

THE APPLICATION OF CONDITION BASED MONITORING  
TECHNIQUES FOR THE EVALUATION OF BUILDING ENERGY  
PERFORMANCE AND HVAC HEALTH

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# LIST OF SYMBOLS

$\sigma$	Standard deviation
$V$	Orthogonal loading vectors
$\Lambda$	Diagonal eigenvalue matrix
$\lambda$	Eigenvalues
$\xi_{\text{NOM}}$	Nominal kernel sample vector
$\xi_{\text{TEST}}$	Test kernel sample vector
$\mu_i$	Kernel mean vector the within class
$\mu_0$	Kernel mean vector of all mapped samples
$d$	Polynomial order
$K$	Kernel matrix
$\overline{K}$	Centred kernel matrix
$K_b$	Kernel between class matrix
$K_w$	Kernel within class matrix
$n$	Number of samples
$s_{\text{TR}}$	Variance of the training set
$x_j$	Observation from the normal operating data
$x_t$	Observation from fault data
$v$	Eigenvector

# LIST OF ABBREVIATIONS

ACR	Actual Consumption Rate
AES	Automated Expert System
AHU	Air Handling Unit
AI	Artificial Intelligence
BCR	Building Consumption Rate
BEMS	Building Energy Management Systems
BER	Buildings Emissions Rate
BES	Building Energy Simulation
CBECS	Commercial Building Energy Consumption Survey
CBM	Condition Based Maintenance
CBS	Case Based System
CM	Condition Monitoring
CUSUM	Cumulative Sum
CRC	Carbon Reduction Commitment
DEC	Display Energy Certificate
DTM	Dynamic Thermal Model
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificates
EPI	Energy Performance Indicator
ES	Expert Systems
EUI	Energy Use Intensity
EWMA	Exponentially Weighted Moving Averages
FDA	Fisher Discriminant Analysis
FDD	Fault Detection & Diagnosis
FM	Facilities Management
HVAC	Heating, Ventilation & Air Conditioning
IES	Integrated Environmental Solutions
KBS	Knowledge Based Systems
KFDA	Kernel Fisher Discriminant Analysis
KNN	K-nearest neighbour
KPCA	Kernel Principal Component Analysis

LPHW	Low Pressure Hot Water
M&T	Monitoring and Targeting
NCM	National Calculation Method
NN	Neural Networks
OAT	Outside air temperature
OR	Operational Rating
PCA	Principal Component Analysis
PLS	Partial Least Squares
PPM	Planned Preventative Maintenance
RBS	Rule Based Systems
SBE	Seasonal Boiler Efficiency
SFP	Specific Fan Power
SPC	Statistical Process Control
SPE	Square Prediction Error
SVM	Support Vector Machines
TCR	Target Consumption Rate
TER	Target Emissions Rate
VRF	Variable Refrigerant Flow

# ABSTRACT

The University of Manchester

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Doctor of Engineering

*The Application of Condition Based Monitoring Techniques for the Evaluation of Building Energy Performance and HVAC Health*

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Carbon emissions generated by the building sector have come under stricter limits with the amendments to Approved Document L: Conservation of Fuel and Power of the building regulations for England and Wales. Building designs are now checked to ensure that new constructions have the designed capabilities to operate with a higher standard of efficiency. However, there are currently no means of ensuring that the mandatory improvements in design and construction are actually translating into real life improvements during the actual operation of the building. Assessment methodologies such as the Display Energy Certificate are applied annually. The large interval between audits has the potential risk that poor performance may go unnoticed for prolonged periods of time. Real time assessment of energy performance that is linked to legislative requirements would aid the process of ensuring reductions in carbon emissions occur in reality. Evaluating the energy performance in real time is not a straight forward task; commercial buildings are complex nonlinear dynamic systems with a number of operating states, functions and features. These factors need to be taken into consideration for the fair appraisal of energy performance.

Condition monitoring has been applied extensively to the field of machine health, in which the state of a system is determined through measuring the parameters that are indicative of its health. Within this thesis, a unique method of real time energy performance has been developed along with the implementation of two condition monitoring strategies for the purposes of state evaluation and fault detection and diagnosis. Kernel based dimensionality techniques have recently gained popularity as a means of modelling nonlinear systems.

It was found that the application of nonlinear condition monitoring strategies for determination of building state was proficient in determining slow developing faults and abrupt changes in building state. However, the occurrences of non-acceptable incipient changes in state were harder to detect. Hence the state evaluation techniques were complemented with component level fault detection and diagnosis techniques. These techniques have the combined ability to address the requirement for assessing the state of operation within a building to allow for fair appraisal of the energy performance.

## **DECLARATION**

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*Dedicated to my parents*

# CHAPTER 1

## 1. Introduction

Reliance on fossil fuel derived energy has become a major issue, raising concerns about the sustainability of the current rate of consumption, the increasing difficulties in extracting fuel from current oil & gas fields and the future exhaustion of finite fuel resources (Perez-Lombarda, Ortiz et al. 2008). Furthermore, the impact of using fossil fuels on the environment and climate change have all led to a shift in the perception of how energy should be generated and consumed. The combination of all these factors has led to the consensus that there is an urgent need to shift the balance of the current fuel mix away from fossil fuels towards sustainable, cleaner and renewable sources. However, the continuing growth in world population and the rising levels of demand for energy over the last several decades have as a consequence meant that energy consumption is still continually increasing. A significant improvement is needed in both the capabilities of renewable systems and the efficiency of current energy consuming systems in order to facilitate this transition towards sustainable energy consumption. The technological capabilities of renewable systems are at present inadequate to offset the energy requirements that are currently serviced by fossil fuel derived energy. Hence in order to aid this transition a greater emphasis must be placed upon improving the efficiency of energy consuming end uses to reduce the levels of consumption and gradually eliminate the reliance on carbon based fuels for power.

The common metric for measuring the levels of fossil fuel energy consumption is carbon (dioxide) or CO<sub>2</sub> emissions (or more commonly: Carbon emissions); there have been several pieces of legalisation that legally enforce a reduction in the carbon footprint of participating states and nations. The most widely known is the Kyoto protocol (UN 1992) which placed a cap on the levels of permissible carbon emissions. In addition to Kyoto the UK Climate Change Act of 2008 was introduced which is an legally binding agreement to cut CO<sub>2</sub> emissions (Ruddock 2009). Given that the building sector is a significant contributor of carbon emissions (Bordass, Cohen et al. 2001), a reduction in CO<sub>2</sub> generated by the building sector is essential for meeting such targets. Legislation specifically

targeting building operation efficiency has been formulated with the EU Energy Performance of Buildings Directive (EPBD) which aimed to promote improvements in building energy efficiency (Parliament 2002; Anderson 2006). The directive instigated a transition in improving energy behaviour within buildings. Amendments were made to Approved Document L (Part L): Conservation of Fuel and Power of the Building Regulations for England and Wales in which mandatory improvements on carbon emissions rates were set (Regulations 2006). Further improvements were consulted upon and implemented in the 2010 version of the Part L regulations (Government 2009; DoCaLG 2010).

## **1.1 Research Background**

Historically, the building sector has been a source of poor energy performance; this has led to the building sector being identified as a key area in which efficiency can be improved (Parliament 2002; PARLIAMENT 2010). The amendments to Approved Document L2A (newly built commercial buildings) have now made it mandatory for all new buildings to undergo a pre and post construction emissions check. In the latter case, several parameters are measured from the building post construction for use in the emissions calculations to ensure that the building has the potential ability to operate below the Target Emissions Rate (TER). However, despite the post construction test proving the building has the designed capability to operate below the TER, without monitoring the actual performance, poor operation of the building or unnecessary energy waste by poorly maintained HVAC would result in the optimal performance not being achieved in reality. To tackle the issue of operational efficiency a secondary piece of legislation was introduced for certain buildings; the Display Energy Certificate (DEC). The DEC utilises the metered energy consumption data annually for benchmarking energy performance (Government 2008b). Retrospectively evaluating performance with an auditing period of a year, leaves open a wide window in which poor performance could potentially go unnoticed. There are currently no methods for relating the targets set by Part L to actual building consumption in real time. Hence it is not possible to determine whether the mandatory improvements in design and operation of a building as dictated by Part L are actually leading to a definitive reduction in energy consumption. The amendments to the Part L regulations are a

welcomed first step; however the net benefit of such legislation will be muted if no actual improvements in energy efficiency occur.

The task of real time energy evaluation has largely been left to Monitoring and Targeting (M&T) software for commercial building, M&T software is typically installed within Building Energy Management Systems (BEMS). These software systems provide a means of evaluating energy performance; however their inability to provide a comprehensive assessment on the state of the building, their use of historical consumption benchmarks and limit thresholds lead to questions over the quality assessment. Buildings are complex systems that operate under a number of varied conditions and can possess a large number of nominal operating states. Furthermore parameters indicative of performance as well as the HVAC systems are all interrelated and interdependent. Examination of each parameter in isolation as is common with monitoring and targeting software does not fully capture the real state of the system. Hence targeting a single parameter that has reached a threshold does not necessarily provide a meaningful evaluation of the entire building. Additionally, measuring current performance against past consumption using historical data has its own drawbacks. In many cases it is not known what level of performance the historical benchmark represents, and therefore a history of past inefficiency would rate the current inefficient performance as efficient. Differentiating between the acceptable and non-acceptable states is essential if a fair appraisal of building performance is to be made. For example, it is important to distinguish between occurrences where the energy consumption is high but acceptable given the circumstance from periods of poor performance. Therefore, it is necessary that the state of the building is taken into consideration when performing energy assessment.

The impact on faults and failures of the building services systems on performance must also be taken into account if buildings are to perform efficiently in the long term. It has been estimated that up to 15-30% of energy wastage within buildings can be attributed to poorly performing HVAC systems (Katipamula and Brambley 2005b; Liang and Du 2007). There has been a significant level of academic interest in applying Fault Detection and Diagnostic techniques to building services plant. However, these are usually applied to a single building service plant system and not to the entire range of equipment that is usually installed within a typical commercial building. It is important to integrate HVAC health with energy assessment to determine the underlying causes of poor energy behaviour.

Furthermore, current research has failed to address the link between the effects of a failure and the impact on the building as a whole with regards to energy performance. Hence, there is no holistic approach currently developed to address these issues.

## **1.2 Research Aim and Objectives**

This research project seeks to develop and implement Condition Monitoring (CM) techniques as a means of evaluating real time energy performance and for the determination of building state in conjunction with fault detection and diagnosis of the HVAC systems. The utilisation of CM strategies has been successfully implemented in other industrial sectors for fault detection and diagnosis. This EngD project plans to adapt the traditional concepts of CM strategies with aim of testing the hypothesis that

*“Condition Monitoring can be applied to the building sector for the improvement of energy performance and maintenance practices.”*

In order to test the hypothesis four objectives were identified from studying the background literature, these objectives are discussed again in the literature review chapters.

- 1. Investigating the means of ongoing energy performance evaluation in real time through the development of appropriate benchmarks*
- 2. Creating a means of evaluating the actual building energy performance against the legislative design performance*
- 3. Developing an assessment methodology capable of distinguishing the various states of health/efficiency of a building*
- 4. Developing a means of performing HVAC fault detection that is capable of working in tandem with energy evaluation techniques*

## **1.3 Engineering Doctorate Programme**

The Engineering Doctorate (EngD) is a 4 year doctoral level programme that is focussed solving an industrial problem. Research is performed in collaboration with an industrial partner for whom the research topic is of commercial interest. The industrial sponsor contributes experience, training, resources and contacts within industry towards the

project. As with a traditional PhD the research engineer is required to submit a thesis at the end of the programme for viva voce examination, in which the scientific and technological contribution to knowledge is examined along with the commercial implications.

### **1.3.1 Professional Development**

As part of the professional development element of the EngD programme, a postgraduate diploma in Management Sciences (awarded by Manchester Business School) was undertaken in the first two years. The diploma consisted of 8 modules with taken four in the first year and four and in second year. The module topics were Production Systems; Industrial Relations; Managerial Economics; Individuals, Groups and Organisations; Total Quality Management; Logistics and Supply; Management Accounting and Marketing Management. These modules enabled the research engineer to better understand the commercial implications of their project and provided a means of understanding how the research project may fit into a wider commercial context.

Additionally, courses and workshops were integrated into the EngD programme to enhance the research engineer's professional development. These courses and workshops helped to improve a wide range of key skills and abilities including effective project management techniques, communication skills, presentation and technical writing and negotiation skills.

## **1.4 Thesis Outline**

Following on from this chapter the literature review is given in two parts in Chapters 2 and 3. Chapter 2 reviews the legislative requirements for energy evaluation for buildings and the current benchmarks used in both academia and in industry for measuring building performance. The current shortfalls and gaps in technology are highlighted in both academic research and commercial software that is currently offered on the market. Chapter 3 provides an introduction to condition monitoring detailing the strengths and weaknesses of various condition monitoring approaches. Chapter 3 goes on to review the condition monitoring research that has been applied for the purposes of building energy evaluation. An overview is then given on fault profiles which details the manner in which faults and failures manifest themselves in process data. Information on the key faults and failures responsible for poor energy performance within building is then provided.

Chapter 4 provides the details of the case study building used in this project for proof of concept testing of the condition monitoring and energy evaluation methodologies. A preliminary investigation is conducted using a dynamic thermal model representation of the case study building to determine the building response to variations in the HVAC parameters.

The next two chapters detail the methodologies that were used to address the gaps in technology and knowledge that were identified in Chapter 2. Chapter 5 details the use of the Target Consumption Rate (TCR) and the Buildings Consumption Rate (BCR) to evaluate the actual energy consumption of the building. A real time evaluation methodology is presented along with two Energy Performance Indicators. The data driven condition monitoring techniques that were used to capture the state and health of the building is then presented. This is followed by the fault cases that were developed to test the effectiveness of the state evaluation techniques. Chapter 6 details the knowledge based methodology that was employed to detect faults with the building HVAC systems independently of the methodologies detailed in Chapter 5. The features of the inference engine that was developed are then presented with further fault cases for testing the knowledge based system.

The results are presented and discussed in Chapters 7 and 8. Chapter 7 presents the real time energy evaluation tool results using two cases. The results of the statistical system are also presented along with its ability to differentiate between nominal and fault states. Chapter 8 provides the test case results from the knowledge based systems in evaluating the HVAC systems.

Chapter 9 discusses the commercial implications of the research performed for this thesis including the potential benefits, drawbacks and current limitations. Finally, Chapter 10 concludes the findings from the research project and discusses recommendations for future investigations.

## **CHAPTER 2**

### **2. Building Energy Performance Evaluation**

The primary role of a typical construction is to provide a comfortable inhabitable environment for the occupants to work or live in, sheltered from adverse external weather conditions (Chadderton 1991). Within commercial buildings a significant proportion of energy consumed can be attributed to those systems utilised to regulate the internal environment (Nicholls 2002; Perez-Lombarda, Ortiz et al. 2008). These systems are collectively categorised as the HVAC (Heating, Ventilation and Air Conditioning) building services systems. In the majority of non-domestic building one or more of these systems are employed. For each system there are a range of methods for achieving the target internal conditions, heating can be done through radiant panels, under-floor heating systems, standalone electric heating. Some buildings may have rooms that require special consideration such as server rooms in which the cooling system may be required to run continuously in order to maintain a low temperature. In addition to this, occupant frequency will have a significant influence on the level of energy consumption and HVAC loads. The external climate will also affect the energy requirements for maintaining a comfortable internal environment. Any evaluation of performance must take these factors into consideration for the provision of a fair appraisal of building efficiency. Aside from the HVAC expenditure, the remaining energy consumption can be attributed to the equipment or end uses installed within the building; however these consumptions are not typically included in the energy evaluation process.

The development of an effective methodology for assessing the energy consumption of commercial buildings is a critical factor for meeting the carbon reduction obligations within the building sector. As the old management adage states “You can’t manage what you don’t measure”. However, determining the performance of a commercial building is not a simple task, unlike domestic properties that have relatively predictable consumption patterns and limited functionality; commercial buildings have a wider range of functionalities and employ a greater range of building services systems. Furthermore, commercial buildings can be structurally complex which creates difficulties in

differentiating nominal operation against periods of inefficiency (Casals 2006). As the number of variables influencing energy consumption increases the greater the challenges encountered in determining the health/state or level of efficiency of the building. Variations in HVAC utilisation throughout each day and weekends, irregular occupation periods, coupled with unpredictable variables such as external weather conditions, all contribute to the difficulties in capturing the operational processes. Furthermore, such variation can mask inefficient behaviour making it harder to determine the efficiency of the building as a whole. Thus there is a real danger present of misdiagnosing the state of building performance if the methodology is unable to differentiate between high energy consumption that is permissible given the circumstances for that period and excessive consumption due to poor performance. To overcome this, a benchmark or method of evaluation is required that provides a means of measuring performance. The next section looks into the current legislative requirements, targeting those specifically aimed at monitoring and assessing energy consumption.

## **2.1 Building Sector Legislation**

Several pieces of legislation specifically targeting the building sector have shaped the current requirements for those involved in the construction and operation of buildings. The following subsections detail the legislative requirements aiming to bring about improvements in building operation efficiency.

### **2.1.1 EU Energy Performance of Buildings Directive**

The Energy Performance of Buildings Directive (referred to as the EPBD) was the initial driver for the improvement of energy efficiency within buildings (Parliament 2002; Anderson 2006). For the purposes of this review the recast version of the EPBD (sometimes referred to as EPBD 2) shall be considered as it contains the most up to date aspirations of the legislation. EPBD 2 continues to focus on promoting the improvements laid out in the 2002 EPBD and introduces new initiatives and provides updates to the previous version. EPBD 2 comprises of 31 articles on proposed initiatives and standards with the most prominent theme being the implementation of energy efficiency strategies

for future energy security and to ensure compliance with Kyoto. In order to bring about an overall 20% reduction in carbon emission, the building sector has been identified as having significant potential for cost effective savings. Additionally, there is mention of the importance of managing energy demand on a macroscopic scale; it is the opinion of the author that to fully understand and achieve a greater level of control over large scale energy demands within the building sector, it must first be clearly assessed on a microscopic level (singular building level). Several relevant pieces from the EPBD are detailed in the following paragraphs.

Article 3 of the recast EPBD details the proposed adoption of a methodology for calculation of the energy performance of a building, this is further expanded upon in Annex I, in which it is stated that

**“The energy performance of a building shall be determined on the basis of the calculated or actual energy that is consumed in order to meet the different needs associated with its typical use.”** (PARLIAMENT 2010).

Additionally, the energy evaluation methodology shall take into account the local climate, the designated function of the building as well as the age of the building. Differentiation between differing types of buildings shall also be taken into account (PARLIAMENT 2010). This is currently being implemented in the form of the Target Emissions Rate (further details on the TER are given in the next section) calculations that utilise NCM functionality profiles and weather data. As previously detailed energy evaluation must integrate such factors to derive a suitable and fair benchmark. Paragraph 2 of Annex I prescribes transparency in energy performance with the inclusion of a benchmark or performance indicator (Campbell 2007; PARLIAMENT 2010).

Article 11 details the requirement for the implementation of Energy Performance Certificates (EPC's) in all new buildings, renovations and buildings which are utilised by the public with a useable floor space greater than 500m<sup>2</sup>. The EPC shall contain include the

**“energy performance of a building and reference values such as the minimum energy performance requirements”** (PARLIAMENT 2010).

This is done for the purposes of providing building owners and operators with the opportunity to compare the EPC performance against the actual performance. However, EPCs are generated every five years during which the condition and performance of the building would undoubtedly change. Further information on EPCs is given further on in this chapter.

### **2.1.2 Approved Document L**

Implementation the objectives/requirements detailed in the EPBD is primarily done through national legislation. Within England and Wales this is predominantly done through Approved Document L (Part L): Conservation of Fuel and Power for England and Wales of the Building Regulations. Part L has undergone several iterations since the 2006 version which introduced the mandatory target emissions rate. The 2013 version of Part L is currently out for consultation. The key points from Part L 2006 are detailed with a section following on highlighting the key changes made for 2010.

The most notable change from previous iterations of the Part L Regulations (pre 2006) is the inclusion of a mandatory target emissions rate (TER) (Regulations 2006). The main focus of Part L 2006 is the cap on energy emissions and the stricter design limits. The ideology behind the stricter limits on standards for building fabric and HVAC plant specification is to ensure that the building has the potential to operate at a lower consumption rate and that as a result this will lead to better energy efficiency in actual operation. However, this does not take into account that the building and its HVAC systems may be operated inefficiently in reality.

The Building Emissions Rate (BER) is derived from the NCM (National Calculation Method) which calculates the theoretical emissions rate for a building. The national calculation method is defined by the Department for Communities and Local Government. The NCM calculations utilises standard data sets for different activity areas and uses a common database of construction and service elements (DoCaLG 2009). Calculation of the BER is done at two stages, firstly at pre construction to ensure that the building is of sound fundamental design and secondly at post construction (handover stage). In the case of the latter, some parametric data from the real building is utilised in the calculation process

(such as air permeability and fan efficiencies). The building is deemed to have passed if the BER is less than the Target Emissions Rate (TER). Calculation of the TER is done by first determining the performance of a notional building. The notional building is of the same shape, size and function as the actual building, it must be of the same orientation and use the same HVAC systems employed. Where the notional and actual building differs is the standards for building fabric, in the notional building they are based on the international standards made reference to in Part L 2002. In addition to this the U-values, solar and light transmittance values, opening sizes, and efficiency values for HVAC are also fixed (Government 2008). The TER is then calculated by Equation 2.1 (Regulations 2006):

$$\text{TER} = C_{\text{NOTIONAL}} \times (1 - \text{ImpvF}) \times (1 - \text{LZC}) \quad \text{Equation 2.1}$$

where  $C_{\text{NOTIONAL}}$  is the carbon emissions ( $\text{kgCO}_2/\text{m}^2/\text{annum}$ ) generated by a notional building, ImpvF is the improvement factor for building efficiency, for a heated and naturally ventilated building the ImpvF is 0.15. LZC is the low and zero carbon energy benchmark, as of 2006 this was set to 10% of the building emissions. Despite the introduction of and amendments to the legislation detailed previously, there are limitations still present when assessing building efficiency.

It is stated in Part L (paragraph 66) that

**“Buildings should be constructed and equipped so that performance is consistent with the predicted BER”** (Government 2008)

Currently the post construction test is regarded as sufficient to fulfilling this aim. Bordass et al (2004) highlight the potential of the legislative requirements as a means of closing the ‘credibility gap’, the difference between the expectations of the designed energy efficiency and that of the actual consumption (Bordass, Cohen et al. 2004). Performance monitoring of the actual building falls outside the scope of Part L and whilst the EPBD 2 is aiming to improve the methodology for assessing buildings it too does not provide a means of determining whether the legislative initiatives actually translate into real improvements in building efficiency. As a result there was a significant amount of research performed that investigated different methods of implementing the efficiency standards in relation to actual building performance (Bordass, Cohen et al. 2001; Maunsell 2003; Roulet and

Anderson 2006; Cohen, Bordass et al. 2006a; Cohen, Bordass et al. 2006b). In 2008 the DEC was introduced in which it addressed the issue of the ‘credibility gap’; DEC’s are discussed in the next section.

The updated 2010 version of Part L has several changes from the 2006 version, the most notable is that the updated version identifies that it is easier (and more cost effective) to achieve a reduced consumption in some buildings than others (DoCaLG 2010). A new method of defining the TER is given based on two approaches the flat rate (requires a 25% reduction on the 2006 TER), and the aggregate approach which uses a newly defined notional building so that all new buildings on aggregate would achieve a national target of 25%.

### **2.1.3 Display Energy Certificates**

The Display Energy Certificate (DEC) is an annual check on performance that uses actual metering data from the building. The DEC came into force on the 1<sup>st</sup> of October 2008 and is required for all public authorities and institutional buildings (with a useful floor space greater than 1000m<sup>2</sup>) that provide a service to a large number of people (Government 2008b). DEC’s grade building performance using a scaled set of grades from A to G, providing the owner/facilities management with a visual measure of how the building has performed in the previous year. Grading is a useful indicator as it acts as praise for good performance and as an incentive for improvement in cases of poor performance. The level of performance or Operational Rating (OR) determines the DEC grade and is calculated using Equation 2.2 (DoCaLG 2008).

$$OR = (\text{Building CO}_2 \text{ emissions} / A) * (100 / \text{Typical CO}_2 \text{ emissions per unit area}) \text{ Equation 2.2}$$

where A is the Building Area (m<sup>2</sup>). Each building is categorised by the building use typical to that type of building, which is then used to select the benchmark (DoCaLG 2008). The benchmark uses standardised conditions for a number of parameters including temperature and occupancy patterns.

There are limitations in the use of the DEC. The DEC annualises building performance thus periods of poor efficiency are not distinguishable from periods in which the efficiency is good or sufficient. This problem is inherent to annual benchmark evaluation methods and possesses the risk of masking the true level of performance throughout the year. For example poor performance during the winter months could be offset by periods where the building is unoccupied. It is not possible to identify the state or time period when poor performance occurs, hence it is difficult to isolate the root causes responsible for increased energy consumption. Retrospectively analysing energy efficiency with an auditing period of a year has the further risk that the causes of poor performance may only be identified long after they have potentially caused months of unnecessary energy wastage.

#### **2.1.4 Energy Performance Certificates**

The EPC is mandatory for all new constructions and for buildings that are rented or sold (Article 7 of the EU directive) (PARLIAMENT 2010). EPC's have a validity period of 10 years and are based upon some parametric values such as HVAC operating specifications. Hence, the EPC is similar to the TER in that it is a theoretical benchmark of what the building could achieve. EPCs also have a grading system that informs the end user of the building performance, with the aim of providing a comparative benchmark against which to measure actual performance. This does not take into account factors that may affect energy consumption throughout the year and hence the EPC has the same drawbacks as the DEC. Additionally, the 10 year validity period leaves a long period of time in which the EPC building rating could become highly inaccurate or obsolete. Furthermore the performance rating may not actually be checked against what is actually going on in the building.

#### **2.1.5 Carbon Reduction Commitment**

The final piece of legislation relating to the performance of buildings is the Carbon Reduction Commitment (CRC). The CRC is a mandatory scheme to improve energy efficiency in large public and private sector organisations (DofEaCC 2010). The CRC scheme only applies to companies that have half-hourly metered electricity consumptions

greater than 6000MWh per annum. Companies and institutions that are participating in the scheme are required to monitor and report their CO<sub>2</sub> emissions each year, each company is allocated a carbon 'budget' and excessive use of energy will require the company to purchase additional credit (each credit allowance is currently £12 per tonne of CO<sub>2</sub>). Furthermore, a league table is to be made publically available showing the best and worst performing companies. The aim of which is to encourage companies to improve their efficiencies to save on costs and reduce their respective carbon emissions. Tools that are able to monitor the efficiency of the buildings in real time would be of commercial benefit, allowing for greater ease in emission/energy budget management and to ensure continued improvement to avoid penalties.

## **2.2 Energy Evaluation Techniques**

Further to the methods of energy assessment detailed previously this section shall review the relevant academic research that addresses evaluation of building performance. The background literature indicates two themes in energy assessment within buildings; the first is the use of externalised benchmarks whereby a comparison is drawn between the energy consumption of the building with that of other similar buildings. The second is the internalised benchmark that offers greater levels of customisation and the use of actual building parameters/data in determining the benchmark. The aim of which is to capture some of the inherent characteristics of the actual building.

External benchmarks draw upon empirical energy consumption data from similar buildings (typically categorised by functionality) as a reference to nominal energy utilisation (Jones and Cheshire 1996). To normalise for differing sizes of buildings the energy consumption is divided by the useable floor space, hence the Energy Use Intensity (EUI) per m<sup>2</sup> is the primary indicator of performance in these studies. There are a wide variety of databases and guides compiling energy consumption data for the purpose of benchmarking energy consumption, the most prominently utilised benchmarks along with the studies utilising them are detailed within this section.

The Energy Star database utilises data from the Commercial Building Energy Consumption Survey (CBECS). The CBECS database is compiled every four years with

the latest survey being carried out in 2011; classifications are drawn along generic building functionalities such as health care, educational and office buildings. Information such as building age, total floor area and occupancy periods are collected during the survey (EPA 2007). A significant drawback in the Energy Star methodology is the regression model utilised to derive the benchmark index only includes physical parameters that relate to the building operation (hours occupied per week, number of office equipment installed) and excludes those parameters that primarily determine the consumption levels such as the efficiency of installed equipment. Another point to note is that data for the survey is collected via telephone conversation and cannot be verified unlike a meter reading.

The CBECS database was used by Sharp (1996) to compare energy usage against actual the consumption of a building whilst determining the parameters that had the greatest impact on consumption for offices (Sharp 1996). Sharp (1996) filtered out data samples that had a weighted average floor space due to inconsistencies between the values given by building operators in interviews and recorded values for floor space. Additionally the weighting factors within the CBECS database were not applied as

*“...the uncertainty that these specific weighting factors would produce appropriate representations since individual building characteristics like those resulting from this analysis can vary so much from building to building.”* (Sharp 1996).

The effects on performance due to different HVAC specifications or variations in building usage are not taken into account when considering a simple normalised  $\text{EUI}/\text{m}^2$  methodology. It can also be argued that taking this approach over simplifies the complexities involving building operation and that, in order to form a credible method of benchmarking factors affecting energy consumption must be integrated (Sharp 1996; Chung, Hui et al. 2006). Chung (2006) attempts to overcome this by integrating various energy influencing parameters within the EUI, however, several assumptions are made regarding occupant behaviour that would in the real world be unrealistic (for example, lights and air conditioning turned off when not used, assuming regular maintenance of HVAC to keep efficiency at good levels). Furthermore, the variations in different buildings properties (location, shape and size) cannot be assumed to be accounted for by normalising the EUI by floor space. Thus the use of  $\text{EUI}/\text{m}^2$  as a benchmark may over simplify the

nature of building energy consumption (Monts and Blissett 1982; Liddiard and Wright 2008).

The CIBSE TM22 provides guidance on evaluating the performance by measuring consumption against the benchmarks from ECON19 which was developed by the Carbon Trust (Liddiard and Wright 2008). The benchmarks applied depend on the building functionality, with classifications for offices, hotels, industrial buildings and so on for a range of building functions. Three modelling methodologies are presented for evaluation; simple assessment for a building with up to 2 energy supplies, general building assessment with zones of differing types of function and non-standard occupancy and energy consumption patterns, and the third is a systems assessment that assesses the consumption against benchmarks for the HVAC systems (CIBSE 2006c). The ECON19 guide specifically targets the performance of office buildings with other guides providing benchmarks for other building functionalities. Office buildings are segregated by their respective complexity with classification groups ranging from naturally ventilated cell offices to air conditioned offices that would typically act as headquarter offices (Energy 2003). End use consumption is also benchmarked including energy for catering, computer rooms and the typical HVAC systems. Energy consumption is categorised as 'Typical' if the consumption is in line with the median, whilst buildings with a significantly lower consumption are rated as 'Good Practice'. The data from the ECON19 database consists of data based upon energy consumption in offices in the 1990's. Thus advancements in technology may render such data irrelevant to operational practices and energy consumption. Additionally, the good practice benchmarks for end uses appear to be taken from different standards, for example the benchmark for cooling may have come from a building with a low demand for cooling, whilst the heating demand from an entirely different building (Liddiard and Wright 2008). Given the interrelated nature of HVAC operation achieving good practice is far more difficult when considering a 'whole' building.

Jones et al (2000) have created their own database from local building stock, thereby attempting to capture the situational relevance (and impact) of typical weather conditions specific to that region, segregating by building functionality (Jones, Turner et al. 2000). However, with any external benchmark large numbers of samples are required to accurately define the energy consumption, by analysing local stock exclusively and whilst

simultaneously grouping buildings by functionality this reduces the number of samples per grouping leading to the possibility of creating inaccurate benchmarks.

The use of external benchmarks has several limitations with the greatest drawback being unrepresentative samples within the data source affecting the reliability of the database to act as a benchmark. Other limitations include the difficulties in determining how normalisation was performed and the potential for inconsistencies in the data collection process. The latter is especially problematic as it would be difficult to isolate and remove such data samples from the database before utilisation. Therefore, depending on the benchmark utilised varying conclusions could be drawn as to the performance of the building. For example, in the Probe studies conducted by Bordass (2001), buildings were selected specifically based upon their 'good' performance thereby skewing the benchmarks to be overly stringent (Bordass, Cohen et al. 2001). Essentially, these assessment methods filter down to a static single figure which acts as a guide for typical performance of buildings with a common functionality within that sector. External benchmarks are unable to capture the intricate characteristics of individual buildings and therefore are unable to provide an assessment that takes into account the parameters that affect building performance.

To overcome the limitations that exist with externalised benchmarks there has been work performed to provide greater levels of customisation in deriving a benchmark for assessment. The aim of which has been to develop a more accurate Energy Performance Indicator (EPI) that attempts to capture the characteristics of the building under observation. Cohen et al (2004) proposed using energy budgeting for the purpose of meeting the EPC requirements and compliance testing. This created the opportunity to tailor EPI's for specific buildings automatically generating the TER (Cohen, Bordass et al. 2004). However, the study placed the focus upon offices and typical office equipment only, significantly narrowing the number of buildings applicable for such a methodology.

Field et al (1997) investigated a means of testing the energy performance of the building by analysing the efficiency of the HVAC end-uses by comparing them with external benchmarks. The aim of which was to segregate each major end use in order to tailor the assessment process for evaluation against the building systems installed (Field, Soper et al. 1997). Whilst this method captured the characteristics of the building HVAC systems it

still used external benchmarks as a means of evaluating them. Aside from the problems stated in the previous section regarding external survey data, variations in HVAC parameters and occupancy periods can affect how the HVAC is assessed regardless of whether additional consumption was as a result of acceptable circumstances or not.

Modelled benchmarks move towards creating a bespoke evaluation of individual buildings to allow for a significantly greater level of accuracy in evaluating the energy performance of the building. A strength of modelled benchmarks is that they do not require the collation of data from similar buildings (Liddiard and Wright 2008). Models typically use consumption data, building functionality and the operating parameters of the installed HVAC systems to evaluate energy consumption based upon the fundamental principles of building operation. Thereby preserving and integrating the inherent characteristics of the building and avoiding the generalisation that is intrinsic to external benchmarks. The main drawback of modelled benchmarks is that they require intensive modelling to ensure that the benchmark consumption is accurate. Given the complex nature of building operation this process can be time and cost intensive. Hence, model based approaches are generally not widely used to model the whole building but rather individual HVAC systems, further details are provided in Chapter 3.

Federspiel (2002) calculated the expected the energy consumption of a laboratory from first principles taking into account the building function and specialist equipment consumption (Federspiel, Qiang et al. 2002). The model developed by Federspiel (2002) used idealised consumption rates to produce a benchmark for laboratory based buildings. By incorporating the features of the energy consuming units a normalised benchmark was extracted for use with both laboratory and non-laboratory buildings. The laboratory based benchmark contained all the relevant information needed to perform analysis for the laboratory, however, generalisation of the benchmark in its application to non-laboratory buildings was the equivalent of using an external benchmark and lacked the robustness of the original modelled benchmark. Whilst modelled based approaches do provide favourable levels of accuracy, the time and cost involved in producing models is prohibitive for widespread implementation for individual buildings. An alternative would be the use of Dynamic Thermal Models which are described later on in this chapter.

A subset of modelled benchmarks is baseline models. Baseline models use historical consumption data to determine the energy required to operate the building as well as to predict future consumption (Dong 2005). Sondregger (1988) created a baseline equation utilising utility bill data that took account of both weather and non-weather related variables to project future consumptions (Sonderegger 1998). Whilst a number of variables were taken into consideration in the development of the baseline equation the study did not take into account HVAC efficiencies and other key features. Overall, baseline models are typically easier to implement but lack the robustness of modelled benchmarks.

### **2.2.1 Degree Days and Historical Data**

Heating and cooling degree days are used for attributing the level of energy required to heat or cool the building when the external temperature falls below (or rises above in the case of cooling) a base temperature (CIBSE 2006a). In the case of heating degree days the base temperature is typically set to 15.5°C. For example, if the external temperature is 12°C on average for a day then the degree days would be equal to 3.5 heating degree days. By performing regression analysis on the energy consumption against the number of heating/cooling degree days a relationship between energy consumption and external temperature can be obtained. The correlation illustrates the base relationship between energy consumption and external temperature hence allowing for the performance of the building to be evaluated without discriminating in cases of greater consumption due to adverse weather conditions. There are problems with exclusively utilising degree days for energy evaluation. Degree days omit all other factors such as HVAC efficiency, irregular occupancy and so on, meaning that they are unable to account for changes in consumption as a result of any other variable aside from temperature changes. There are a multitude of possible factors that could affect energy consumption apart from external temperature. Furthermore, use of data points in the regression analysis that have increased consumption as a result of non-temperature related variables can skew the correlation trend, giving a misleading relationship between temperature and energy consumption. Hence, when analysis of consumption trends is performed variables aside from temperature need to also be considered (Sonderegger 1998).

Historical energy data can provide an insight into the energy consumption behaviour of a building. Given a relatively predictable HVAC load and similar external weather conditions year on year, performance can be analysed for greater or lower consumption. However, there are difficulties in determining the operating efficiency of the building in the past. Therefore in most cases it is not possible to determine whether the past consumption data utilised for comparison was of good or bad behaviour. Additionally, historical consumption data fails to provide information on variables that are influencing the energy behaviour as the consumption data is considered in isolation. Finally, it may take several years of building operation to gain sufficient data for analysis; this is a significant disadvantage especially in the case of new buildings.

### **2.3 Building Energy Management Systems**

Building Energy Management Systems (BEMS) are typically installed in the majority of sizeable commercial buildings; these systems are employed to provide control over the internal environment for occupant comfort (Nicholls 2001). Modern BEMS typically comprise of a central BMS station and intelligent outstations (Levermore 2000). The central station contains the software that is used to control the internal environment, run the daily operational profiles, supervise the outstations and store data that is sent from the outstations. The outstations are the units that control the plant equipment; outstations receive input from sensors and through closed loop control feedback mechanisms generate an output in the form of controlling actuators, valve positions and other systems to regulate the internal atmosphere. These systems have the ability to log a range of process parameter data, this data can be retrospectively analysed or through the use of on-line monitoring systems evaluated in real time. On line evaluation refers the assessment of the current state of the system by using each new set of incoming data for evaluation. Currently, the commercial state of art for building energy evaluation lies with Monitoring and Targeting (M&T) software installed within BEMS that use the incoming data to analyse energy performance.

### 2.3.1 Monitoring and Targeting Software Systems

Monitoring and Targeting (M&T) software typically measures and logs the energy consumed for end uses and highlight the areas where excessive consumption is occurring. Use of M&T software has largely replaced the need for manual energy audits as the software algorithms not only collate the data but are also capable of providing analysis on the current state of performance. M&T systems tend to operate in four stages; monitor the energy consumption and derive a base energy load, determine a residual between expected energy consumption and actual energy consumption, CUSUM (CUMulative SUM) charts are typically applied to determine the cumulative increase or decrease in energy consumed over a set period of time. The next stage is identification of the possible reasons for excessive consumption aided by the results from the CUSUM charts and out of bound threshold limits. The final stage is to set targets for future consumption by taking measures to reduce the consumption of end-uses that are responsible for the increased energy expenditure and to monitor for deviations, thus repeating the cycle. In addition to this, many M&T software systems utilise historical consumption or set limit thresholds (via CUSUM analysis) for out of bounds alarms, variations in external temperature are typically dealt with by degree days (Pennycook 2001).

The key limitation of M&T software is that they generally use historical energy data for evaluation which may then be used to set benchmarks or limit thresholds. Given the shortcomings previously detailed in using historical data its use as a benchmark for performance within M&T software has considerable disadvantages. Setting the maximum consumption level for a given system or end use is akin to using a limit threshold. Setting a threshold for systems that operate without the influence of other variables is acceptable, for example, setting a threshold on the maximum boiler outflow temperature to 80°C would suit the needs of monitoring the outflow temperature during occupied periods as it can be evaluated in isolation to the rest of the building. However, setting a maximum value for energy consumption (even after compensating for external temperature) does not take into account the variety of acceptable causes for increased consumption. They do not take into account plausible reasons for excessive consumption hence there is the potential of misdiagnosing the consumption trends. The converse also applies, for example, a faulty sensor that leads to a reduction in heating being supplied and therefore reducing HVAC energy consumption may be overlooked or seen as an improvement in performance.

## **2.4 Dynamic Thermal Model (DTM)**

There has been the development of numerous DTMs over the last several decades that simulate building operation and energy behaviour. Systems such as Energy Plus, DOE-2 and BES (Building Energy Simulation) Test were developed to test and optimise building design by simulating the operation of a building (Judkoff and Neymark 1995; Crawley, Lawrie et al. 2000; Hirsch, Winkelmann et al. 2001). SBEM is better known within the UK and has been specifically developed to test building designs to determine if they meet the Part L TER. The Virtual Environment by Integrated Environmental Solutions (IES) is another commonly used software platform used to evaluate building design. Virtual Environment also has a Part L compliance tool used for generation of EPCs and for calculating the pre and post construction performance. The post construction IES compliance tool integrates the actual features of the building in simulating the BER. This includes important factors such as location, weather data, building orientation and physical characteristics of the actual building including the number and types of rooms. Furthermore, HVAC parameters and the U-values are also used to simulate the building behaviour. In essence the DTMs provide a bespoke assessment of the building.

