Performance Monitoring of an Offshore Gas Compressor

In a world where success and profit go hand-in-hand, oil and gas companies are pressured to meet production targets on a daily basis. Oil and gas production generates money and any downtime caused by equipment failure has the possibility of crippling a business. Any downtime is an issue in this industry but if underlying causes could be predicted and prevented before a system reached an unrecoverable stage, companies could save millions that would otherwise be lost revenue.

Compressors

Offshore equipment is monitored to prevent any unnecessary downtime but unfortunately for some, such as compressors, there is a lack of effective monitoring. This is critical because, along with the gas turbine, it is the highest cost offshore item in terms of capital and operational expenditure but is the least technically and operationally understood.

Offshore gas compressors are used for various tasks including reservoir management, production enhancement and the transmission of gas. It is often the case that the conditions that the compressors were designed for are different now – this can include varying gas flows, different gas compositions and pressure ratios. The compressors must be running constantly because a loss of production will result in a loss of money if a compressor is taken offline to be upgraded or for critical maintenance.

Monitoring an important item of equipment such as a compressor is essential as it can be difficult to obtain replacement parts or units if a failure was to occur. Adopting a preventative maintenance strategy with regard to compressor monitoring can prevent downtime costs from arising before failures occur or shutdown is mandatory.

A common cause of compressor downtime is a fault with the bearings. This initiated an investigation to analyse the bearings of an offshore gas compressor, using statistical modeling techniques, with the view of predicting failures and therefore reducing unplanned downtime.

Statistical Modelling Techniques

Multivariate statistical process control (MSPC) methods can be used to monitor offshore equipment onshore. Models of a compressor's operation can be created using the MSPC techniques of Partial Least Squares (PLS) and Principal Component Analysis (PCA) to prevent downtime from occurring or, at the very least, keep it as minimal as possible. The models use historical data and can help to predict compressor problems before they become critical and allow essential maintenance to take place before downtime becomes unavoidable. The models can also be used to detect when a component in the compressor process has changed.

Typically, process variables are monitored one variable at a time. If the process variable is within its control limits, the process is considered to be in normal operating conditions. However, if the variable deviates from its control limits, an alarm is sent to an operator. The problem with this scenario is that if many variables are deviating from their control limits in a short period of time, the system becomes uncontrollable as the operator will be unaware of the interdependency between variables.

PCA is a method of identifying patterns in data and allows the data to be illustrated in a way that highlights the similarities and differences between variables. It is concerned with the coordinate transformation of data in order to represent it with fewer dimensions. The idea is that the data originates from the underlying structure to the process and is usually simpler to understand than the state of each individual variable. A new set of independent variables (latent variables) is created which are linear combinations of the original variables with the elimination of variables that have the least impact on the system. This gives a representation which can simplify understanding.

With regard to compressor monitoring, PCA can be used to determine the number of normal operating modes of the compressor by analyzing the 'scores'.

PLS is a regression technique used for process modeling. In a similar manner to PCA, PLS analysis converts input process data into input latent vectors, and the output process data into output latent vectors. Regression analysis is then performed to determine the relationships between the input and output variables. PLS predicts the value of output variables from measured input variables. For example, it could be possible for a person's weight (output variable) to be predicted as a function of their height and gender (cause variables). Linear regression could be used to analyse the correlations among height, weight and gender in a set of data. These correlations can then be used to estimate the person's weight in a new set of data given only their height and gender (StatSoft Inc. 2003). In this manner PLS can be used to create soft sensors which can be used to monitor abnormal behavior or purely to understand relationships between the variables. PLS analysis can be used to detect any unexpected changes in the compressor's bearing temperatures.

Compressor Monitoring

Statistical models can be built using a wide range of clean data to model a compressor working within its operational limits. A PLS analysis can be used primarily to determine any drifts in the inputs and PCA can used to determine the relationships between the inputs and modes of operation.

An offshore gas compressor has many variables and it is impossible for one person to fully understand all the correlations among them. Using intelligent monitoring can simplify the process by filtering the data through several layers while increasing its quality.

System Layer	Technique to Increase Data Quality
IT Infrastructure	Validate Data
Control System	
Instrumentation	Detect Instrument Faults
Plant Equipment	Detect Equipment Mode
	Mode-Specific Equipment Monitoring
Process	Detect Process Mode
	Mode-Specific Process Monitoring

The models were built using raw data from offshore and contained process variables – suction and discharge pressures and temperatures, flow rate, recycle valve, power and speed – as well as bearing temperatures and gas composition data. The data was cleansed to eliminate any 'bad' points in the data – this included null data values, points that were bad due to noise – i.e. points that were more than three standard deviations from the mean – and any obvious errors due to instrumentation – i.e. flat-lining. After this initial cleansing, the correlations among the various variables could be determined as shown in Figure 1. This information helps in understanding how certain variables impact others.

