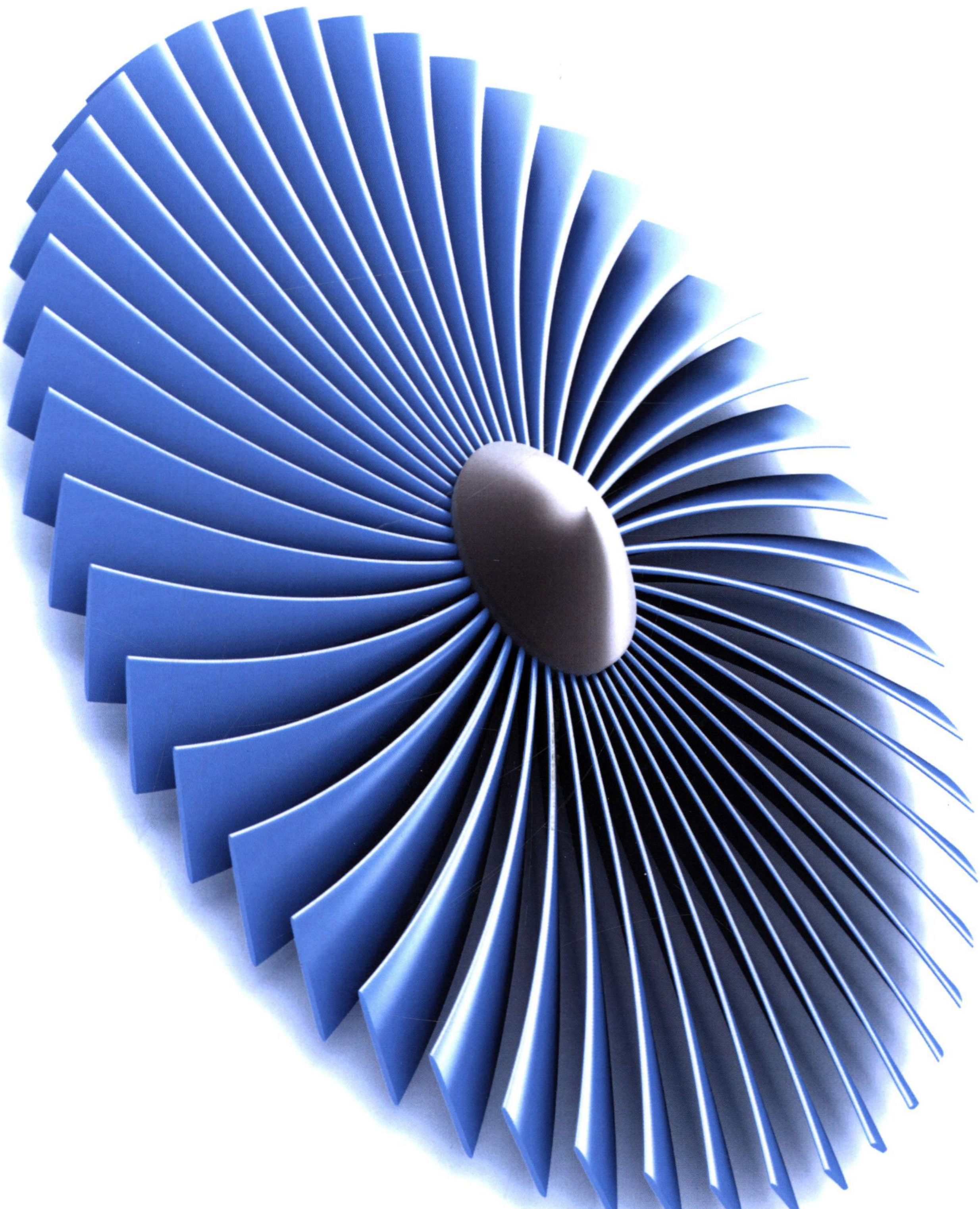
Developments in Gas Turbine Technology

Contributors: Li Pan, et al.