Given that post construction performance testing is now mandatory, the use of DTMs will undoubtedly become common place. The DTMs have the ability to model a wide range of buildings and functionalities. They are easier to develop than modelled benchmarks as the DTM software environment has all the necessary functions and calculation processes built in.

## **2.5 Summary & Project Objectives**

The main aim of the EPBD and Part L is a genuine improvement in building efficiency. However, the legislation fails to bridge the gap between the legislative design requirements and the daily operational performance. Providing a link between the design and operational efficiency is essential for tangible improvements in energy efficiency within the building sector. The current means of assessing building energy performance largely rely upon the use of historical data, external benchmarks, rudimentary limit thresholds or monitoring and targeting software. These techniques do not possess the ability to assess the operational

performance against legislative targets and more significantly they are incapable of capturing the complex, multivariate processes of building operation. Capturing and assessing the building characteristics and operational state is crucial to providing an unbiased assessment. Hence, there is no current methodology in place that is able to provide a link between the design and operational performance of commercial buildings whilst concurrently capturing the process state to allow for a fair assessment of performance.

It is the author's opinion that real time energy evaluation would provide a means of overcoming the drawbacks of the current methodologies and help further the goal of improving energy efficiency in the building sector. Development of a dynamic energy assessment tool would allow for faster feedback of building performance and would remove the burden of performing manual audits. Hence objective one of the research project is:

- 1. Investigating the means of ongoing energy performance evaluation in real time through the development of appropriate benchmarks*

As previously noted a major shortcoming in the current legislation is that it fails to address the link between theoretical performance and what occurs in reality, whilst the building may have the theoretical potential ability to pass the TER this may not actually translate into real improvements in building efficiency. Real improvements are required if commitments to Kyoto and other initiatives are to be met. Thus objective two of the research project is:

- 2. Creating a means of evaluating the actual building energy performance against the legislative design performance*

In order to fairly appraise building performance the evaluation methodology must be able to distinguish between nominal and poor performance as part of the energy assessment process. Commercial buildings can be complex with many interrelated parameters which result in numerous nominal and abnormal states of operation. Therefore the evaluation technique must be able to assess the building as a whole, taking into account the multitude

of parameters that influence performance in order to relate the state of the building to the current rate of energy consumption. Thus objective three is

*3. Developing an assessment methodology capable of distinguishing the various states of health/efficiency of a building*

## CHAPTER 3

### 3. Introduction to Condition Monitoring

In the previous chapter it was highlighted that in order to effectively evaluate the energy performance of a building it is necessary to capture the intrinsically complex nature of building operation to provide an accurate assessment. The methodology employed must be able to determine the state or health of the building in real time whilst concurrently having the capability to identify and differentiate between nominal and poor behaviour. Additionally, faults and failures of the HVAC systems that lead to poor energy behaviour must also be identified and displayed to the end user to promote a cycle of continuous improvement. Condition Monitoring (CM) systems provide a means to achieve these objectives. CM is the process from which the health or state of a system is determined by measuring the parameters that are indicative of its health (Rao 1996; Davies 1998; Korbicz, Koscielny et al. 2004; Randall 2011).

CM was initially developed as a maintenance tool known as Condition Based Maintenance (CBM). CBM was applied within the manufacturing industry to determine the state of health for manufacturing equipment (Davies 1998). Preceding the introduction of CBM the two most common maintenance practices were run to failure and Planned Preventative Maintenance (PPM). Whilst the former method would lead to abrupt and unexpected breakdowns the machine could usually be operated for longer periods of time. Whereas the planned preventative maintenance approach reduced the likelihood of a breakdown occurring, however with PPM machine downtime increased as the plant was serviced regardless of the state of health of the machinery (IMechE 1992; Tavner, Ran et al. 2008). The primary aim of CBM was to provide an alternative to these techniques and to enable an intelligent proactive maintenance strategy. By determining the symptoms of failure it was possible to take maintenance action only when a fault was likely to occur on a 'needs driven' basis. The application of CBM techniques to the manufacturing industry has had a positive impact; as a result CM was borne as broader approach to system health evaluation based upon the same fundamental principles as CBM. Korbicz et al (2004) define CM as ability to determine the current state of a system by utilising the current information about

the system, thus allowing for diagnosis and the ability to provide a prognosis by predicting the future states (Korbicz, Koscielny et al. 2004).

As the CM state of art has developed the ability of CM systems to analyse and evaluate complex and sophisticated systems has also advanced. Evidence of which is clearly seen in the application (both research and industrial) of CM approaches to safety critical and technologically advanced industries such as the aviation and nuclear sectors (Mackey and Fenner 1999; King, Bannister et al. 2009; Stephen, West et al. 2009; Alvarez, Aragonés et al. 2010).

The practical application of CM not only captures the state of the building but detects diagnoses faults and failures; therefore the CM process is sometimes referred to as Fault Detection & Diagnosis (FDD) (Isermann 1984; Isermann and Balle 1997; Korbicz, Koscielny et al. 2004). The main steps involved in FDD are described in the following section.

### **3.1 Fault Detection and Diagnosis**

The primary goal of FDD is to automate the process of detecting and identifying the symptoms of faults and mapping them to their causes (Palade, Bocaniala et al. 2006). A large number of approaches have been developed, typically referred to as CM strategies which are detailed in section 3.2. Regardless of the means in which FDD is implemented, all strategies are based upon the same fundamental concepts.

The initial stage of FDD is the definition of the characteristics of the system or object under consideration. This is required in order to identify the nominal operating envelope as well as potential fault paths and failure modes (Isermann 2011). An important criterion used for selecting the appropriate CM strategy is the ability of the CM method to capture the necessary complexities of the system. CM methods that are unable to do so would perform unreliably in differentiating between nominal behaviour and fault occurrences (Payne, Hall et al. 2001). The system characterisation process also involves identifying the parameters that are indicative of the state of the system. The measurement techniques used to obtain parameter data in traditional CBM are largely inapplicable or impractical for

evaluation of building performance. Techniques such as analysing the lubrication for debris or obtaining vibration measurements of the HVAC equipment (Davies 1998) are not typically performed as part of the maintenance practices in buildings. However, the use of process parameter data such as temperature values, valve positions and meter readings that are logged by the BEMS are useful for determining the state of the building (Randall 2011). Furthermore, this process parameter data can be easily logged and stored in the BEMS and would therefore, provide a practical means of applying condition monitoring.

Once the state of the building is suitably defined, the CM system is then used to monitor for abnormal states. In CM the fault detection process relies upon the assumption that the occurrence of a fault will result in a change within the process data. It is this change in parameter that is detected by the fault detection method; this in turn requires setting thresholds to differentiate between nominal states and fault states. Early methods of detecting faults included the use of threshold limits in which an upper and lower boundary was set. Parameter values above or below these threshold limits were considered as abnormal states for that parameter or the process as a whole. Statistical process control methods such as the CUSUM (Cumulative SUM) or Exponentially Weight Moving Average (EWMA) control charts were also used to determine in control and out of control process states by setting threshold limits (Kourti 2009). However, single value limit thresholds for parameters are inadequate for the majority of modern day systems (MacGregor and Kourti 1995). Furthermore, univariate process control systems such as CUSUM and EWMA charts show poor fault detection properties when applied to multivariate systems (Lee, Yoo et al. 2004). In the majority of commercial buildings, the operation of the HVAC systems is a multivariate process as a result of the numerous interdependent variables. Fine tuning of detection boundaries is often required to avoid TYPE I (missed alarm) and II (false alarm) errors. Typically, there is a payoff between the number of missed alarms and false alarms leading to the issue of sensitivity for the fault detection method. The fault detection itself does not typically convey any information on the root causes of faults or what the actual fault is. Thus diagnosis methods are implemented.

Once a fault has been detected, the CM system analyses the change in features of the parameter data to ascertain the causes of the fault. The most popular methods of performing fault diagnosis are through the use of data classification techniques in statistical

systems or inference models in knowledge based approaches. It should be noted that within the context of this project poor or inefficient energy performance shall be classified as a deviation from the norm and thus representative of a faulty state of building operation.

Over the last several decades Condition Monitoring has developed from relatively simplistic measurement and threshold setting techniques to complex methodologies that are capable to monitoring and diagnosing a wide range of faults for multivariate systems. The following section shall describe the main CM approaches that are used for process monitoring.

## **3.2 Condition Monitoring Strategies**

There are numerous CM strategies that perform fault detection and diagnosis ranging from heuristic qualitative based systems to artificial intelligence methodologies. Condition monitoring approaches are commonly categorised into three broad classifications (Chiang, Russel et al. 2001; Wang 2003; Venkatasubramanian, Rengaswamy et al. 2003a):

1. Data driven techniques
2. Knowledge Based Systems
3. Model/Analytical models

The CM strategies within each of these classifications possess their own advantages and disadvantages, the subsequent sections detail the various strategies and their respective strengths and weaknesses.

### **3.2.1 Data Driven Systems**

Data driven systems rely on exclusively on process data to capture the nominal or fault states of a system. Historical data is sometimes used to train the data driven methodologies in defining nominal and abnormal states of operation. The preferable method of obtaining training data is the collection of process data under controlled conditions to ensure that the training data is free from noise and anomalous disturbances. Data driven approaches have the ability to analyse complex systems as a whole. There are two main subgroups for data

driven systems, statistical and non-statistical approaches. The most well known non-statistical method is Neural Networks (NN). Neural Networks imitate human learning by using 'experience' of the process obtained from training data to make observations about the state of the system (Swingler 1996; Wang 2003). Considerable research has been performed in using NNs for fault diagnosis, namely through classification of the process data (Venkatasubramanian, Rengaswamy et al. 2003c). A typical Neural Networks consists of a number of interconnected process elements, each process element can have many inputs upon which an individual bias or weighting may be applied. The process element computes the total input with respect to each inputs weighting. Despite the high number of possible inputs only one output from the processing element is possible and depending upon the threshold the process element may or may not produce an output (Wang 2003). In a typical NN numerous processing elements are interconnected, the process elements are arranged into one of three layers; the input layer which receives external outputs, the hidden layer which has inputs and outputs within the Neural Network and the output layer which produces the final output outside of the system (Palade, Bocaniala et al. 2006). Neural networks have the advantage of being able to compute solutions to a wide range of processes and problems. They do not require prior knowledge of the process itself and can handle both discrete and continuous data. Furthermore, NN are able to derive functions for non-linear processes and thus they have a significant advantage over traditional statistical and model based approaches (further details given within the next several sections). However, the use of Neural Networks does have the significant disadvantage in that the decision making process is not traceable (as it occurs within the hidden layer) and as such Neural Networks are effectively black boxes in which it is not possible to determine how the NN came to a particular output. Aside from Neural Networks other non-statistical process monitoring techniques of note include Genetic Algorithms and Fuzzy Logic Systems.

There are numerous statistical methods in the field of process monitoring; the most widely applied techniques are Principal Component Analysis (PCA), Partial Least Squares (PLS) and more recently Fisher Discriminant Analysis (FDA) (Chiang, Russel et al. 2001). These three techniques have all been applied for the purposes of reducing the dimensionality of complex processes to evaluate the state of a system (Chiang, Russel et al. 2001). PCA seeks to reduce dimensionality within a process by maximising the variance within a linear combination of variables (Rencher 1995). Essentially it allows for the visualisation of

multivariate data by generating new variables called principal components. For systems with a significant numbers of variables the complexity can be greatly reduced by replacing the process variables with 2 or 3 new principal component variables representing the characteristics of the system. This multivariate approach is particularly effectual when the process under consideration has multiple interrelated variables that continuously interact. The principal components are commonly able to capture the variance of process variable data within 2 or 3 principal components for linear systems (MacGregor and Kourti 1995).

Partial Least Squares also seeks to reduces dimensionality by maximising the covariance between a predictor (independent) matrix and a predicted (dependent) matrix (Geladi and Kowalski 1986). A common approach in using PLS for process or quality monitoring stacks the predicted matrix with product quality data and the predictor matrix with the process variables (Manne 1987; Chen, McAvoy et al. 1998), from which it is possible to deduce the state of the system.

Fisher Discriminant Analysis (also known as Linear Discriminant Analysis) has been employed extensively in pattern classification research (Chiang, Russell et al. 2000; Chiang, Kotanchek et al. 2004). Unlike classification techniques such as Bayes Classifier, FDA does not suffer from the problems of dimensionality as process data is projected onto a lower Fisher feature dimension. FDA operates by maximising the distance between classes and reducing the scatter within classes (Duda and Hart 1973). Hence, FDA is able to maximise the distance between the nominal process class and the various classes that represent different faults. The weakness of statistical techniques is that there are very few methods for tackling non-linear processes. Furthermore, good quality training data is a requisite which may not be readily available; the use of noisy or poor quality training data would significantly diminish the effectiveness of the system.

The strength of all data driven methods is that no prior knowledge of the system is required in order to perform FDD, however quality training data is required in order to adequately define the nominal case. Additionally, the use of process data for known faults is sometimes used to train the data driven system in defining the fault states for diagnosis purposes.

### 3.2.2 Knowledge Based Systems

Knowledge Based Systems (KBS) are rooted on Artificial Intelligence (AI) methodologies and techniques, commonly referred to as Expert Systems (ES). They utilise human knowledge and experience of a system to identify, diagnose and provide solutions for faults and failures that would ordinarily require human expertise (Janusz and Venkatasubramanian 1991; Wang 2003; Venkatasubramanian, Rengaswamy et al. 2003b). There are various manifestations of KBSs that have been developed however, they all utilise the same fundamental principle in that they make use of human knowledge and experience to provide a diagnosis on the state of the system (Jackson 1999). The two most prevalent KBS techniques are Rule Based Systems (RBS) and Case Based System (CBS). The basic premise for the expert system is that the end user supplies information and facts to the Expert System, the Expert System then returns a diagnosis on the fault/state of the system and provides a remedial solution if needed. The principal elements of expert systems are shown in Figure 3.1.

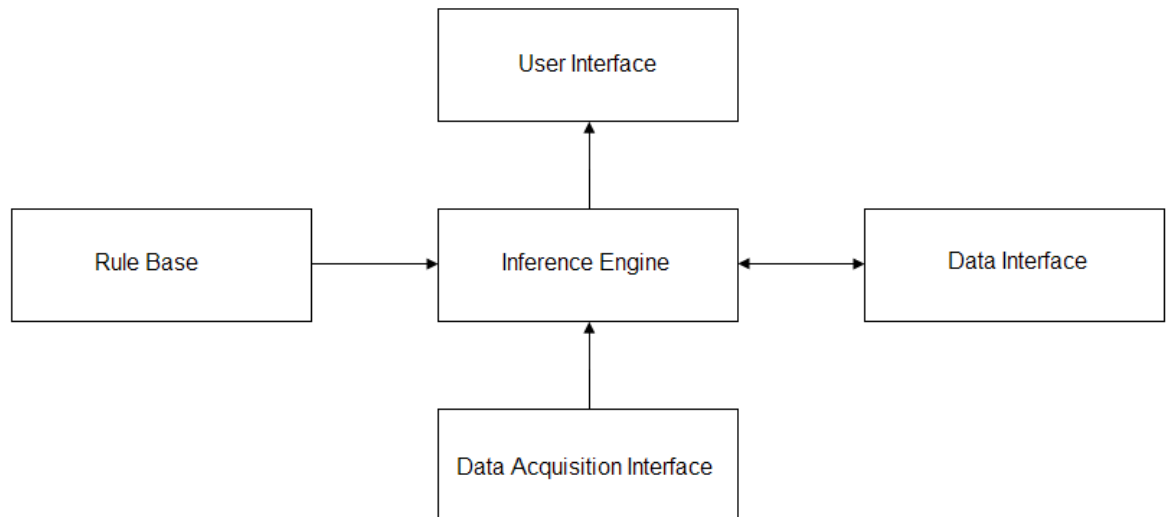


Figure 3.1 – Rule based expert system (Davies 1998)

The two key elements that Expert Systems contain are the knowledge or rule base and the inference engine. The knowledge/rule base consists of inference rules that describe fault hypotheses which are used by the inference engine to infer if the state of the parameters are reflective of a fault state (Prasad and Davis 1992). Inference rules use either forward or

backward chaining to reach a conclusion (Giarratano and Riley 1994; Venkatasubramanian, Rengaswamy et al. 2003b). Further details on backward and forward chaining are provided in Chapter 6. Converting human knowledge into computer programming can be done relatively simply using IF/AND/OR statements. However, for complex nonlinear systems with interrelated variables it would require substantial programming in order to create a robust method of evaluating the system (Luker and Schmidt 1991). Hence, Expert Systems are typically employed at machine component/plant level.

CBSs use past fault case data instead of rules. Diagnosis is performed by matching the cases that most fit the information provided by the user. CBSs use human reasoning and past failure data to analyse the current state of a system. CBSs are problematic in that past cases may be inaccurate and changes in the system are difficult to amend. Whereas with RBSs new rules can be implemented, fine tuned and eliminated with relative ease.

KBSs do not need large amounts of training data unlike data driven systems. Furthermore, the decisions making process is easily traceable. However, the fault modes of the system must be well understood in order to create the rules. Therefore, a pre-requisite of KBS is the need for expert knowledge of a system. User interfaced systems rely on the user being sufficiently knowledgeable in that specific knowledge domain to supply facts. Additionally, fault diagnosis is reliant upon the user to querying the Expert System. Thus the human operator is responsible for the fault detection phase. Furthermore, the fault rule base is static hence the Expert System is unable to explain novel changes in the building state that are not currently described in the fault rule database.

### **3.2.3 Model Based Systems**

Model based approaches create mathematical models to represent the system under consideration (Isermann 2011). They describe the relationship between the input to the system and the output that is measured (Patton, Frank et al. 2000). The relationship is derived using the fundamental principles that govern the process. The model aims to emulate the system operating under nominal conditions. The model uses the same input data as the actual system and calculates what the output should be. The measured output

from the system is compared to that of the model output; discrepancies between the two are called residuals (Isermann 1984). The residuals represent deviation of the system from a nominal state to an abnormal state, thus faults are detected when a residual is generated (Kothamasu, Huang et al. 2006). Generation of residuals can be performed in a number of ways; the most common methods are the use of parity equations, observers and parameter estimation (Isermann and Balle 1997; Patton, Frank et al. 2000). Model based methods are generally used for fault detection purposes. However, by extracting the features of the residual, fault diagnosis can be performed through the use of structured residual sets.

The key problem with utilising a model based approach is that the output from mathematical model rarely matches with the actual system unless considering only very simplistic or basic systems. There is generally a payoff between the complexity of a system and the performance of the model based approach (Isermann 1984). In cases where the process is nonlinear there are difficulties in developing a practical means of applying model based FDD (Venkatasubramanian, Rengaswamy et al. 2003a; Frank, Ding et al. 2000). Methods were developed to overcome nonlinearity and improve correlation between the model and the process, however in such cases this resulted in greater levels of uncertainty in the mathematical model (Gertler and Yin 1996; Venkatasubramanian, Rengaswamy et al. 2003a). Noisy signals or unknown disturbances can also lead to large numbers of false detections. This can lead to difficulties in distinguishing between nominal and fault conditions.

### **3.3 CM Building State Evaluation and HVAC maintenance**

Evaluation of the building state for energy and FDD purposes can be performed in one of two ways, bottom-up or top-down (Claridge, Liu et al. 1999; House and Kelly 1999). The bottom-up approach evaluates buildings from a component level, analysing the state of health of each individual HVAC system and its subcomponents. The top-down approach applies whole building diagnostics. Each method has its own advantages and disadvantages, however, in order to perform an accurate assessment of the building a holistic technique is required in which both approaches are used. The academic literature surveyed revealed that the majority of FDD applications to the building industry has taken the bottom-up approach in which condition monitoring strategies were applied to

individual HVAC systems. The complete list of works is exhaustive; the review provided by Katipamula and Brambley (2005a, 2005b) provides an overview of the work performed for HVAC fault detection and diagnosis (Katipamula and Brambley 2005a; Katipamula and Brambley 2005b). Bottom-up approaches analysing individual HVAC systems in isolation are not directly relevant to the work performed in this thesis, hence condition monitoring methods that take the top-down approach or combine both approaches are reviewed here.

Seem (2007) defined a methodology from which abnormal energy consumptions were identified using daily consumption and peak energy readings (Seem 2007). Essentially, this method used deviations in the energy consumption to perform fault detection on building systems. The aim of which was to provide feedback on issues such as poor building control or poor design of ventilation services. Seem (2007) did not take into account the characteristics of the building and relied purely upon energy based deviations. There are a number of plausible explanations that could relate to the cause of the deviation which may not be identifiable from energy readings alone.

Work by Doukas et al (2007) made use of a rule based system for the purposes whole building energy evaluation (Doukas, Patlitzianas et al. 2007). Doukas et al (2007) integrated a database that held information on the building characteristics. The inclusion of the building characteristics is a useful tool in providing a benchmark. However, the use of the rule based approach for whole building state evaluation on a large commercial building would severely lack the depth to analyse the nonlinearities of the building operation without extensive mapping of the numerous states of operation. Whilst the building characteristic database is useful determining the operation envelope, independent variables such as external temperature and varied occupancy would constitute a novel situation for which the rule base would need continual maintenance and updating in order to remain relevant.

Katipamula et al (2003) presented the Outdoor-Air-Economiser (OAE) module of the Whole Building Diagnostician (WBD) (Pratt, Bauman et al. 2002; Katipamula, Brambley et al. 2003). The OAE module used rules derived from engineering principles to determine the state of the OAE akin to a model based approach. So far the work presented for the

WBD has been exclusively on ventilation systems such as the OAE and Air Handling Units.

### **3.4 Faults and Failures**

Faults are defined as non-permitted deviations from the normal operating envelope of a system that results in an adverse effect on performance (Patton, Frank et al. 2000). Failures are said to occur when a fault results in the total inability of a system to perform its required task. Faults can occur due to a number of reasons such as poor operation of the system, degradation of components, disturbances and external shocks (Isermann 1984; Owoo and Suen 2002). Faults are typically classified by the manner in which they express their presence within the parameter data; this is commonly referred to as the fault profile. There are 3 general fault profiles that are most commonly used for fault detection and diagnosis. The hard/abrupt fault leads to a sharp near instantaneous step change in the feature of the parameter data. Incipient faults are slow developing faults that occur over time and the third fault profile is the intermittent fault in which the fault may manifest itself sporadically or at frequent intervals, the magnitude of the feature change may also vary over time. The 3 fault profiles are illustrated in Figure 3.2 (Isermann and Balle 1997)

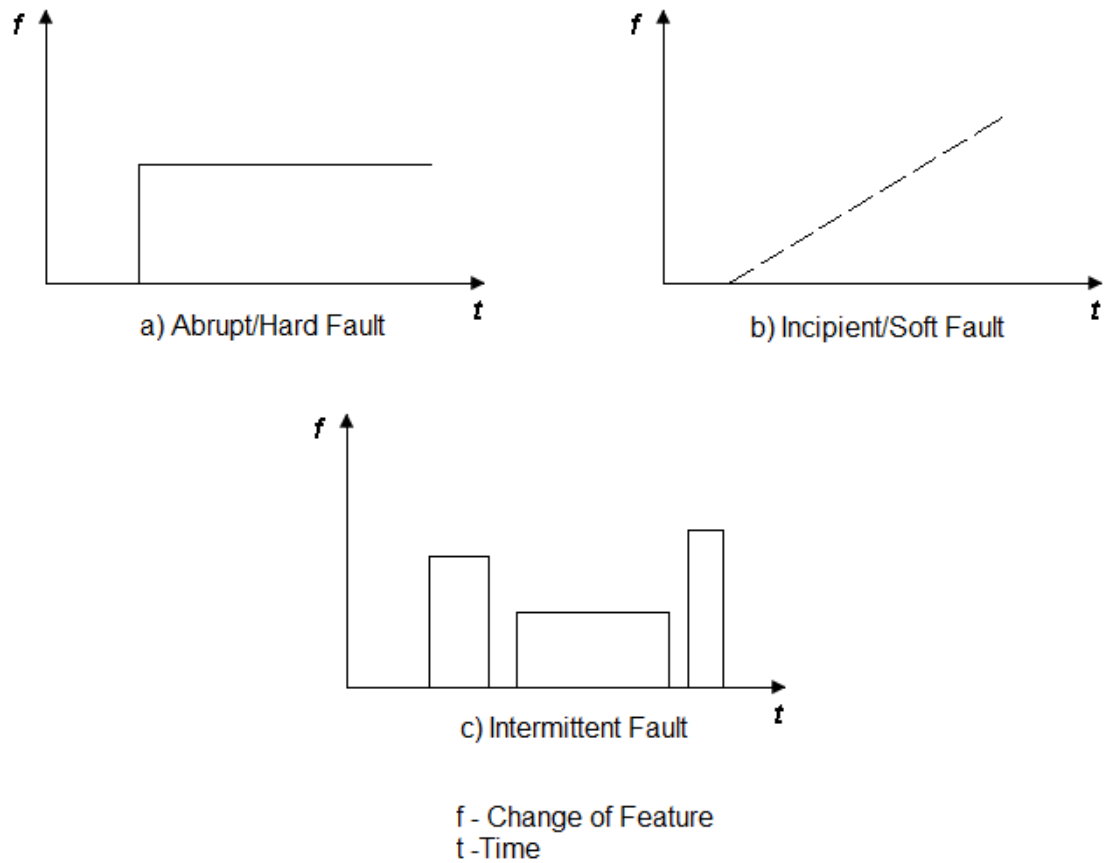


Figure 3.2 – Overview of fault profiles (Isermann 1984)

The next section looks into the common faults related to building operation.

### 3.4.1 Building Sectors Faults and Failures

They are four main factors that are responsible for poor efficiency within buildings, these are given along with the most common faults for each group in Table 3.1 (Haves 1999; CIBSE 2004a).

Table 3.1 – Fault groupings

<i><b>Fault Classification</b></i>	<i><b>Most common faults</b></i>
Building construction	<ul style="list-style-type: none"> <li>- Degradation of building fabric</li> <li>- Errors during the construction process</li> </ul>
HVAC	<ul style="list-style-type: none"> <li>- HVAC inefficiencies</li> <li>- Mechanical faults and failures in HVAC system</li> </ul>
Control	<ul style="list-style-type: none"> <li>- Poor or incorrect programming of BEMS control profiles</li> <li>- Fault masking via control based compensation</li> </ul>
Human	<ul style="list-style-type: none"> <li>- Unnecessary energy wastage</li> <li>- Poor maintenance practices</li> </ul>

The faults that are taken into consideration for this thesis are the HVAC faults and the faults relating to the poor operation of the building which may be as a result of human based errors or poor HVAC operation/maintenance. It is important to be able to classify both these faults given that up to 15-20% of wasted energy can be attributed to poorly performing HVAC systems (Katipamula and Brambley 2005a). The construction based faults/errors have been largely addressed by Part L. Specific control based problems are the responsibility of the controls companies, however the faults that occur as a result of poor control set ups can be identified through the use of FDD. This includes the compensation of faults by the control systems as state evaluation methodologies are able to extract the feature changes within the parameters.

### 3.5 Summary & Project Objectives

As was detailed in the previous chapter determining the state of the building is essential for assessing building energy performance. Evaluation of large commercial buildings is a complex task as a result of the multitude of interrelated variables and numerous nominal operating states that can occur. Thus, objective 3 of the research project was

*“Developing an assessment methodology capable of distinguishing the various states of health/efficiency of a building”*

The condition monitoring strategies detailed within this chapter provide a means of state determination for the system under consideration. However, in order to develop a truly holistic approach a method of performing FDD on the HVAC systems is required. Thus objective 4 of the project was to

*“Developing a means of performing HVAC fault detection that is capable of working in tandem with energy evaluation techniques”*

The condition monitoring strategies provide the means to tackle both top-down and bottom-up evaluation of the building and its HVAC systems. Furthermore, they have been shown to possess the capabilities to address the various fault groups that affect building performance.

## **CHAPTER 4**

### **4. Case Study Building – Middleton Technology School**

A case study building was selected to test the Condition Monitoring strategies detailed in Chapters 5 and 6. The Middleton Technology School is a further education building located in the North West of England. The school is a 3 storey building built in 2009 thus falling under the Part L 2006 Regulations. Therefore all analysis that utilises BER data is based upon the requirements of the 2006 Regulations. The occupancy levels are comparable to those of a secondary school, for example unoccupied during summer months for summer holidays. There is a range of room function types within the building ranging from offices and meeting rooms to laboratory teaching rooms. There are a variety of HVAC systems installed to regulate the internal environment; the relevant systems are described below.

The heating is predominantly served by 3 gas fired condensing boilers via the Low Pressure Hot Water (LPHW) heating system. The LPHW has two variable temperature circuits. The first circuit distributes heat via radiant panels, radiators and the door heaters, whilst the second serves the ground floor under-floor heating system. Additionally, a third circuit is located within the plant-room, providing constant temperature heating to the domestic hot water service calorifier indirect coil. The variable and constant temperature pumsets are regulated by the BEMS. There is sufficient sensor coverage to detect faults for the boiler system including identification of the faulty boiler and the cause of the fault alarm. The radiant panels are automated with 2 port control valves that act in response to the sensor feedback of local temperature sensors, whilst the radiators are regulated by the thermostatic control valves on the flow connection.

There are 8 heat recovery Mitsubishi Lossnay units (heat transfer is achieved via cross flow heat exchangers) installed in the ceiling voids supplying fresh air and removing foul air from landlocked rooms as well as special purpose rooms such as the hot metal areas and nursery washroom.

The ground and second floor have natural ventilation for specified rooms in which acoustically treated air transfer grilles have been installed. These grilles are inlets to passive ducts that allow the passage of air from the atrium into the rooms and from rooms to the atria. The grilles operate in conjunction with the automatic windows located at the top of the atrium to control the flow of air, all of which is controlled by the BEMS.

Two Variable Refrigerant Flow (VRF) systems are installed with the first serving the second floor ICT room and the second serving the first floor learning resource centre. Within these rooms, heat pumps have been installed to provide local air conditioning via ceiling void mounted fan coil unit cassettes, these systems (VRF) are controlled via the centralised AC system with each unit being controlled locally from the wall mounted controller.

Whilst many of these HVAC systems have connections to the BEMS for control purposes, not all of the parameter data from these systems are logged. The following section shall detail the parameter data that is accessible from the BEMS for use in this project.

## **4.1 BEMS Monitored Parameters**

The case study BEMS is able to monitor a wide range of process parameter data. However, due to the setup of the BEMS by the controls company a significant number of parameters are not logged or stored. The reasoning behind this decision is that the client (building owner) did not require this data to be logged. The data that is accessible from the BEMS can be categorised into six groups:

- Meter / Energy data
- Radiant panel Temperatures
- Control setpoints
- Natural Ventilation: Atrium window opening percentage
- Valve positions
- Weather station data: External temperature

This data is sampled and stored every 15 minutes by the BEMS. The majority of control set-points were static and thus of little use, however the remaining parameter data did contain useful information that was used in the methodologies detailed in the following 2 chapters. Whilst the accessible number of parameters is not comprehensive there is sufficient amount of data available for the purposes of this project.

## 4.2 Case Study DTM Model

A Dynamic Thermal Model (DTM) representation of the case study building was built in the IES Virtual Environment software program. The IES modelling environment is able to emulate the operation of a building throughout the year using parameters such as the building fabric U-values, occupancy frequency and NCM HVAC profiles to simulate the building behaviour. The Manchester weather file was selected for use in the simulations as it was the closest weather measurement location to the site of the building. Parametric data such as the U-values for external/internal walls and windows were selected using the fabric/material data supplied by the construction firm. The building functionality was set to educational; the functionality also dictates the occupancy profile and HVAC utilisation throughout the year. The HVAC equipment specifications were entered based upon the information supplied by the manufacturers. The DTM was used to produce the BER figures for the post construction handover evaluation. A visual representation of the case study building in the IES software environment is shown in Figure 4.1.

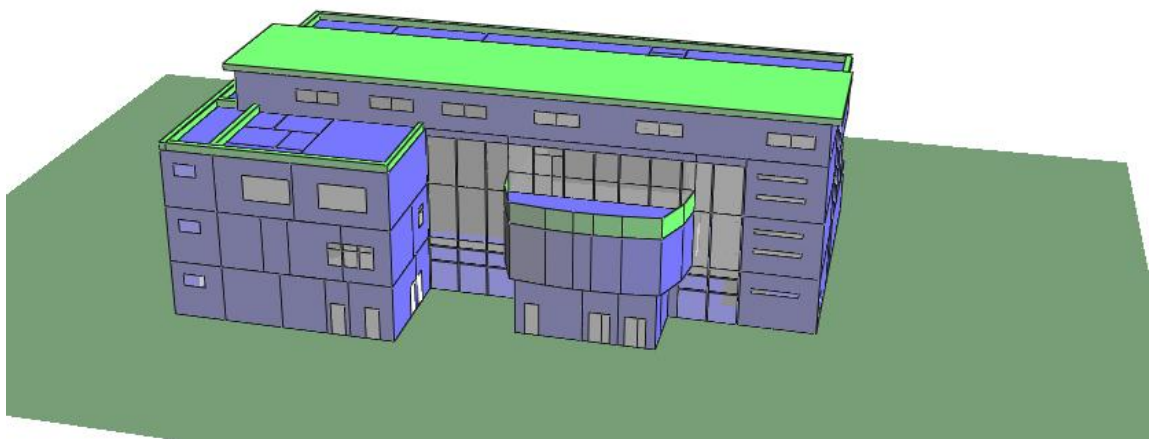


Figure 4.1 – DTM representation of the case study building

Taking into account the fact that all new buildings must be tested post construction, usage of software packages for Part L emissions testing shall become commonplace. This provides the opportunity to obtain and store useful energy consumption data, thereby creating the opportunity to utilise such data for the application of performance evaluation. The DTM can be viewed as an equivalent to modelled benchmarks given that it integrates the fundamental features of the building in the energy calculation process. The DTM forms an alternative to using external benchmarks and would provide a bespoke consumption benchmark for each building. Hence they are of significant value for the purposes of evaluating energy efficiency within buildings. The data obtained from the DTM model is an integral part of the real time evaluation methodology detailed in the subsequent chapter.

It should be noted that the data obtained from the DTM may not wholly reflect the performance of the real building; this is due to the real building potentially having differing occupation frequencies, lux levels and the addition of external lighting. These factors are not taken into account when calculating the BER. However, by adjusting the BEMS data (as detailed in section 5.1.1) the DTM of the case study building was able to achieve an accurate fit as shown in section 5.1.2.

### **4.3 Characterisation of Building Behaviour**

To provide an understanding of the characteristics of the building and its behaviour under varied conditions, fault tests were run altering the operating parameters within the DTM to measure the building response. Whilst the real case study building may not respond in the exact same manner, given that the DTM integrates the key features of the case study building the results are expected to provide a reasonable approximation. The heating and ventilation systems were selected for testing as they service the majority of the building whereas the air conditioning and cooling systems are limited to a few rooms. The purpose of the fault tests was to identify two important characteristics about the case study building. Firstly, determining which faults had the largest effect on energy consumption, and secondly, identifying how these faults would manifest themselves in the process data. Additionally, determining the suitability of the CUSUM and EWMA charts to detect faults was also tested (more details are provided in the following section).

Two sets of experiments were run; set 1 varied the efficiency of the heating and ventilation systems by increasing and decreasing the Seasonal Boiler Efficiency (SBE) and the Specific Fan Power (SFP) respectively. The SBE is given by Equation 4.1 (Maunsell 2004):

$$SBE = 0.5 * (Eff_{15\%}) + 0.2 * (Eff_{30\%}) + 0.3 * (Eff_{100\%}) \quad \text{Equation 4.1}$$

where  $Eff_{\%}$  represents the efficiency of the boiler at 15%, 30% and 100%. The Specific Fan Power (SFP) is given by Equation 4.2 (Eastop and Watson 1992).

$$SFP = \frac{\sum P}{q_v} \quad \text{Equation 4.2}$$

where the summation of P (kW) is the electrical power used by the sum of all the fans (both supply and extract) in the ventilation system and  $q_v$  ( $m^3/s$ ) is the total amount of air passing through the fan. For each test set, the efficiency was increased and decreased over the range of 10% (-10% to +10%) in increments of 5%.

The second set of tests introduced a fault to the heating system only; this was due to restrictions in the DTM program not allowing for variation of the necessary ventilation parameters required to replicate faults cases. A sensor / HVAC fault was investigated in which the set point for initiating heating to a room was increased from the nominal value of 19 °C to 30 °C. The aim of which was to emulate a fault that resulted in no heating being supplied to the room such as the temperature sensor providing an incorrect reading. Given that there are a large number of rooms, it would have not been feasible to apply this fault variation to all rooms, thus the fault test was applied to a single room. It was decided that the Multi-conference meeting room was to be used. The fault test simulation was performed for the months of May and November representing the warmer and cooler periods in which the building is operating under normal occupancy. The data for the second week of the selected months were extracted and slotted into the data set of the original model that had no changes applied, thus giving the impression that the fault occurred at the start of the second week and was resolved after one week. Running the simulation for the entire year with these fault conditions would yield very little useful

information as it would be improbable that the fault would persist for such a period without remedial action being taken.

It was hoped that a third set of tests investigating the effects of poor occupant behaviour could have been tested by varying the occupancy frequency parameters. However, in order to do so it would have required modification of all heating, lighting and occupancy profiles for each individual room, given the large number of rooms this process was impractical and was therefore not tested.

The total energy consumption data was extracted from the model for analysis. In order to analyse the data, the data from the tests were compared against a base model in which no parameters had been changed. The following section details the analysis techniques implemented to analyse the results of the preliminary tests.

#### 4.3.1 Model Data Analysis

Analysis of the resulting data was performed by two sets of techniques. The first was to utilise the statistical approach of covariance and correlation. This determined the variance observed of each test case against the base model. Covariance describes the level of variance between two sets of data and is defined by Equation 4.3 (Rice 2007).

$$Cov(A, B) = \frac{\sum_{i=1}^n (A_i - \bar{A})(B_i - \bar{B})}{n - 1} \quad \text{Equation 4.3}$$

where A represents the base model energy consumption and B the test case energy consumption,  $A_i$  and  $B_i$  are observations from their respective data sets.  $\bar{A}$  and  $\bar{B}$  are the means of their respective sets. n is the number of samples and was set to 24 to assess daily variations. To standardise the covariance value to a value between 1 to -1 Equation 4.3 was divided by the product of the standard deviations of A and B as shown in Equation 4.4 - 4.5 thus giving the correlation.

$$COR(A, B) = \frac{Cov(A, B)}{\sigma_A \sigma_B} \quad \text{Equation 4.4}$$

where:

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}} \quad \text{Equation 4.5}$$

where  $\sigma$  is the standard deviation,  $X_i$  is an observation from the data set, and  $\bar{X}$  is the mean of the data set. A resulting correlation value of greater than 0 up to a value of 1 indicates that the data sets move up/down together, 0 would indicate independence between the datasets and a value less than 0 to -1 would indicate a divergence. A value of one would indicate perfect correlation in that the datasets move together in equal magnitude. Thus the correlation value is able to indicate the level of dissimilarity that occurs due to the variation in parameters. It should be noted that a value of one does not necessarily equate to identical datasets.

The second set of techniques was the use of Statistical Process Control (SPC) charts, namely CUSUM (CUMulative SUM) and EWMA (Exponentially Weighted Moving Averages) charts. The CUSUM method allowed for calculation of the cumulative effect of the variations of each test case. This was done by adding the cumulative difference between the nominal data and the test case data for each sample point. For the CUSUM methodology the sum of 24 data points were used to form each observation. For illustrative purposes a rudimentary method of fault detection was implemented by setting a limit threshold. The threshold was arbitrarily set at 30% of the total energy consumed, thus when the difference in energy consumption between the original dataset and the test cases exceeded 30% it indicated that a fault had occurred. A point to note for the EWMA and CUSUM charts is that they analyse the variable under consideration in isolation and do not take into account the state of any other variables. This in effect disregards the correlation between the various interdependent parameters and as was previously highlighted would be unsuitable for exclusive implementation as a FDD system.

EWMA charts have been utilised for SPC in the manufacturing industry to monitor for out of bounds parameters. EWMA is different to a normal moving average in that it gives a weighting to a observation dependent on the age of the sample (with the most recent having the highest value), the EWMA is given by Equation 4.6 (Ryan 2007).

$$EWMA_t = \lambda X_t + (1 - \lambda)EWMA_{t-1} \quad \text{Equation 4.6}$$

where the initial value of  $EWMA_t$  ( $EWMA_0$ ) is the mean of the training data,  $\lambda$  dictates the weighting given to the previous data entries and is typically set to 0.3 and  $X_t$  is the ‘newest’ data observation. The variance of the EWMA ( $s_{EWMA}$ ) is given by Equation 4.7

$$s_{EWMA} = \left( \frac{\lambda}{2 - \lambda} \right) s_{TR} \quad \text{Equation 4.7}$$

where  $s_{TR}$  is the variance of the training set, in this case the base set data. The upper and lower control limits are given by Equation 4.8 and 4.9 respectively.

$$UL = EWMA_0 + k\sigma_{EWMA} \quad \text{Equation 4.8}$$

$$LL = EWMA_0 - k\sigma_{EWMA} \quad \text{Equation 4.9}$$

where the factor  $k$  is typically set to the arbitrary value of 3 and  $\sigma_{EWMA}$  is given by Equation 4.10.

$$\sigma_{EWMA} = \sqrt{s_{EWMA}} \quad \text{Equation 4.10}$$

The upper and lower control limits were used for determining the points at which there is significantly higher or unusually lower energy consumed. The daily totals were summed to form a single observation. In order to avoid skewing the mean value due to the reduced consumption over the weekend only the consumption data for the week days were considered in the evaluation. For both the EWMA and CUSUM charts it was assumed that the building was performing optimally at the start of the month and the deviations in the test data occurred from that point onwards.

