useful information on gas circulator condition can be determined from the analysis of vibration response to the LPR event. This paper presents an investigation into asset vibration during an LPR. A machine learning classification approach is used in order to define each transient instance and its behavioral features statistically. Classification and reasoning about the regular transients such as the LPR represents the primary stage in modeling higher complexity events for advanced event-driven diagnostics, which may provide an enhancement to the current methodology, which uses alarm boundary limits.

Key Words: Condition monitoring, vibration, machine learning, UK reactors

1 INTRODUCTION

1.1 Gas circulator units

CO_2 gas is the primary circuit coolant used in the UK-design Advanced Gas-cooled Reactor (AGR), maintaining safe temperature of the fuel assemblies and transferring the created heat to the secondary steam cycle boilers. This gas is propagated through the core by gas circulator units, of which there are eight per reactor. Circulation begins under the reactor core structure, with part of the flow making its way through the fuel channels and the rest circulating around the area surrounding the graphite core. The heated gas then returns down to the foot of the core, through the moderator itself, before passing through the boilers and back to the circulator units. Each circulator can operate at variable speed in the event of plant events such as reactor shutdowns, but fine regulation of the gas flow is made by alterations to the inlet guide vane (IGV) angle [1]. Figure 1 illustrates the gas flow through the reactor core facilitated by the circulators.

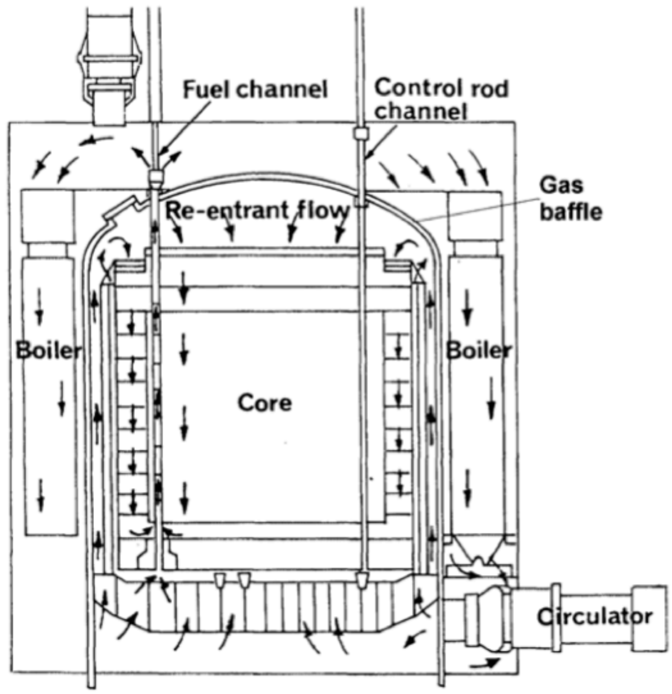

Figure 1. Schematic of CO_2 coolant through the AGR core by means of the gas circulator unit. Diagram courtesy of [1]

These machines therefore represent a key asset in the operation of the AGR, with their function critical in maintaining safe and reliable generation. Condition monitoring of the circulators is achieved through extensive vibration analysis common throughout the general rotating machinery discipline, with alarm-driven strategies employed by the operator to discern incidences of short-term asset anomaly or deviation. Machine state change or fault emergence provides the corresponding notifications to the system and monitoring engineers to take necessary operational or maintenance action.

The duty cycle experienced by these assets can be considered relatively dynamic, with multiple normal regimes of operation corresponding to operational events. Each of the units is required to operate in variable load regimes during maintenance and refueling cycles. As a result, analysis and reasoning about the health and condition of the gas circulators is important in ensuring continued operation in the AGR during the program of plant life extension currently underway in the UK nuclear industry.

1.2 Low power refueling

One of the major features of the AGR design is the functionality of *low power refueling* (LPR), providing the ability to replenish fuel channels at a reduced load while providing continued generation. This is achieved through the 'castling' of reactor generation; bringing the generated load down to approximately 70% and 30% full capacity intermittently to provide alternating periods of medium and low power. During these low periods, the operator has the ability to refuel selected channels without the necessity of shutting down the entire reactor.