About the Book

In any event, gas turbines are very effective machines for efficiently converting temperatures of 1100 to 1500°C or higher on a large scale, and it can safely be said that, in the examination of various cycles, gas turbines will play an important role as an effective means of converting combustion energy in the future. In the future, the demand for highly efficient power generation using various alternative fuels is expected to increase. In addition to conventional fuels, there are fuel gases that are generated from natural waste such as biogas, and low pollution liquid fuels such as DME (dimethyl ether) as well as GTL (gas-to-liquid) artificially produced from natural fossil fuels. These fuels are expected to be used in the future. Gas turbine combined-cycle systems burning natural gas represent a reliable and efficient power generation technology that is widely used. A critical factor in their development was the rapid adaptation of aero-engine technology (single crystal airfoils, sophisticated cooling techniques, and thermal barrier coatings) in order to operate at the high rotor-inlet temperatures required for high efficiency generation.

Developments in Gas Turbine Technology aims to deliver an modernized picture as well as a perspective vision of some of the major developments that characterize the gas turbine technology in diverse applications, from marine and aircraft propulsion to industrial and stationary power generation. A chapter on current aero engine technology and some insight on the future of aircraft propulsion is given providing an excellent discussion on counter-rotating fan designs. Additionally, influence of heat transfer on the performance at an adiabatic operating point of a gas turbine, and a method for determining the actual operating point knowing the amount of heat transfer is presented.

In the current economic and environmental context dominated by the energy crisis and global warming due to the CO2 emissions produced by industry and road transportation, there is an urgent need to optimize the operation of thermal turbomachinery in general and of gas turbines in particular. This requires exact knowledge of their typical performance. The performance of gas turbines is usually calculated by assuming an adiabatic flow, and hence neglecting heat transfer. While this assumption is not accurate for high turbine inlet temperatures, it provides satisfactory results at the operating point of conventional machines because the amount of heat transferred is generally low (less than 0.5% of thermal energy available at the turbine inlet). Internal and external heat transfer are therefore neglected and their influence is not taken into account. However, current heating needs and the decentralized production of electrical energy involve micro Combined Heat and Power (CHP) using micro-gas turbines (20-250 kW). In aeronautics, the need for a power source with a high energy density also contributes to interest in the design of ultra-micro gas turbines. In addition differences in demand between day and night tend to increase with the spread of air conditioners. As a result, the expectations of gas turbine combined plants, which play an important role as controllable thermal power plants, are becoming greater. In the future, intermediate capacity, high efficiency plants with a low utilization factor of approximately 40 per cent will be required. So combined cycle gas turbines will diverge into base load operating systems that emphasize efficiency, and middle range machines with high efficiency, minimized initial costs, and high operating maneuverability. Although an increase in combustion temperature leads to a rise in overall thermal efficiency, the completely effective use of heat energy with a maximum possible combustion temperature of 2000 to 2500°C which can be achieved by fossil fuels involves many technological issues that must be solved.

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Preface

In any event, gas turbines are very effective machines for efficiently converting temperatures of 1100 to 1500°C or higher on a large scale, and it can safely be said that, in the examination of various cycles, gas turbines will play an important role as an effective means of converting combustion energy in the future. In the future, the demand for highly efficient power generation using various alternative fuels is expected to increase. In addition to conventional fuels, there are fuel gases that are generated from natural waste such as biogas, and low pollution liquid fuels such as DME (dimethyl ether) as well as GTL (gas-to-liquid) artificially produced from natural fossil fuels. These fuels are expected to be used in the future. Gas turbine combined-cycle systems burning natural gas represent a reliable and efficient power generation technology that is widely used. A critical factor in their development was the rapid adaptation of aero-engine technology (single crystal airfoils, sophisticated cooling techniques, and thermal barrier coatings) in order to operate at the high rotor-inlet temperatures required for high efficiency generation.