#### 4.4 Test 1 – Efficiency Variation Results

The efficiency test case data for the heating and ventilation systems were compared to the dataset obtained from the model with the original HVAC parameters. The SBE and SPE were increased and decreased in increments of 5% up to plus and minus 10% to assess the impact on energy consumption. Figure 4.2 shows the for the correlation values for May for the heating system (calculated using from Equation 4.4).

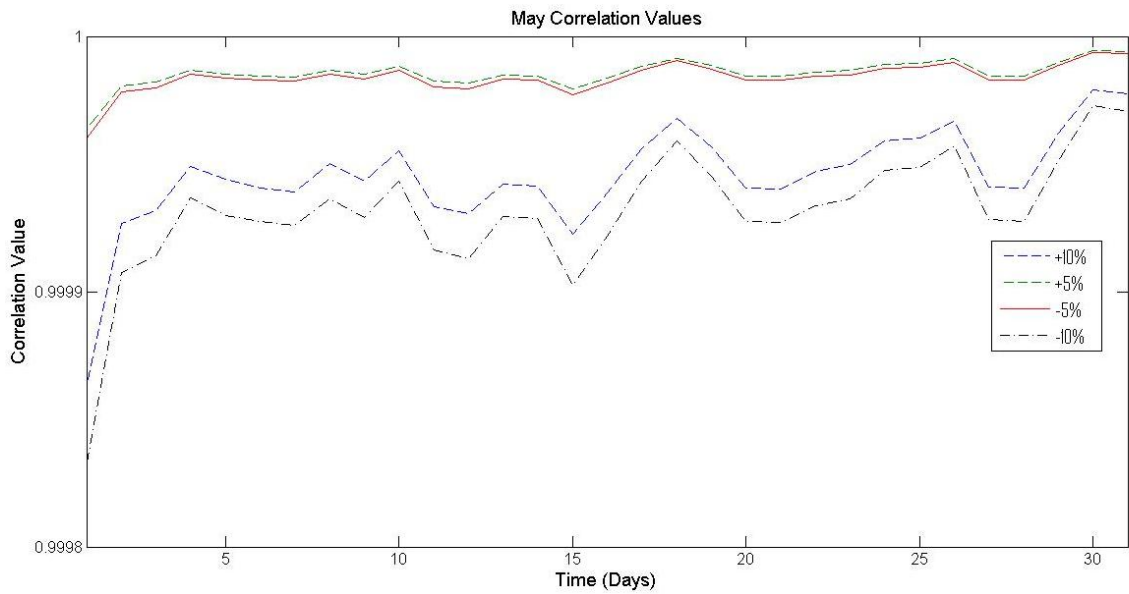


Figure 4.2 – Heating efficiency correlation value for May

As can be seen in Figure 4.2, smaller efficiency changes (plus and minus 5%) display greater correlation as the magnitude of difference between the changes in energy consumed is not as large as the  $\pm 10\%$  test cases. It is also shown that in both cases that a reduction in efficiency, test case -10% and -5%, leads to a greater deviation than improving the efficiency. The correlation analysis for November, shown in Figure 4.3, illustrates that variation in heating efficiency results in a larger deviation during the colder periods. Given that the heating load remains constant for all test simulations and that the heating system is under greater demand during the colder periods, inefficiencies in the boiler systems are more pronounced as more energy is needed to serve the same heating demand.

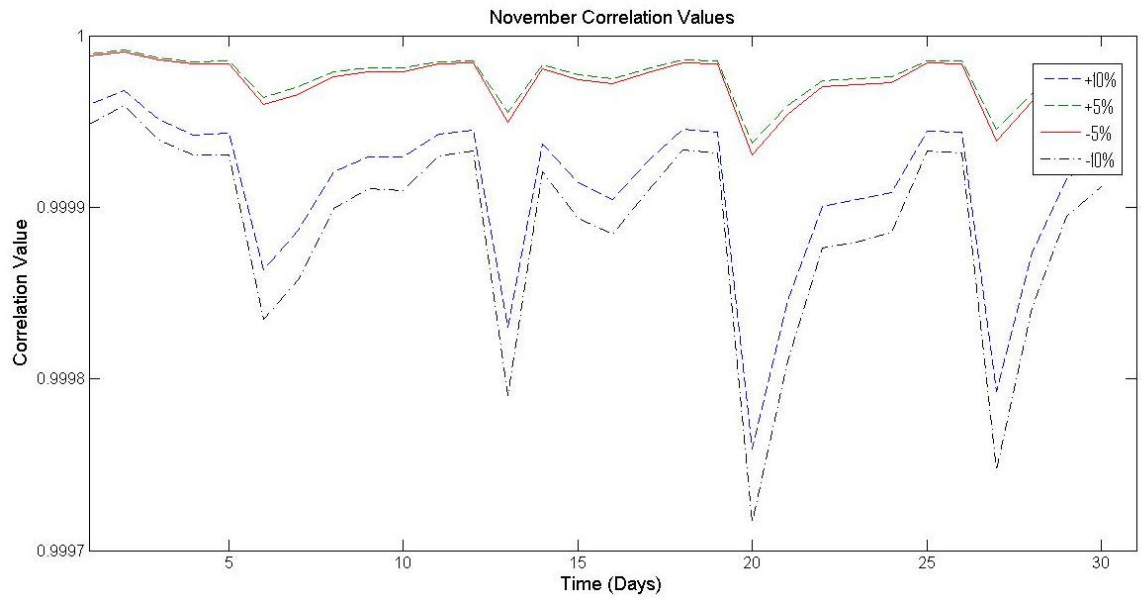


Figure 4.3 – Heating efficiency correlation for November

In both Figures 4.2 & 4.3 the peaks and troughs in the trend lines all follow the same general pattern this is due to the DTM software algorithms recalculating the energy consumption with only one changed parameter for each test case. As a result there was a strong correlation value (approaching 1) exhibited. Figure 4.4 displays the changes in correlation throughout the year; this was done by taking the monthly correlation average for each test on efficiency.

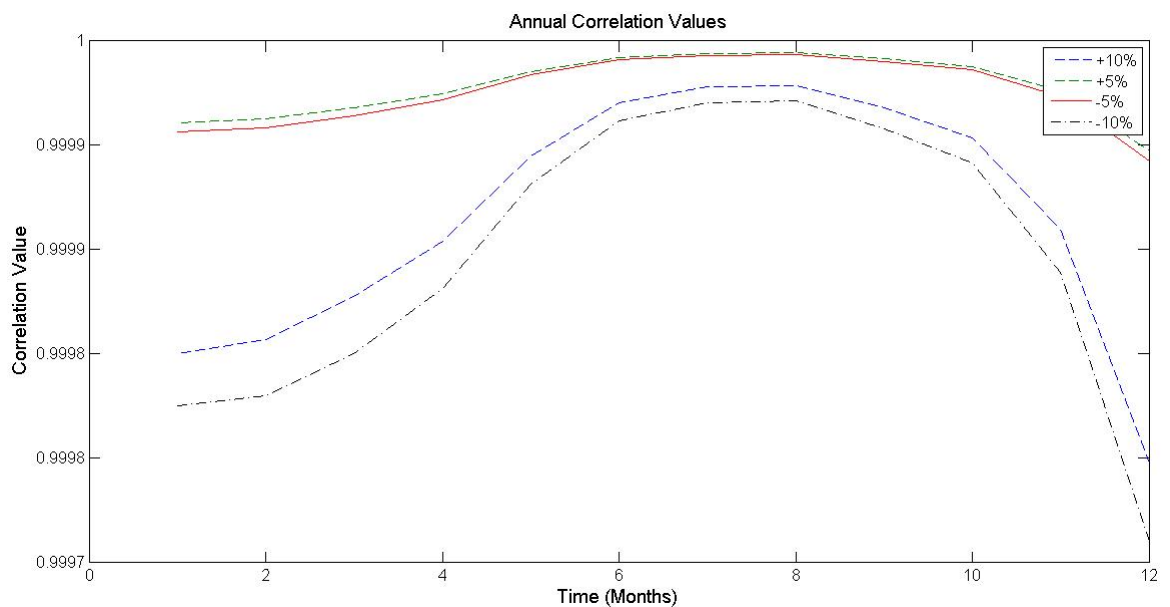


Figure 4.4 – Monthly correlation averages for heating efficiency

The results from the heating efficiency variations confirms the expected result that due to greater utilisation of the heating system in the winter and autumn months, a greater variation from the base set is observed as improvements and inefficiencies both become more pronounced.

The variations in the ventilation efficiencies (changes in the SFP) resulted in a minimal change. Figure 4.5 illustrates the variation in SPF results in a minimal change in deviations from the base dataset.

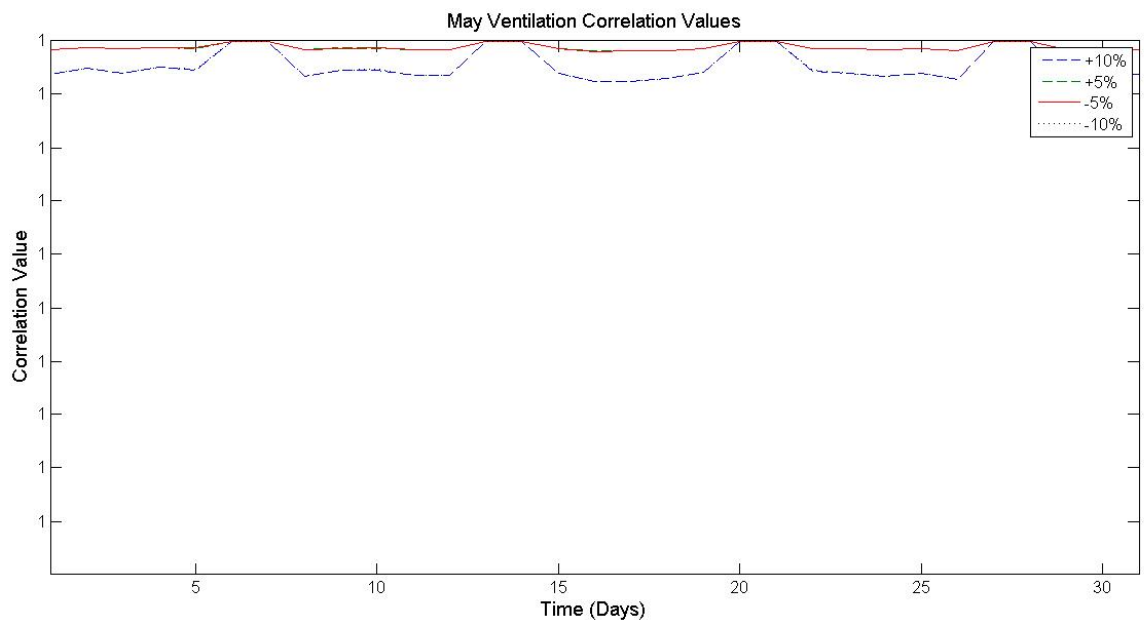


Figure 4.5 – May ventilation efficiency correlation

The results for November have not been included here as it shows no significant differences from Figure 4.5. Similarly the monthly averages showed that there was negligible variation in correlation throughout the year. Thus it can be seen that changes in ventilation have a negligible effect when compared to heating variations. This is further demonstrated in the CUSUM/EMWA charts. Figure 4.6 shows the heating CUSUM chart for November, with the threshold limits in black (30% of the total energy consumed for that month). The lower threshold is equally important as it could signify a failure in HVAC plant thus leading to an unusually lower consumption.

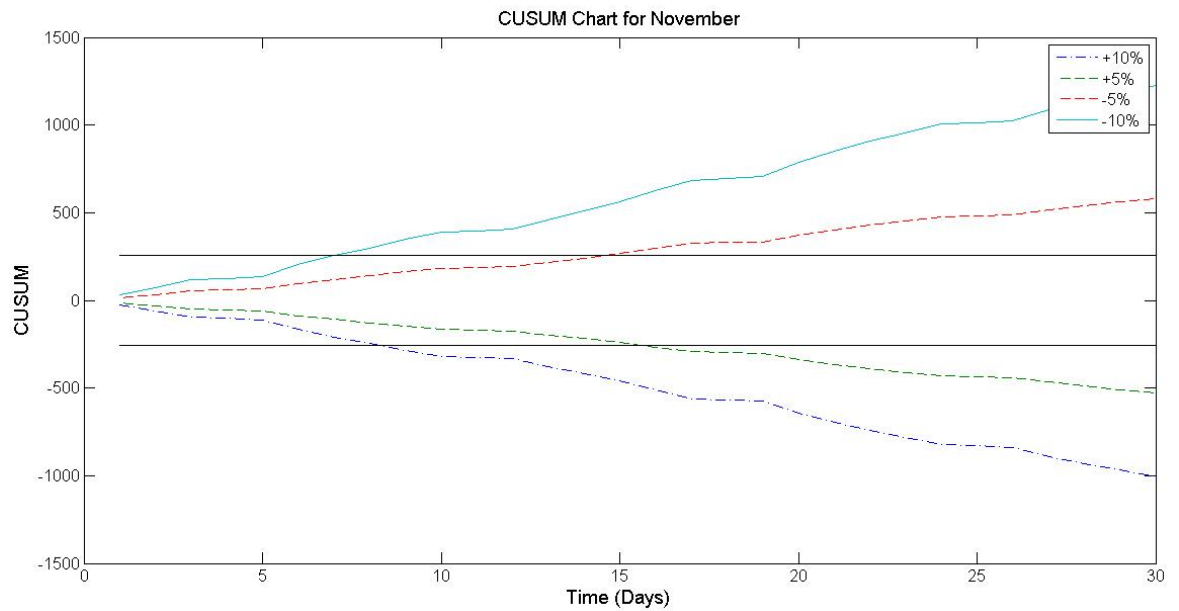


Figure 4.6 – November CUSUM chart (heating efficiency)

The CUSUM chart for November has been presented here as both the CUSUM graphs for May and November have similar trend patterns. Figure 4.7 displays the ventilation CUSUM chart for November.

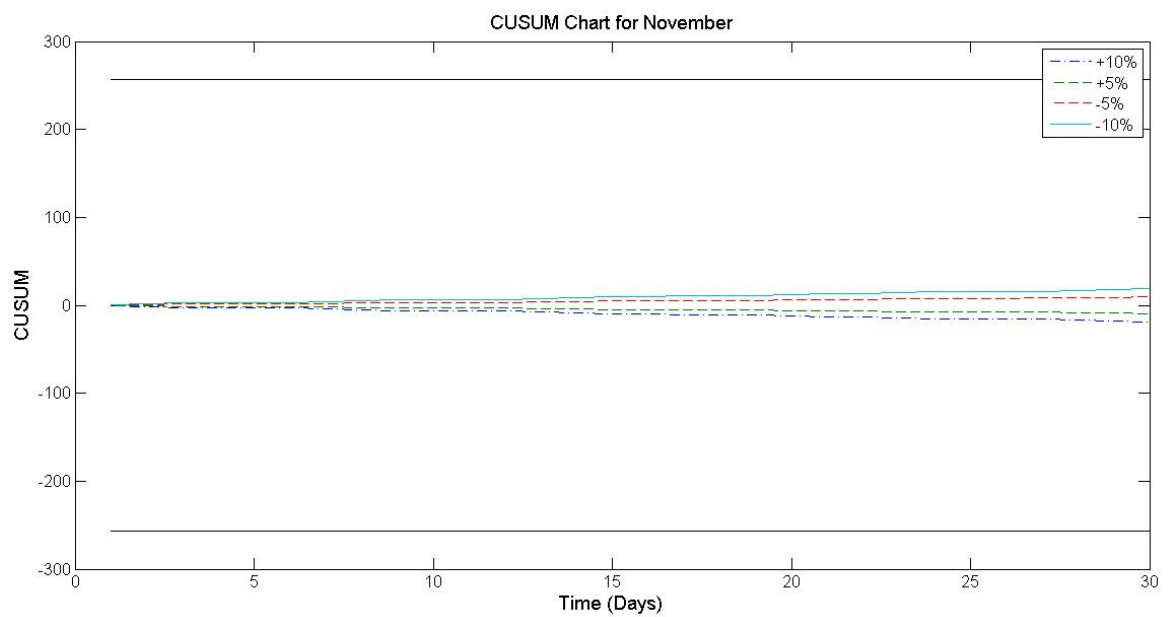


Figure 4.7 – CUSUM chart for November (ventilation)

As can be seen in Figure 4.7 the cumulative sum of differences for the ventilation system is significantly smaller than that of the heating system and does not cross the threshold boundary unlike the CUSUM for the heating system in Figure 4.6. This illustrates a key deficiency in utilising threshold limits for individual parameters in isolation. Whilst the 30% energy consumption limit was viable means for detecting large scale deviations (such as inefficiency in the heating system) it was unsuited to act as a threshold with faults related to the ventilation efficiency due to the change in energy consumption manifesting itself inside the boundary limits.

The EWMA chart with the upper and lower limits for the heating efficiency test case for the month of May is shown below in Figure 4.8.

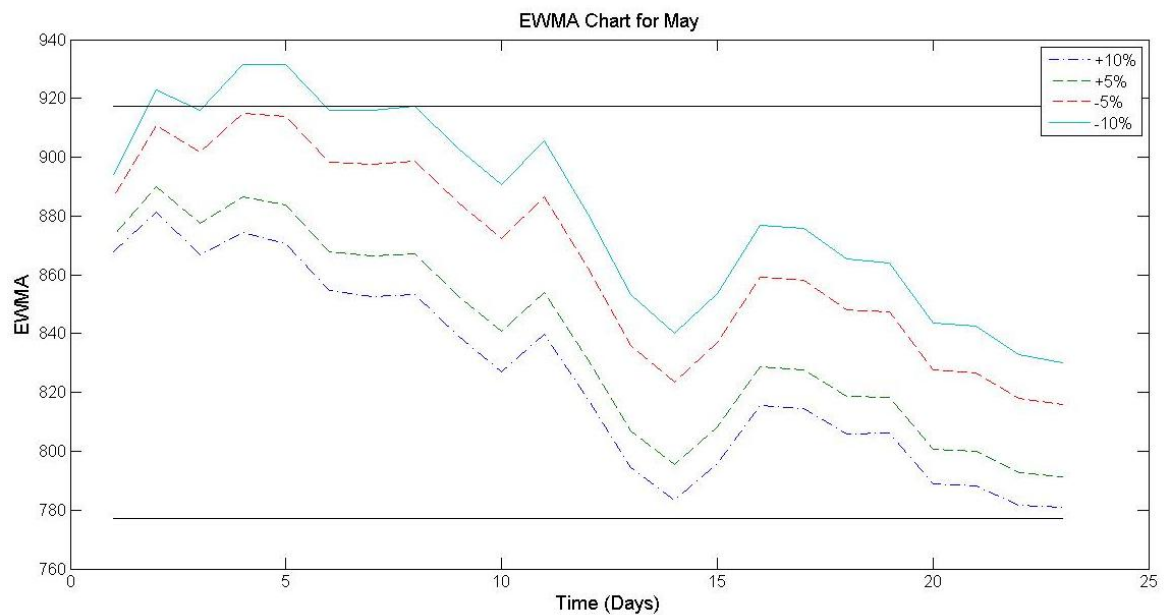


Figure 4.8 – EWMA chart for May (heating efficiency)

As can be seen from Figure 4.8 the threshold for the upper limit has been breached due to the greater levels of energy consumed due reduced efficiency in the heating system. A significant advantage in using the EWMA approach over the CUSUM method is that is able to operate in real time and can identify the day(s) in which there was excessive consumption. However, unlike the CUSUM method, the EWMA charts are unable to log daily cumulative additional consumption, thus faults that slowly develop over time resulting in an increase in consumption are not detectable. As with the CUSUM chart a

similar problem is seen in setting the threshold. Figure 4.9 shows the EWMA chart for ventilation efficiency test cases for the month of May.

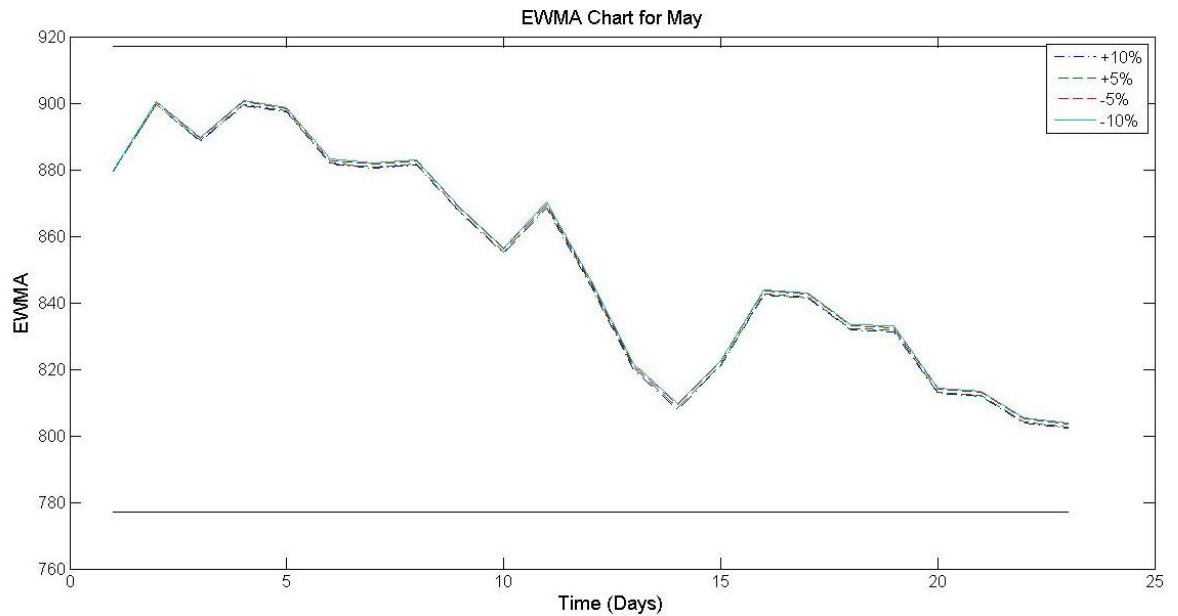


Figure 4.9 – EWMA chart for May (ventilation efficiency)

It can be seen from Figure 4.9 that EWMA charts suffer from the same inability to set adequate thresholds for detecting faults with both the heating and ventilation efficiency tests. Whilst the threshold limits can be reduced by changing the value of  $k$ , it would lead to a greater number of false alarms triggered by acceptable changes in the heating consumption. As has been previously mentioned threshold limits are unable to factor in the variables that influence the overall energy consumption, thus unable to differentiate between acceptable high energy consumption and low unacceptable energy consumption.

## 4.5 Test 2 –Fault Introduction Results

The results of the emulated sensor/HVAC fault introduced a problem with the heating system for multi-conference room in the second week for the months of November and May. As would be expected the correlation results shown in Figure 4.10 for November show a deviation from the base set data for that period after a week (7 data samples) the correlation value returns to a value of 1.

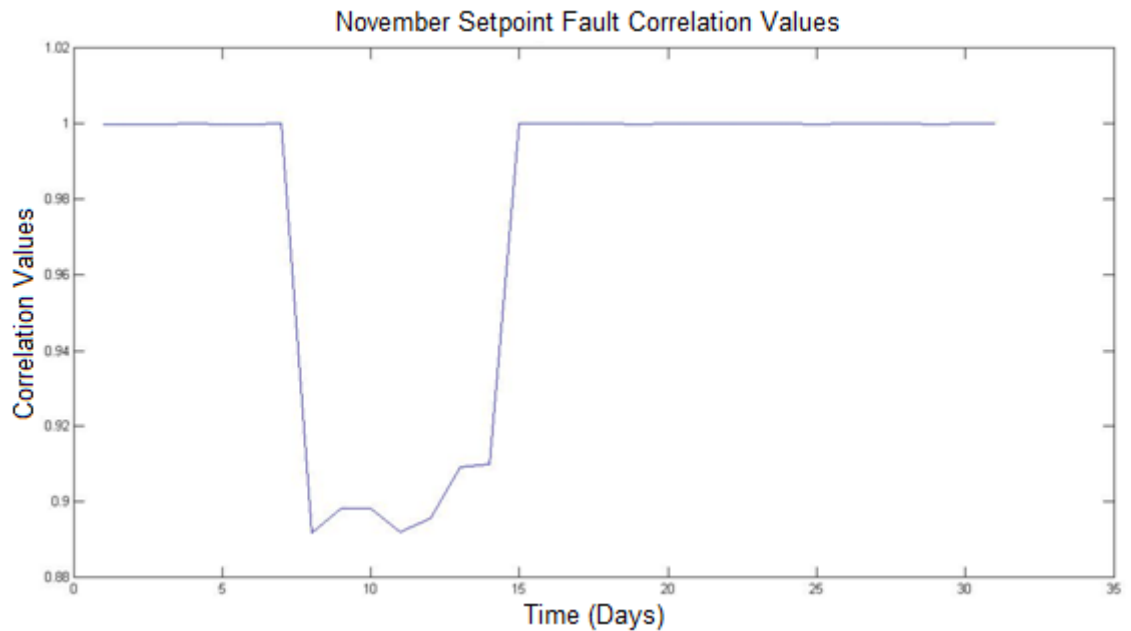


Figure 4.10 – Introduced fault correlation for November

The correlation test shows that the DTM model is clearly able to identify the periods in which the fault has occurred even at local room level. The correlation value shown in Figure 4.10 is lower than that of the heating efficiency tests as the test energy consumption trend did not move with the original data set but instead expressed independence. This is due to the heating efficiency test trends mirroring the movements of the base dataset trend with the only difference being the quantity of energy consumed. Whereas with the fault correlation seen in Figure 4.10 the change energy consumption does not move with the original dataset but is independent to it. The May results showed a similar result but with a smaller deviation, giving an approximate average correlation value of 0.96 compared to 0.9 for November. The variation in the daily consumption is shown in Figure 4.11.

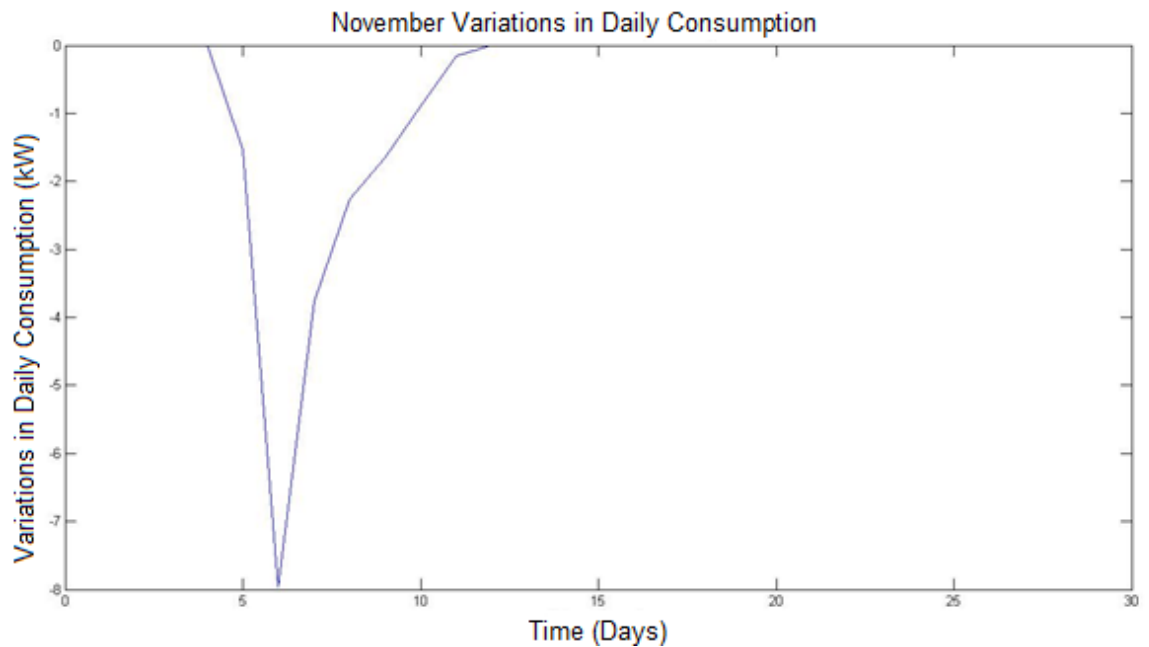


Figure 4.11 – Daily consumption comparison for November with introduced fault

The fault data was introduced on a Monday thus explaining the large initial change and the gradual trail off at the end of the week in which the weekend period occurs. The May graph showed a similar pattern but with a lower change in consumption. Figure 4.12 shows the CUSUM chart however, usage of the previously set thresholds were not able to detect the fault, the same occurs with the EWMA charts.

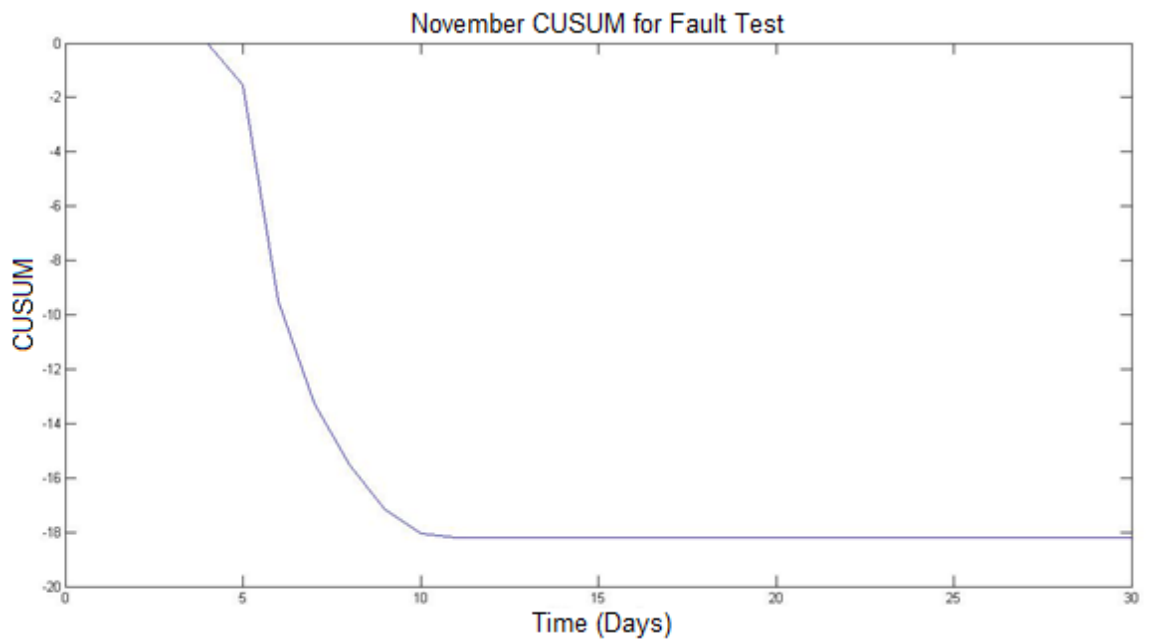


Figure 4.12 – CUSUM chart for November with fault introduced

The inability to detect smaller changes at local level further highlights the need to find an alternative means of fault detection in order to account for the numerous ways in which faults express themselves in the process data.

## 4.6 Summary of Test Results

The results of the test cases showed that faults with the heating system lead to a far larger energy consumption penalty. The DTM was able to successfully evaluate changes to the building system on both a local (room) level and a global whole building level and whilst the actual building may not vary in the exact same manner it does provide an insight into how the fault may manifest itself the process data. Figure 4.13 and 4.14 show the annual percentage change (against the base dataset) in energy consumption due to variations in efficiency. Figures 4.13 shows that a 10% reduction in heating system efficiency leads to 4.55% change in total energy consumption over the period of a year compared to 0.05% for ventilation as shown in Figure 4.14.

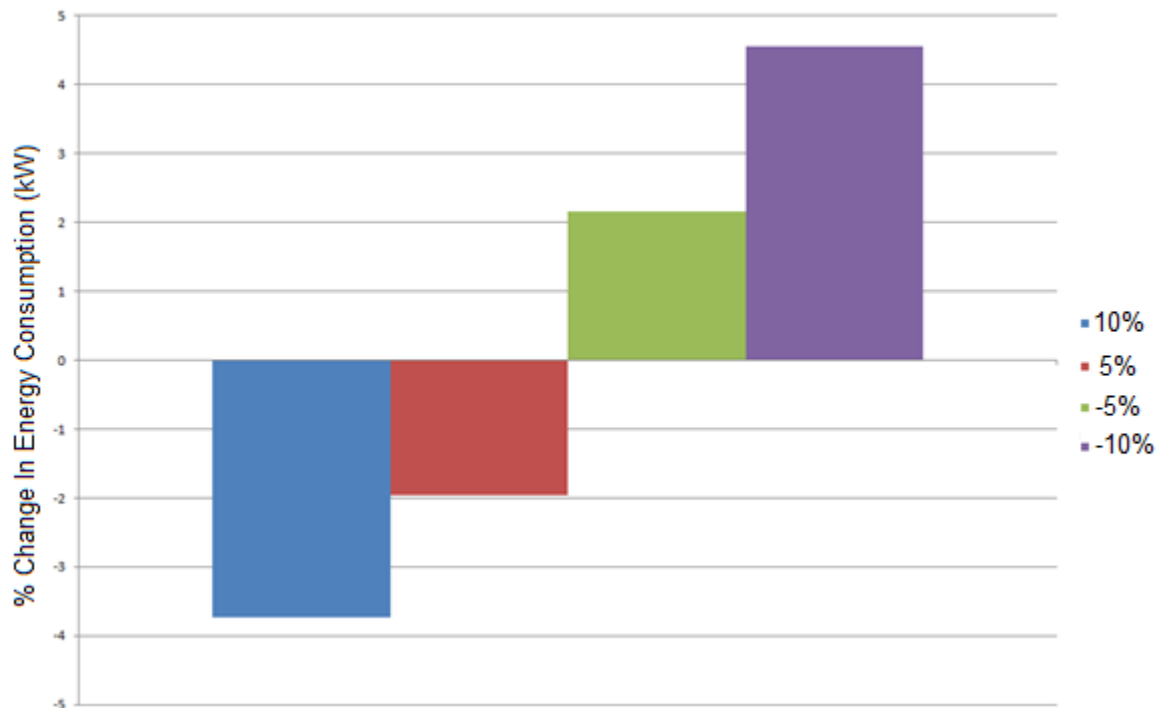


Figure 4.13 – Annual Energy percentage difference (heating efficiency)

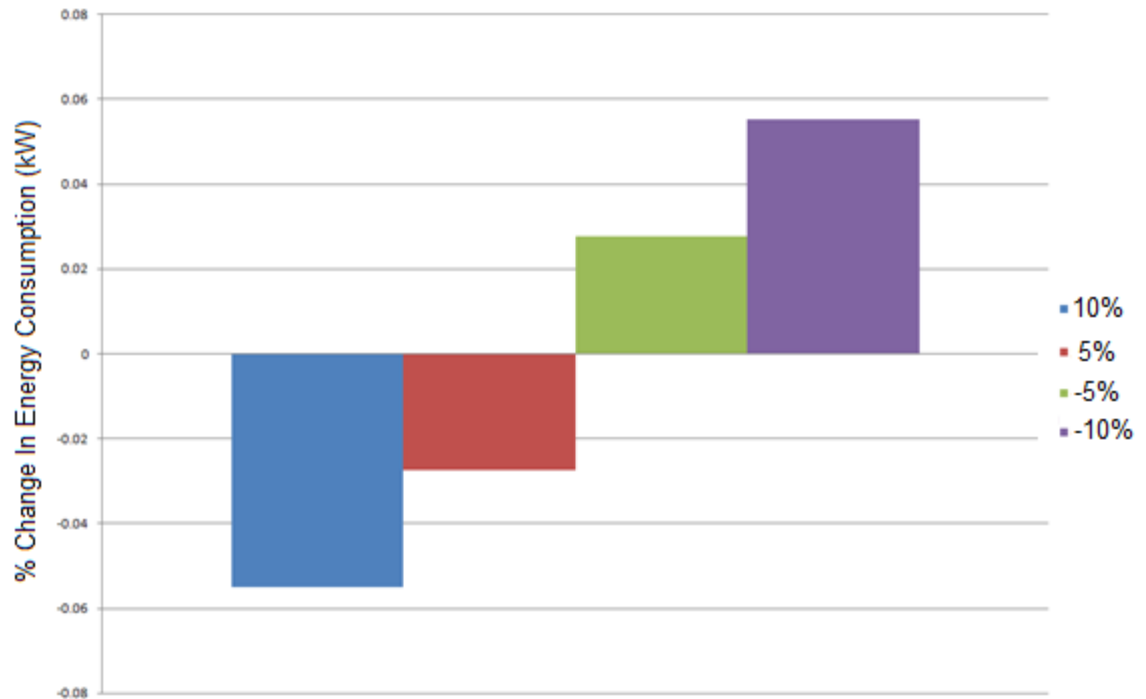


Figure 4.14 – Annual Energy percentage difference (ventilation efficiency)

The covariance/correlation analysis was successfully able to detect changes in the energy consumption for both increased and reduced consumption; however it only has the capability of measuring two parameters against each other and is therefore not suitable to monitor several parameters in concurrently. Furthermore, correlation analysis is only able to detect a change but not the direction of the change (increased or reduced consumption). The efficiency variation tests showed that the disparity between the trend lines is far larger for the heating system than for the ventilation system. As a result neither the CUSUM nor the EWMA charts were successfully able to detect both faults, variation of the threshold limits would lead to missed faults or false alarms. Hence, performing fault detection by monitoring parameters isolation (using threshold limits) was unsuited for the purposes of the project as they lacked the depth required to accurately detect faults.

## **CHAPTER 5**

### **5. Whole Building Energy Evaluation Methodology**

In Chapter 2 the current methods of evaluating building energy performance including the legislative requirements were detailed along with the academic research and commercial methods of energy evaluation. The present shortcomings in effectively evaluating the energy consumption were identified from which the objectives of this research project were set. The techniques evaluated in Chapter 3 provided a means of determining the state/health of the building. The research approach taken within this project was to develop a ‘whole building’ energy evaluation method applied in real time through the use of the DTM energy data as a benchmark. The DTM data (post construction design) acted as a benchmark against which the actual consumption was compared. Additionally, two indicators of performance were developed to provide feedback on building performance. The second method analysed a selection of energy, HVAC and temperature process parameters from the BEMS for determination of the building state through the use of data driven statistical techniques. The data driven CM system operated on a whole building level and a HVAC component level simultaneously. The purpose of which was to provide an in-depth assessment of the state of the building and to identify the possible root causes responsible for poor energy performance. The use of a rule based system (detailed in Chapter 6) was employed to address the issue of HVAC FDD to provide a holistic evaluation of building health.

All CM modelling processes were performed within the Matlab programming environment using data from the case study BEMS, which was extracted on a weekly basis. Fault cases were developed utilising the information obtained in Chapter 4 to test the CM systems. The CM architecture was segregated into two parts in which there are three methods of health evaluation techniques applied as illustrated in Figure 5.1.

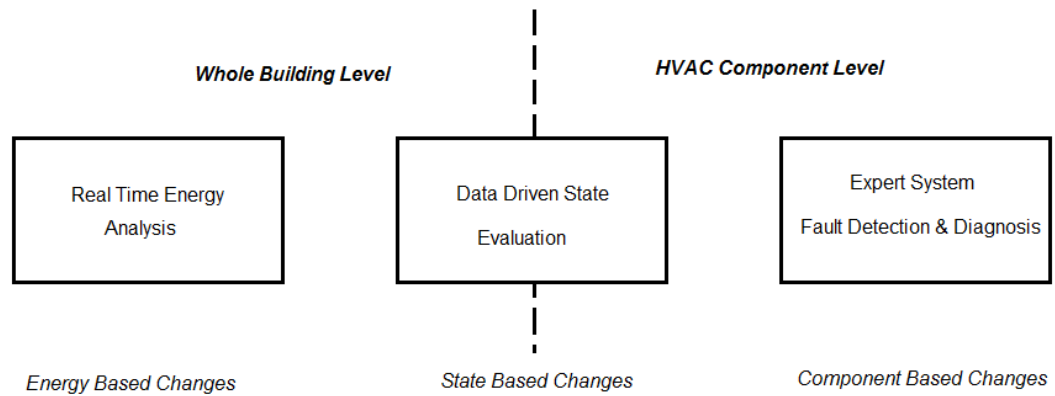


Figure 5.1 – Condition monitoring methodology architecture

Unfortunately, the author was unable to gain access to the maintenance logs and was therefore unable to correlate the parameter trends against fault occurrences in the actual building. Therefore, in order to test the capabilities of the CM systems fault cases were designed under the assumption that the data from the BEMS represented nominal operating conditions. The exception being the unoccupied periods in which the off peak loads was adjusted for the real time evaluation tool.