Figure 2 provides an example of the common load duty cycle experienced and the corresponding vibration response to these events. Typically, an LPR will consist of 6-8 refueling periods, dependent on the logistic requirements. The ability to refuel while on load provides a benefit to the continued operation and effective generation of the AGR design. However, operation in this manner introduces the potential for dynamic conditions across a wide range of the tolerances of the machine in a relatively short period of time.

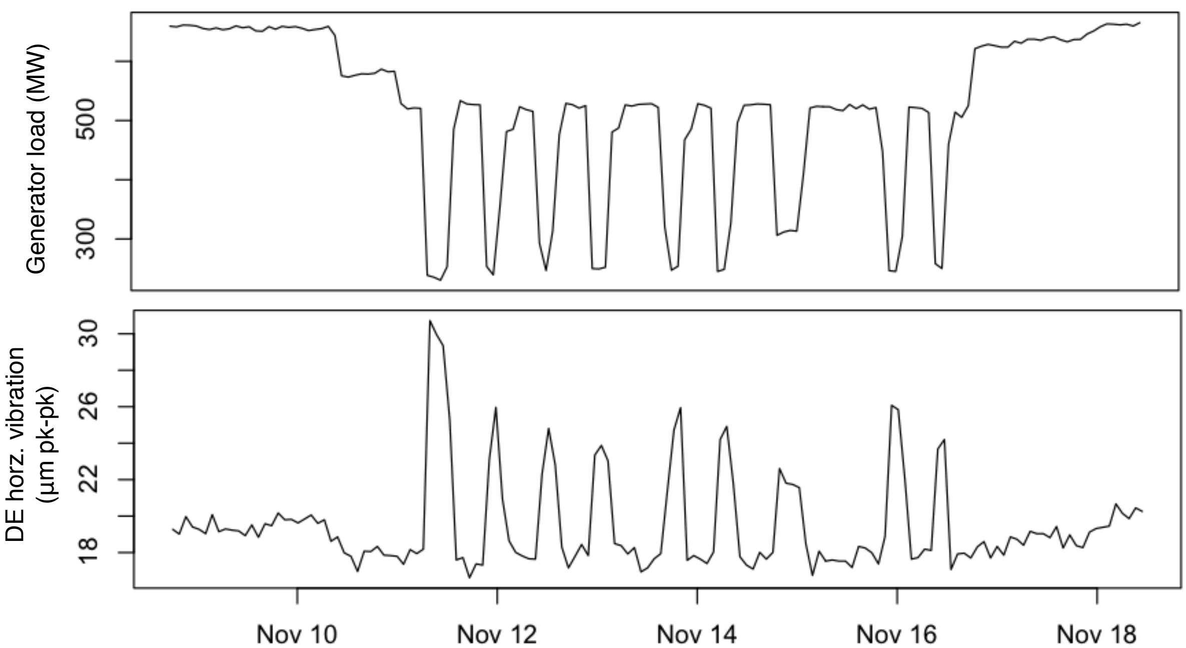

Figure 2: Example LPR event, illustrating load castling and corresponding vibration response

The alarm-based analysis of the AGR rotating assets currently does not consider the LPR or any of its inherent vibration response features in the general view of machine health beyond overall levels of vibration. Scrutiny of the online refueling event parameters and continued behavior is postulated to yield useful system metrics for ongoing analysis of asset response to the event and any corresponding change of state through the long-term operation history of the circulator.

This paper provides a preliminary investigation into the vibration response of gas circulator units during online refueling events through the use of automatic classification techniques. The construction of an automatic LPR classifier provides the first step towards integration of advanced system events in self-tuning diagnostic systems for nuclear rotating machinery decision support. Alongside this, the potential for any condition and degradation metrics for the circulators extracted from the evolution of refueling events is discussed. Due to the regularity and importance of the LPR event, a useful precursor to failure could provide early alerts to condition monitoring engineers regarding future operational behaviors of this particularly operation-critical reactor asset.