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In the current economic and environmental context dominated by the energy crisis and global warming due to the CO_2 emissions produced by industry and road transportation, there is an urgent need to optimize the operation of thermal turbomachinery in general and of gas turbines in particular. This requires exact knowledge of their typical performance. The performance of gas turbines is usually calculated by assuming an adiabatic flow, and hence neglecting heat transfer. While this assumption is not accurate for high turbine inlet temperatures, it provides satisfactory results at the operating point of conventional machines because the amount of heat transferred is generally low (less than 0.5% of thermal energy available at the turbine inlet). Internal and external heat transfer are therefore neglected and their influence is not taken into account. However, current heating needs and the decentralized production of electrical energy involve micro Combined Heat and Power (CHP) using micro-gas turbines (20-250 kW). In aeronautics, the need for a power source with a high energy density also contributes to interest in the design of ultra-micro gas turbines. In addition differences in demand between day and night tend to increase with the spread of air conditioners. As a result, the expectations of gas turbine combined plants, which play an important role as controllable thermal power plants, are becoming greater. In the future, intermediate capacity, high efficiency plants with a low utilization factor of approximately 40 per cent will be required. So combined cycle gas turbines will diverge into base load operating systems that emphasize efficiency, and middle range machines with high efficiency, minimized initial costs, and high operating maneuverability. Although an increase in combustion temperature leads to a rise in overall thermal efficiency, the completely effective use of heat energy with a maximum possible combustion temperature of 2000 to 2500°C which can be achieved by fossil fuels involves many technological issues that must be solved.

Contents

1

APPLICATION OF STATISTICAL METHODS FOR GAS TURBINE PLANT OPERATION MONITORING

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INTRODUCTION

Within a large modern combine cycle gas turbine (CCGT) power station, it is typical for thousands of process signals to be continually recorded and archived. This data may contain valuable information about plant operations. However, the large volume of data accompanied with inconsistencies within the data often limits the ability to identify useful information about the process. Utilising data mining techniques, such as Principal Component Analysis (PCA) and Partial Least Squares (PLS), it is possible to create a reduced order statistical model representing normal plant conditions. Such a model can then be utilised for fault identification and identifying possible improvements in key performance indicators such as thermal efficiency. Moreover, the gas turbine performance can be affected by changes in ambient conditions. A long term nonlinear PLS techniques can be applied here to investigate the seasonal changes in gas turbine. In this chapter, an approach to establish a long term statistical model for gas turbine will be given, and the application of the model in fault detection and performance analysis will be demonstrated.

THE DATA MINING TECHNIQUES

Within the power station, data are continuously collected and archived representing thousands of data points including temperatures, steam flow rates, pressures, etc. Potentially this data may contain valuable information about unit operation. However, collecting a large amount of data does not always equate to a large amount of information, leading to a lot of databases being regarded as data rich, but information poor. The task of extracting information from data is known as data mining, which is defined as the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. Data mining is the nontrivial process of extracting valid, previously unknown, comprehensible and useful information from large databases (Weiss and Indurkhya, 1998). Also, data mining is a generic term for a wide range of techniques which include intuitive, easily understood methods such as data visualisation to complex mathematical techniques based around neural networks and fuzzy logic (Wang, 1999; Olaru and Wehenkel, 1999). Applications are found within diverse areas such as marketing (Humby et al., 2003), finance (Blanco et al., 2002) and industrial process control (Martin et al., 1996). However, despite being a widely applied technique, it is reported that three quarters of all companies who attempt data mining projects fail to produce worthwhile results (Matthews, 1997). Unfortunately, this indicates that the potential of data mining techniques, with regard to the available data is often overestimated than the reality. The act of data mining is itself part of a larger process known as knowledge discovery in data, KDD, which encompasses not only the analysis of data, but the gathering and preparation of data and the interpretation of results. Extracting knowledge from large data sets can be achieved through exploratory data analysis to discover useful patterns in data, in the form of relationships between variables. Many techniques are applied as classification tools, to categorise new data following the analysis of a historical data set. In this chapter, the first method discussed in Section 2.1 is machine learning techniques which use a logical induction process to categorise a series of examples, resulting in decision tree and rules set which can be implemented in decision making processes. Typical application areas are fault diagnosis in industrial machines (Michalski et al., 1999) and the assessment of power system security (Voumvoulakis, 2010) Case based reasoning methods as discussed in Section 2.2, are commonly applied to decision making tasks where previous experience is desirable, but may not be available. Case based reasoning provides an inexperienced user with exposure to experiences from others, through a set of historical 'cases', and has been of particular use in areas such as fault diagnosis (Wang et al. , 2008; Yan et al. , 2007) and system design and planning (Hinkle and Toomey, 1995). Finally, Section 2.3 discusses multivariate statistical techniques, namely principal component analysis and partial least squares regression, which have been successfully applied to a range of applications areas including chemistry (Wold et al., 1987), manufacturing (Oliveira-Esquerre et al., 2004), and power system analysis (Prasad et al., 2007). It is also extended to finance (Blanco et al, 2002) and medicine (Chan et al, 2003) area. Principal component analysis and partial least squares regression are particularly popular in the area of chemometrics, where they are employed in the monitoring of processes which generate large and highly correlated data sets (Yoon and MacGregor, 2001; Kourti et al., 1996).