## 5.1 Real time energy evaluation methodology

Chapter 2 highlighted the need to bridge the gap between the design performance and actual performance of the building. Whilst the DEC was able to perform this role, the large time period between audits had significant disadvantages such as the degradation of performance in between audits. Evaluation performed on a weekly or daily basis would be more beneficial as it would reduce the time frame in which feedback would be delivered allowing for a virtuous cycle of continuous improvement (Cohen, Standeven et al. 2001; Bordass, Cohen et al. 2004). Furthermore, real time evaluation avoided the drawbacks of the DEC allowing for identification of the periods in which inefficient behaviour occurred. This would allow for isolation of the root causes of poor performance. In order to achieve this, an appropriate benchmark was needed. A benchmark based upon the simulated energy consumption data from the DTM was selected over external benchmarks given the drawbacks highlighted in chapter 2. Whilst the increasing levels of customisation for external benchmarks afford greater flexibility they are generally static annual figures that

are unsuited for real time evaluation. The DTM based benchmarks provided a closer contextual fit to the building.

As detailed in chapter 2 and 4, the process of post construction modelling allows for the evaluation of the building with the inclusion of actual parameter information. This creates a simulated model in which the energy consumption of the actual building can be compared against. The DTM is the equivalent to the model based approach detailed in chapter 3 in that it uses physical equations and mathematical models to determine energy loads whilst incorporating building specific characteristics such as the on-site HVAC systems, building fabric U-values, building function and occupation frequency. Location and typical weather conditions are also taken into account using a weather data file. Hence for the purposes of the project the DTM model using the NCM methodology for calculating energy consumption was utilised. This allowed for the development of a benchmark that is contextually relevant to the building in question and more importantly created bespoke Energy Performance Indicators (EPI). Additionally, the use of a DTM allowed for the data to be extracted and analysed on an hourly basis which provided a level of flexibility typically not available to external benchmarks. The EPI's detailed in section 5.2.2 provide the basis of a bespoke performance indicator without the need for an additional separate model by using the post construction model.

There was not sufficient metering coverage to differentiate between gas and electrical consumption; hence conversion to Carbon emissions was not performed. Therefore, whilst the legislation refers to carbon efficiency or reduction of carbon emissions, the work performed here shall focus on energy efficiency. The simulated energy consumption is analogous to the energy equivalent of the BER. Hence, the simulated Building Consumption Rate (BCR) is used in lieu of the BER and Target Consumption Rate (TCR) in place of the TER. For clarity the Actual Consumption Rate (ACR) is the energy consumption from the case study building.

The post construction Part L test was run in the DTM; the key annual post-construction values obtained for energy consumption are displayed in Table 5.1.

Table 5.1 – Case Study Building DTM Annual Consumption Figures

<i>Key Values</i>	<i>Consumption (kWh/annum)</i>
<i>Simulated Building Consumption Rate</i>	252690.70
<i>Notional Building Consumption Rate</i>	352519.45
<i>Target Consumption Rate</i>	264389.58

The figures in Table 5.1 provide a snapshot of the simulated performance over the period of the year. An initial test was performed to segregate the consumption values into monthly energy budgets. This was done by simply dividing the monthly BCR values by the annual BCR to provide a ratio which is then multiplied by the total TCR value. Table 5.2 provides the monthly ratios and target figures for the case study building.

Table 5.2 – Monthly allotted TCR

<b>Month</b>	<b>Simulated Total Consumption –BCR (kWh/month)</b>	<b>Weighting</b>	<b>Monthly - TCR (kWh/month)</b>
<i>Jan</i>	31454.96	0.124	32911.24
<i>Feb</i>	26962.77	0.107	28211.08
<i>Mar</i>	24596.25	0.097	25734.99
<i>Apr</i>	22043.09	0.087	23063.63
<i>May</i>	19520.21	0.077	20423.95
<i>Jun</i>	13901.37	0.055	14544.96
<i>Jul</i>	11803.68	0.047	12350.16
<i>Aug</i>	11786.24	0.047	12331.91
<i>Sep</i>	12692.67	0.050	13280.31
<i>Oct</i>	22572.73	0.089	23617.78
<i>Nov</i>	28965.71	0.115	30306.74
<i>Dec</i>	26391.01	0.104	27612.84
<i>Total</i>	252690.70	1.000	264389.58

Figure 5.2 graphically illustrates the monthly target method in which the Target Consumption Rate (and simulated Building Consumption Rate) is displayed throughout the year. This approach took into account seasonal variations in consumption and provided monthly targets as a benchmark; it is also more reflective of the building consumption patterns throughout the year. However, assessment would have to be performed

retrospectively on a monthly basis which still possessed the disadvantages of the longer auditing periods albeit on a reduced scale.

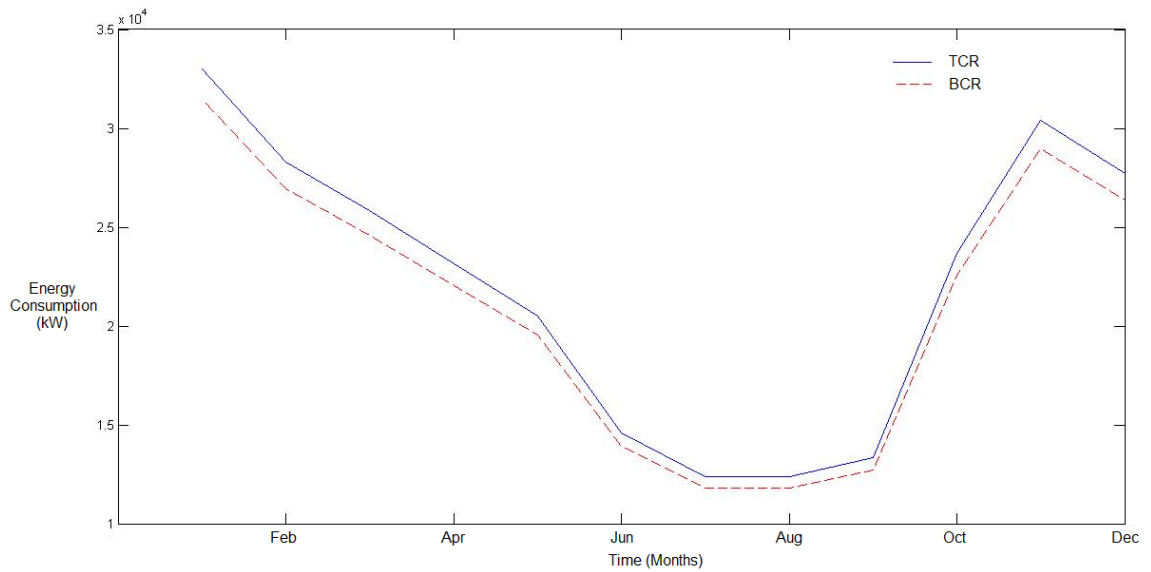


Figure 5.2 – Monthly BRC and TCR values

The methodology developed for the purposes of evaluating the real time energy performance took the next iterative step. Two EPIs were implemented in which the first provided a dynamic target, with a secondary EPI that measured the real time energy consumption against the simulated (BCR) consumption for grading purposes. Before the EPIs were applied, the data from the BEMS was first calibrated as there are differences between the parameters utilised to calculate the BCR and the output from the BEMS data. Additionally several assumptions were necessary in order to make use of the DTM data, this is further detailed in the following section.

### 5.1.1 Data Calibration

To provide a like-for-like evaluation of the building energy consumption against the BCR and TCR, calibration of the BEMS data was required. The data from the DTM post construction model contains real parametric data however, in accordance with the National Calculation Method the occupancy of the actual building does not be the same as the NCM template used within the model, for example out of hours or weekend classes in which the

building is occupied. Hence, care was taken to ensure that the occupancy periods matched up between the DTM and actual building. This was done by checking the energy consumption peaks. The energy consumption of the lifts, small power and external lighting are not included in the simulated building calculations, these were removed from the energy consumption total for the case study building. This allowed for a fair assessment of the building as energy usage from the lifts and small power are mainly influenced by human behavioural patterns and the specification of the equipment installed, and as such have no impact on the health of the building itself. The removal of these three end uses provided a reasonable approximation between the DTM and the real energy consumption, further details are provided in the following section. Additionally two other assumptions were made. Firstly, the difference between the modelled and real building lighting lux levels were negligible. Secondly, it was assumed that the energy consumption of the external lighting was a relatively small percentage of the total energy consumed and that it would not adversely affect the energy evaluation process by neglecting the external lighting consumption.

### **5.1.2 Validation of model**

The total energy consumption results obtained from the DTM model was compared to that of the actual building. For illustration purposes the Figure 5.3 compares the actual energy consumption of the building against the DTM simulate BCR.

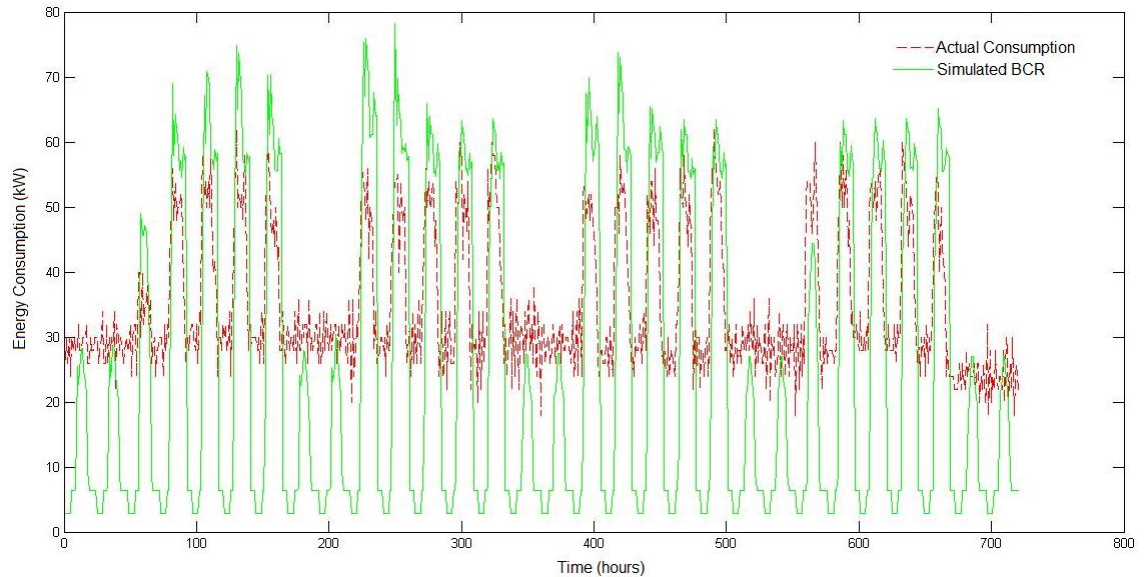


Figure 5.3 – Total energy consumption comparison for May

Figure 5.3 shows that the operation pattern and peaks are in agreement, however, during the unoccupied periods (evenings/nights and weekends) there is a significant discrepancy. Analysis of the BEMS data showed that the HVAC consumption is the primary cause of the difference between the actual and modelled energy consumptions. Inspection of the control setup of BEMS showed that HVAC systems were still utilising a significant amount of energy even during the unoccupied periods leading to the increased consumption. The design specification for the off-peak/unoccupied periods for the HVAC was that the main HVAC systems were to be turned off (or on a reduced load) during these periods. However, due to the incorrectly configured controls setup the HVAC systems were left running. To illustrate the energy evaluation methodology two cases shall be presented one in which the off peak load of the BEMS data was untouched and a second case where the off peak loads was adjusted to emulate the intended/designed HVAC consumption patterns.

### 5.1.3 Degree Day Adjustment & Occupation Profiles

To ensure that variations in seasonal consumption were accounted for, regression analysis was performed on the heating degree day data to determine an approximate the level of additional energy consumed attributable to external temperature conditions. Given that there are limited cooling systems installed within the case study building only heating

degree days analysis was performed. The base temperature was selected as 15.5°C. The external temperature sensor at the case study building in combination with the energy consumption data was utilised to extrapolate the relationship between energy consumed and external temperature. The temperature data for the occupied periods was averaged to calculate the degree days. Data samples for the non-occupied periods (in this case weekends and school holidays) were omitted to avoid skewing the trend line.

As previously detailed the actual occupational frequency of the building may differ from the NCM functionality template, as the template is simply used for energy/emissions calculation purposes. It was not necessary to create occupation profiles for this project as the occupation profiles/periods were fitted retrospectively. For the practical application of the system, care would need to be taken to ensure that correct and fair evaluation occurs. The addition of an algorithm to adjust energy consumption due to variations in occupational frequency could be implemented to allow facilities management to make amendments as needed. A sensor based means (for example swipe card login data or PIR motion data) could also be a means of determining the level of occupancy and would be more desirable as it would automate the process and reduce the possibility of human errors.

#### **5.1.4 Energy Performance Indicators**

Two EPIs were developed by the author; the first was a dynamic Target Consumption Rate which was calculated using a rolling average as shown in Equation 5.4 and utilised the data from the DTM. A second EPI provided a grading system that aimed to provide a similar output to the DEC/EPCs. The EPIs were adjusted for variations in external temperature. Figure 5.4 gives an overview of the real time evaluation architecture used to evaluate the data of the case study building.

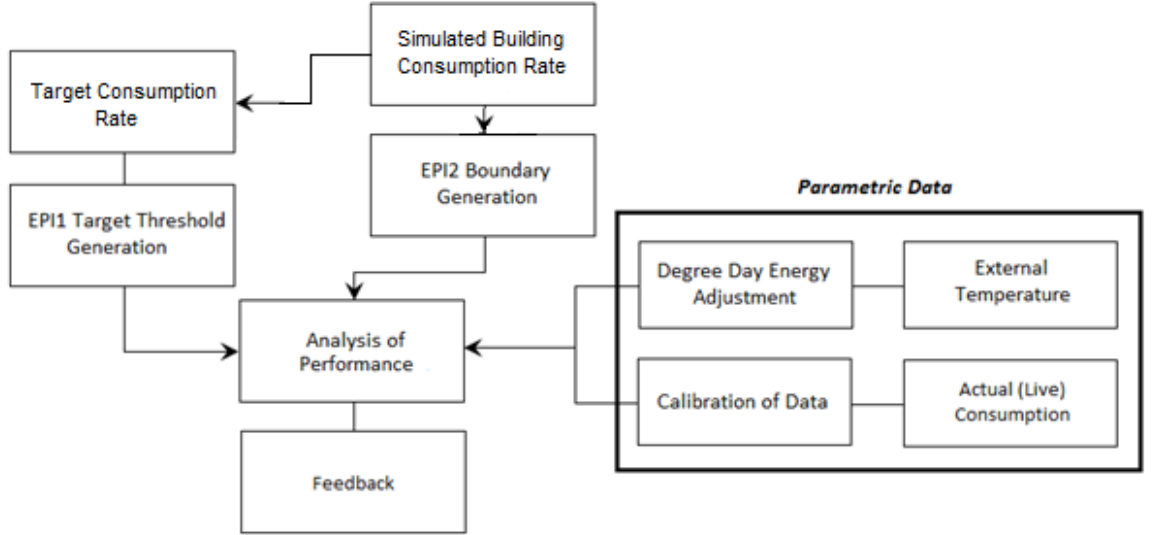


Figure 5.4 – Real time performance architecture

In order to determine an upper limit for energy consumption a dynamic method of target setting is proposed. The DTM provides the total BCR and TCR for the building annually as well as the BCR hourly consumption. Utilising the cumulative consumption over the last 28 days (4 complete weeks) of operation a weighting was derived by Equation 5.1.

$$W = \frac{\sum_{N=1}^{28} BCR_{28-N}}{BCR_{Total}} \quad \text{Equation 5.1}$$

where,  $W$  is the weighting,  $BCR_{N-28}$  is the summed simulated daily consumption for the last 28 days of operation,  $N$  represents the day operating in the range of the last 28 days.  $BCR_{Total}$  is the total simulated consumption of the building for the year. The weighting is then multiplied by the annual TCR ( $TCR_{Total}$ ) to determine the upper limit for energy consumption as shown in Equation 5.2.

$$TCR = W * TCR_{Total} \quad \text{Equation 5.2}$$

Substituting Equation 5.1 into Equation 5.2 gives the complete equation as shown in Equation 5.3

$$TCR = \frac{\sum_{N=1}^{28} BCR_{28-N}}{BCR_{Total}} * TCR_{Total} \quad \text{Equation 5.3}$$

The TCR was re-calculated on a daily basis to provide a dynamic daily target. The first EPI (EPI1- dynamic TCR) was then compared with the total consumption of energy of the real building over the last 28 days on a rolling basis. This would inform the end user of whether the building was operating above or below the target threshold.

The second EPI graded the actual energy consumption against the BCR, the purpose of which was to provide the end user with qualitative measure of performance. The rating system was determined by use of the relationship shown in Equation 5.4.

$$Rating = \frac{\sum_{N=1}^{28} ACR_{28-N}}{EPI1} \quad \text{Equation 5.4}$$

where  $ARC_{N-28}$  is the total energy consumed for the last 28 day in the case study building. In the case of the building consuming the same amount of energy as the first EPI1 the performance rating would be 1, the band thresholds (size of increments) for each rating was obtained by first substituting Equation 5.3 for the EPI1 (given that EPI1 is akin to the TCR) into Equation 5.4 thus giving Equation 5.5.

$$Rating = \frac{\sum_{N=1}^{28} ACR_{28-N}}{\sum_{N=1}^{28} BCR_{28-N}} * \frac{BCR_{Total}}{TCR_{Total}} \quad \text{Equation 5.5}$$

From Equation 5.5 if the consumption of the actual building were equal to the BCR the rating would be equal to the ratio of the  $BCR_{Total}$  to  $TCR_{Total}$ , for the case study DTM the ratio was 0.95. This provides the rating band increments of 0.05 between ratings. Table 5.3 displays the ratings and thresholds for the case study building, where ACR is the actual consumption rate of the building.

Table 5.3 – Compliance and advisory thresholds

<i>EPI 1 : Performance Threshold</i>	<i>EPI 1 : Output</i>	<i>EPI 2 : BCR Comparison</i>	<i>EPI 2 : Output</i>
<i>ACR=&lt;TCR</i>	<b><i>Acceptable</i></b>	<i>&lt;0.95</i>	<i>Very Good</i>
		<i>0.95-0.99</i>	<i>Good</i>
		<i>0.99&lt;EPI2 &lt;1.01</i>	<i>Satisfactory</i>
<i>ACR&gt;TCR</i>	<b><i>Unacceptable</i></b>	<i>1.01-1.05</i>	<i>Poor</i>
		<i>&gt;1.05</i>	<i>Very Poor</i>

The satisfactory rating band was set to 0.02 to create a region for the ‘Satisfactory’ rating rather than have a single value limit. In conjunction with the energy evaluation the health and state of the building was also assessed through the use of a data driven CM system that forms the second whole building evaluation tool.

## 5.2 Building State Evaluation and Fault Detection & Diagnostics

There were a number of CM approaches that were initially considered to perform whole building state evaluation. The advantages and disadvantages of each CM system were taken into consideration before selecting an appropriate methodology. The large number of operating states within typical commercial building (dependent upon several factors, including independent variables such as external temperature) meant that implementation of a knowledge based system for whole building evaluation was not feasible without extensive modelling. Whilst the development of a knowledge based model can be effective for smaller systems such as the HVAC systems it is difficult to build a robust enough model evaluate the whole building without it being prone to false or missed alarms. A model based approach for state evaluation of the building requires the inclusion of more than just energy data thus the DTM could not be used. Given the multivariate and non-linear nature of building operation, development of an accurate mathematical model would be difficult. Furthermore, without sufficient sensor coverage of the HVAC and non-HVAC parameters the level of uncertainty would render the model inaccurate and of limited use. As a result, a data driven methodology was deemed most suited to handle the complexities of building operation. As was highlighted in chapter 3 there are a variety of data driven methods, however the two main subgroups are statistical and non-statistical

methodologies. Neural Networks have the ability to compute non-linear processes effectively and efficiently provided that there is sufficient training data. However, Neural Networks act as ‘black boxes’ and hence it is not possible to trace the decision making process within the hidden layer. This is a critical feature as decisions need to be traceable in order to seek out the root causes of faults and failures. Hence a statistical based technique was selected. In order to analyse the large quantity of process data, dimensionality reduction techniques were selected. Initially three systems were tested; these were Principal Component Analysis (PCA), Partial Least Squares (PLS) and Fisher Discriminant Analysis (FDA). These three systems are all capable of handling large quantities of data and are able to capture the state of a system by evaluating the data in a lower dimension space (Chiang, Russel et al. 2001; Heijden, Duin et al. 2004). These dimensionality reduction techniques have been the focus of CM research and have been employed for health / quality monitoring within industrial processes (Zhonggai and Fei 2004; Fuente, Garcia et al. 2008; Facco, Doplicher et al. 2009; Yongsheng, Pu et al. 2010). The traditional applications of these three systems are only suited for linear processes (Chiang, Russel et al. 2001). As a result the initial testing found that these systems were unable to adequately represent the nonlinear building state leading to poor fault detection properties. Furthermore, the inability of these systems to map the non-linear components of the parameter data led to a greater number of false alarms. As a result the non-linear equivalents were investigated. The nonlinear method of Kernel PCA was used in which the data was mapped into a higher feature space in before PCA was performed (further details in section 5.2.2). Unlike PCA, PLS did not have a well established nonlinear equivalent for process monitoring and was therefore not tested. Whilst non-linear Kernel based FDA methodologies do exist, the most notable strength of FDA is in its ability to maximise the distance between data groupings (Duda and Hart 1973). Hence FDA was found to be more effective for the diagnosis phase with the ability to maximise the distance between nominal and fault data clusters. The final FDD architecture that was used in this project is shown in Figure 5.5.

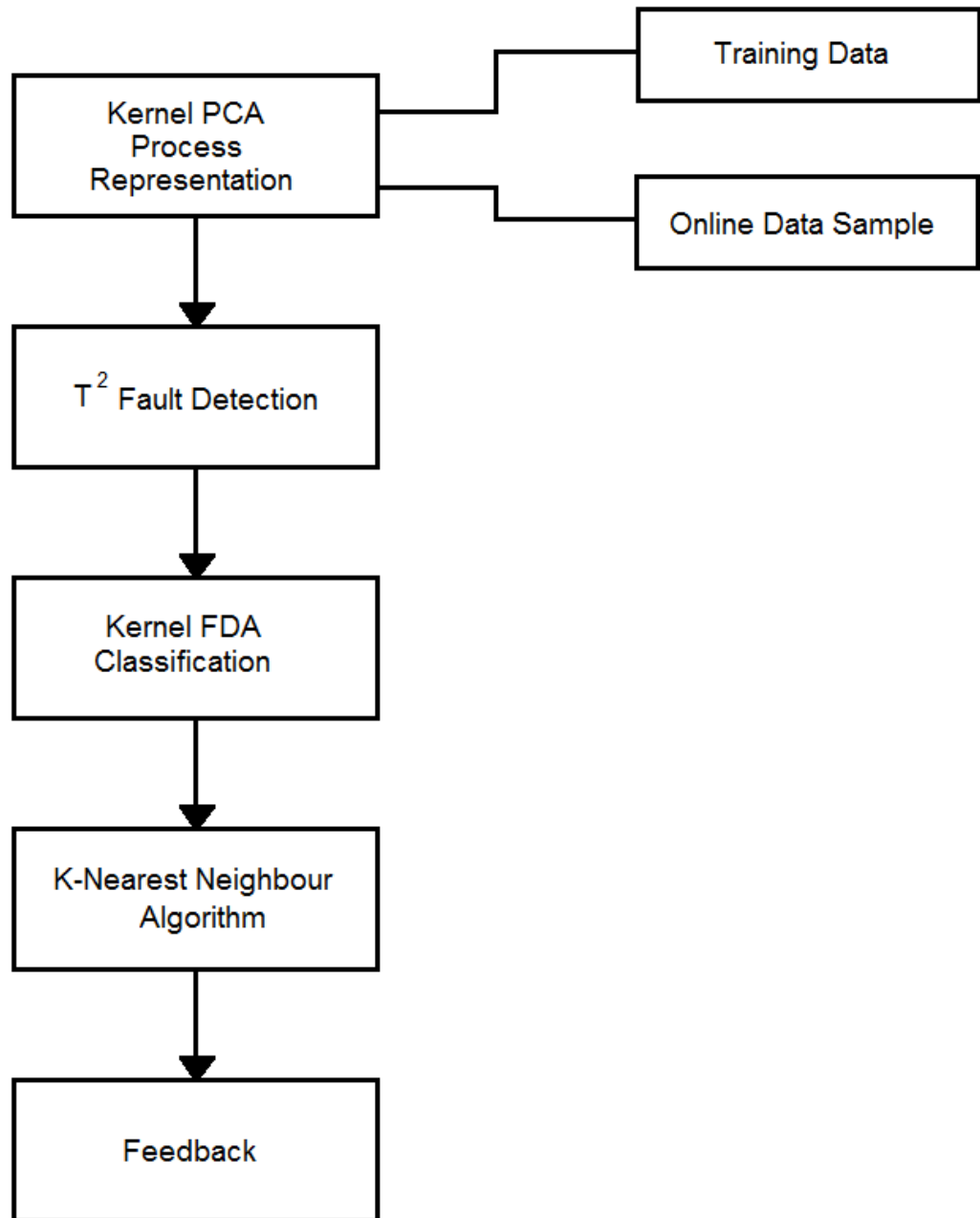


Figure 5.5 – Data driven approach overview

Kernel Principal Component Analysis (KPCA) was used to create a representation of the building in a lower dimension feature space. Hotelling's  $T^2$  (Jackson 1959) statistic was utilised for the fault detection phase. Kernel Fisher Discriminant Analysis (KFDA) in conjunction with K-nearest neighbour algorithms was used as a novel means of performing fault diagnosis. The subsequent sections provide further details for each of these techniques.

Application of the data driven systems required training data to define the nominal state. Typically, historical data or data collected under supervised conditions is utilised for this purpose. However, due to the lack of availability of such data, the data extracted from the BEMS was used under assumption that the BEMS data was analogous to the behaviour of the building under nominal operating conditions. The months of February and May were selected to test the data driven methodology as this provided two seasons with varying external weather conditions and kept the results to manageable levels.

An overview of PCA theory is given in the next section which then built upon in subsequent sections detailing Kernel based PCA.

### 5.2.1 Principal Component Analysis

The initial application of the PCA methodology utilised the DTM data as the training data. This was due to the DTM data possessing a more distinguishable relationship between the parameters given that they were generated using fixed profiles and functions. Hence the data did not contain any disturbances to nominal operation such as extended operating hours or faults with the HVAC that would pollute the training data with noise. Furthermore, any detected ‘faults’ were easier to isolate as a result. Pre-treatment of the data was performed to prevent certain variables from having a disproportionate weight (those with large operating ranges) in the evaluation process. In order to pre-treat the data, the training data was auto-scaled by subtracting the mean of a variable from the observations of that variable as the aim was to capture the variation from the mean. The observations were then divided by the standard deviation for each variable thus scaling each variable to its respective unit variance. The training data set was then stacked into the matrix  $T_D$  shown in equations 5.6.

$$T_D = \begin{bmatrix} T_{11} & \cdots & T_{1m} \\ \vdots & \cdots & \vdots \\ T_{n1} & \cdots & T_{nm} \end{bmatrix} \quad \text{Equation 5.6}$$

where m is the number of variables and n is the number of observations (data points) being utilised to build the PCA model. Ordinarily the training data would aim to contain all

necessary information to explain the acceptable variance within the process. However, the normal range of values for certain parameters change over time such as external temperature meaning that the nominal variance is not static. Recursive PCA techniques are sometimes used to overcome this problem, however in the case of this project, the training data shall be separated into months thereby performing a rudimentary form of recursive modelling.

The training data consisted of the building services consumption, the lighting consumption, the total energy consumption and the external temperature. The covariant matrix was then constructed for the training data as shown in Equation 5.7 (Rencher 1995; Patton, Frank et al. 2000).

$$S_{TD} = \frac{1}{n-1} T_D^T T_D \quad \text{Equation 5.7}$$

where  $T_D^T$  is the transpose of the matrix  $T_D$  and  $S_{TD}$  is the covariance matrix. Eigenvalue decomposition of  $S_{TD}$  was then performed through Equation 5.8.

$$S_{TD} = V \Lambda V^T \quad \text{Equation 5.8}$$

where  $V$  is the orthogonal loading vectors (also known as the transformation matrix) and  $\Lambda$  is a diagonal matrix contains the non-negative real eigenvalues in decreasing magnitude. The loading vector corresponding to the largest value of  $\Lambda$  ( $\Lambda_{11}$ ) is the first principal component that captures the largest amount of variance. Selecting the loading vector columns corresponding to the largest eigenvalues created a loading matrix  $PC_L$  containing the principal components to be utilised, shown in Equation 5.9 (Chiang, Russel et al. 2001).

$$PC_L \in K^{m \times a} \quad \text{Equation 5.9}$$

where  $K$  is a matrix containing the principal loading vectors, and ‘a’ is the number of number of largest eigenvalues that have been retained. Projecting the data points on to the newly reduced dimension place was done via Equation 5.10

$$Z = T_D PC_L \quad \text{Equation 5.10}$$

where  $Z$  is a matrix containing the projections of  $T_D$  in the new dimension space, commonly referred to as the scores (commonly called T-scores) matrix.

#### 5.2.1.1 PCA Fault Threshold Generation & Detection

Defining the fault threshold was done utilising two statistics that observe the reduced dimensionality space generated by PCA, Hotelling's  $T^2$  statistic (Jackson 1959) and the Square Prediction Error (SPE - commonly referred to as the Q statistic) (Johnson and Wichern 1992). Hotelling's  $T^2$  statistic detects the distance of each observation point from the centre of the data set (in the case of PCA, the zero mean centre). If the sample covariance matrix shown in Equation 5.8 is invertible, then the  $T^2$  is defined by Equation 5.11

$$T^2 = z^T z \quad \text{Equation 5.11}$$

where the vector of scores,  $z$  is given by Equation 5.12

$$z = \Lambda^{-1/2} V^T x \quad \text{Equation 5.12}$$

where  $x$  is an observation vector within the matrix of variables. Application of the  $T^2$  statistic for threshold generation is dependent upon the level of significance ( $\alpha$ ) from a normal multivariate distribution ( $X^2$ ). Equation 5.13 was used to define the threshold boundary.

$$T_\alpha^2 = \frac{m(n-1)(n+1)}{n(n-m)} F_\alpha(m, n-m) \quad \text{Equation 5.13}$$

where  $F_\alpha(m, n-m)$  is the upper critical point of the F (continuous probability) distribution with  $m$  and  $n-m$  degrees of freedom (Rencher 1995). The  $T^2$  statistic can be applied directly to principal component observations using Equation 5.14.

$$T_{\alpha}^2 = x^T PC_L \Sigma_a^{-2} PC_L^T x \quad \text{Equation 5.14}$$

To allow for the use of smaller eigenvalues should they contain essential data to the process the Q statistic was utilised as given in Equation 5.15

$$Q = r^T r \quad \text{Equation 5.15}$$

where r is the residual vector, given by equation 5.16

$$r = (I - PC_L PC_L^T) x \quad \text{Equation 5.16}$$

where I is the identity matrix. The Q statistic is primarily used to observe the threshold of lower eigenvalue loading vectors, the Q statistic distribution was approximated to Equation 5.17 (Jackson and Mudholkar 1979).

$$Q_{\alpha} = \theta_1 \left[ \frac{h_0 c_{\alpha} \sqrt{2\theta_2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right]^{1/h_0} \quad \text{Equation 5.17}$$

where;

$$\theta_i = \sum_{j=a+1}^n \sigma_j^{2i} \quad \text{Equation 5.18}$$

and

$$h_0 = 1 - \frac{2\theta_1 \theta_3}{3\theta_2^2} \quad \text{Equation 5.19}$$

These two statistics are typically used as a means of observing any fault points within the process. As a test of traditional PCA they were used to detect any faults within the nominal data. Those points were then evaluated for the causes of the threshold breaches the results of which are shown in section 7.2.1.

### 5.2.2 Kernel Principal Component Analysis

Traditional PCA makes the assumption that the process data is linear and as a result PCA performs poorly when nonlinearities are present (Dong and McAvoy 1996; Cho, Lee et al. 2005). Kernel PCA was developed with the aim of overcoming the non-linear problem, it does so by mapping the input space into a feature space using a nonlinear mapping and then calculating the Principal components in the feature space (Scholkopf, Smola et al. 1998). The process monitoring concepts detailed by Cho et al (2005) and Lee et al (2005) was applied to the nonlinear data from the case study building via Equations 5.20 – 5.43 (Cho, Lee et al. 2005; Ji-Hoon, Jong-Min et al. 2005). The full mathematical proof of which has been verified in numerous published articles (Scholkopf, Smola et al. 1998; Lee, Yoo et al. 2004; Cho, Lee et al. 2005). Taking the case where the training samples are part of the set  $R$  as shown in Equation 5.20, where the mean is zero.

$$x_1, x_2, \dots, x_N \in R^M \quad \text{Equation 5.20}$$

Using a nonlinear mapping  $(\Phi : R^M \rightarrow F)$  the training data was mapped onto a high dimensional feature space  $F$ , where  $F$  has an arbitrarily high number of dimensions. The covariance matrix was then built in the feature space  $F$  via Equation 5.21.

$$C^F = \frac{1}{N} \sum_{j=1}^N \Phi(x_j) \Phi(x_j)^T \quad \text{Equation 5.21}$$

The eigenvalues of the covariance matrix were extracted in the high feature space by solving Equation 5.22.

$$\lambda v = C^F v \quad \text{Equation 5.22}$$

where  $v$  is the eigenvector of  $C^F$  and is considered to be a linear combination of the mapped input, given that the eigenvalues do not equal zero.  $\lambda$  is the eigenvalues. Equation 5.22 can be re-written as

$$\lambda v = C^F v = \frac{1}{N} \sum_{j=1}^N (\Phi(x_j) \cdot v) \Phi(x_j)^T \quad \text{Equation 5.23}$$

Multiplying both sides of 5.21 by  $\Phi(x_k)$  gives the following form:

$$\lambda(\Phi(x_k) \cdot v) = \Phi(x_k) \cdot C^F v \quad \text{Equation 5.24}$$

By using the Kernel trick Equation 5.24 can be expressed in the simpler form of Equation 5.25.

$$\lambda \alpha = \frac{1}{N} K \alpha \quad \text{Equation 5.25}$$

where K is the gram matrix

$$K \in R^{N \times N} \quad \text{Equation 5.26}$$

And where the coefficients,  $\alpha = [\alpha_1 \alpha_2 \dots \alpha_N]^T$  result in

$$v = \sum_{i=1}^N \alpha_i \Phi(x_i) \quad \text{Equation 5.27}$$

K is obtained by solving the eigenvalue problem of

$$N \lambda \alpha = K \alpha \quad \text{Equation 5.28}$$

In order to solve the eigenvalue problem a kernel function is used, kernel functions take the general form of:

$$k(x, y) = \langle \Phi(x), \Phi(y) \rangle \quad \text{Equation 5.29}$$

The kernel functions tested in this project were linear, polynomial and Gaussian and are given by Equations 5.30 – 5.32 respectively

$$k(x_i, x_j) = x_i^T x_j \quad \text{Equation 5.30}$$

$$k(x_i, x_j) = \langle x_i, x_j \rangle^d \quad \text{Equation 5.31}$$

$$k(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}} \quad \text{Equation 5.32}$$

Where  $d$  is the polynomial order and  $\sigma$  is determined through fine tuning of the kernel. The gram matrix  $K$  is first centred before the application of PCA. The centred gram matrix  $\bar{K}$  is given by Equation 5.33.

$$\bar{K} = K - 1_N K - K 1_N + 1_N K 1_N \quad \text{Equation 5.33}$$

Where  $1_N$  is given by

$$1_N = \frac{1}{N} \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 1 \end{bmatrix} \in R^{N \times N} \quad \text{Equation 5.34}$$

Using the centred  $\bar{K}$  kernel matrix the eigenvalue shown in Equation 5.35 was solved.

$$N\lambda\alpha = \bar{K}\alpha \quad \text{Equation 5.35}$$

In which

$$\langle \alpha_k, \alpha_k \rangle = \frac{1}{\lambda_k} \quad \text{Equation 5.36}$$

For the nominal operating data (training data) the selected nonlinear principal components was extracted via Equation 5.37 to gain the KPCA equivalent T-scores,  $t_k$ .

$$t_k = \sum_{i=1}^N \alpha_i^k \bar{k}(x_i, x) \quad \text{Equation 5.37}$$

The  $T^2$  statistic was then obtained using Equation 5.38

$$T^2 = [t_1, \dots, t_p] \Lambda^{-1} [t_1, \dots, t_p]^T \quad \text{Equation 5.38}$$

The confidence limit or threshold boundary was obtained using Equation 5.13. The  $T^2$  values for the nominal data were then checked to ensure that the nominal case fell within the threshold limits. In cases where the operating data falls outside the  $T^2$  threshold the threshold would ordinarily be adjusted.

### 5.2.3 KPCA Fault Detection

The fault case data described in section 5.2.7 was analysed one sample at a time to perform to the fault detection process described below. This was done as means of emulating the practical application of the KPCA in which the latest incoming data from the BEMS would be used to determine the state of the building, as would occur in an online monitoring system.

Detection of the fault case data was done through the following steps. Firstly the fault test sample was pre-treated within the nominal data set to have a zero mean and unit variance. The kernel vector was mapped to  $R$  as shown in Equation 5.39.

$$k_t \in R^{1 \times N} \quad \text{Equation 5.39}$$

And was obtained by

$$[k_t]_j = [k_t(x_t, x_j)] \quad \text{Equation 5.40}$$

where  $x_j$  is the normal operating data and  $x_t$  is the fault data. The test kernel vector was mean centred by

$$\overline{k_t} = k_t - 1_t K - k_t 1_N + 1_t K 1_N \quad \text{Equation 5.41}$$

where  $I_t$  is obtained from

$$1_t = \frac{1}{N} [1, \dots, 1] \in R^{1 \times N} \quad \text{Equation 5.42}$$

The fault test T-scores were extracted using

$$t_{Tk} = \sum_{i=1}^N \alpha_i^k \bar{k}(x_i, x_t) \quad \text{Equation 5.43}$$

The  $T^2$  value was obtained from the T-scores of the test data using Equation 5.38. The  $T^2$  statistic provided reasonable results given that the variance captured within the principal components was high. However, for the SPE methodology the control limits were extremely large and thus ineffective at capturing the state, this is primarily due to the arbitrarily high number of dimensions for the feature space (Cho, Lee et al. 2005).

In traditional application of PCA for process monitoring, contribution plots are often used to isolate the parameters that contribute greatest to the threshold breaches. However, performing fault isolation in KPCA is not simple as the relationship between the original data and feature projections are nonlinear. Furthermore there are difficulties in linking the high feature space contributions back to normal space variables (Choi, Lee et al. 2005). Hence as a result fault isolation was not performed as part of the data driven FDD.

#### 5.2.4 Fault Diagnosis (Pattern Classification)

The final stage in the FDD process was to diagnose faults through classification techniques using the KPCA T-scores for the nominal and the fault test cases. This was done in two stages, KFDA (Kernel Fisher Discriminant Analysis) was used to project the T-scores onto a lower dimension feature space upon which the data was separated between classes (Zhang, Yan et al. 2007). The second phase was to introduce smaller fault samples which contained similar but not identical characteristics to the fault cases to determine if a K-nearest neighbour (KNN) algorithm was able to effectively classify the fault under the belief that the faults would migrate away from the nominal cluster towards the fault cluster

it was most similar to. Incoming data samples that fell within the nominal cluster would be considered as normal building operations, whereas those that migrated away were considered fault states. This in itself provides a secondary method of fault detection.

The application KFDA for classification is verified within numerous published journal literature, this project utilises the following theorem shown in Equations 5.44 – 5.49 (Guo, Li et al. 2003; Zhang, Yan et al. 2007) for the purposes of maximising the separation between the nominal T-scores and the fault case T-scores that was collated from the KPCA method.

The T-scores for the nominal data and fault data were loaded into an array in which there were M classes and each class has  $N_i$  samples with N being the total number of data samples. Using the nonlinear mapping  $\Gamma$  the T-scores were mapped on a high dimensional feature space similar to KPCA. The mathematical derivations have been omitted as they are not explicitly required; the full derivation can be viewed in the paper by Zhang et al (Zhang, Yan et al. 2007). The equations that are pertinent to the methodology are detailed here.