2 ROTATING PLANT CONDITION MONITORING

The ongoing analysis of the condition in rotating assets in energy generation is of great importance for both continued safety and economic operation. This is particularly true with regards to the regulatory requirements for assets in the primary circuit of nuclear reactors, including the circulator units. Engineers now utilize integrated condition monitoring environments and software suites with the functionality to set operational boundaries, often corresponding to ISO-standard limits. Such analysis provides clear event flagging from an often onerously large dataset of available information to the engineer, for quick identification of system problems or anomalies. The wide adoption of more sophisticated condition monitoring techniques has prompted research into the use of automatic and intelligent techniques in vibration-based monitoring.

Vibration analysis remains a mainstay in the condition monitoring industry, with long-term analysis of primary and secondary machine assets within both nuclear and non-nuclear scenarios. The generic family of rotating plant items has a distinguished history [2] in the utilization of vibro-acoustic signals as a major observable for both automated fault diagnosis [3, 4]. Well-understood fault signatures allow for automated anomaly and fault diagnosis to greatly reduce low-level data analysis of engineering teams, who often have multiple machines to continually monitor. Reactor coolant pumps used throughout PWR designs are the closest relative of the AGR gas circulator in both functionality and operational characteristics. While the performance metrics between the families of primary reactor assets differ, vibration is nonetheless a key machine observable [5] in the analysis of coolant pumps and their corresponding faults and condition.

Techniques of greater diagnostic and analytic sophistication continue to be presented in recent times for the monitoring of rotating plant. Self-tuning diagnosis [6] can provide advanced decision support on a machine specific basis, taking into consideration the individual characteristics of the particular asset under examination. Such an approach provides a framework for the automatic identification of system events in a symbolic manner, allowing for both rudimentary and complex duty cycle events to be identified, modeled and reasoned about. These techniques build parametric models of machine normality from historic operational data to be used in both the automated diagnosis of non-fault false positive alarm instances and the long-term trending of machine state.

Machine state estimation and its links to predictive analysis of rotating assets has also been investigated recently in numerous publications [7], with the utilization of machine learning and statistical methods providing estimates of rotating machinery condition and remaining useful life. Techniques such as support vector machines (SVM) have been used in combination with principal component analysis (PCA) have seen application to this particular problem.

3 APPROACH

3.1 Data considerations

The operational changes and corresponding vibration response examined in this investigation are primarily focused on the generator load and overall amplitude vibration observables, mainly the horizontal magnitude for the drive-end (DE) of the gas circulator unit. The selection of these as the primary system view was made to provide a rudimentary representation of the gas circulator undergoing the LPR event with well-understood system properties. A total of 21 LPR events are examined in the period between mid-2004 to mid-2010, taken from a single gas circulator unit. This particular circulator was selected in order to ascertain the existence of any vibration-based metric precluding the failure. The classifier for the LPR is trained on a variety of subsets of this data and then tested on both future LPR and non-LPR data instances to demonstrate classification success. Each LPR instance is truncated in the same manner to maintain 'like-for-like' as far as possible, with 25 points of 'Online' behavior being included in each subset before and after the event. However, the LPR duty cycle itself is somewhat variable due to differing numbers of channels being refueled in each campaign. Discussion of this and other factors are covered in later sections of this paper.

3.2 LPR classification

Primarily, the LPR itself and its corresponding observables require to be classified from historical data for use within self-tuning analysis systems. While the manual identification of LPR events by the engineer is simplistic, the long-term analysis of multiple machine instances brings forward the requirement for an automated technique to extract these event periods. Automated detection of refueling events requires not only multivariate analysis of operational and corresponding vibration observables but also the extraction of the behavioral membership data from each instance to allow for further in-depth trending analyses.

The online refueling event has been divided into three load-driven behaviors for rudimentary classification: *online*, *upper* and *lower*. 'Online' represents the full load operation of the circulation immediately before and after the LPR event, 'Upper' corresponds to the higher 'castling' level between the replenishment of individual channels during the LPR and 'Lower' is the analogous low load state, during which channel refueling periods take place. The limits for these bounds of behavior are annotated in Table I.

Table I. LPR behavioral boundaries

Behavior	Generator load
Online	load ≥ 600MW
Upper	400MW ≤ load < 600MW
Lower	load < 400MW

These boundaries provide the supervised learning classes for classification technique. Examining each event in feature space, these three classes can be separated into their three component clustered behaviors. Non-linear classification in feature space lends itself to the use of kernel machines, most importantly the support vector machine (SVM) statistical learning technique.