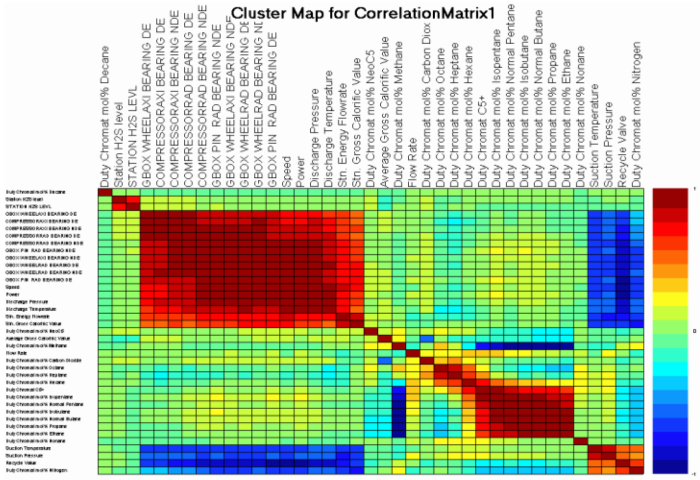

Figure 1 - Correlation Matrix

After cleansing, the validated data was partitioned into five equipment modes using Boolean expression to represent the following modes of shutdown, idling, start up, full load and normal operation. The method used to this point was repeated for another dataset in order to have "model data" as well as "test data". Once the data was classified into the appropriate modes, PCA was to analyze the data classed as "Normal" to determine the number normal of operating modes. The 2-D Scores graph illustrated that there were two modes of operation that were considered as normal as there are two main clusters of points – this is shown in Figure 2.

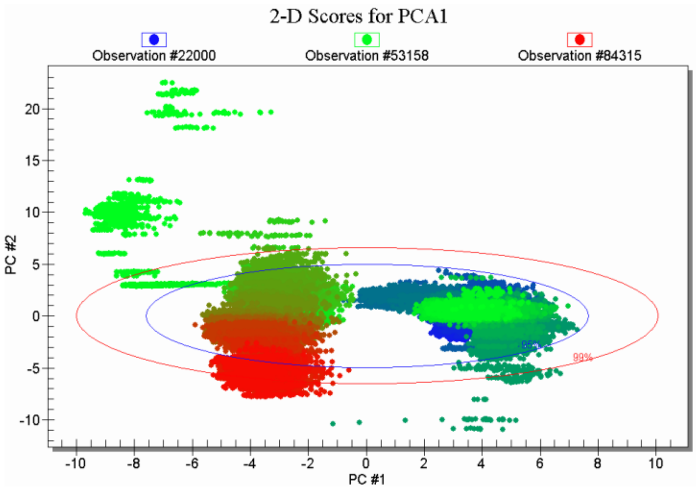

Figure 2 - 2-D Scores PC #1 and PC #2

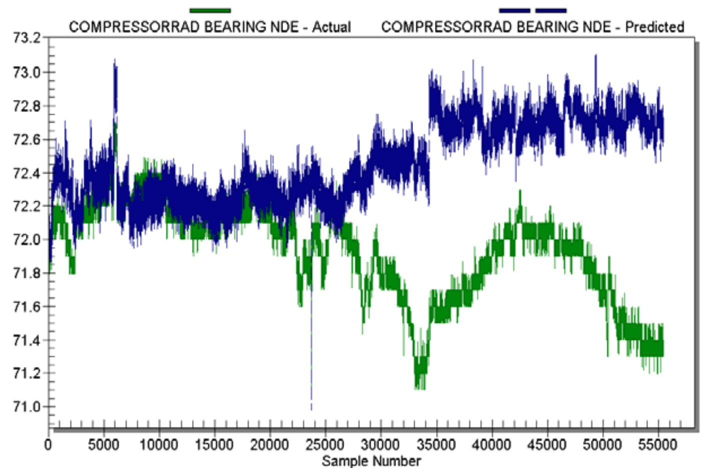

Figure 4 - Bearing Data Deviating From Model Predictions

Using only the data classed as "Normal Operation", PLS was used to monitor each bearing respectively. The information from the variables in the model data (correlations etc.) was gathered for each respective bearing and then applied to the test data to generate predicted bearing temperatures. These predictions were then compared with the actual bearing temperatures from the test data to determine if any component in the process had changed. Figure 3 shows an example where the data for the bearing matches the predictions almost exactly. In contrast, Figure 4 illustrates a graph of when the bearing data deviates from the predictions. It was concluded that this was due to some parameter in the process being different in the test data that the model data did not take into account which could denote a problem with the bearing.