The kernel sample vector and is defined as

$$\xi_x = (K(t_1, t), \dots, K(t_N, t))^T \quad \text{Equation 5.44}$$

Using Equation 5.44 the kernel sample vectors for the nominal case ( $\xi_{\text{NOM}}$ ) and the fault cases ( $\xi_{\text{TEST}}$ ) were obtained. These kernel sample vectors were considered to be different classes. The kernel between class matrix,  $K_b$  and kernel within class matrix  $K_w$  was then calculated using Equations 5.45 and 5.46 respectively.

$$K_b = \sum_{i=1}^M \frac{N_i}{N} (\mu_i - \mu_0)(\mu_i - \mu_0)^T \quad \text{Equation 5.45}$$

$$K_w = \frac{1}{N} \sum_{i=1}^M \sum_{j=1}^{N_i} (\xi_{x_j} - \mu_i)(\xi_{x_j} - \mu_i)^T \quad \text{Equation 5.46}$$

where the kernel mean vector the within class,  $\mu_i$  and the kernel mean vector of all mapped samples,  $\mu_0$  are given by Equations 5.47 and 5.48 respectively.

$$\mu_i = \left( \frac{1}{N_i} \sum_{j=1}^{N_i} K(t_1, t_j^i), \dots, \frac{1}{N_i} \sum_{j=1}^{N_i} K(t_N, t_j^i) \right)^T \quad \text{Equation 5.47}$$

$$\mu_0 = \left( \frac{1}{N} \sum_{i=1}^N K(t_1, t_i), \dots, \frac{1}{N} \sum_{i=1}^N K(t_N, t_i) \right)^T \quad \text{Equation 5.48}$$

The kernel sample vectors for the nominal case ( $\xi_{\text{NOM}}$ ) and the fault cases ( $\xi_{\text{TEST}}$ ) were then projected to the optimal kernel Fisher Discriminant (lower Fisher Dimension). The optimal kernel Fisher Discriminant was obtained by solving the generalised feature equation as shown in Equation 5.49.

$$K_b a = \lambda K_w a \quad \text{Equation 5.49}$$

where  $a$  is the vector coefficients.

The sample faults (test case samples defined in section 5.2.7) were then projected onto the feature space. The sample faults had similar characteristics to one of the fault cases. In order to diagnose the fault samples a K-Nearest Neighbour (KNN) algorithm was used to calculate the Euclidean distance between the nominal, fault case and fault sample clusters on the projected feature space. The KNN classifier attributed each fault sample observation to the nearest data cluster (either the nominal data cluster or one of the 5 fault case clusters).

### 5.2.5 System Training Methodology

The training used in data driven techniques would ideally contain all the necessary parameter variations that are representative of nominal building behaviour. The lack of availability of training data meant that in order to test the data driven methodologies it was necessary to make the assumption that the BEMS data represented the nominal building operation. It was also assumed that this training data contained all the nominal variations

that would typically occur. The training data consisted of a range of process parameter data that is described in the following section.

The training data was then segregated into two groups, one that contained the training data for the occupied hours and the other containing the unoccupied hours. Segregating the data by the operational state of the building led to improved accuracy of the methodologies employed. This was due to the segregation limiting the operating range for each parameter thereby improving the CM systems ability to detect smaller variations from the nominal state. For example the maximum and minimum values for the total energy consumed ranged from, on average, 25-55kW over a 24 hour period. By segregating the data this range became 45-55kW for occupied periods and 25-35kW for unoccupied periods. Figure 5.6 illustrates the segregation boundaries.

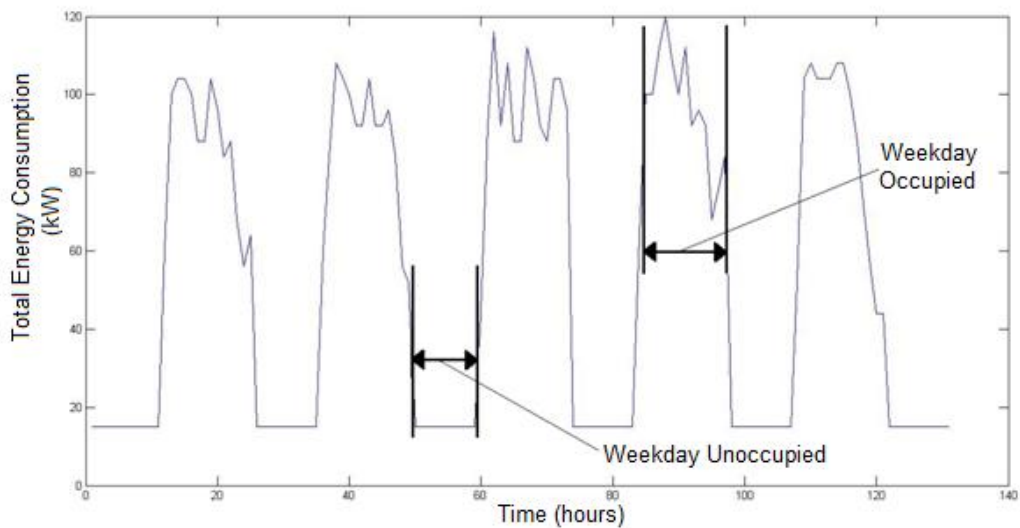


Figure 5.6 – Segregation boundaries of PCA model

The data observations for the month were separated into their respective groupings, forming two training matrices  $T_{DAY}$  and  $T_{UNOC}$ . Where  $T_{DAY}$  contained all the data for the occupied periods and  $T_{UNOC}$  contained the data for the unoccupied periods such as the weekends and evening/nights for weekdays. Table 5.4 details the segregation sections by time.

Table 5.4 – Time based segregation

Segregation Band	Time period
Weekday – Occupied	0800-1700 hrs
Weekday – Unoccupied	1715 – 0745 hrs
Weekend	1700hrs Friday – 0700hrs Monday

Given that the unoccupied periods were known to contain excessive HVAC consumption, only the occupied training matrix ( $T_{DAY}$ ) was used in the methodologies described previously.

### 5.2.6 Process Parameters

The parameters that were selected for the state evaluation methodologies included energy, temperatures and HVAC data. Whilst there were more parameters available not all were necessary for the purposes of demonstrating the abilities of the methodologies presented in this thesis. The four main groups of parameters that were utilised are detailed in Table 5.5.

Table 5.5 – Data driven process parameters

<i>Parameter Group</i>	<i>Parameter</i>
<i>HVAC - Temperature sensors</i>	Atrium under-floor heating flow temperature Boiler flow temperature Boiler return temperature Multi conference room radiant temperature Radiant heating flow temperature Atrium vent temperature
<i>HVAC - Valves and Window Actuator positions</i>	Natural ventilation north facade Natural ventilation south facade Multi-conference radiant valve
<i>Temperature</i>	GF Atrium temperature Zone 1 / 2 / 3 Outside air temperature (OAT)
<i>Energy Meters</i>	Mechanical services consumption GF/1F/2F lighting consumption Multi conference consumption Total energy consumption

GF – Ground Floor

1F – 1<sup>st</sup> Floor

2F – 2<sup>nd</sup> Floor

The data was sampled at 15 minute intervals. It was assumed that these parameters contained enough information to describe the nominal state of the building. Several of these parameter values were changed to create the fault cases detailed in the following section. Whilst certain parameters were not change for the fault cases such as the OAT and lighting energy consumption, these parameters were needed to define the nominal relationship/variance between parameters.

### **5.2.7 Fault Test Cases and Fault Samples**

To test the CM methodologies five test cases were devised. The aim of the fault tests was to determine the capabilities of the proposed CM systems at handling a range of fault types that were expressed in the process data using various fault profiles. The five fault cases aimed to simulate both the poor operation/maintenance of the building (Fault 1 and 2) and HVAC faults and failures (Faults 3, 4 and 5). In the methodology presented in this thesis, the diagnosis process requires supervision to classify any newly generated clusters outside of the nominal case with an appropriate fault label. Hence, given the that deviations in the process data are classified through supervision, the actual faults themselves are not so important here but rather the ability of the methodologies to successfully detect, separate and diagnose (for different fault characteristics and profiles) the expression of the fault data from the nominal case.

Table 5.6 provides an overview of the fault test cases.

Table 5.6 – Test fault cases for statistical condition monitoring methodology

<i>Test Case:</i>	<i>HVAC System</i>	<i>Fault</i>	<i>Fault Profile</i>	<i>Affected (modified) Parameters</i>
1	Heating	Poor efficiency	<ul style="list-style-type: none"> <li>- Step Change</li> <li>- Slow developing / incipient</li> </ul>	HVAC energy consumption Total Energy consumption
2	Ventilation	Poor efficiency	<ul style="list-style-type: none"> <li>- Step Change</li> <li>- Slow developing / incipient</li> </ul>	HVAC energy consumption Total Energy consumption
3	HVAC Valve	Stuck radiant panel valve	Abrupt – Step change	Multi-conference valve Multi-conference radiant panel temperature HVAC energy consumption Total Energy consumption
4	Heating	Central atrium heating fault/failure	Intermittent	Ground Floor atrium temperature sensors HVAC consumption Total consumption
5	Ventilation	Central Atrium window actuator failure	Intermittent	Natural ventilation north facade Natural ventilation south facade GF atrium temperature sensors Atrium vent temperature

Fault 1 and 2 related to reduced efficiency of the HVAC systems, namely the heating and ventilation systems, imitating poor HVAC maintenance practices. Three types of degradation patterns were used. The first introduced a 10% reduction in efficiency. Using the findings in Chapter 4, this was equivalent to increasing the HVAC energy consumption by 4.5% for Fault 1 (heating) and 0.055% for Fault 2 (ventilation). The second and third methods used a linear and parabolic degradation in efficiency over time in which the efficiency was nominal at the start of the month and was degraded to 15% reduced efficiency at the end of the month. The fault profiles for faults 1 and 2 was a step change for the 10% reduction case and slow developing for the linear and parabolic cases. This test case also measured whether the  $T^2$  statistic was an appropriate threshold to handle both large and small changes to the process parameter data.

Fault 3 represented a fault with the radiant panel valve in the multi-conference room in which the room is left without heating. Whilst it would have been preferable to utilise local temperature sensors, these sensors were not connected to the BEMS. Thus the radiant panel temperature was used instead. The fault symptoms were applied abruptly in the second week using a step change in the process parameter data. The effects of the fault was a reduction in energy consumption for the HVAC system, a drop in the radiant panel temperature to 10°C and a radiant panel valve position set to closed.

The fourth fault was an intermittent fault in the heating system in which heating was not supplied to the central atrium zone via the under-floor heating system. The heating output slowly fell over time indicating a fault with the heating circuit valve. The heating circuit valve was not directly monitored hence the cause of the fault was inferred by the changes in the parameter data. This was emulated by reducing the internal temperature of the ground floor atrium by greater amounts over time and allowing it to vary with the external temperature. There was also a slight decrease made to the HVAC and total energy consumed to represent the reduced energy load. The intermittent profile was such that the fault only clearly manifested itself in the process data when there was a need for heating. The fault was further masked as the ground floor atrium temperature varied with the external temperature and was not step changed to a fixed value.

The fifth fault was intermittent breakdown in the atrium chimney windows actuators. The actuator positions were not opening as fully despite the need for it. The ground floor atrium

temperature was slightly increased to represent a lack of exhaust in the atrium and was also varied with the external temperature in moving up or down. The atrium vent temperature steadily increased during the day time periods fell during the nights/evening.

The fault case parameter changes were applied to the BEMS data for February and May. The fault data was then analysed one sample at a time, emulating an online monitoring strategy, to determine the ability of the KPCA to model the data and the  $T^2$  statistic to detect faults. The T-scores from the fault cases were then collated so that each fault case was considered to be a distinct and separate class to the nominal class. To test the ability of KFDA and the KNN algorithms, fault samples were designed. The fault samples were created by first selecting 12 random data samples from each month and applying a change in the process parameter. Three fault samples were devised in which the applied changes resembled the parameter changes of fault cases 1, 3 and 4. The changes made to the fault samples were similar but not identical to the changes applied to the fault cases. For fault sample 1, the heating efficiency was reduced by 7% leading an increase in both the HVAC and total energy consumption. Fault sample 2 was an approximation of fault case 3, however unlike fault case 3 the valve was able to open up to 10% and the radiant panel temperature was able to increase to 15°C. No changes were made to the energy consumption for fault sample 2. Fault sample 3 approximated fault case 4, the temperature and HVAC consumption data for fault case 4 was increased by 5% and reduced by 2% respectively Table 5.7 summarises the properties of the fault samples.

Table 5.7 – Fault samples characteristics

Fault Sample	Parameter change	Fault case approximation
1	7% reduction in efficiency leading to a reduction in HVAC and total energy	1
2	Multi-conference valve – maximum value 10% Multi-conference radiant panel temperature - 15°C	3
3	Ground Floor atrium temperature sensors – increased 5% more than fault test case 4 data HVAC consumption – 2% reduction on fault case 4 consumption	4

The aim of introducing fault samples was to determine if the KFDA and KNN algorithms would be able to successfully detect the migration away from the nominal case in order to attribute the fault sample to the fault case it was approximating. The results from the state evaluation methodology are presented in 7.2.

## CHAPTER 6

### 6. HVAC Fault Detection and Diagnosis Methodology

The data driven building evaluation tool detailed in the previous chapter was supplemented with an additional method focussed on diagnosing faults and failures specifically targeting the operation of the HVAC systems, thereby creating a holistic approach to building state evaluation. In order to perform HVAC diagnostics an Expert System was implemented. As detailed in Chapter 3, Expert Systems (ES) aim to simulate a ‘human’ knowledge domain by emulating the reasoning process of an expert (in that field) on the state of health of a system (Jackson 1999). Typically an expert system is supplied with the qualitative state of several relevant process parameters by the user from which an diagnosis similar to the judgement of an expert in the field is returned by the ES (Rao 1996; Jackson 1999). The traditional application of an ES for fault detection and diagnosis has a significant drawback in that there is no linkage between the fault detection and fault diagnosis stages. Fault diagnosis only occurs when the end user notices a problem with the system and queries the ES. Thus leading to the possibility where noticeable deterioration may be needed for the fault to be detected. This problem is further compounded if the symptoms of a fault can be masked by overcompensation by the control system or if the fault profile is incipient or intermittent. A system that removes the need and reliance upon the end user to perform the fault detection phase would be an enhancement to the traditional ES. This would provide a method by which continual and consistent focus is placed upon on the performance and state of the HVAC systems whilst bridging the gap between fault detection and diagnosis.

The Automated Expert System (AES) developed for the purposes of this project collated parameter information from the BEMS and converted them into rules from which the AES determined the state of the HVAC systems. Whilst this method removed the need for human fault detection it did possess one disadvantage in that observed/heuristic symptoms such as the “Air Handling Unit is making a rattling sound” cannot be utilised in the diagnosis process and as such the AES is reliant on the need for sufficient process information to make accurate decisions. However, it is likely that a significant proportion of heuristically observed fault symptoms would also manifest themselves in deviations in

the measured process data. Hence, it is envisaged that application of the AES will not be significantly impeded by the lack of user input. The basic operating premise for the Automated ES is shown in Figure 6.1 which is an adaptation of the traditional ES methodology shown in Figure 3.2.

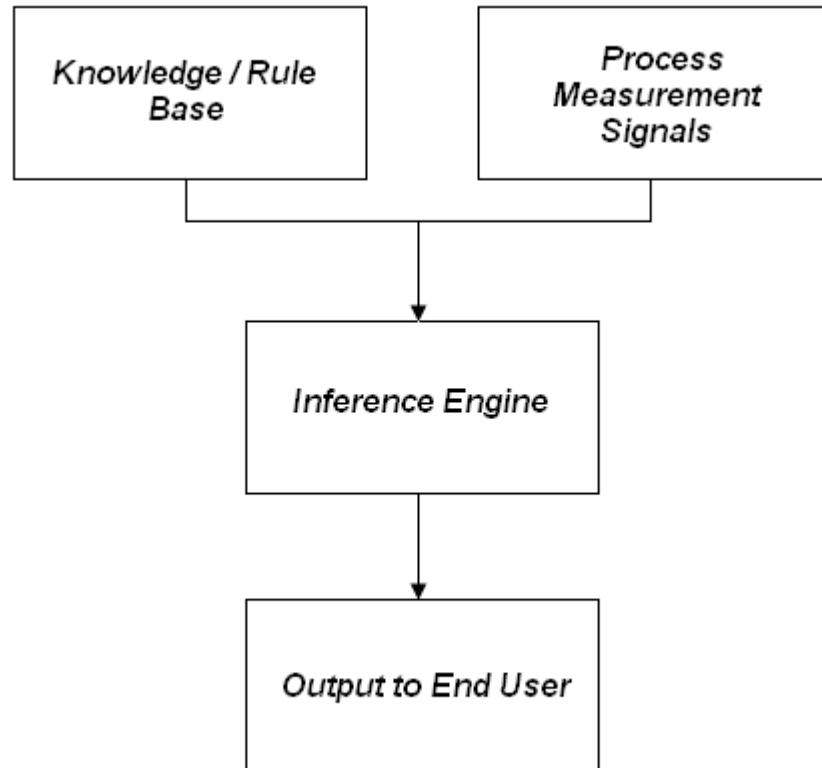


Figure 6.1 – Automated expert system architecture (Adapted from - (Davies 1998)).

The AES used an inference engine to combine the rule base and the BEMS data to interpret the state of the HVAC systems and to infer whether or not a fault had occurred. The rules contained within the rule/knowledge base represent the states of the process parameters when a fault has occurred. Traditional Expert System inference engines use fault rules such as Fault 1 has occurred if Rule 1 and Rule 2 have been triggered. Where Rule 1 and 2 describe the state of a parameter, for example the Radiant Panel Temperature is greater than 84°C or the Flow rate is equal to zero. However, the AES used a Fuzzy Expert System approach in which the process parameter data was converted to qualitative class/rule for comparison with the Fault rule database. Figure 6.2 illustrates the full architecture of the AES.

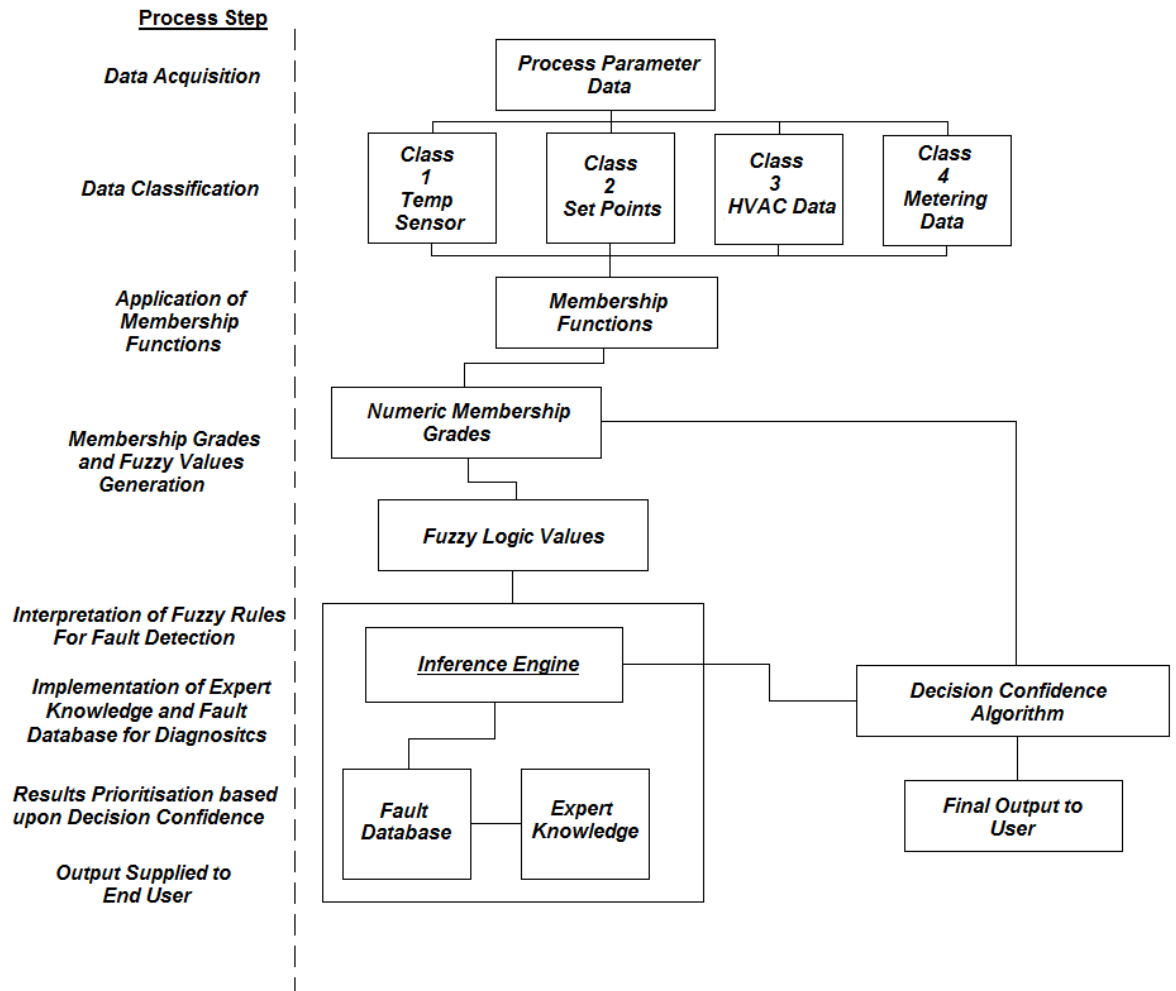


Figure 6.2 – Complete automated expert system architecture

The AES converted the process parameter data into a fuzzy value and a membership grade for each qualitative class; this allowed the inference engine to detect faults by comparing the state of the system against user defined fault rules via the fault database. Qualitative statements were used to describe the state of a parameter such as “hot/warm/cool” for temperature readings as opposed to numerical values in the same manner as the traditional ES methodology. The Fuzzy values were then used within the inference engine and compared against the fault rules. The fault rules contained the states of the relevant parameters that which indicated a fault had occurred. The use of fuzzy rules in an ES is typically referred to as a Fuzzy Expert System. Fuzzy ES have the benefit of being able capture the state of a problem in a more natural fashion (Kandel 1991). This allows for a natural evolution of the fault database with new rules and fine tuning of the current fault rules as user experience grows.

Once a fault has been detected and diagnosed, the membership grade values were then utilised for use by the decision confidence algorithm which arranged the probability of a fault by the supporting evidence, this is critical to differentiate between faults with similar fault symptoms. The end user is then supplied with the diagnosis made by the AES, a list of potential fault causes may also be supplied along with the decision confidence of each of those faults occurring.

The process steps of the AES are further expanded upon in the following sections.

## 6.1 Inference Rules, Membership Grades and Parameter Classification

The automation of the ES required that process parameters were converted into both qualitative fuzzy values and numeric membership grades for use by the inference engine and fault confidence calculations respectively. Fuzzy Logic uses ‘vague’ classifications as opposed to ‘crisp’ number sets (Zadeh 1965; Chen and Tan 1994). Traditional classification methods deal in absolute (truth) values, for example, the ‘truth’ that a set ‘X’ (consisting of the elements  $(x_1, x_2, \dots, x_n)$ ) belongs to the universal set U can be represented by Equation 6.1 (Buckley and Eslami 2002):

$$X_U(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases} \quad \text{Equation 6.1}$$

where the elements within the set of X can be mapped within the domain of [0, 1] in which a value of either 0 (not belonging to U) or 1 (belonging to U) is attributed to the element, for example this could correspond to the on/off states of a control switch. Whilst this is sufficient for classifying the state of a parameter with only two possible states, it is insufficient for classification of parameters that contain a range of values for which a number of subjective states can occur.

Membership equations were used to derive a membership grade of a monitored parameter based upon its level of membership to a qualitative class. Membership equations define the level (grade) of membership to a class or group, for example as illustrated in equation 6.2, a value of x greater than 100 has full membership to the class ‘Open’.

$$X_{OPEN}(x) = \begin{cases} 0 \rightarrow \text{if } x < 10 \\ x/10 \rightarrow \text{if } 10 \leq x \leq 99 \\ 1 \rightarrow \text{if } x > 100 \end{cases} \quad \text{Equation 6.2}$$

Equations 6.2 is shown graphically in Figure 6.3.

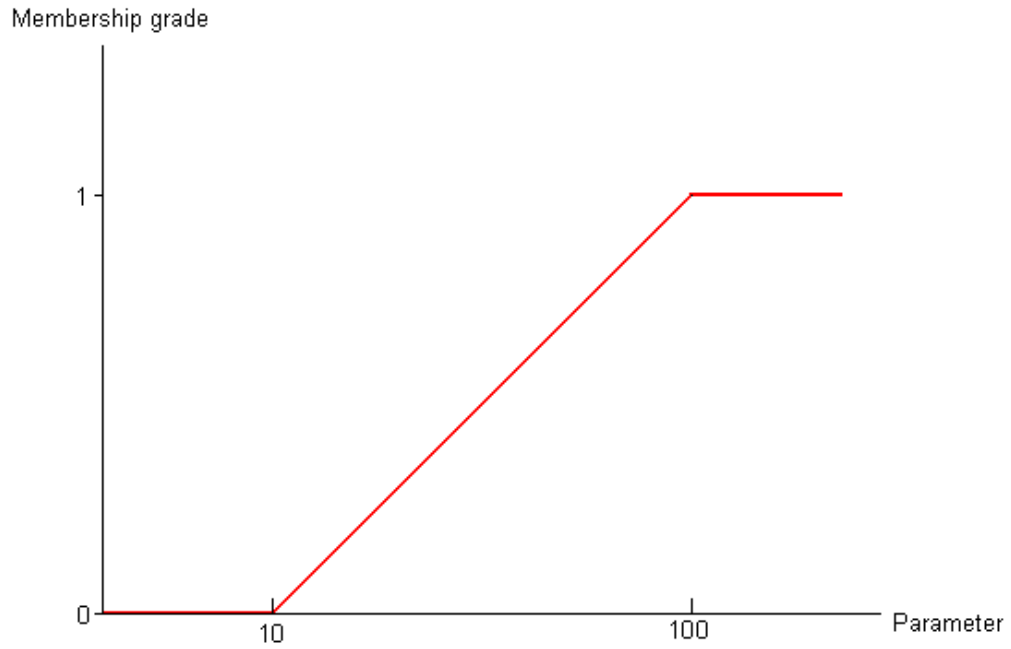


Figure 6.3 – Single class membership grade

Since the majority of parameter groups contain several classes, multiple classification boundary lines were plotted corresponding to each group, overlaps were intentionally included to prevent the alpha cuts (boundaries) from becoming discrete intervals as shown in Figure 6.4.

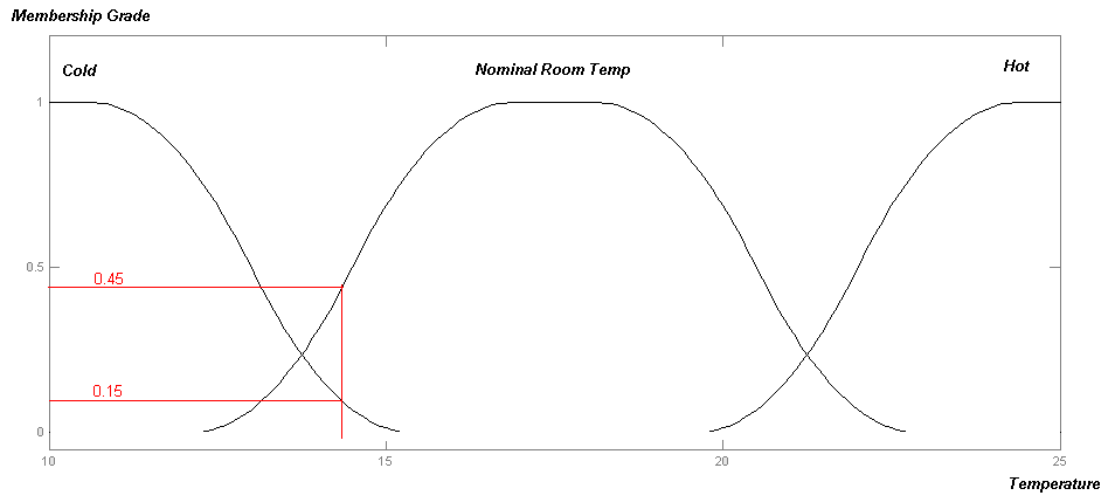


Figure 6.4 – Example room temperature fuzzy classification

Figure 6.4 illustrates that at a room temperature of 14°C the parameter has a 0.15 membership to the class ‘Cold’, and a 0.45 membership to the class ‘Nominal Room Temperature’. Overlaps in the class boundaries ensured that certain premises were not entirely disregarded if the parameter value bordered close to the upper or lower limit of a class. For example, if the temperature in Figure 6.4 was 12.5°C then with no overlaps the classification would be ‘nominal room temperature’ only dismissing the premise that the room temperature was ‘cold’.

The application of AES utilised a several selected HVAC parameters that were converted into fuzzy values and membership grades. These parameters were grouped into 3 broad classifications based upon their nominal operating range as shown in Table 6.1.

Table 6.1 – Parameter groupings

<i><b>Group</b></i>	<i><b>Parameter Information</b></i>	<i><b>Nominal Operation Range</b></i>
1	Boiler flow/return temperatures Sensor data	53 - 85 °C
2	Valve and actuator data	0 – 100%
3	Local Heating Temperature Sensor data	17 - 27 °C

The temperature based parameter values (group 1 and 3) were converted to fuzzy values and membership grades using a generalised bell shaped curve membership function with the parameters a, b and m (Equation 6.3).

$$f(x; a, b, m) = \frac{1}{1 + \left| \frac{x - m}{a} \right|^{2b}} \quad \text{Equation 6.3}$$

The values of a, b and m were amended to create the appropriate classification boundaries using the ‘gbellmf’ function in Matlab. For group 2 a trapezoidal membership function (trapmf - Matlab function) was utilised due to it providing broader peaks for each class as shown in Equation 6.4.

$$f(x; c, d, e, f) = \begin{cases} 0, & x \leq c \\ \frac{x - c}{d - c}, & c \leq x \leq d \\ 1, & d \leq x \leq e \\ \frac{f - x}{f - e}, & e \leq x \leq f \\ 0, & f \leq x \end{cases} \quad \text{Equation 6.4}$$

The parameter values for Equation 6.3 and 6.4 along with the number of Classes and Fuzzy Values are shown in Table 6.2.

Table 6.2 – Membership parameter values and fuzzy value classifications

<i>Group</i>	<i>Parameter</i>	<i>Number of Classes</i>	<i>Fuzzy Values</i>	<i>Membership Equation Parameters</i>
<i>1</i>	- Boiler Flow Temp  - Boiler Return Temp  - Radiant Flow Temp	4	Cool	$a - 8, b - 6, m - 50$
			Warm	$a - 4, b - 4, m - 62.5$
			Hot	$a - 4, b - 4, m - 72.5$
			Very Hot	$a - 8, b - 6, m - 85$
<i>2</i>	- Natural Ventilation North Facade  - Natural Ventilation South Facade  - Conference Room Radiant Panel Valve	4	Closed	$c - 0, d - 0, e - 20, f - 30$
			Mostly Closed	$c - 20, d - 30, e - 45, f - 55$
			Mostly Open	$c - 45, d - 55, e - 70, f - 80$
			Open	$c - 70, d - 80, e - 100, f - 100$
<i>3</i>	- Conference Room Radiant Temp  - Atrium Vent Temperature	3	Cool	$a - 2, b - 5, m - 17$
			Warm	$a - 2, b - 5, m - 22$
			Hot	$a - 5, b - 5, m - 27$

The conversion of data to fuzzy values was then utilised by the inference engine to analyse the state of the building against the fault rule database. External temperature and energy consumption data was omitted as the AES was built to target HVAC specific changes only, with the data driven methodology providing whole building process monitoring for independent verification of the results. In the actual application external temperature and energy consumption could be taken into consideration to further define the fault rules, however given the deterministic nature of the fault rules detailed later on in the chapter it is not required.

## 6.2 Inference Engine Architecture

The diagnosis of the HVAC systems was performed within the inference engine; the inference engine interpreted the fuzzy values to determine the state of the system. There are several ways of enabling an inference engine including semantic nets, procedural representations and production rules/frames (Giarratano and Riley 1994). For fault detection and diagnosis production rules are the most relevant method. Production rules/frames determine if an outcome has occurred if a sequence of states representing a fault is activated. For example IF Rule 1 AND Rule 2 are true THEN Fault 1 has occurred, in the case of the AES the rules described the fuzzy state of a parameter. Fault detection can be performed in two manners, the first being forward chaining. Forward chaining selects the rules and tests the fault hypothesis for any matching sequences, whilst conversely backward chaining tests each fault hypothesis and checks to see if the relevant that rules match, both systems should essentially arrive at the same conclusions (Giarratano and Riley 1994). Backward chaining has been implemented with the AES. Each fault hypothesis (referred to as fault rules and detailed in section 6.3) was evaluated using the current state of the relevant fuzzy parameter values. Hence interpreting the state of several parameters as a human expert would do to form a judgement on the health of the system.

### 6.2.1 Inference Engine Features

The AES was designed to be able to deal with incipient, intermittent and abrupt faults and failures. Additionally, through the use of a decision confidence algorithm faults with similar symptoms can be ordered by supporting evidence, the decision confidence algorithm is detailed in section 6.4.

In order to enable the fault detection features of the AES the following the fault rule array structure was created as shown in Equation 6.5.

$$F_N = \{E_1, E_2, E_3\} \quad \text{Equation 6.5}$$

$F_N$  was the  $N^{\text{th}}$  fault rule which consisted of 3 elements. The element  $E_1$  indicated to the inference engine the time required for a fault to fully propagate.  $E_1$  held the number of consecutive cycles a fault rule needed to be triggered before the fault was confirmed and reported to the end user. It should be noted that once a fault rule was triggered it was analysed by the decision confidence algorithm regardless of whether the fault has reached the full number of cycles of  $E_1$ . The element  $E_2$  was the number of clear cycles in which the fault symptoms were not triggered needed to reset  $E_1$ . This allowed for detection of slow developing (incipient) and intermittent faults to be investigated by setting  $E_2$  to a large figure. Slow developing and intermittent faults were separated by  $E_1$  values, in which intermittent faults had a smaller  $E_1$  values than incipient faults. The elements  $E_3$  contain the parameter states that constituted the fault rule,  $E_3$  was an array that contained the name of the parameters that were indicative of the fault and also contained the state those parameters would be in for that fault to have occurred.

Given the nature of fuzzy logic the value of a parameter could belong to two possible fuzzy states with their respective membership grades due to the overlap between fuzzy classes. Therefore the state of the HVAC system could also be represented by more than one state. The total number of combinations is given by  $c^r$  where  $c$  is the number of possible fuzzy states in this case 2 and  $r$  is the number of rules that possessed more than one fuzzy state. Each of the HVAC parameter states was then compared against their corresponding values in the fault rules to determine if they triggered a fault signal. The fault rules that were triggered are then analysed for the level of evidence supporting that particular fault hypothesis. For the purposes of testing the methodology 4 test cases have been developed, these test cases are detailed in the following section.

### **6.3 Automated Expert System Fault Test Cases**

To test the automated expert system methodology faults were designed that simulated abnormal behaviour in both the ventilation and heating systems. In order to develop the faults the assumption was made that the data from the BEMS was characteristic of normal HVAC operation. This provided a nominal baseline from which the parameter data was altered to create fault events. The fault events were deterministic and were primarily used to illustrate the capabilities and operating principles of the AES. The fault cases used to

test the AES are labelled here as “AES Fault Case” to differentiate from the fault test cases used in Chapter 5. The design philosophy of the faults was to test the AES at both plant and room level using differing fault profiles. Additionally, AES Fault Cases 1 and 2 had similar symptoms but different fault profiles for the purpose validating the decision confidence algorithm.

The BEMS data was analysed to determine the nominal states of the HVAC parameters. The relationship between the HVAC parameters under various conditions was identified; this information was then used to alter the data for each fault event. The BEMS data for the month of May was selected for alteration.

AES Fault Cases 1 and 2 introduced a fault with the heating system. It was initially envisaged that there would be further heating fault events using the parameters monitoring the central atrium. However, there was no easily identifiable correlation between the parameters. Given that not all the parameters were logged by the BEMS there was the possibility one of the unlogged parameters held the connecting relationship between the parameters. Hence, for AES Fault Cases 1 and 2 the boiler flow and return temperatures as well as the radiant flow temperature was reduced in an incipient manner for fault 1 and an intermittent manner for fault 2.

AES Fault Case 3 was identical to fault test case three used in chapter 5 in which there was a problem with the radiant panel valve for the multi-conference room. The fault symptoms were identical, thus the valve position set was to 0 and the radiant temperature reduced to 10°C.

AES Fault Case 4 relates to a motor actuator failure for the automatic windows in the atrium chimney. The data was altered to reflect a slow degradation in the window actuators ability to fully open. For AES Fault Case 4 the value of  $E_2$  was set to a large number (150) as the use of the atrium chimney windows for ventilation in the month of May only occurs for three periods with the rest of the time remaining closed.

Fault rules were then developed that described these fault events for fault detection and diagnosis purposes. Table 6.3 details the faults rules their characteristics, each numbered fault rule corresponds to the fault number described above.

Table 6.3 – Expert system fault rules

<i>Fault Rule</i>	<i>HVAC System</i>	<i>Fault</i>	<i>Fault Profile</i>	<i>E<sub>1</sub></i>	<i>E<sub>2</sub></i>	<i>E<sub>3</sub></i>
F <sub>1</sub>	Heating	Reduced output from Boiler(s)	Slow developing	20	5	Boiler Flow Temp = WARM Boiler Return Temp = WARM Radiant Heating Flow Temp =COOL
F <sub>2</sub>	Heating	Intermittent drops in boiler output	Intermittent	10	40	Boiler Flow Temp = WARM Boiler Return Temp =WARM Radiant Heating Flow Temp = COOL
F <sub>3</sub>	Heating (distribution)	Valve stuck / control sensor issue	Abrupt	4	4	Conference Radiant Valve = CLOSED Conference Radiant Temperature = COOL
F <sub>4</sub>	Ventilation	Slow actuator failure for south side Facade	Slow developing / Intermittent	20	150	Natural Ventilation North Facade =CLOSED Natural Ventilation South Facade =CLOSED Max Vent Atrium Space Temp = HOT

The  $E_1$  and  $E_2$  numbers displayed in Table 6.3 are tailored to describe different fault profiles. For example, in AES Fault Case 1, an incipient fault is accounted for by keeping a large  $E_1$  value (number of consecutive cycles before the fault is confirmed) and a small  $E_2$  value. Thus, a persistent slow developing fault can be differentiated from other faults with differing fault profiles such as intermittent faults which require large  $E_2$  values to avoid the fault rule being disregarded.

Whilst there were other parameters available for use, the parameters listed in Table 6.2 provided sufficient information to analyse the introduced faults with adequate depth for proof of concept testing.

## 6.4 Decision Confidence

In order to determine the confidence of the output from the AES, a confidence algorithm was incorporated into the system. This was also used for differentiating between 2 faults with similar fault symptoms by selecting the fault that had the greatest amount of supporting evidence. The decision confidence algorithm was based upon Equation 6.6

$$DC = \frac{\sum_{i=1}^G MB_G}{G} * \frac{FC}{E_1} \quad \text{Equation 6.6}$$

where  $G$  is the number of parameters that make up the fault rule in  $E_3$ ,  $MB$  is the membership grade of each parameter. The Fault Counter (FC) counted the consecutive number of times a fault rule was triggered. FC was capped to a maximum value of  $E_1$ . Essentially, Equation 6.6 derived the average membership grade value for all the parameters that had matched their counterparts in the fault rule. The fault counter was used to differentiate between long term and intermittent faults and to confirm abrupt faults quickly. A DC value of 1 may not always be obtained even after a fault is confirmed as the parameters do not necessarily need to have full membership to a fuzzy class to trigger the fault rule.

## 6.5 Data Fusion

A method of data fusion was investigated to combine the outputs from the data driven and expert system methodologies. In the data driven system the number of incoming samples belonging to a fault classification cluster could be used as a measure of confidence. Combining the two methods could be done relatively simply using Equation 6.7.

$$OUT_{Conf} = 0.5 * DC + 0.5 * CC \quad \text{Equation 6.7}$$

where  $OUT_{Conf}$  is the total confidence of the output, and  $CC$  is classification confidence of the data driven system.  $CC$  is given by Equation 6.8.

$$CC = \frac{C_s}{T_s} \quad \text{Equation 6.8}$$

where  $C_s$  is the number of samples attributed to a fault cluster and  $T_s$  is the total number of samples used. For example, if the data driven system revealed that the latest incoming samples had 70% ( $CC$  equal to 0.7) of the observations closest to fault 3 and the AES revealed that  $DC$  was equal 0.8 for fault 3 then the total confidence output would be equal to 0.75. Given the deterministic nature of the fault cases the results of Equation 6.7 would be predetermined, furthermore the AES and data driven systems only shared one common fault case (fault 3) thus the data fusion method was not applied.

# CHAPTER 7

## 7. Performance Evaluation: Results and Discussion

The results for the real time evaluation method and the data driven CM system are presented here. The months of February and May were selected as they provided a suitable difference in external temperature to test the robustness of the CM systems.