Machine Learning

Machine learning techniques are those that use logical or binary operations to 'learn' a task from a series of examples, such as symptoms of medical or technical problems, leading to the diagnosis of the problem through the use of decision trees and rule sets which classify data using a sequence of logical steps (Michalski et al., 1999). Decision trees are simple top down learning structures, which use Boolean classifiers to 'grow' a tree through recursive partitioning of the sample data using the available attributes. The development of a decision tree starts with the inclusion of all the training data in a root node, resulting in both correctly and incorrectly classified data. In order to 'grow' the tree, the data is recursively split by each attribute until all the attributes in the data have been used. Each node in the final tree, known as a leaf, represents a test on one of the attributes, and the branches from the node are labelled with the Boolean outcomes of the test (Quinlan, 1996). The basic algorithm of building a decision tree, also known as ID3/C4.5 algorithm, follows a down rule (Quinlan, 1993). In the beginning, all the data is collected in the root node, and the data is recursively subdivided into fewer branches by assessing the information gain of each attribute in the training data to split the data further, until the terminal node which only contains one attribute is obtained (Quinlan, 1993). Rule induction is achieved using a bottom up structure, starting with a rule that specifies a value for every available attribute on the decision tree, thereby making the rule as specific as possible. This rule is known as the seed and further rules are developed from it by successfully removing attributes one at a time, until more general rules are acquired. Any rule which includes a counter example is regarded as incorrect and is therefore discarded from the process. The rule learning terminates by saving a set of'shortest'rules. Also a new "RBDT-1" algorithm is devolved for learning a decision tree from a set of decision rules that cover the data instances rather than from the data instances themselves. The method's goal is to create on-demand a short and accurate decision tree from a stable or dynamically changing set of rules (Abdelhalim, A. 2009). The primary advantage of decision trees is that their simplicity makes them very intuitive to users. However, large data sets call result in vast trees which can be 'needlessly' complex resulting in a largely unusable knowledge base : the ideal tree is as small and linear as possible. Due to their simple nature, decision trees are not suitable for more complex data structures and this is demonstrated by trees that, after pruning, still remain too large to be comprehensible.