The SVM, also referred to as the maximum margin classifier, empirically generalizes classification margins in feature space [8] from provided training data with corresponding class labels. For each decision boundary, the separating hyperplane classifying the input data can be defined as:

$$f(\underline{x}) = \underline{w}^T \underline{x} + b \tag{1}$$

where $\underline{w}^T$ is the weight vector and b is the hyperplane bias, both parameters which require to be optimized for each classification boundary. SVMs utilize a simple decision function, $sign(f(\underline{x}))$, to separate test data as either belonging to the class or not. The SVM also has the ability to work in multi-class scenarios, allowing for the multiple behaviors of the LPR to be identified and for corresponding hyperplane boundaries to be optimized. In such scenarios, each class is distinguished against the rest of the training data. An example trained SVM is shown in Figure 3, illustrating the decision boundaries and the LPR test data classified into each of the three behaviors. The SVM achieves its optimality through extended the potential margin into feature space until it reaches the extremities of the class(es) in question, of which the corresponding data points are referred to as the 'support vectors'. The decision boundaries created by successfully trained SVMs will be considered as a potential metric for behavioral change later in this paper.

The classification of the LPR is made through use of training data from early in the available life cycle of the circulator data. This trained model provides the benchmark from which future instances of online refueling are measured against. The classification is verified through a windowed analysis of later refueling regimes embedded within other routine operation behaviors from the duty cycle. This technique utilizes the trained SVM model to flag any LPR event instances to distinguish from the non-refueling event data.

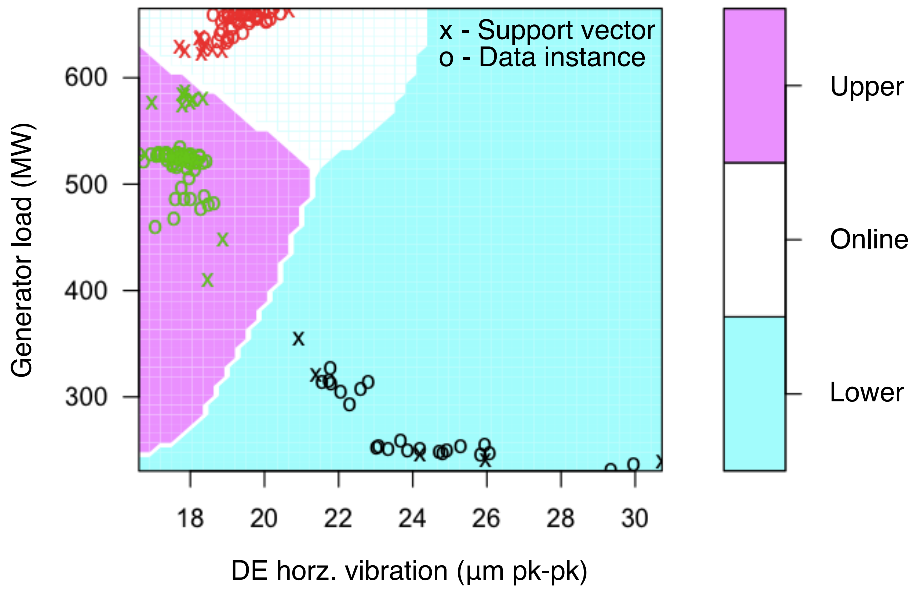

Figure 3: Trained SVM classifier example for generator load and DE horizontal vibration, showing the three behavioral classes of the LPR with corresponding training data. Note that data instances marked 'X' are the support vectors of their corresponding class.

Once successfully trained, the model is then windowed over unlabelled test data in order to determine periods of LPR instance. Each time series instance is classified into one of the three behavioral classes defined by the trained SVM, which is then used to reason about the current operational state of the circulator unit. Note that both the vibration and load parameters are considered by the SVM in order to provide a machine response view of refueling, rather than a simple operationally driven classification method. This particular setup will allow for the more detailed analysis of the vibration response to the LPR in later work.