### 7.1 Real Time Energy Evaluation

The real time energy evaluation methodology detailed in section 5.1 utilised the DTM BCR values to compare the actual energy consumption against the Part L based design consumption. This section presents the results and discussion of this methodology with two cases, section 7.1.1 evaluates the original BEMS data without amendments to the off peak load and 7.1.2 evaluates the BEMS data where the HVAC off peak hours were adjusted to emulate the HVAC being switched off during unoccupied periods. The output from both cases was then further assessed taking into account the impact of adverse external temperatures resulting in additional energy consumption.

#### 7.1.1 Case 1 – Original BEMS Data

The daily consumption levels are shown in Figure 7.1 for February. The simulated BCR shows good correlation during the occupied periods and significant dissimilarity during the weekend and evening periods comparable to that of the May consumption graph shown in chapter 5.

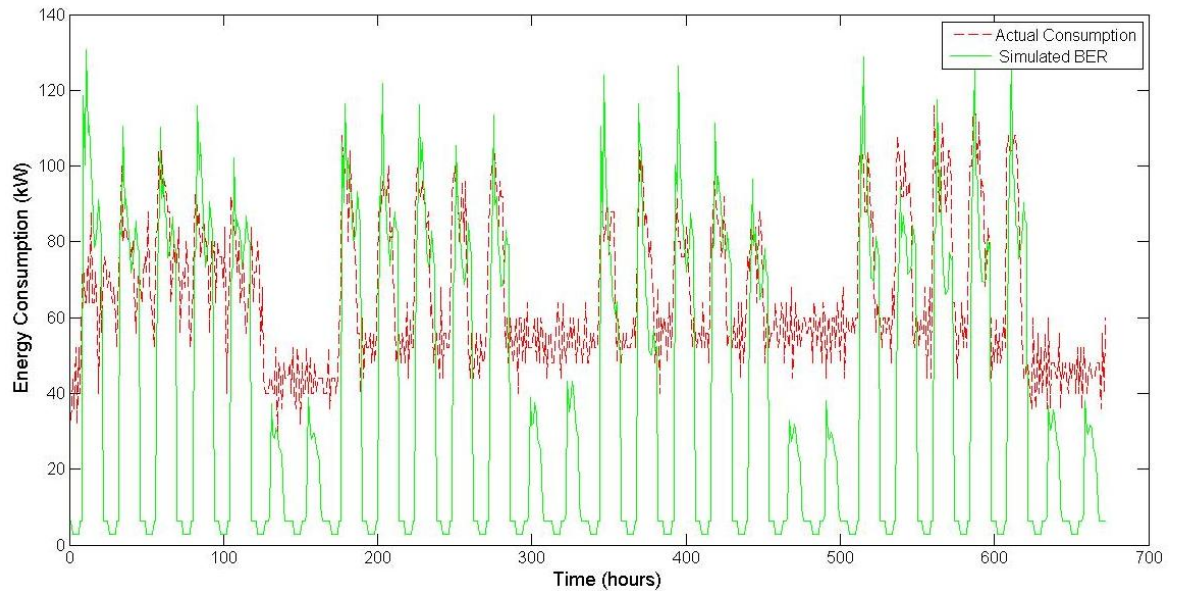


Figure 7.1 – February daily energy consumption comparison

As a result of the difference in off peak consumption the energy performance indicator (EPI 2) rated the energy performance of the building as being in the ‘very poor’ rating band and far greater than that of the TCR. Figure 7.2 shows the dynamic performance indicator.

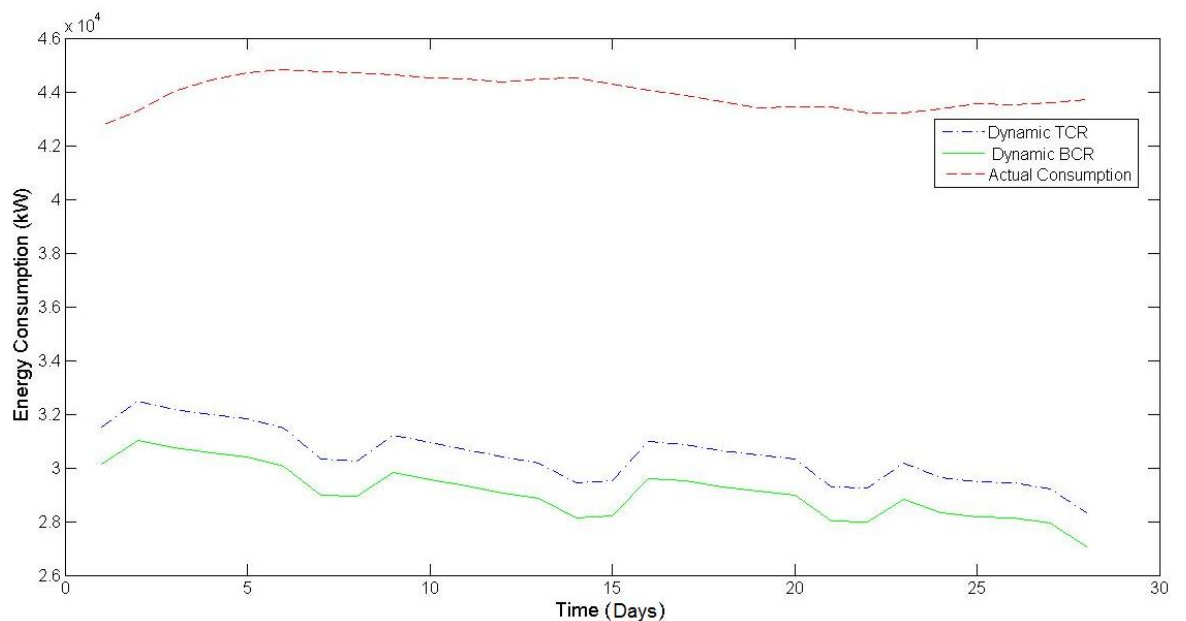


Figure 7.2 – Dynamic energy consumption evaluation for February

As can be seen from Figure 7.2 the actual consumption is significantly higher than both the dynamic TCR and BCR. Comparison of the actual energy consumption against the TCR/BCR for May can be seen in Figure 5.3. Figure 5.3 displayed similar off peak HVAC consumption properties as February. Thus the energy consumption for the month of May was also higher than the TCR for the majority of the time as shown Figure 7.3.

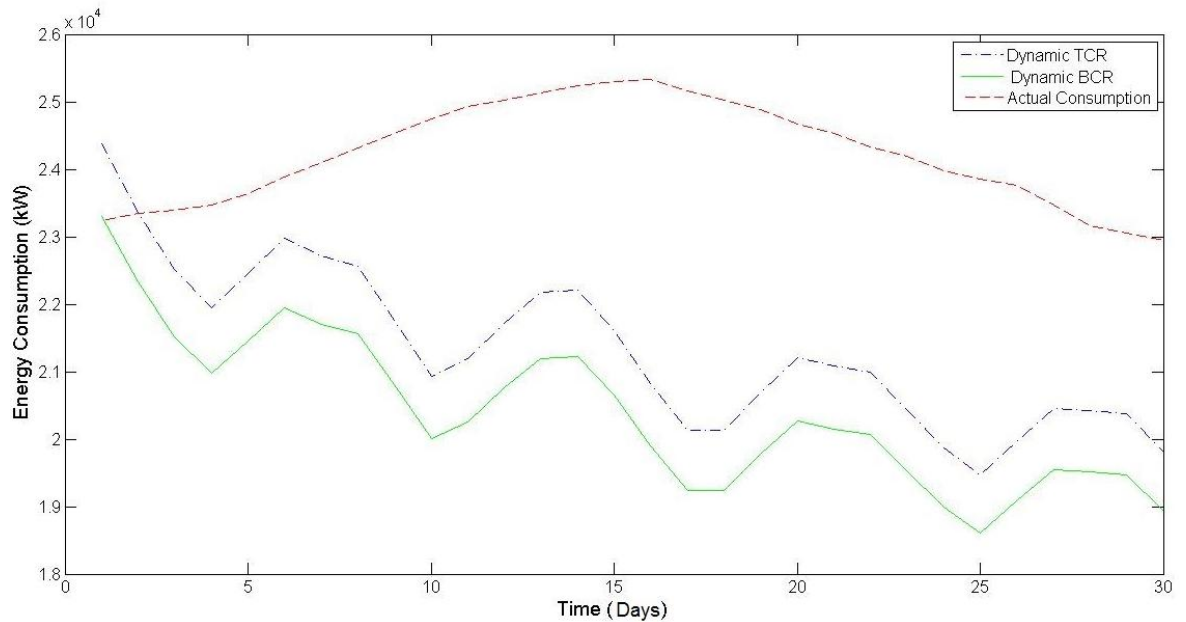


Figure 7.3 – Dynamic energy consumption evaluation for May

For both months the significantly higher energy consumption is attributable to the HVAC consumption. The first two days of the May evaluation show the building achieving a lower consumption rate than the TCR; this is mainly due to the better energy performance of the building in April. The previous months performance has a strong influence on the evaluation given that the past 28 days consumption is used to calculate the actual consumption rate. The distance between the actual consumption and the TCR is also much smaller when compared to February. In addition to April's performance this can be attributed to the lower off peak consumption, approximately 30kW compared to 40kW for February.

### 7.1.2 Case 2 – Adjusted off peak BEMS Data

The off peak load was set to a flat rate of 15kW this is approximately half the value of the peaks calculated by the DTM during the weekend. The assumption was made that the building was operating nominally during these periods and the high HVAC consumption detailed in the previous section was a result of poor BEMS configuration that was remedied. The same adjustments were applied to the previous months (January and April) for balanced evaluation of the energy consumption. This adjustment alters the perception of the building performance significantly, which was seen to be in better alignment with the DTM consumption as shown in Figure 7.4 for the February consumption.

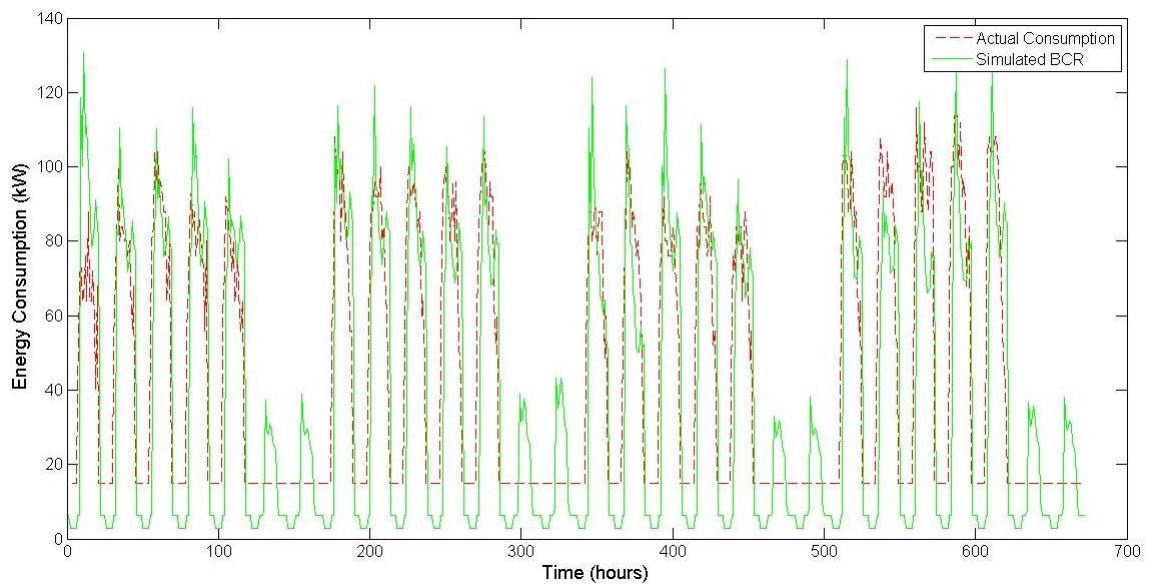


Figure 7.4 – February daily consumption with base load removed

As a result of the adjustments the building performance was found to be far better than the case 1 results as would be expected. Figure 7.5 shows the dynamic energy evaluation for February with adjusted off peak consumption.

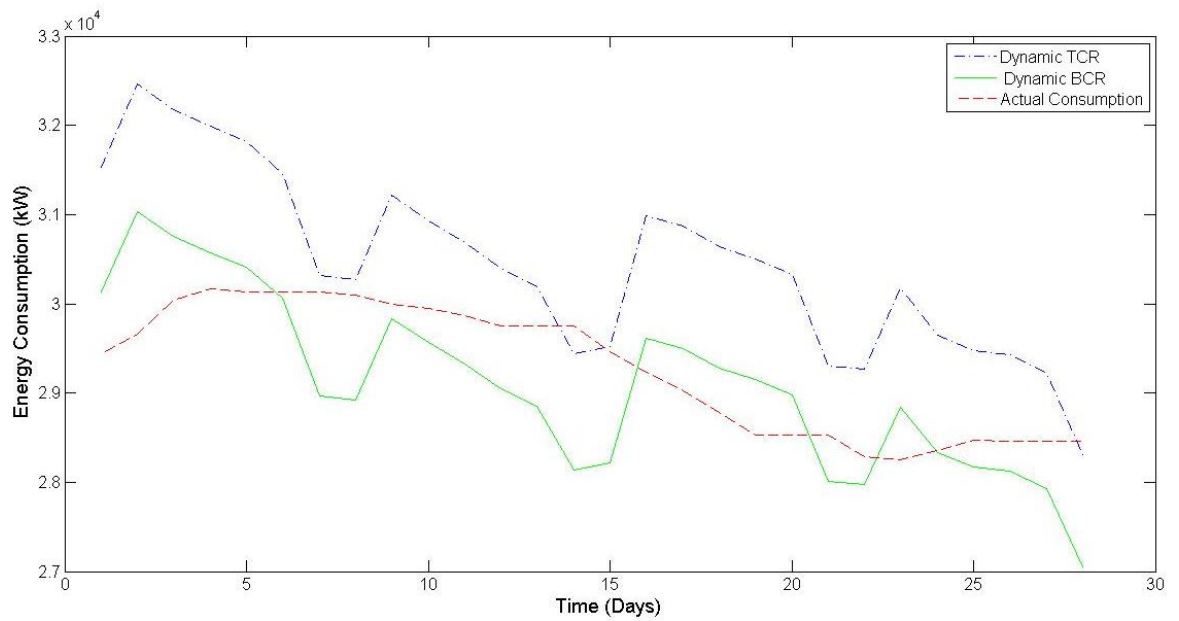


Figure 7.5 – Adjusted dynamic energy consumption evaluation for February

Figure 7.5 displays a range of performance ratings in which the building was seen to have a ‘Good’ or ‘Very Good’ performance for the majority of the time. A single data point in which the actual performance is greater than the dynamic TCR is observed on Day 14. However, it would be acceptable to assume that this is an anomalous reading given that the performance of the building returns to improved levels later on. Persistent failure to achieve a lower consumption than the TCR would provide a stronger indication that the building health is not acceptable and that action must be taken to remedy the root causes of poor performance. For the month of May the simulated BCR is compared with the adjusted BEMS data in Figure 7.6

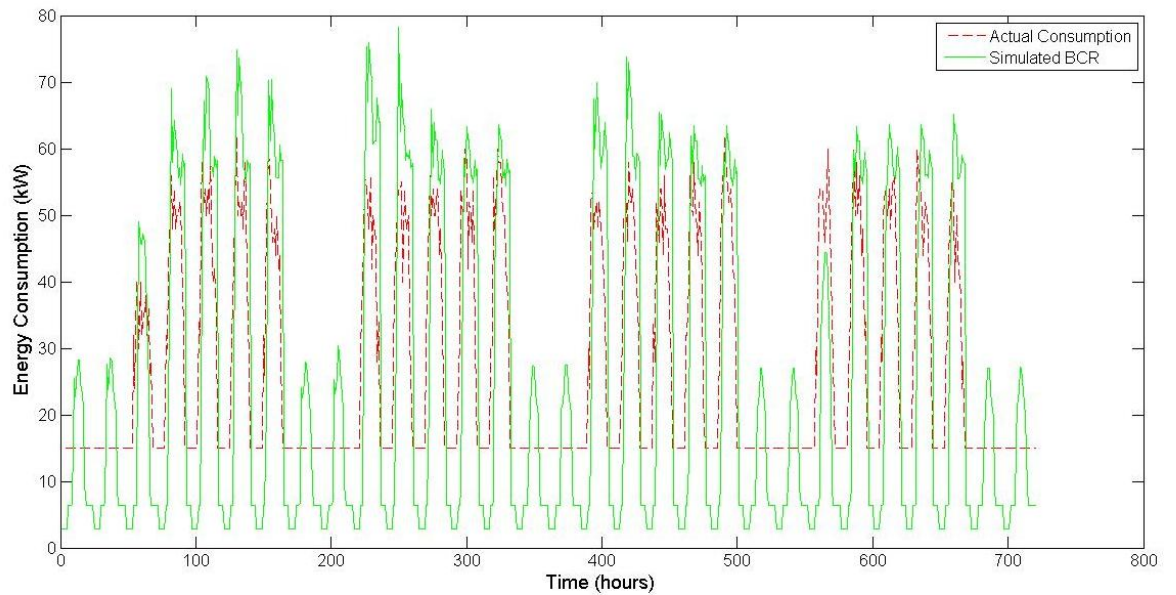


Figure 7.6 – Adjusted consumption profile for May

The adjusted data results in a better performance for the building consumption against the dynamic target as shown in Figure 7.7.

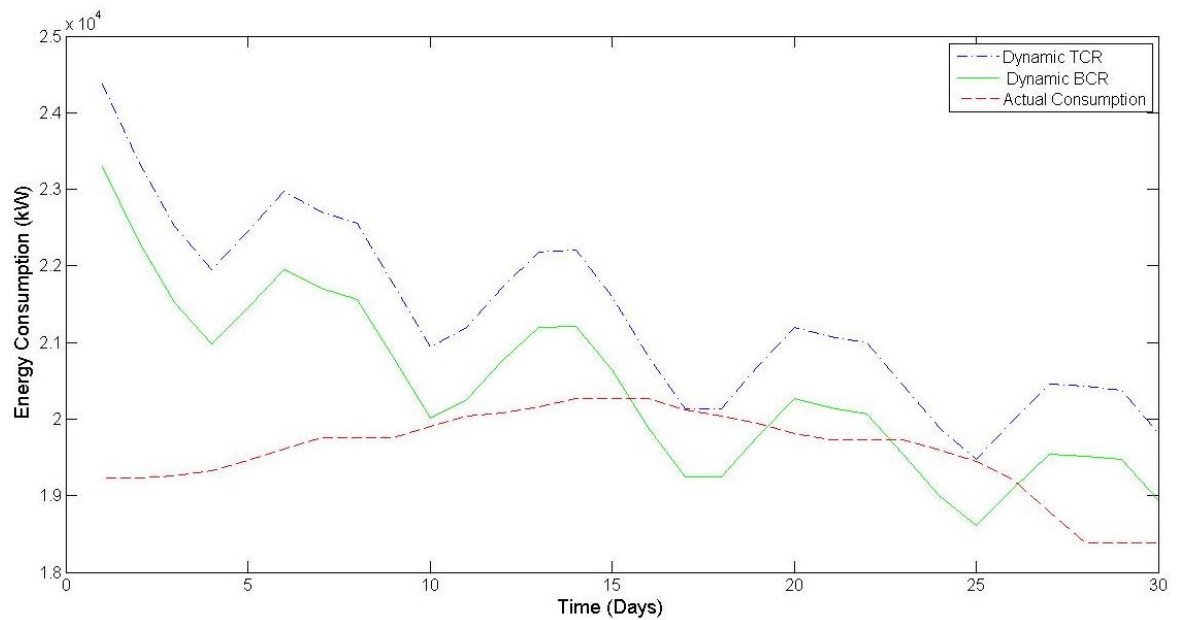


Figure 7.7 – Adjusted dynamic energy consumption evaluation for May

As with the unadjusted case, the month of May performs more favourably than that of February. To account for increased energy consumption due to adverse external temperatures degree day analysis was performed, which is detailed in the following section.

### 7.1.3 Degree Day Adjustment

The adjustment for external temperatures conditions was only applied for additional heating loads with the base temperature for heating degree days set at  $15.5^{\circ}\text{C}$ . As can be seen in Figure 7.8 the actual temperatures measured at the building weather station indicated that the external temperature for February was significantly colder than that of the CIBSE weather file utilised by the DTM.

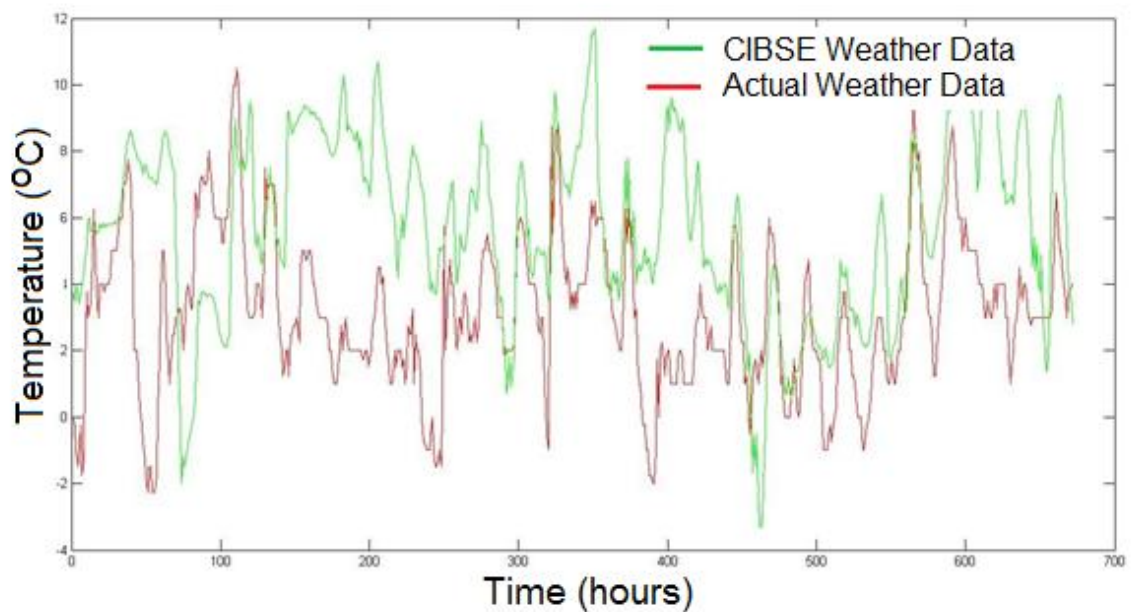


Figure 7.8 – CIBSE and actual weather data comparison

A plot of the energy consumption against the heating degree days is shown in Figure 7.9 from which a relationship between the daily energy consumption and external temperature is obtained by regression. The external temperatures recorded for use in the heating degree analysis did not include the temperatures for weekend and unoccupied periods.

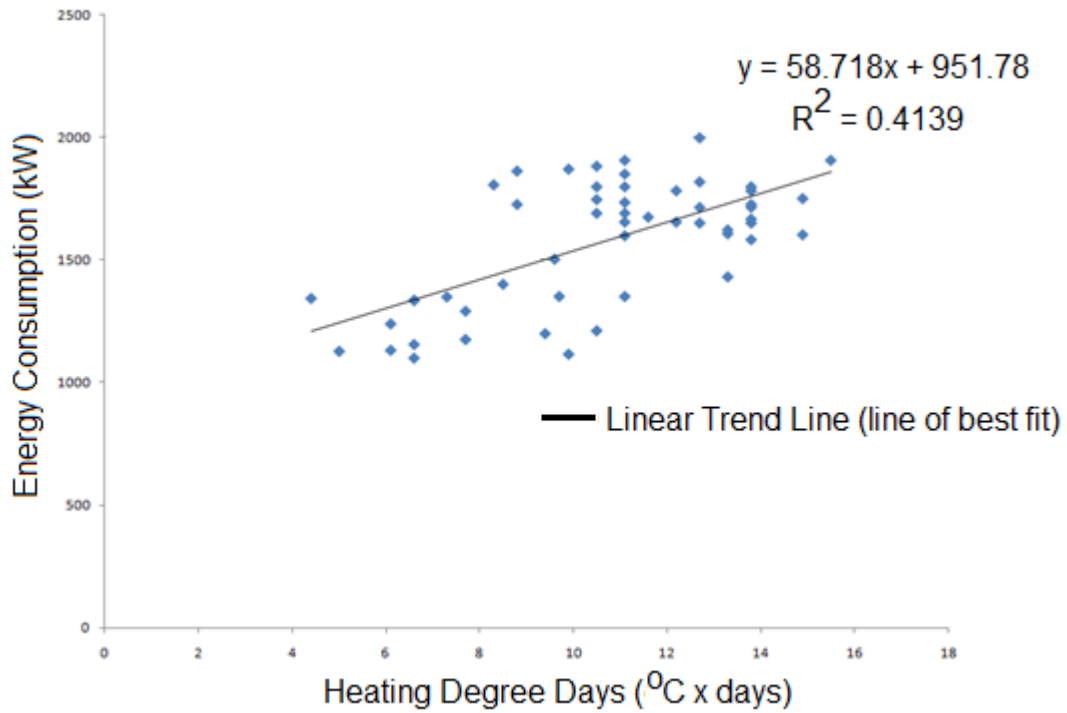


Figure 7.9 – Heating degree days regression analysis

Figure 7.9 shows the correlation ( $R^2$ ) between the two parameters is relatively weak with an  $R^2$  value of 0.413. However, the general trend line does concur with the BEMS data that the cumulative baseload energy consumption is approximately 950kW per day. A point to declare is that 2 outlier data points were removed as they distorted the trend line disproportionately. Whilst using heating degree days can provide a means of linking energy consumption and external temperature it would be inaccurate to assume a linear relationship applies. Furthermore, the heating system was not individually sub-metered hence the total energy consumption was used to evaluate how the building as a whole responded to temperature changes. As was detailed previously heating degree days do not take into account non-temperature related changes in energy consumption. As a result of these factors and the weak correlation a reduction weighting of 0.413 was applied to any additional energy allocation to avoid the TCR becoming too lenient. Thus Equation 7.1 gives the final relationship (which includes the removal of the baseload):

$$AddEnrg = 58.72 * HDD * 0.413 \quad \text{Equation 7.1}$$

where AddEnrg is the additional energy allotment and HDD is the heating degree day.

#### 7.1.4 Final evaluation output

Application of the heating degree day adjustments were made to the original BEMS data, the results of which are shown in Figures 7.10 and 7.11.

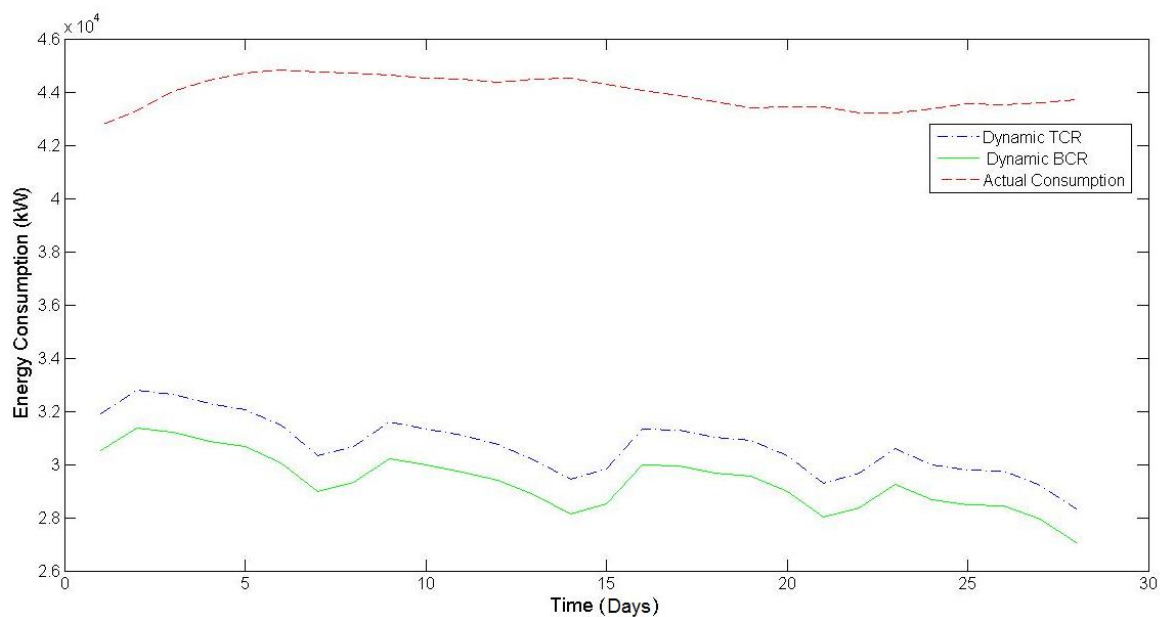


Figure 7.10 – Weather adjusted evaluation for February

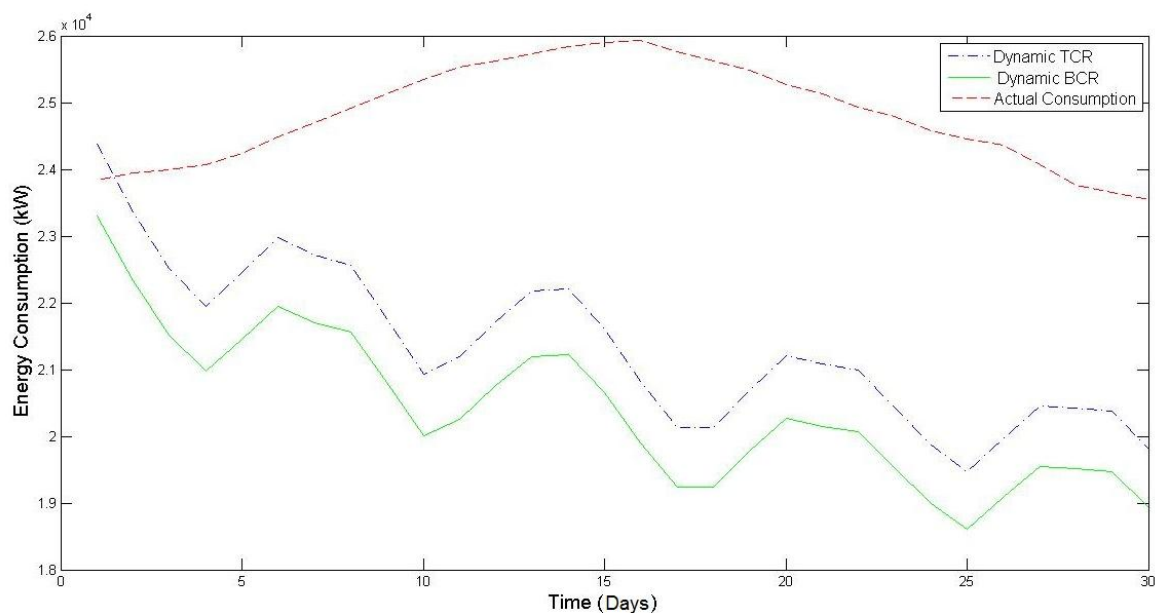


Figure 7.11 – Weather adjusted evaluation for May

Whilst there is a slight reduction (the dynamic TCR and BCR trend lines are shifted up) in the distance between the actual consumption and the TCR in both cases the actual

consumption still remained significantly higher. This was as a result of the higher off peak consumption offsetting any additional energy allocated via the heating degree day adjustments. For the second case in which the adjustments to the off peak consumption were made a visible shift occurs in building performance when comparing figures 7.5 and 7.7 to the final evaluation trend-lines shown figures 7.12 and 7.13 respectively.

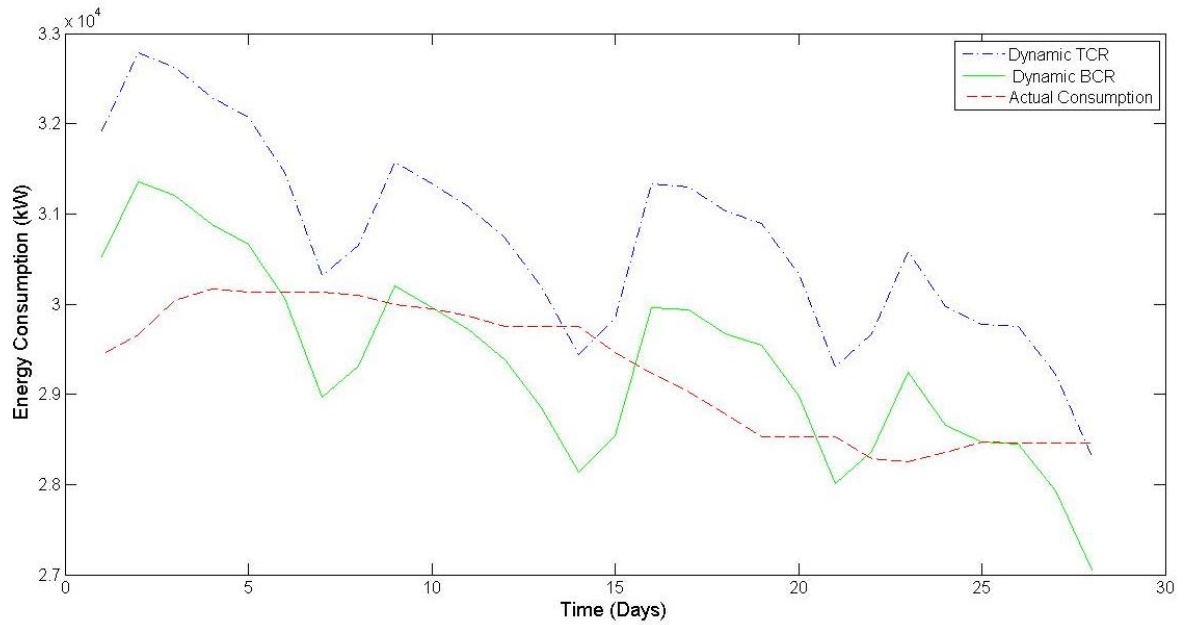


Figure 7.12 – Weather and data adjusted evaluation for February

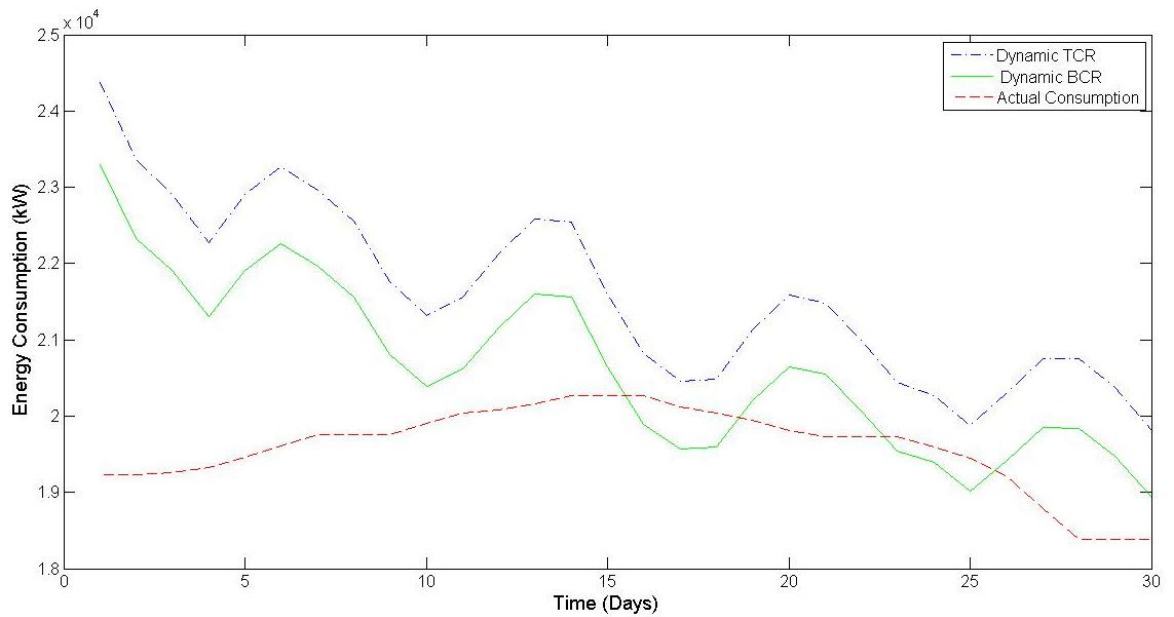


Figure 7.13 – Weather and data adjusted evaluation for May

The heating degree day adjustments resulted in the building having a better rating for a greater number of days. Given that non-occupied periods are not adjusted for heating degree days these points remained static thus for day 14 on the February graph the actual consumption still exceeds both the dynamic BCR and TCR. Whilst the evaluation graphs are useful for monitoring the trends a qualitative output would be of greater value to the end user. In order to do this Energy Performance Indicator 2 (EPI2) values were plotted against time, the graph was segregated with the boundaries of each rating classification. Figures 7.14 and 7.15 illustrate the EPI2 output for the months of February and May respectively. The EPI2 graphs for the unadjusted data were omitted from this section as they simply showed that the building was operating poorly for the majority of the time.

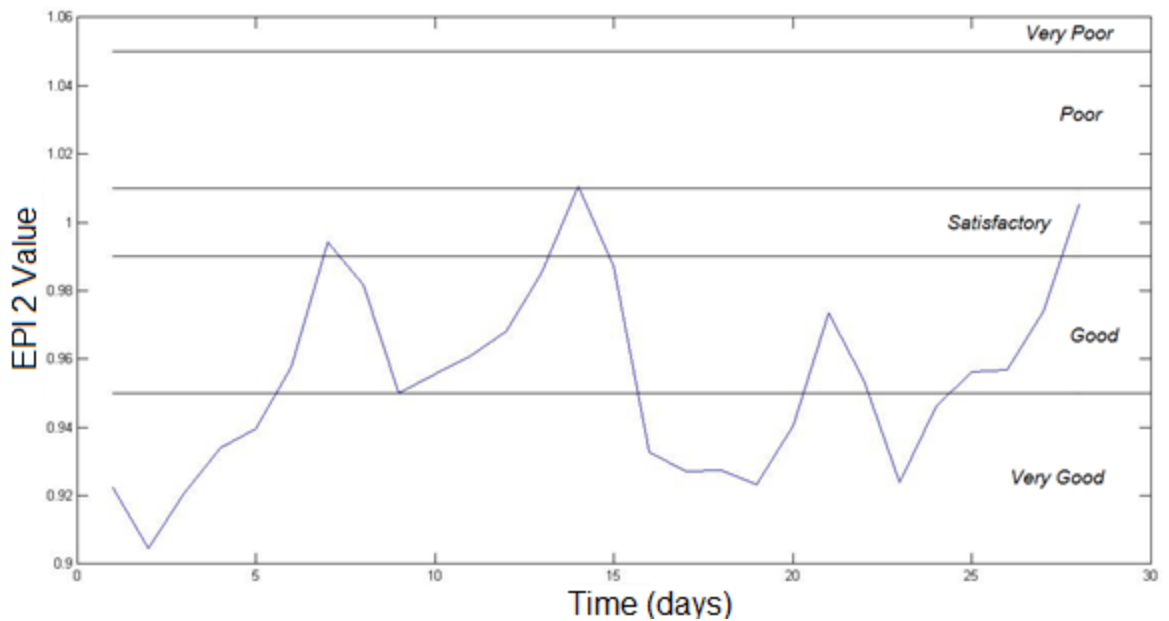


Figure 7.14 – EPI2 plot for February (adjusted off peak load and weather)

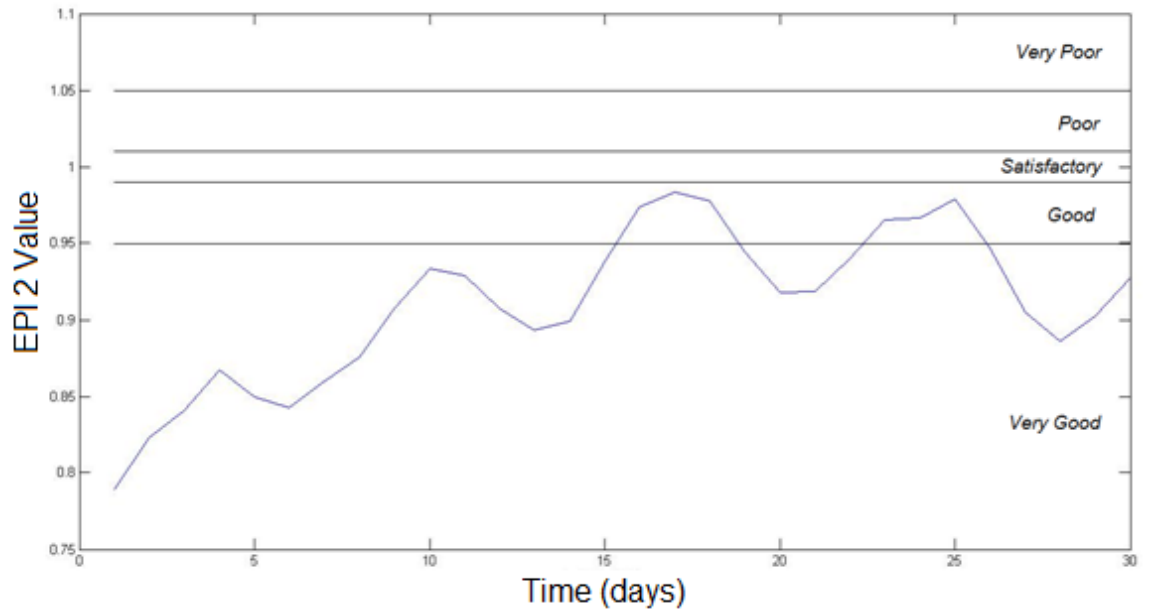


Figure 7.15 – EPI2 plot for May (adjusted off peak load and weather)

The output from the evaluation methodology as shown in figures 7.14 and 7.15 have the potential to be integrated into a BEMS providing the facilities management with a clear indication of the performance of the building on a daily basis. Removal of the weekends would provide a method of reviewing the performance of the previous 28 days of operation and the potential to extrapolate possible future consumption. For example, if the energy performance was slowly degrading (trending upwards) this methodology would deliver feedback to the end user who could then take action to ensure that energy efficiency is improved upon to avoid a negative change in the buildings rating. Conversely, improvements in the energy consumption would be clearly distinguishable in terms of affect on performance promoting a virtuous cycle of continuous improvement. The use of colour coding for each classification band would provide a dynamic alternative to the DEC that could be displayed on screen.