Case Based Reasoning

Case based learning acquires knowledge from solutions to prior problems and employs it to derive solutions to the current problems. Once a current problem occurs, the similar case and previous solution are retrieved and possibly revised to better fit the current problem. The new solution can be retained into the case base in case to solve future problems. As a result, case based reasoning (CBR) systems are effectively used as lookup tables where 'the system' interrogates an indexed database of relevant cases, and one or more similar cases are retrieved and applied to discover an appropriate solution (Watson, 1999). A significant issue in CBR is indexing, which limits the search space, thereby reducing case retrieval times. There are many methods for indexing, such as check list based indexing, which identifies predictive features for a case (inductive learning methods may be used) and places them on a list which is then used for indexing, and difference based indexing which selects features as indices that best differentiate one case from another. The user can also manually implement an indexing system, and it has been suggested that selection of indices by the user can be more effective than algorithms for practical applications (Kolodner, 1993). The indexed cases can then either be stored sequentially, making the system easy to maintain but slow to query for larger case sets, or using a hierarchical structure, which will organize cases so that only a small subset are considered during retrieval, thereby reducing search times (Smyth et a1., 2001). CBR is a self-maintaining system, the database of historical events is updated when new cases occurred and adding to the system's problem solving resources. The advantage of CBR is that it does not require a large number of historical data patterns to achieve satisfactory levels of performance□a CBR model may be created from a small number of cases and the case base can be refined over time (Hinkle and Toomey, 1995). CBR is particularly useful when studying data which has complex internal structures when there is little domain knowledge, enabling the sharing of experience. Despite these benefits, CBR can be unsuitable for large scale applications as retrieval algorithms are inefficient when faced with handling thousands of cases. Maintenance of the case base, with respect to adding new cases and the removal of out date cases, may also be a problem as it is largely left to human intervention (Watson and Marir, 1994).

Multivariate Statistical Techniques

Statistical methods are employed to analyse the relationships between individual points in a data set, determining characteristics such as the average value and distribution of the data. The simple statistical measure represents a univariate approach to data analysis, which lacks the ability to constructively analyse large, multivariate data sets as the interactions between variables are ignored (Martin et a1., 1996). In contrast, multivariate statistical analysis describes methods capable of observation and analysis of the multiple variables required for system monitoring (Kourti and MacGregor, 1995). This section discusses the multivariate techniques, principal component analysis (PCA), least squares regression and partial least squares (PLS), as they are more suitable to the analysis of large data sets than univariate methods. Principal component analysis (PCA) is a statistical technique useful for identifying underlying systematic structures in data and separating it from noise (Wold et al., 1987). The identification of patterns in data structures allows PCA to be applied to problems requiring a reduction in the dimensionality of a data set, for example image processing(Bharati et a1., 2003), or monitoring of industrial processes including chemical and microelectronics manufacturing processes (Wise and Ricker, 1991: MacGregor and Koutodia, 1995). These objectives are achieved by transforming variables, which are assumed to be correlated, into a smaller number of uncorrelated variables called principal components (PCs), providing a simpler description of the data structure. Each successive PC accounts for the most significant variability in the data in a particular direction, with the reduction in dimensionality achieved, the original data set can be represented by few PCs. PCA is a useful tool when large data sets containing highly correlated variables are to be managed. PCA achieves reductions in data dimensionality, thereby simplifying future observation of variables : plotting a few PCs is significantly more convenient than plotting all original variables. Furthermore, the comparison capabilities between the historical information used to construct the model and newly presented data is a desirable characteristic for system monitoring applications (Martin et a1., 1996). Fault identification can also be undertaken by analyzing the contribution of the independent variables to each PC (MacGregor et a1., 1994). Projection to latent structures, also known as partial least squares (PLS), is developed to solve the multi-collinearity problem in linear least squares regression (LSR) which can determine the best linear approximation for a set of data points (Freund and Willson, 1997). The benefit of PLS is achieved by identifying a set of uncorrelated, latent variables. This avoids the co-1inearity problems encountered by likelihood-ratio (LLR) test and utilises some of the techniques associated with PCA, with the new latent vectors composed of scores and orthogonal loading vectors. PLS regression is a robust, multivariate linear regression technique which is considered to be more suitable for the analysis and modelling of noisy and highly correlated data than LLR as parameters do not exhibit large variation when new data samples are included (Otto and Wegscheider, 1985). A high number of variables, with respect to the number of data samples, are also permissible in PLS, which can result in the modelling of noise for LLR(wise and Gallagher, 1996). In summary, PLS is capable of producing robust, effective models, despite operational data limitations, for example, imprecise measurements and missing data (Oliveira-Esquerre, 2004). The ability to predict dependent data values, especially in the case of product quality data, which is often measured infrequently, is useful in process monitoring (MacGregor, 2005). The proficiency of PLS dealing with the highly correlated and collinear data is also frequently utilized in its application to process monitoring (Kresta, 1994).