4 RESULTS

In order to validate the trained LPR classifier, a case study of historical circulator data is examined as proof of concept for the approach. At this stage, discrimination is primarily required to be made between online behavior and refueling behavior. Distinguishing refueling events from more complex operational regimes represents a future area of research in this area and is discussed in later sections of the paper. Figure 4 provides a test data case taken over approximately a year of reactor operation. During this period, a total of 5 LPRs, an outage and a discernable load event occurred. Classification of each of these events is achieved through windowing the time series data (set window size = 11) and comparing each windowed incremental population with the trained classifier. The results annotated in Figure 4 illustrate the percentage of each window instance being classified into each behavior.

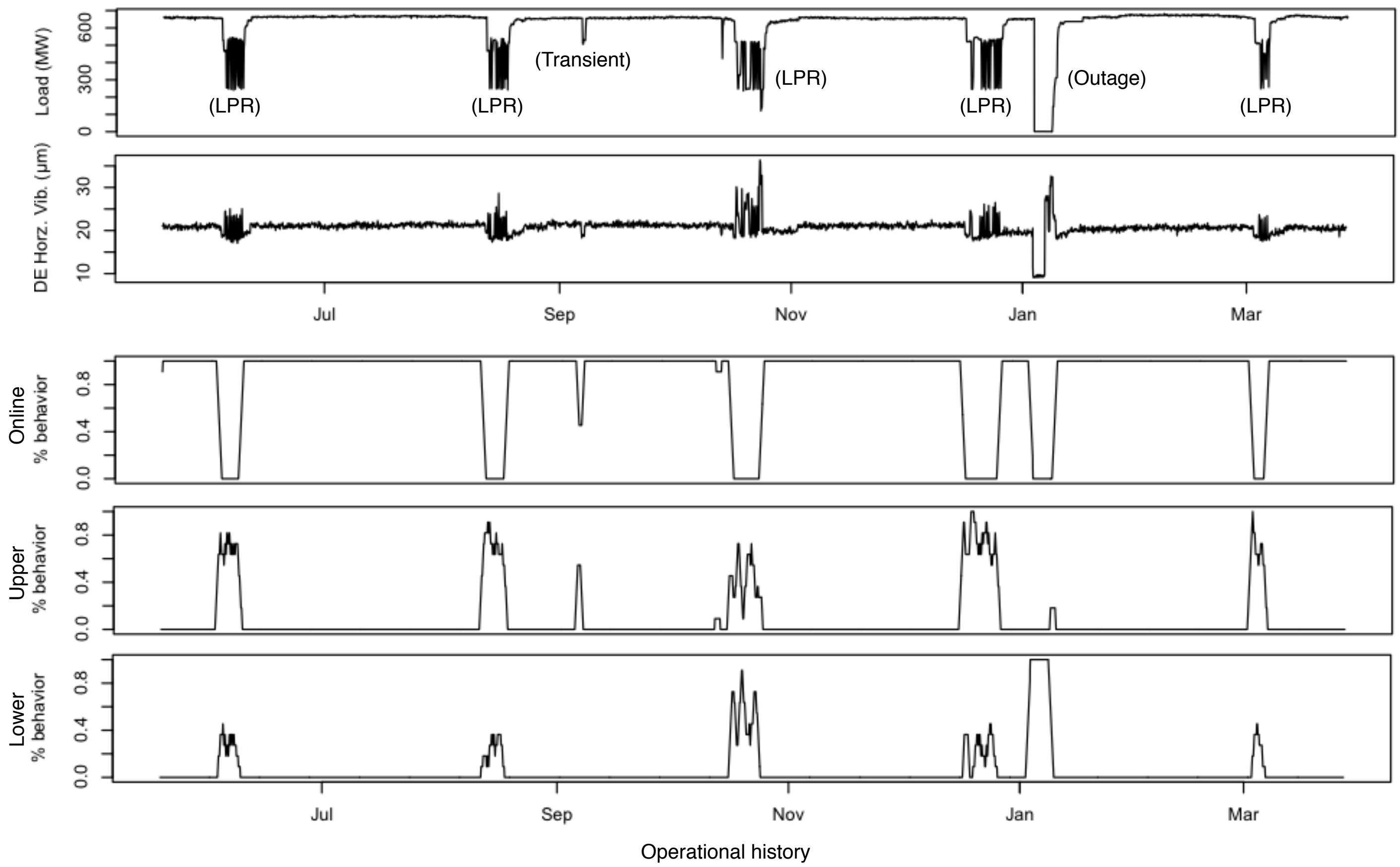

Figure 4: Windowed classification using trained SVM classifier, showing the population percentages of the three behavioral classes of the LPR with corresponding load and vibration annotated. This case was taken during the period May 2008 – April 2009. Each labeled LPR corresponds to a similar event as illustrated in Figure 2.