The real time evaluation approach could potentially be integrated within any BEMS system given that all processor intensive phases are completed prior to integration into the BEMS. The DTM calculation of the dynamic BCR and TCR need only be performed once and stored on the BEMS database, therefore only requiring adjustments for adverse weather conditions to be made. Given that many BEMSs are programmable for flexibility and that external temperatures are now routinely logged it would be a relatively simple task to

seamlessly integrate into the calculation of the daily EPIs into any BEMS. However, there are limitations to the system in that additional holidays or unoccupied periods that are not covered by the occupancy profile in the DTM would require adjustment as they would unfairly provide greater performance rating than was achieved. The variations in occupancy prevent the system from becoming fully automated and would require time and effort from the end user to regularly check and update the occupancy frequencies. Furthermore, changes to the HVAC or building construction would require re-calculation of the DTM output.

## **7.2 CM Building Evaluation**

This section first presents the initial findings from the traditional application of PCA for process monitoring highlighting the weaknesses of PCA when applied to non-linear data. The nonlinear methodology results are then given in which the fault test cases were used to test the ability of the nonlinear method to detect and diagnose faults. In order to keep the results manageable the months of February and May are presented using the day time data only.

### **7.2.1 Traditional PCA method**

Initially, the traditional method of PCA was applied to the DTM data to investigate the effectiveness of PCA for state evaluation of the building. The aim of which was to establish two key features about the ability of PCA, firstly to ascertain how well PCA was able to model the nonlinearities within the data and secondly to determine the number of principal components needed to capture over 90% of the variance. The DTM data was used for illustrative purposes as the correlations between the ‘fault’ points (points that breached the  $T^2$  and SPE thresholds) and the variance of the parameters was easier to observe. The data was segregated by occupied and unoccupied time periods as per the methodology detailed in chapter 5. The energy consumption and weather energy data were stacked into the occupied training data matrix. The traditional method of PCA was then applied. A visualisation of the T-score plots for the training data was obtained for the month of February. In order to capture over 90% of the variance the first 4 Principal Components

were needed. For illustration purposes the 3D and 2D plots are shown selecting the first 3 principal components in Figure 7.16 and the first 2 principal components in Figure 7.17.

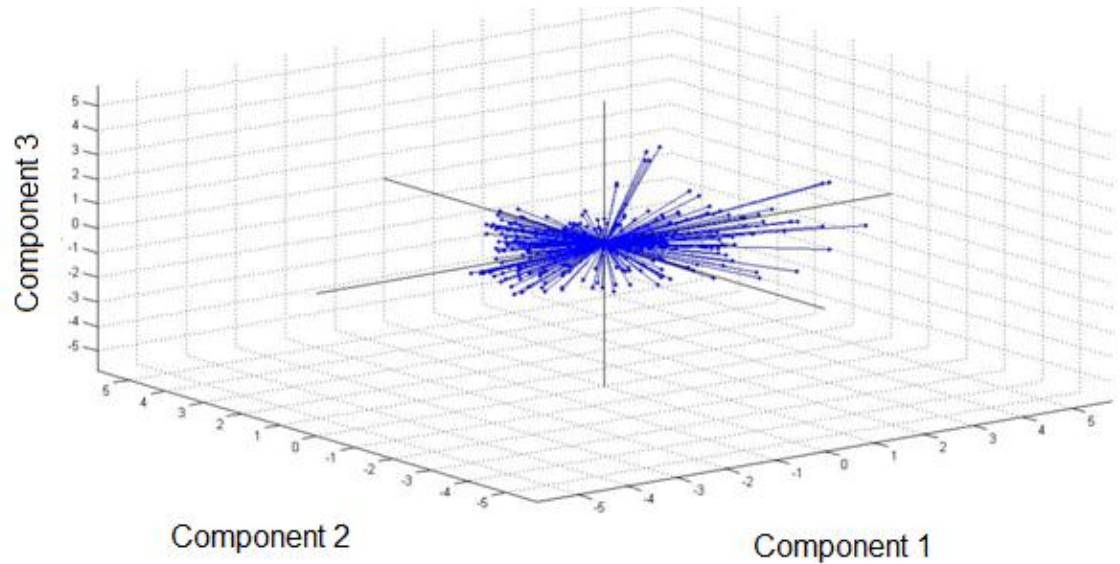


Figure 7.16 – 3 Principal Components for DTM February data

The scatter points of the T scores shown in Figure 7.16 represented the PCA model for the nominal operation of the building. The  $T^2$  threshold defines an elliptical boundary, points within this boundary are considered to be ‘in-control’. There is a wide level of scatter from the mean-centre displayed within the first 3 principal components. This is more clearly observable in Figure 7.17 which plots the first two principal components.

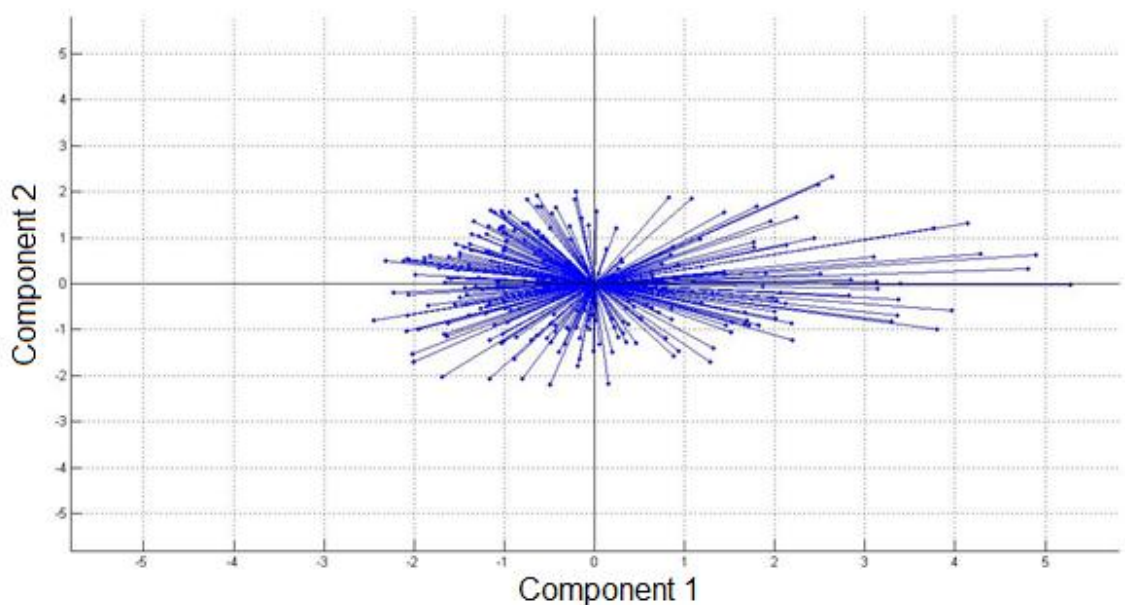


Figure 7.17 – 2 Principal Components for DTM February data

The lack of T score clustering was problematic as it demonstrated less variance captured along the main principal component axis. A PCA representation of process that contained low captured variance would lead to difficulties in differentiating between nominal operating data and data that represented a faulty state of operation. The  $T^2$  and SPE values were then obtained and plotted against the process data. A plot of the process parameters against the occurrences where the  $T^2$  and SPE limits were breached is shown in Figure 7.18.

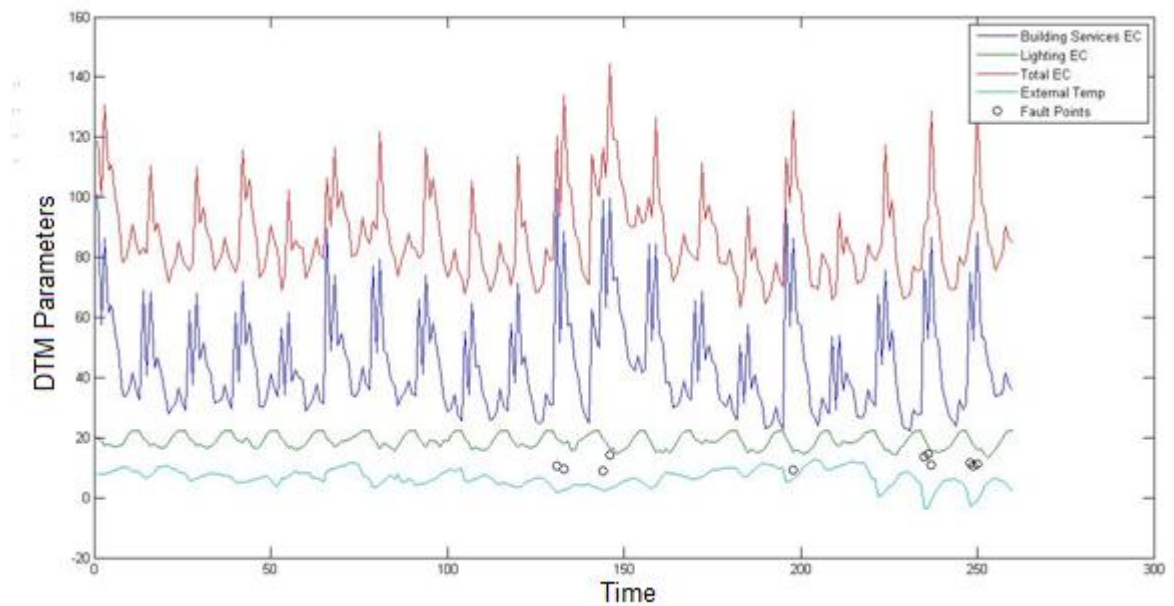


Figure 7.18 – Process variance PCA Fault Points

Figure 7.18 shows that the majority of the fault points occur when the variations in energy consumption do not move proportionally or linearly with the external temperature. Increasing the Alpha confidence value would expand the confidence region; however this would potentially lead to a greater number of missed faults leading to issues with sensitivity. Furthermore, it does not overcome the problem of the inability of PCA to model nonlinearities. The key values used in the computation are shown in Table 7.1 along with the number of false alarms (threshold breaches).

Table 7.1 – PCA data for day time segregation

<i>Month</i>	<i>PCA Parameter</i>	<i>Value</i>
February	Alpha confidence	95%
	Sample size	260
	Number of Principal components (to capture 90% variance)	4
	Threshold breaches	11
May	Alpha confidence	95%
	Sample size	296
	Number of Principal components (to capture 90% variance)	4
	Threshold breaches	6

The inability of the traditional PCA method to represent nonlinear processes made it unsuitable for capturing the process state of building operation. In addition to this, the need for a high number of principal components to capture the nominal variance was a significant disadvantage. Non-linear methods of PCA were then employed to overcome these issues and the results of which are presented in the next section.

### 7.2.2 Kernel PCA

In order to create a KPCA representation of the building a suitable kernel function had to be selected. The kernel functions tested were linear, Gaussian and Polynomial. The selection criterion of the kernel was that it needed to capture at least 90% of the variance within the first 3 (preferably 2) principal components and that the projections of the data on the lower dimension space should display clustering along the first principal axes. The reduction of scatter and the ability of KPCA to model the nonlinearities were crucial to creating an effective means of modelling the building state.

### 7.2.2.1 Kernel Evaluation

Implementation of the Linear, Gaussian and Polynomial kernel functions all adequately mapped nonlinearity of the data thus the projected T-scores were able capture a high proportion of variability within the first principal component alone. The T-score plots within this section are for the month of February using the occupied training matrix data. The 3D plot of three principal components for the Gaussian kernel is shown Figure 7.19.

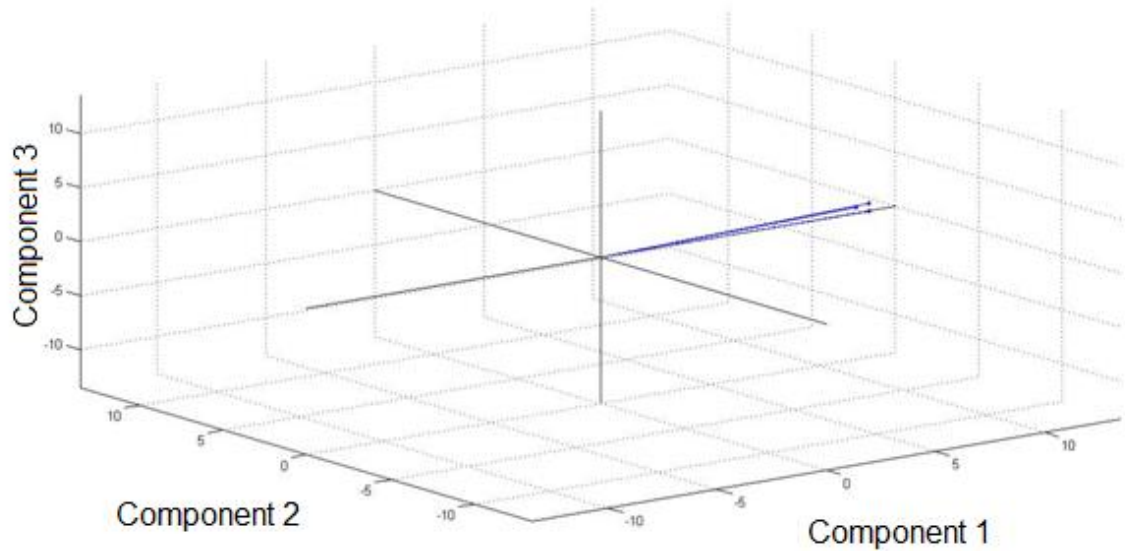


Figure 7.19 – Gaussian kernel process representation – 3 principal components

As can be seen in Figure 7.19 the T-scores are predominantly located along the first principal component, the T-scores are also packed into a far tighter packed cluster. Given that all three kernels displayed favourable clustering of the T-scores in the first two principal components, the second and third components were also analysed to determine the level of clustering within the lower principal axes. Figure 7.20 shows the Gaussian kernel T score plots for the 2<sup>nd</sup> and 3<sup>rd</sup> principal components.

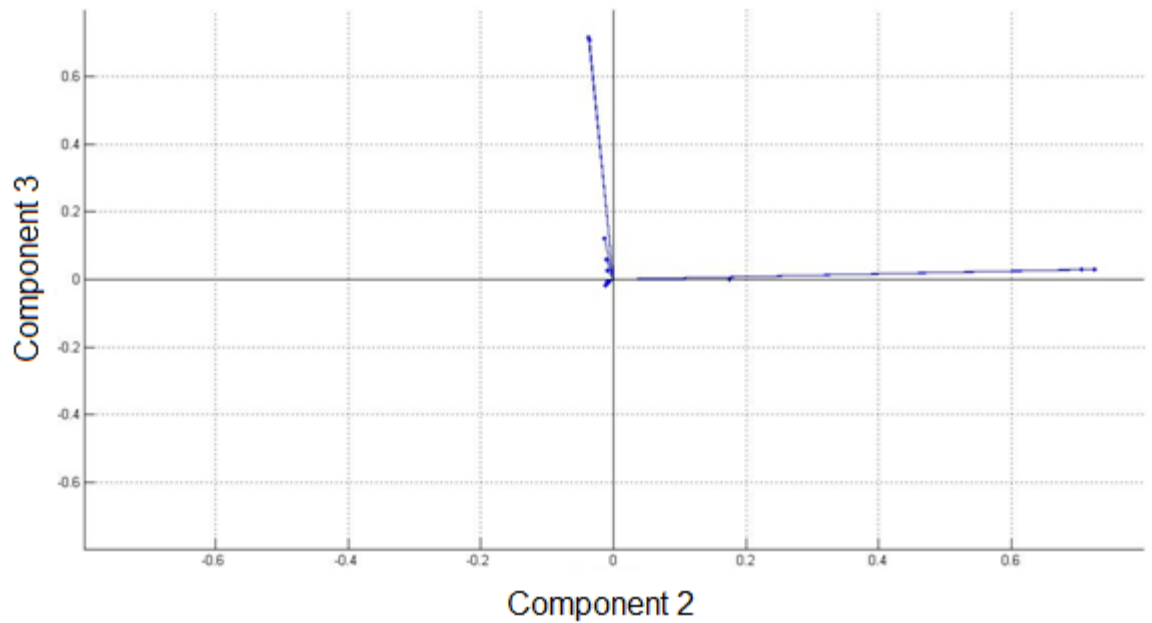


Figure 7.20 – Gaussian kernel process representation – 2<sup>nd</sup> and 3<sup>rd</sup> principal components

Whilst it may appear that there is significant clustering shown in Figure 7.20 where the axes meet, the two points located further away from the main cluster region obscure the separation of the T scores located at the centre. A 3<sup>rd</sup> order polynomial kernel function was then tested. The first and second principal components for the polynomial kernel representation are shown in Figure 7.21.

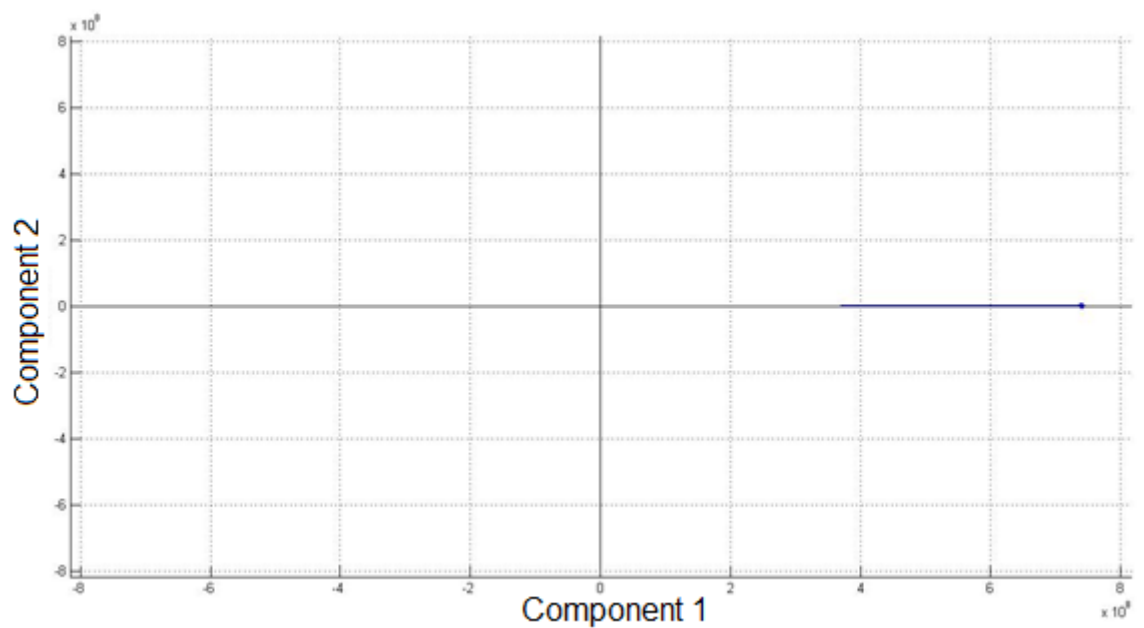


Figure 7.21 – Polynomial kernel 1<sup>st</sup> and 2<sup>nd</sup> principal components

Figure 7.21 shows slightly better clustering than the Gaussian T scores and similarly strong levels of variance captured along the first principal component. The scatter for the 2<sup>nd</sup> and 3<sup>rd</sup> principal components is shown in Figure 7.22.

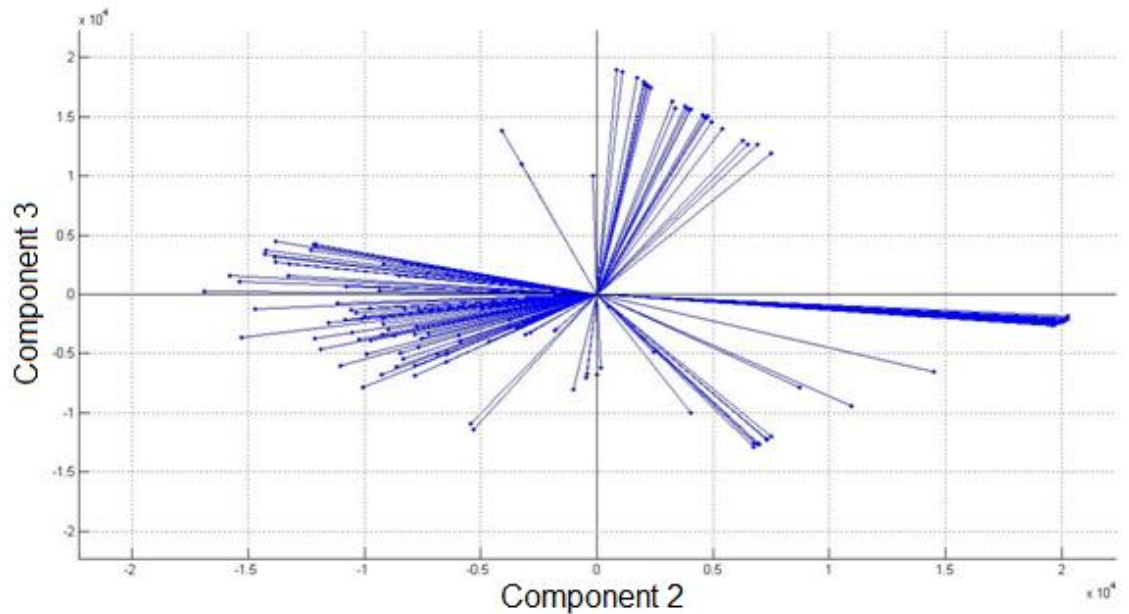


Figure 7.22 – Polynomial kernel 2<sup>nd</sup> and 3<sup>rd</sup> principal components

In Figure 7.22 there are 3 main clusters of the T scores all within a closer distance to each other than the Gaussian kernel. However, there are several smaller secondary clusters and in between and a moderate amount of scatter. The linear kernel function produced a similar T-score plot to the polynomial kernel for the 1<sup>st</sup> and 2<sup>nd</sup> principal components which was nearly identical to Figure 7.21 only differing on the scale of the axes. The 2<sup>nd</sup> and 3<sup>rd</sup> Principal component plots for the linear kernel displayed two main clusters and are shown in the following section. Table 7.2 summarises the variance capturing properties of the kernel functions.

Table 7.2 – Kernel function variance captured

Kernel	Variance captured		
	PC 1	PC2	PC3
Linear	99.9997	99.9999	100.0000
Gaussian	99.9913	99.9957	100.0000
Polynomial (3 <sup>rd</sup> order)	99.9994	99.9998	100.0000

Whilst all three kernels were able to adequately capture the variance within the data, the linear kernel function had significantly less scatter between clusters on the 2<sup>nd</sup> and 3<sup>rd</sup> principal components and was therefore selected as the kernel function for the KPCA methodology. The following section shows the KPCA representations of the case study building using the linear kernel.

### 7.2.3 KPCA Process Representation and $T^2$

The linear kernel function representation of the building process for the 2<sup>nd</sup> and 3<sup>rd</sup> Principal components is shown in Figure 7.23 for February. Whilst there is scatter present there are two main clusters of data in which the majority of T – scores can be associated with.

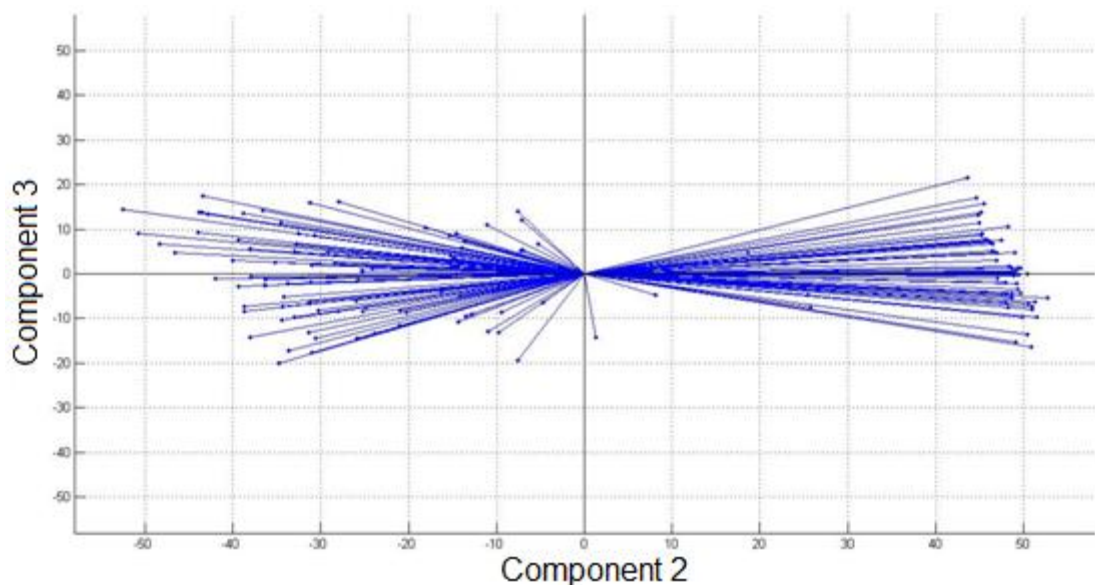


Figure 7.23 – Linear kernel 2<sup>nd</sup> and 3<sup>rd</sup> principal components (February)

The T-scores shown Figure 7.23 was assumed to be representative of the nominal state of the building. To determine whether the  $T^2$  limit threshold required adjusting, the  $T^2$  values for the nominal case were calculated. The  $T^2$  limit for February was 6.1524. Figure 7.24 shows the  $T^2$  plot for February.

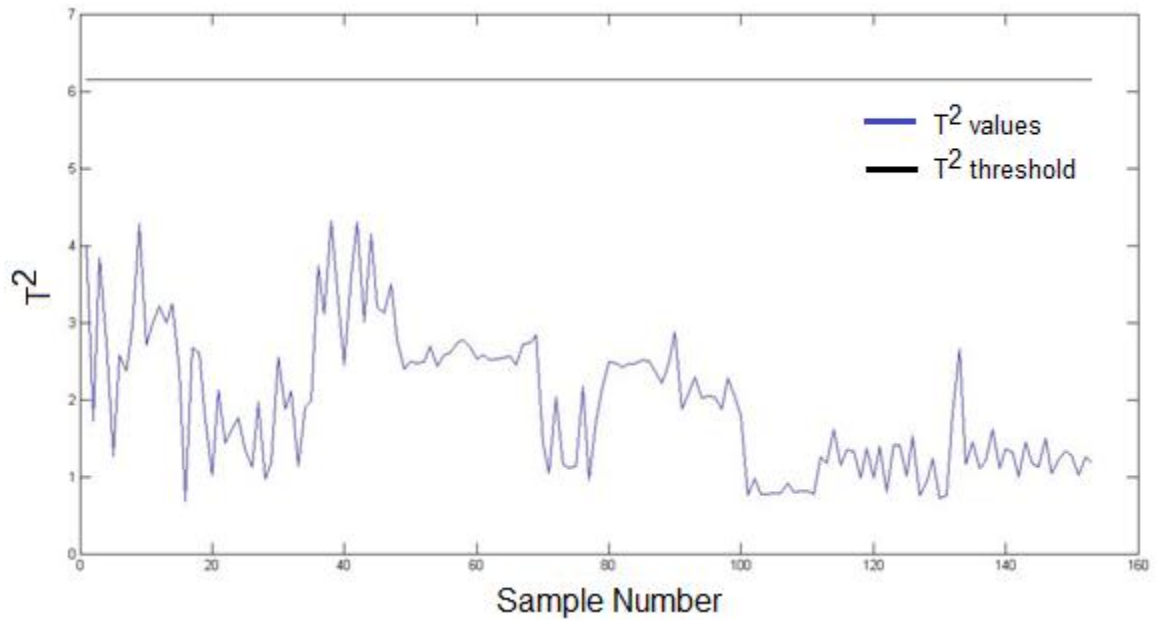


Figure 7.24 –  $T^2$  Threshold plot for February (nominal case)

In Figure 7.24 there are no threshold breaches signifying that the current threshold was adequate albeit significantly higher than necessary. The identical process was performed for the month of May. Figure 7.25 shows the 2<sup>nd</sup> and 3<sup>rd</sup> principal component T-score plot for the occupied training matrix for May.

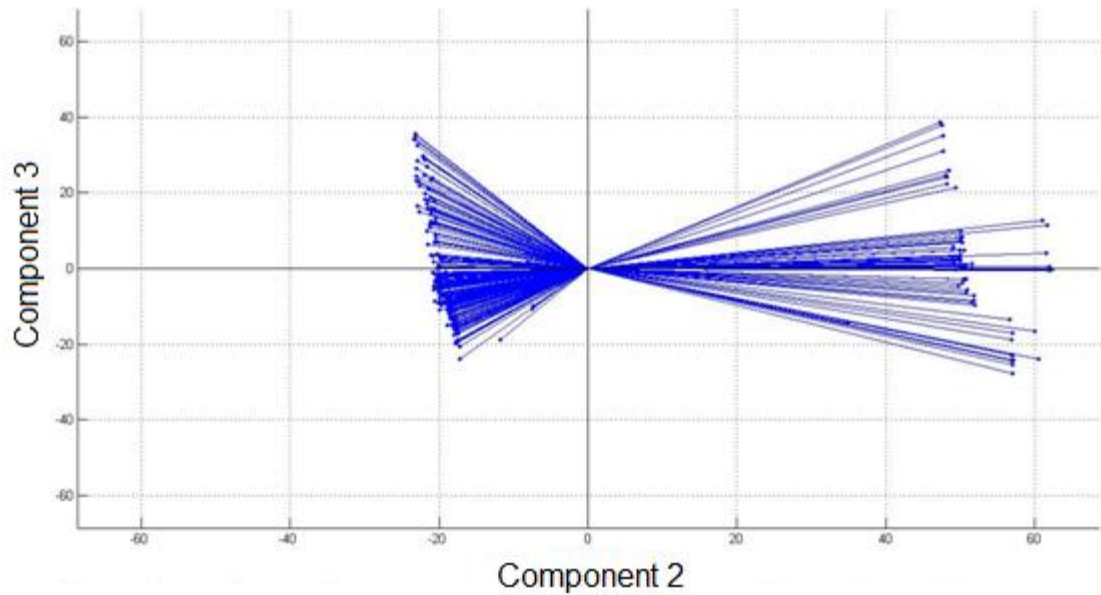


Figure 7.25 – Linear kernel 2<sup>nd</sup> and 3<sup>rd</sup> principal components (May)

Figure 7.25 shows a similar clustering pattern to the February T-score plot. Although for the May data a greater number of the T scores are located closer to the two main clusters giving reduced scatter between clusters. The  $T^2$  threshold for May was 6.1138. Figure 7.26 shows the  $T^2$  plot for the nominal operating data.

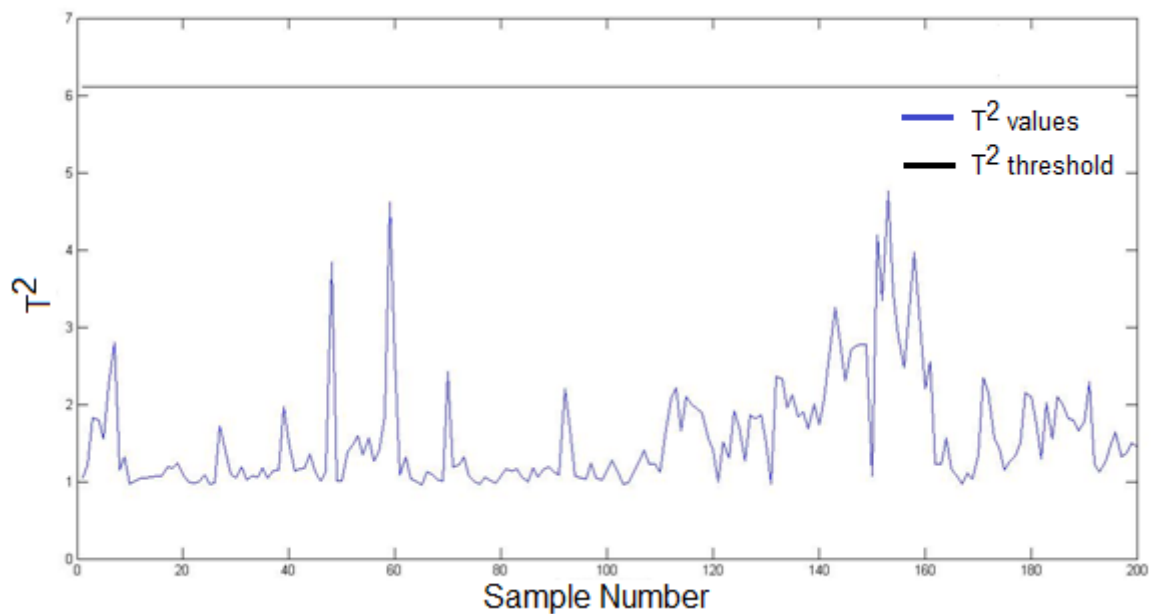


Figure 7.26 –  $T^2$  Threshold plot for May (nominal case)

The  $T^2$  values fall all below the threshold limit, thus the alpha confidence region was kept at 95%.

#### 7.2.4 Fault Detection

The fault cases described in Chapter 5 contain a varied number of fault profiles; test case 1 & 2 varied the energy consumption of the HVAC and total energy consumption in several ways. A flat rate increase in consumption was used to represent a 10% degradation in the heating and ventilation HVAC efficiencies. These flat rate changes produced similar  $T^2$  plots with only variations in magnitude for the  $T^2$  value. Figure 7.27 shows the  $T^2$  plot for test case 1 with the 4.5% change in energy consumption representing a 10% degradation in the heating efficiency.

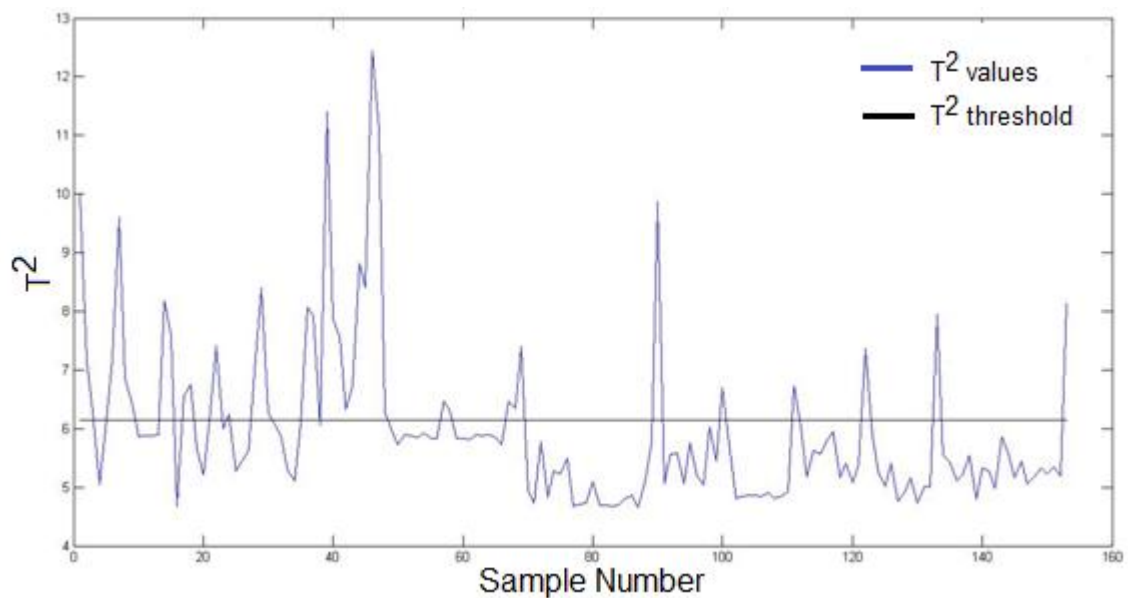


Figure 7.27 – Fault case 1  $T^2$  plot (10% degradation in heating efficiency)

In Figure 7.27 a significant number of threshold breaches occur within the first 50  $T$  score samples. The nominal data encompasses a range of operating variances captured by the KPCA, the  $T^2$  plot for the nominal data shows certain peaks such as the one at approximately sample 10 for the February  $T^2$  graph. This  $T$  score represented one of the normal variances that the case study building experiences but is closer to the threshold than the other  $T^2$  values and therefore and further changes that occur at this condition (such as the fault cases) leads to quicker threshold breaches. Instantaneous detection is possible by

lowering the threshold to a point just above the highest peak, leading to any changes instantaneously breaching the threshold. In order to do so it would require that the training data is comprehensive in that it contained all known acceptable variances. In reality this can rarely be achieved for a complex system with unknown variables such as external temperature and varied occupancy. However, in the case of the February  $T^2$  limit, the detection rate would benefit greatly from a reduction to approximately 4.5. A  $T^2$  limit of 4.5 is the minimum value needed to pass the nominal case and produce a stronger detection rate. Changing the threshold limit to this value would be valid but care would need to be taken to ensure that a well developed nominal and fault database was built and tested before applying such changes. For the purposes of illustrating the KPCA and  $T^2$  fault detection abilities for different fault profiles the threshold limit has been kept to the original value as changing the threshold limit would achieve a near 100% detection rate for all test cases with the exception of fault case 2. However in test case 2 the detection rate would be significantly improved.

Figure 7.28 illustrates the  $T^2$  values for fault case 2 in which the 10% degradation in ventilation efficiency results in 0.55% change in energy consumption.

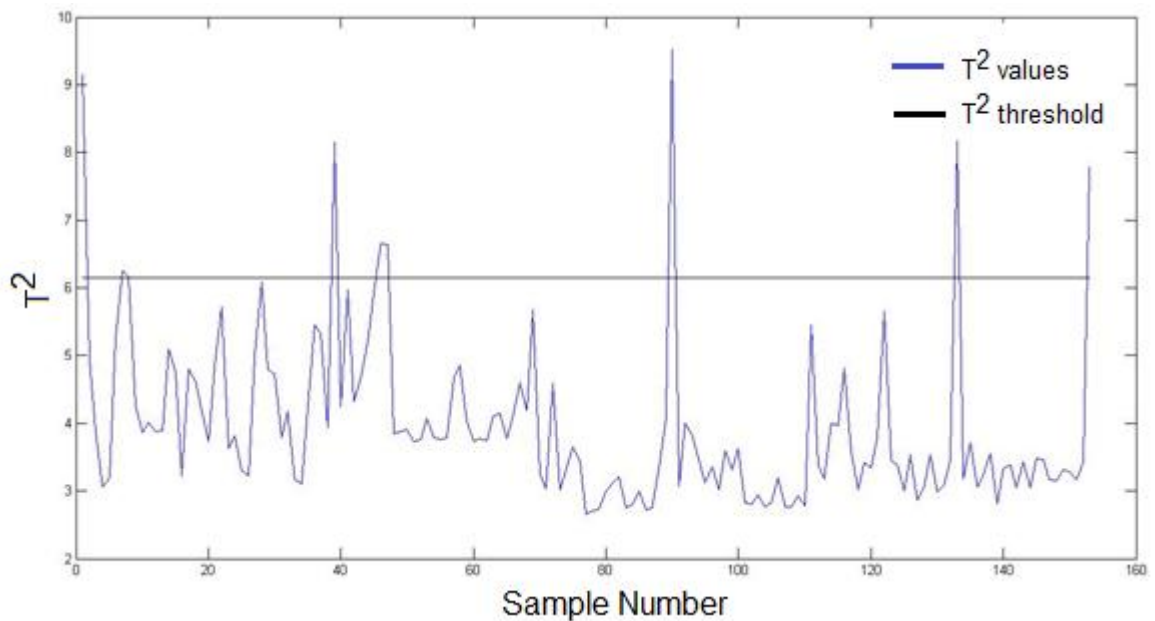


Figure 7.28 – Fault case 2  $T^2$  plot (10% degradation in ventilation efficiency)

Figure 7.28 shows a similar upwards translation of the  $T^2$  values from the nominal case; however fewer peaks breach the threshold limit. Hence in this case a poorer detection rate

is observed under the original threshold. However, unlike CUSUM/EWMA charts smaller changes to the process data were still detectable using the same threshold limit.