Method Selection

A selection of data mining techniques has been presented in this section and the characteristics of each shall now be considered with respect to the problems and available data presented by power plant monitoring and analysis. Data derived from power plant monitoring can potentially consist of thousands of sensor measurements generated on a second by second basis. The data recorded is highly correlated, due to multiple sensors, which are in place to introduce redundancy into the measurements, and parallel paths within the system, for example, the steam and gas circuits. Data quality is also a factor, with noisy signals and missing data as the common problems. The correlated structure and data quality considerations present in power plant monitoring records bear strong similarities to other application areas discussed in this section, such as chemical process control(Ma et al., 2009; Ahvenlampi and Kortela, 2005), manufacturing (Oliveira-Esquerre et al., 2004; Baharati et a1., 2004; Hisham et al., 2008) and medicine (Chan et a1., 2003). When monitoring a process which records a vast array of sensor data, individual analysis of each signal by a human operator is clearly not possible. The data analysis techniques discussed in this section can be applied to this problem as they identify essential correlations within the data. This simplifies the monitoring process by identifying the most relevant process signals and thereby reducing the search space. When undertaking system monitoring, there are three main objectives. The first is the detection of a change in process operation and its nature - should this be a sensor fault, faults within the process or a change in product quality or system performance. Once a change in process behaviour is detected, diagnostic tests are then required to identify the cause of the change, which may require analysis of recent process data and/or consultation with an experienced operator. Finally, with the source of the change ascertained, a solution should then be identified and implementation of corrective action undertaken, if appropriate (Cinar and Undey, 1999). This may require either disabling the source of the problem, or in the event of a faulty sensor reading, reconstruction of the value. The methods presented here provide different solutions to the process monitoring problem. Clustering, machine learning and CBR are diagnostic tools, which compare current fault conditions to historical examples of faults. While these techniques will identify the nature of the problem, they are not capable of detecting its occurrence or providing signal reconstruction in the event of a sensor fault. Statistical methods offer a model based approach, where process operation data is compared to a system model, based on 'normal' operating conditions. This provides continuous process monitoring, which can supply early warning of a small process change and offers operators the opportunity to take action to prevent the fault becoming more serious. In particular, PCA and PLS can supply the operator with information as to which process variables are outside normal limits (MacGregor et a1., 1994). This serves to focus the operators' attention on the problem area, allowing process knowledge to be used to identify the source of the problem. Not all of the techniques discussed in this section are capable of providing a solution that enables preventative action to be taken for CCGT power plant.

CBR, providing a historical event that is similar to the currently observed event, is also of little use in this instance, as it again offers classification of new events, however, an explanation of the similarities identified between cases is unavailable. Cluster analysis and 'rules' may be useful in identifying groups of similar events, as their aim is to suggest correlations in data. Once similarities have been identified for events resulting in groupings with common characteristics further investigation would be required to identify the relationships between variables that cause these groupings. A more complete solution is offered by statistical methods. Both PCA and PLS are capable of identifying correlations within data, while PLS also offers the ability to extend this to identifying the correlations which are predictive of a dependent quantity. The correlations identified within the data can then be studied using the scores and loading vectors obtained, indicating the contribution of variables, if any, to the variation of the dependent parameter. The historical data is suitable for the development of a system model, by means of PCA and PLS, which can be applied to continuous monitoring. Archived data is available, detailing sensor data, for example temperatures, pressures, etc, throughout the plant at regular intervals. Once the PCA and PLS models are developed, it can provide a relatively straight forward model which has both the ability for online fault monitoring and offline performance analysis. For practical application, those PCA and PLS models are required for fast online response within 20 seconds, and reasonable prediction accuracy in a wide operation range. With PCA and PLS identified as possessing properties that are useful in relation to the problems posed by power plant and power system operation, the statistical modelling methods will provide the most suitable approach for operation monitoring and performance analysis of CCGT power station.