Therefore, periods of online behavior have universally high membership of the 'Online' class, which events have variable membership of the 'Lower' and 'Upper' classes. Classification of the LPR distinct from other events can occur when both Upper and Lower classification increase notably for periods of operation. In the counter examples of outages and other discernable non-LPR events, only a single class of the trained SVM provides a noted increase in the classification rate, with 'Lower' increasing during outage and 'Upper' increasing during the example load transient.

The training of the SVM used to classify the LPR instances was made through aggregation of early LPR instances in the life cycle of the circulator. For comparative purposes, the retraining of the SVM was undertaken at various points on the operation history lifetime. Figure 5 overleaf illustrates the evolution of the classifier hyperplanes in comparison to the original training data used on the outset. It can be seen from Figure 5 that the decision boundary evolution is sufficient at later stages of the circulator operational history for points of the original training data to supercede their original class boundary, resulting in misclassification. This suggests a discernable change in behavioral response of the circulator with repeated LPR campaigns and general routine operation.

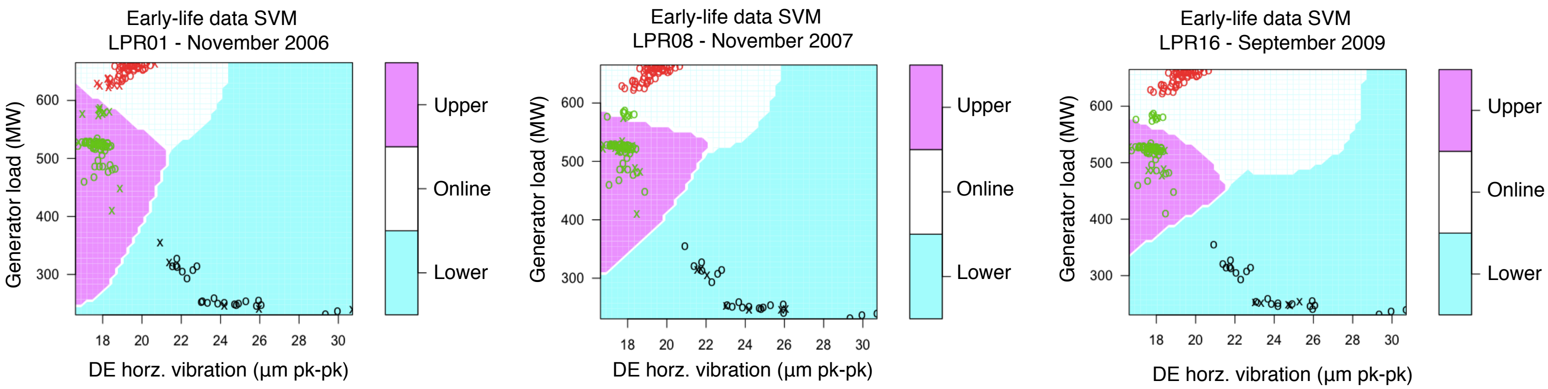

Figure 5: Retrained SVM models with later LPR instances through machine use compared with the single training data of the first LPR. The left mapping shows the training data used with the model. The evolution of the SVM hyperplanes is shown comparatively with this initial training data.

5 DISCUSSION & FUTURE WORK

The major outcome of this research has been a development of the SVM LPR classifier for use in the repeated classification and extraction of refueling events from historical data for use within a knowledge-driven symbolic diagnosis system. As a primary investigation of the classification technique, one of the next stages should be to investigate the parametric optimality of the SVM technique in LPR classification. A thorough study in the systematic experimentation of the SVM parameters such as the cost function and learning rate could provide a standardized approach in the use of SVMs for refueling identification.