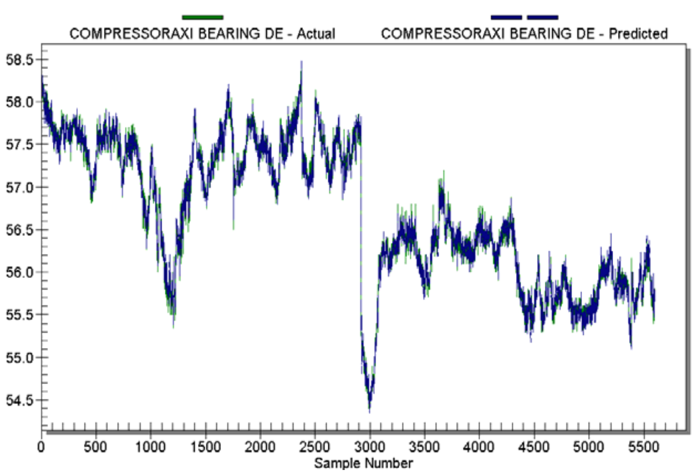

Figure 3 - Bearing Data Following Model Predictions

Barriers To Effective Performance Monitoring

The lack of performance monitoring on offshore assets is due to insufficient knowledge of the techniques available and the impact they can have on an asset. A fundamental and crucial step in monitoring a piece of equipment is to obtain data but unfortunately, due to the lack of performance monitoring being carried out, it is often unavailable to onshore specialists. The reasoning behind this is the belief that the data is only useful offshore – this is not the case. When available onshore, the data can be analysed by specialists in a number of ways to find trends, create models, determine operating modes or predict failures etc.

Often when data is available onshore, there can be another problem when creating models – compression. Data is often compressed to create smaller files but then cannot be used to create models. This is because the models must be able to detect small changes in the data which are no longer evident when compressed. The resulting data has a significant loss of information which is unsuitable for creating models.

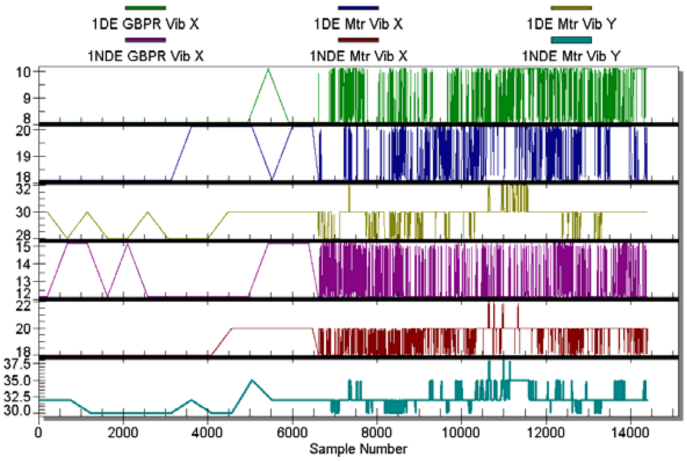

Figure 5 - Comparison of Compressed and Uncompressed Data

Thermodynamic Models

Currently, the monitoring that exists offshore is predominantly through the use of thermodynamic models. Unfortunately, those models are dependent on accurate instrumentation as well as a constant composition. This means that they are unable to cope with any changes in conditions. As the statistical models are data-driven, they are easier to retrain making them more robust compared to thermodynamic models. For effective condition monitoring, a combination of both statistical and thermodynamic models could be implemented. The statistical model could be used to identify the operating mode, while the thermodynamic model used for analysis of the process.

Conclusion

The results of this investigation show that PCA and PLS can be used to analyze the performance of an offshore gas compressor. The PCA results reveal a great deal of information regarding the compressor's operation and show success in determining the number of normal operating modes. The results from the PLS models for each bearing temperature show that PLS is able to predict when a bearing temperature is deviating from what is expected in the model. It can be assumed that if the model was able to account for all modes of normal operation, the PLS analysis would be able to detect any deviations due to potential bearing failures or other equipment issues.

If a bearing began to fail, there would be an increasing difference between the predicted and actual temperatures. This difference could be used to trigger an alarm to send a notification to an onshore specialist based on real-time data. The notification could be in the form of an email that is automatically generated when the actual temperatures are out,-with the specified range of predictions. This early warning will allow them to investigate the current operation of the compressor and prevent any unnecessary downtime by providing essential maintenance before the compressor would be required to shut down.

This investigation demonstrates that PCA and PLS have the potential to prevent avoidable downtime occurring with a compressor. It must also be noted that as these statistical modeling techniques are concerned with the correlations between variables, they are not specific to compressors and could be adopted for monitoring other types of rotating machinery both onshore and offshore.

References

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