On primary investigation, the characteristics exhibited by the windowed classification technique give the ability to discern automatically between online and LPR event behaviors, through monitoring of the class membership proportions as the window progresses through the time series data. While the distinguishing features between online refueling and other dynamic conditions are not as simplistic, the patterns exhibited by the class membership proportions during LPR periods have the potential to be used as a diagnostic feature. The cyclic nature of the LPR lends itself to a particularly distinct class membership trace, which could be used to identify refueling during particularly change-heavy periods of historical data.

The next stages in implementing LPR-driven decision support will be to examine engineering knowledge surrounding the practice of online refueling and utilize the automatic detection of the event in the knowledge-driven diagnosis of such events. In order to use the technique within the process of an automated system, some further study is required regarding the heuristic rules for the population percentages in the LPR identification from the windowed classifier technique presented. This process should be undertaken with due consideration to the knowledge engineering process and validation requirements of knowledge-based systems in engineering scenarios. A system with the ability to not only detect and classify each LPR campaign through historical and current operation for each circulator would provide a particularly useful view for both the online and long-term historical analyses of these critical assets. Comparing the features exhibited on an inter-machine basis would also inform the general theory of degradation with regards to the gas circulators, an area that requires further investigation and analysis.

Re-training of the classifier with later chronological data in the operational lifetime of the circulator provided discernable variation in the margins optimized by the SVM technique. While this provides implications to the classification process, requiring re-training at later dates of operation, this change in system response to the LPR has the potential to be used as a state change metric. This remains a particularly early stage analysis of the feature, however, and it remains uncertain whether a detectable metric from the hyperplane parameters could be extracted or reasoned about. The next stages for this particular feature will be to statistically model any change in decision boundary parameters and compare to further well-defined fault condition historical operation data. The evolution of the classifier in parallel with other feature vector parameters common to vibration analysis needs to be considered in order to ascertain if a meaningful vibration metric for system condition or degradation can be reasoned about and used in the predictive monitoring of the circulator units.

6 CONCLUSIONS

In conclusion, this paper has presented a classification approach for low power refueling on AGR gas circulator units using both operational and corresponding vibration data. This technique is to be embedded in future prototype vibration diagnosis systems used in the analysis of the circulator units. Alongside this, initial analysis of the long-term vibration response of the circulators with age has been presented, illustrating potential state change in the classifier model.

7 ACKNOWLEDGMENTS

The authors would like to acknowledge EDF Energy and the EPSRC for funding this research project through the UK Nuclear Engineering Eng.D programme. The views presented in this paper are of the authors alone and do not necessarily represent those of EDF Energy.

8 REFERENCES

1. E. Nonbol, ‘Description of the Advanced Gas Cooled Type of Reactor (AGR)’, *Riso National Laboratory Report*, *Roskilde*, *Denmark* (1996)
2. P. J. Tavner, “Review of condition monitoring of rotating electrical machines,” *IET Electric Power Applications*, **2**, pp.215-247 (2008)
3. S. Ebersbach and Z. Peng, “Expert system development for vibration analysis in machine condition monitoring” *Expert Systems with Applications*, **34**, pp.291-299 (2008)
4. B.S. Yang *et al.*, “VIBEX: An Expert System for Vibration Fault Diagnosis of Rotating Machinery Using Decision Tree and Decision table”, *Expert Systems with Applications*, **28**, pp.735-742 (2005)
5. M. W. Tretheway et al., “A spectral simulation approach to evulate probabilistic measurement precision of a reactor coolant pump torsional vibration shaft crack monitoring system”, *Journal of Sound and Vibration*, **310**, pp1036 – 1056 (2008)
6. J. J. A. Costello *et al.*, “Self-tuning diagnosis of routine alarms in rotating plant items”, *The Eighth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies*, Cardiff, UK (2011)
7. H-E, Kim *et al*, “Machine prognostics based on health state estimation using SVM,” *Proceedings of the Third World Congress on Engineering Asset Management and Intelligent Maintenance Systems Conference*, (2008)

8. V. N. Vapnik, *The Nature of Statistical Learning Theory*, Springer, New York (1995).