Test 1 also used a linear and a parabolic increase in energy consumption representing a linear degradation in the heating efficiency from 0% at the start of the month to 15% at the end of the month. Figures 7.29 and 7.30 show the  $T^2$  chart for the linear and parabolic degradation to the heating system efficiency.

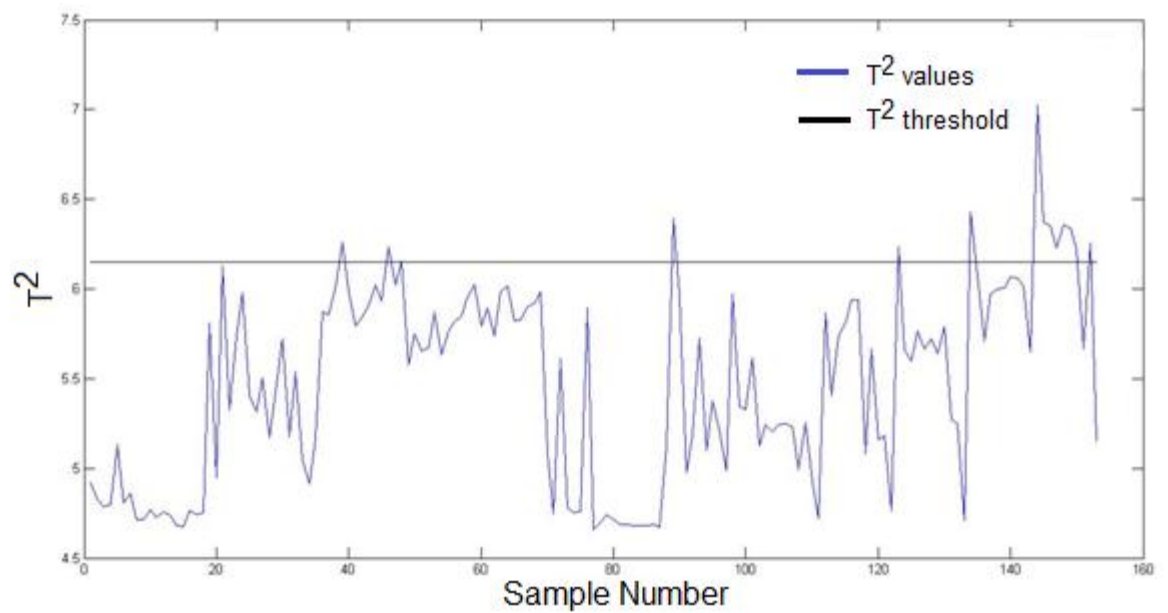


Figure 7.29 – Fault case 1  $T^2$  plot (Linear degradation)

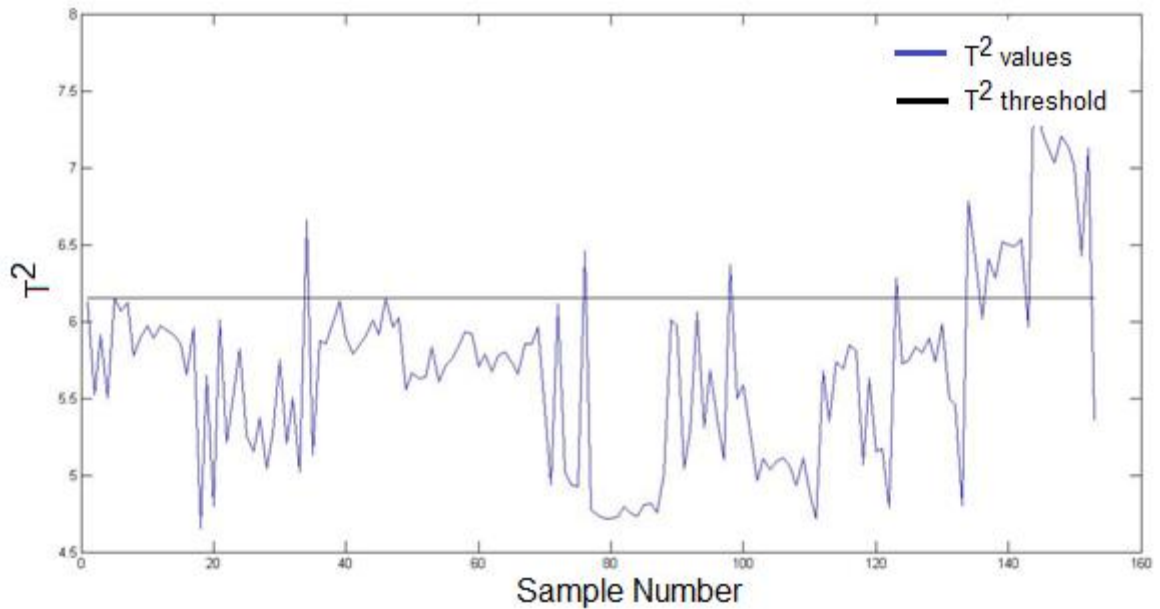


Figure 7.30 – Fault Case 1  $T^2$  plot (Parabolic degradation)

The linear and parabolic test cases show similar patterns in that the fault is only detected when there is sufficient change in the energy consumption from the nominal operating conditions to breach the threshold. Detection of the parabolic deviations was more apparent than for the linear case towards the end of the month. As was stated previously, the conditions at which the fault changes were applied had an influencing effect on whether the  $T^2$  value resulted in crossing the threshold boundary or not. Whilst this may appear to infer that the fault detection system is only effective for certain operating conditions, the boundary change discussed previously would have been effective for detecting all the faults presented. Furthermore, with greater levels of training data fine tuning this boundary would have less associated risk of false or missed detections.

Fault test 3 introduced a step change in the process parameter in which 4 parameters deviate from the nominal case. Figure 7.31 shows the  $T^2$  plot for Fault test 3. The changes to the process data occurred at sample 40.

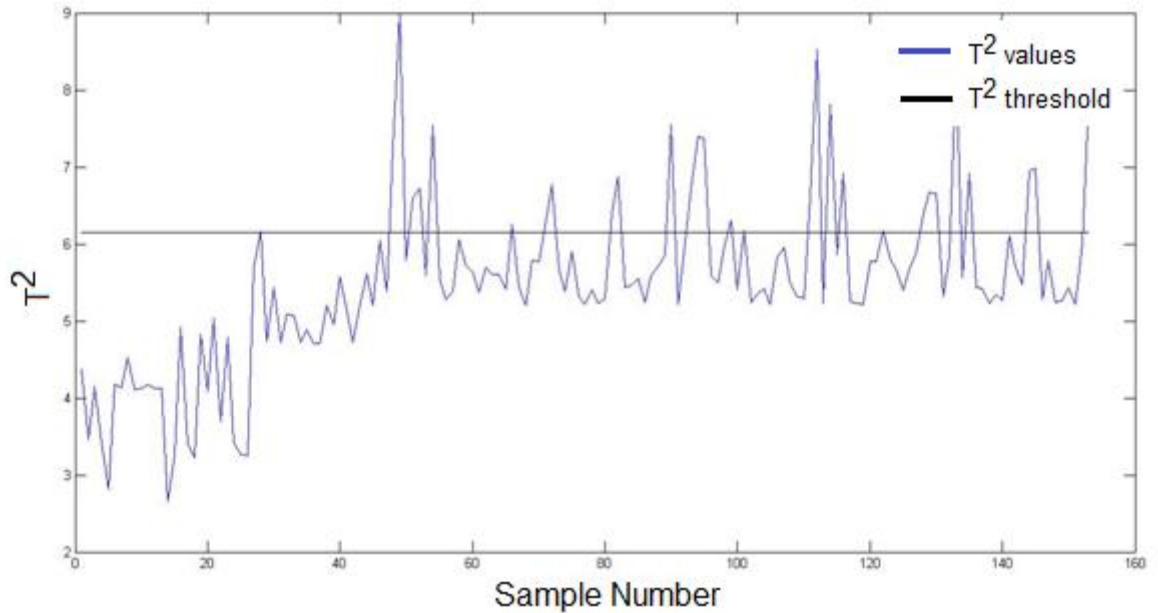


Figure 7.31 – Fault case 3  $T^2$  plot

Figure 7.31 shows a step increase in the  $T^2$  values occurring from sample point 40 at which the parameters were changed to emulate the fault of a stuck valve in the multi-conference room. A far better detection rate is observed in step changes than for slower developing faults as would be expected in any FDD methodology. Furthermore, the sudden step change away from the nominal operating range is exhibited by a continuously high  $T^2$  value. Step changes are statistically independent to the nominal variance thus lead to a greater increase in the  $T^2$  plot.

The KPCA methodology was proficient in detecting incipient and abrupt faults that had significant parameter changes applied. However, for intermittent faults the system did not perform as well comparatively. Figures 7.32 and 7.33 show the  $T^2$  plots for fault case 4 & 5.

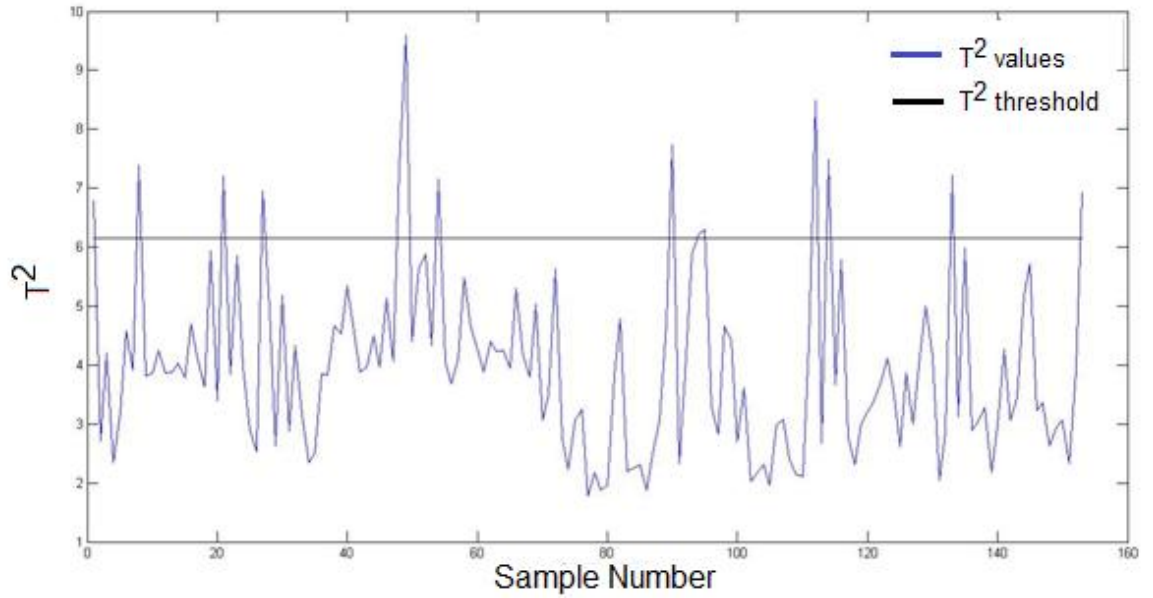


Figure 7.32 – Fault case 4  $T^2$  plot

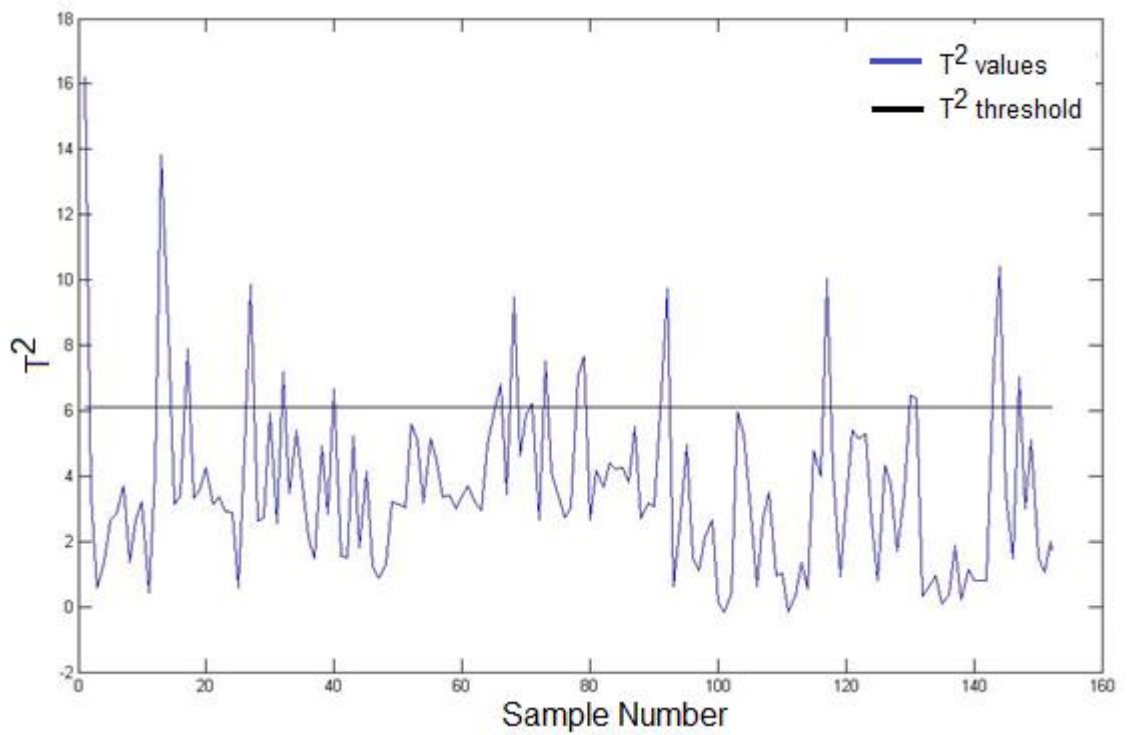


Figure 7.33 – Fault case 5  $T^2$  plot

As can be seen in Figures 7.32 and 7.33 a similar occurrence to test 2 (Figure 7.28) can be observed in which a certain number of peak breach the  $T^2$  limit but with the majority of points only slightly higher than the nominal case. The increased level of detections compared to fault test 2 can be attributed to a higher number of parameters that were altered to simulate the fault. The intermittent nature of the fault and the fact that certain

parameters still varied with the nominal case (albeit by a different amount) resulted in the oscillations in the peaks with no sustained increase in  $T^2$  values. Fault test 5 was easier to detect than fault test 4 and this may have been due to the alterations made to the window opening positions. As was detailed in Chapter 6 the atrium windows are used only sporadically but the change applied reduced the nominal opening position by 50% intermittently. This would result in a larger change in feature; however, given that it is not possible to map the parameters responsible for the faults back to the normal input space it cannot be confirmed.

The May results reported similar findings for the test cases with comparable proficiencies in detecting the various fault profiles. This in itself confirms the ability of the KPCA to capture the state of operation (including the nonlinearities) so that the external temperature variable did not mask fault or hinder the detection rate by a significant amount. Given the similarities in the results for February and May only test case 2 is presented here to illustrate the primary difference between the two sets of results. The most notable difference between the February and May results was a higher detection rate for May. This was in part due to the greater number of samples used (31 days in May compared with 28 days in February) which resulted in a lower  $T^2$  limit. However, the key factor was the significant spike in  $T^2$  values observed in the latter quarter of the nominal case. Figure 7.34 shows the  $T^2$  plot for the 10% degradation in ventilation efficiency.

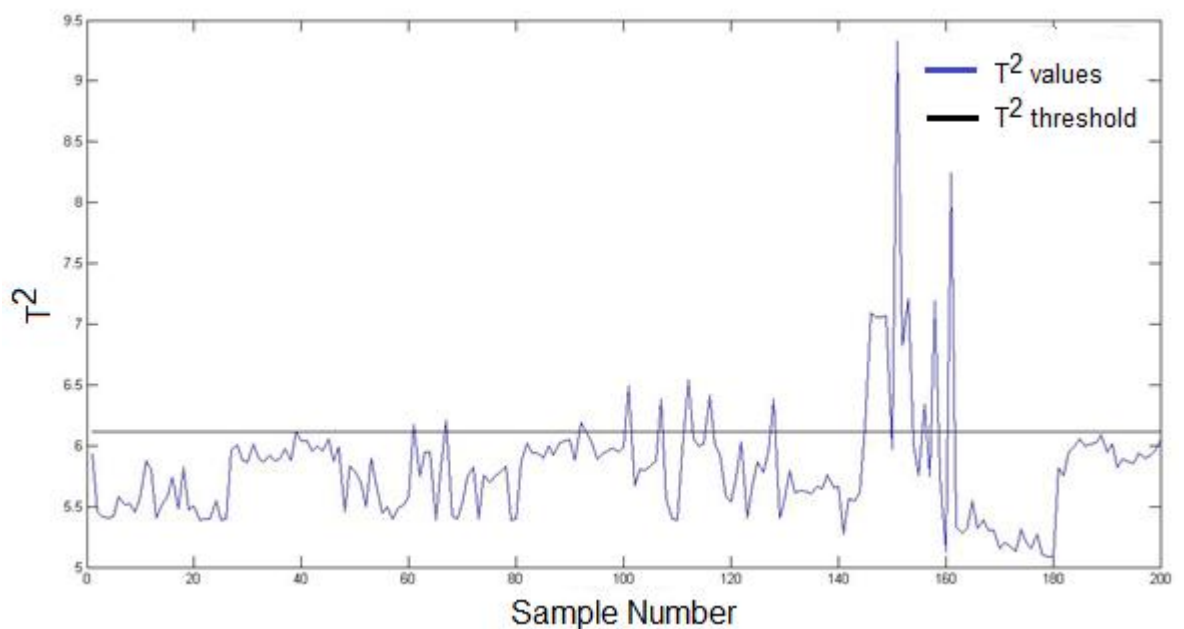


Figure 7.34 – May  $T^2$  plot (10% degradation in ventilation efficiency)

The higher detection rate is mainly attributable to the large peak located at the 150<sup>th</sup> sample region. Overall, the trend is similar to the February test case 2 results with the  $T^2$  values shifted up compared to the nominal case. Comparing Figure 7.34 with 7.28 (February Test 2 – 10%) there are a greater number of the data points are far closer to the boundary threshold. The number of fault detections for May and February are summarised in Table 7.3.

Table 7.3 - Summary of February and May fault detection

Test case	Number of successful detections For February	Number of successful detections For May
Test 1 – 10%	34	42
Test 1 Linear	14	21
Test 1 – Parabolic	21	35
Test 2 – 10%	10	23
Test 3	30	43
Test 4	14	15
Test 5	24	31

There are two disadvantages to using the KPCA and  $T^2$  statistic for fault detection. The first drawback of the  $T^2$  fault detection methodology is the requirement for faults to manifest at certain operating periods in order to ensure detection. However, with sufficient training data the nominal variances would be better defined thus the  $T^2$  limit could safely be adjusted. In cases where training data is sparse the diagnosis methodology presented in this thesis could be utilised as a secondary fault detection system. Data sample migration from the nominal class to a fault class could be used as a secondary indicator of building state. The second disadvantage is that performing fault isolation in KPCA is not a simple task and has associated difficulties. Hence the primary function of the classification techniques is to trace the feature changes in the parameters to a fault via supervised classification as an alternative means of connecting the parameter changes to a fault or non-fault (permitted deviation) event.

### 7.2.5 Fault Diagnosis

The fault diagnosis methodology employed KFDA to maximise the separation between the nominal and fault case T-scores. The limitation of using only 5 fault cases was that it allowed for perfect classification of the fault samples, in reality there would be a multitude of possible fault states thus the results were not reflective of how the diagnosis methodology would perform in practical applications. It was found that the strengths and weaknesses of the classification process were more effectively highlighted by using the 2<sup>nd</sup> and 3<sup>rd</sup> principal axes T-scores. This allowed for demonstration of the potential problems that could be encountered in the comprehensive application of the CM methodologies. Furthermore, the fundamental characteristics for each fault profile were the same regardless of whether principal components 1 and 2 were used or 2 and 3, the only difference being the scale of the separation.

A Gaussian kernel function was employed as it was the most effective kernel function at separating the T-score clusters. Figure 7.35 shows the nominal T-score cluster for February.

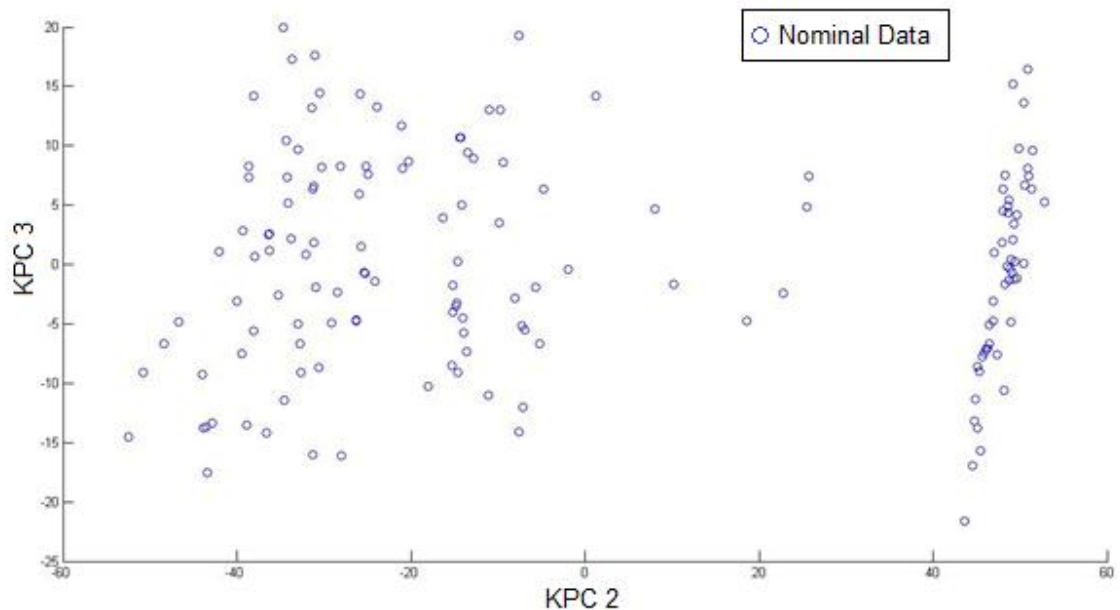


Figure 7.35 – Nominal T-score scatter for February

There was significant dispersion of the cluster on the left hand side but as was previously noted there are two general clusters observable. The fault test T-scores were then collated and plotted with the nominal case. Figure 7.36 shows the nominal T score scatter along with T-scores for test case 1 (10% increase).

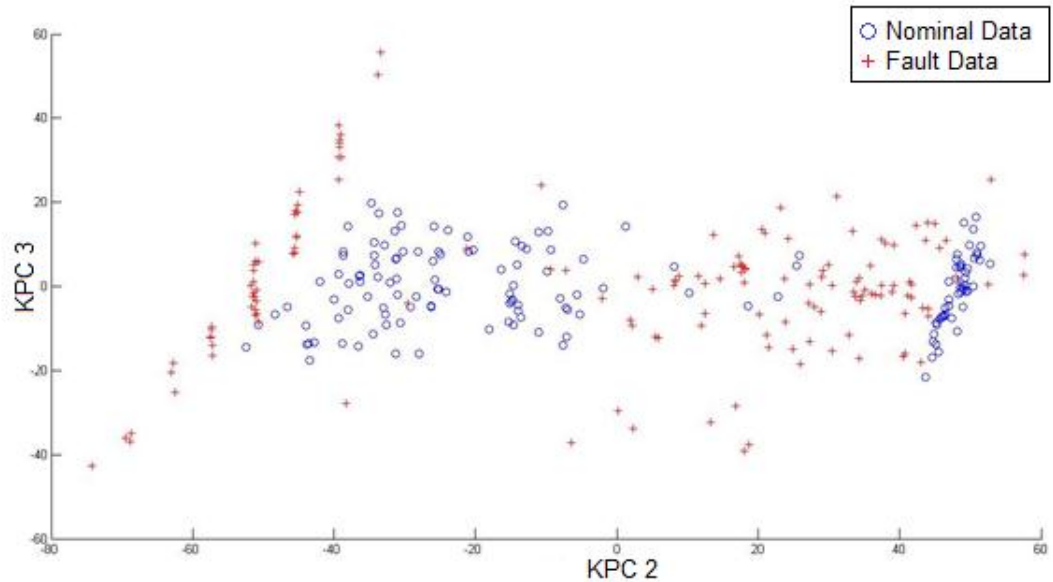


Figure 7.36 – Nominal and fault case 1 T-score scatter

The fault T-scores shown in Figure 7.36 also shows two main clusters of scatter. Furthermore the scatter between the two classes (nominal and Fault case) was interspersed. Classification of the scatter groups was difficult as a result. Application of the KFDA provided a clear separation between the classes as is shown in Figure 7.37.

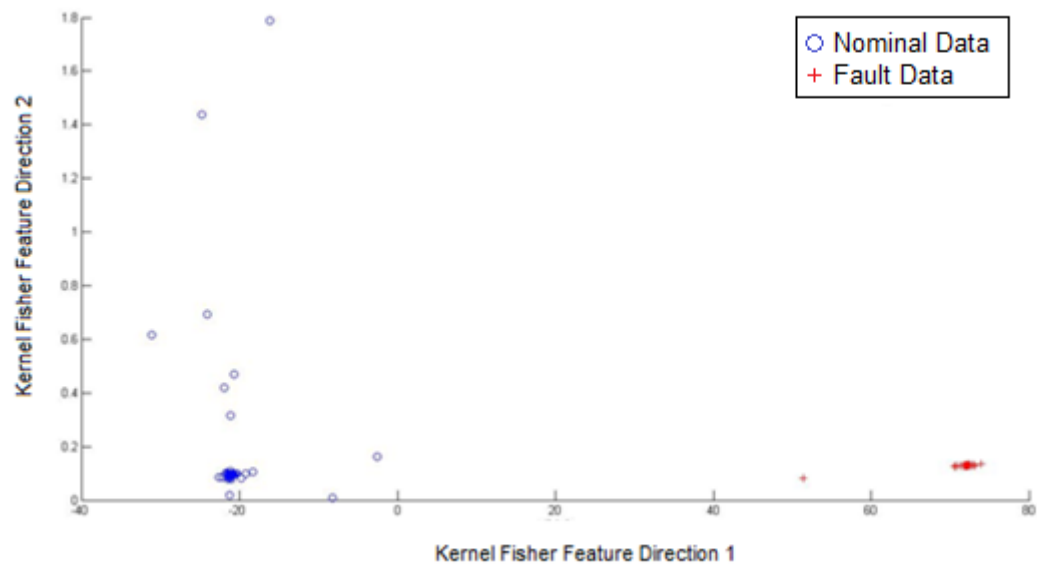


Figure 7.37 – Nominal and fault case 1 KFDA scatter

Figure 7.37 shows significant separation between the fault class and the nominal case. Some minor scatter is observed along the Second Fisher Direction however, the two clusters are successfully separated along the first Fisher feature Direction. Fault test 1 for the linear increase in HVAC consumption had a greater level of scatter present when compared to Figure 7.36. The linear increase test case scatter is shown in Figure 7.38.

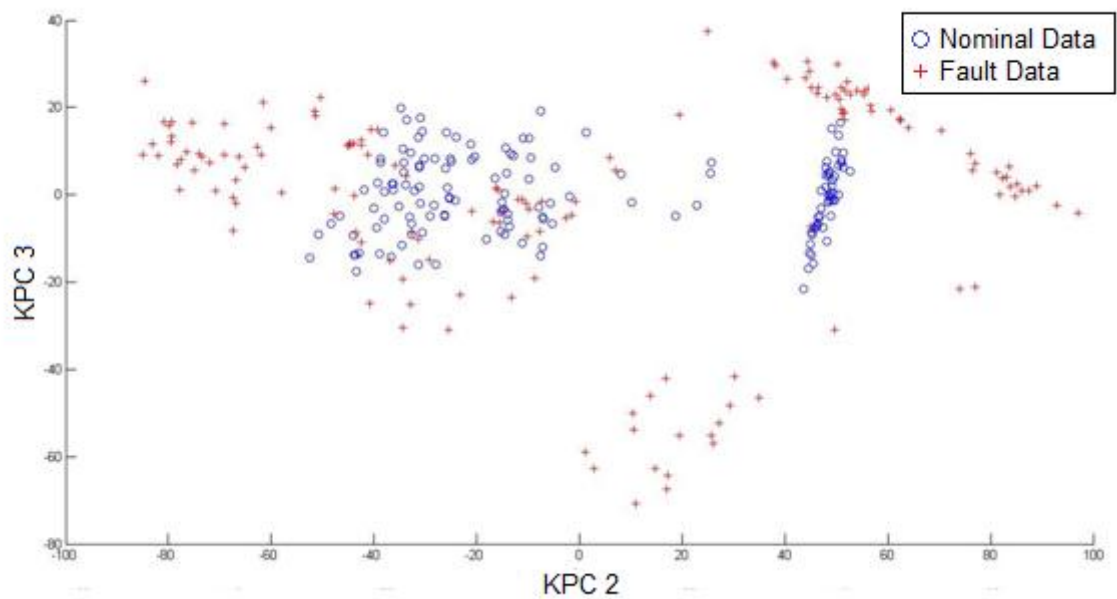


Figure 7.38 – Nominal and linear case T-score scatter

The fault data in Figure 7.38 has four main cluster regions with a greater level of overlap on the left side cluster of the nominal T scores. The parabolic T score scatter had different cluster regions but did not illustrate any noteworthy differences to Figure 7.38 and thus is not presented here. Despite the increase in overlaps in T-score scatter the KFDA methodology was able to provide proficient separation between the faulty data and the nominal data as seen in Figure 7.39 for the linear case and Figure 7.40 for the parabolic case.

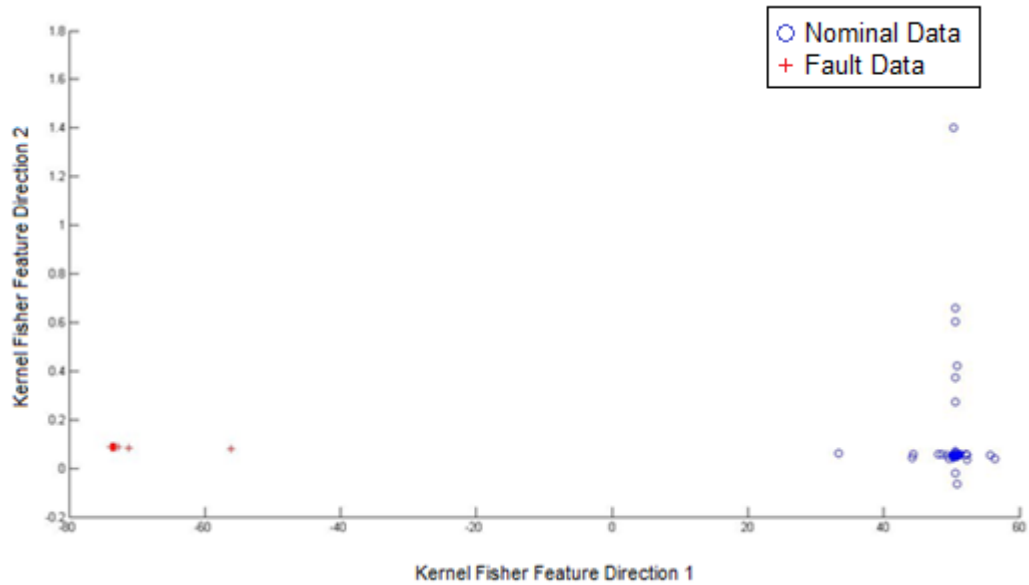


Figure 7.39 – Nominal and linear case KFDA scatter

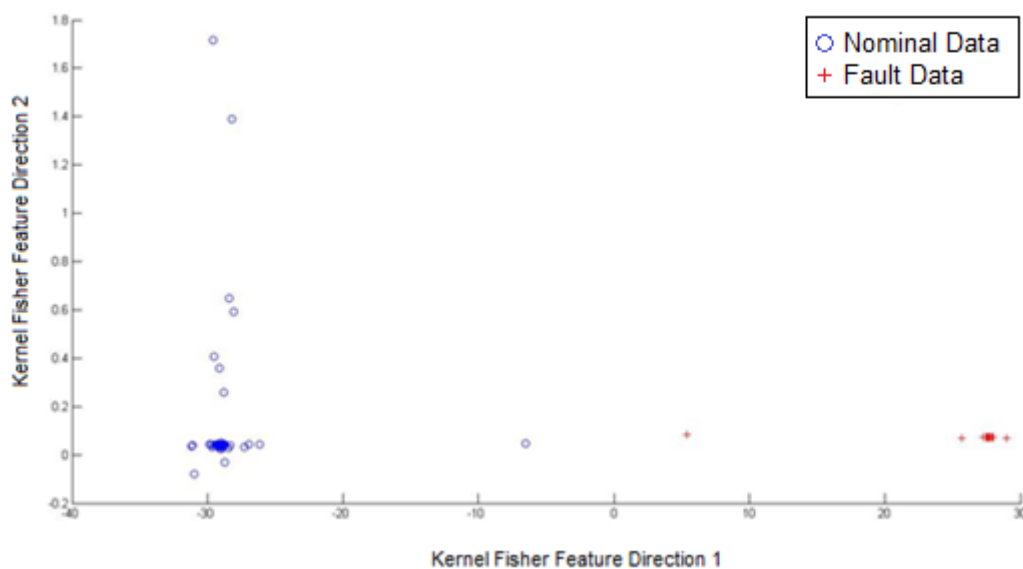


Figure 7.40 – Nominal and parabolic test case KFDA scatter

In both Figure 7.39 and 7.40 the data separated the most along the first Fisher Feature Direction with minimal scatter present on the second feature direction. In Figure 7.40 there are two points residing between the two main classes however, given that the majority of the scatter points have been segregated, the effects of these two points would not be significant. The results from fault case 1 so far show that the KFDA is successful at separating the classes of incipient faults.

The abrupt step change in fault case 3 alters the spread of the fault case T scores. Figure 7.41 shows a higher level of congregation in the fault scatter with the majority of the T score points located along an elongated scatter group. However, there is a secondary smaller collection of T scores located on the right hand side.

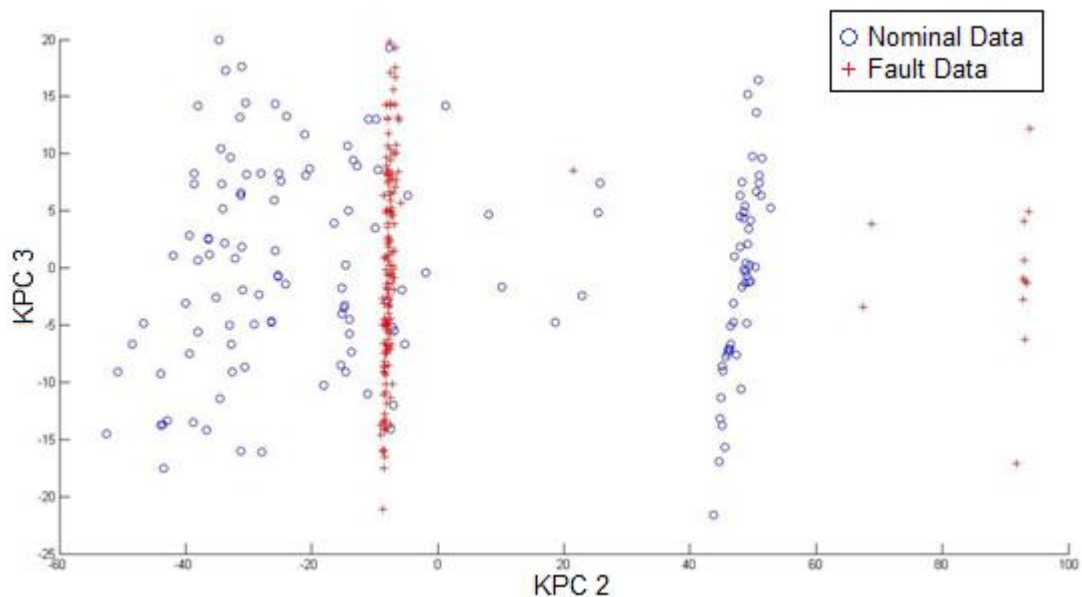


Figure 7.41 – Nominal and fault case 3 T-score scatter

Despite the greater levels of clustering in the 2<sup>nd</sup> and 3<sup>rd</sup> principal components seen in Figure 7.41 there was less separation achieved using the KFDA method as can be seen in Figure 7.42.

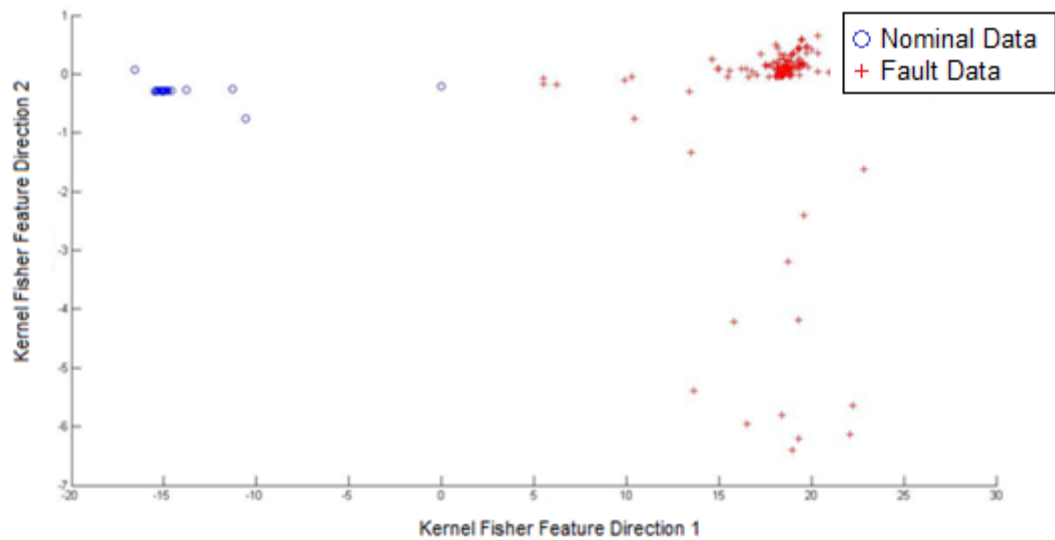


Figure 7.42 – Nominal and test case 3 KFDA scatter

There is a significantly greater level of scatter for the fault case T-score projections compared with the previous cases. Whilst the step change showed a greater level of clusters along the principal component axes there was less separation on the Fisher Feature Space. However, overall there are still two distinct clusters observable. Additionally, the scatter of the nominal case is far less than that of the fault case; in the previous fault cases the converse was true. The KPCA T-score scatter graphs for Test 4 and 5 shared similar characteristics and thus only Test 4 is presented here. Figure 7.43 shows the T-score scatter for Test 4.

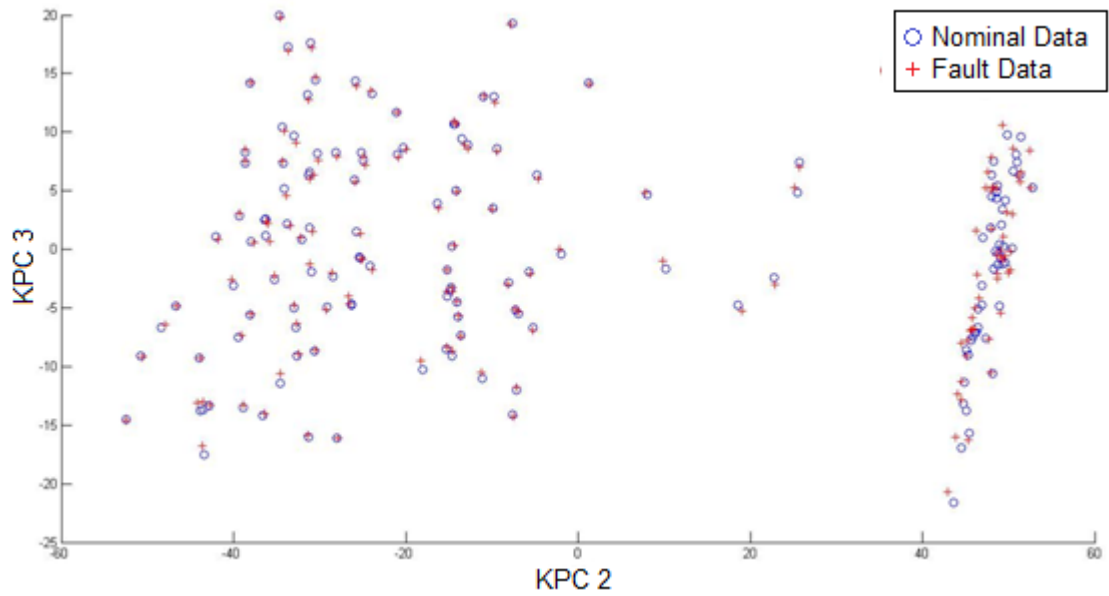


Figure 7.43 – Nominal and fault case 4 T-score scatter

Given that the atrium temperatures vary with external temperature there are no strong lines of distinction between the classes. Intermittent faults or those that move with nominal case but on a lesser scale do not produce a strong change in feature in the process data. Hence, the KFDA separation of the class is not as strong as with the previous test case shown as in Figure 7.44 and also in Figure 7.45 for test case 5.

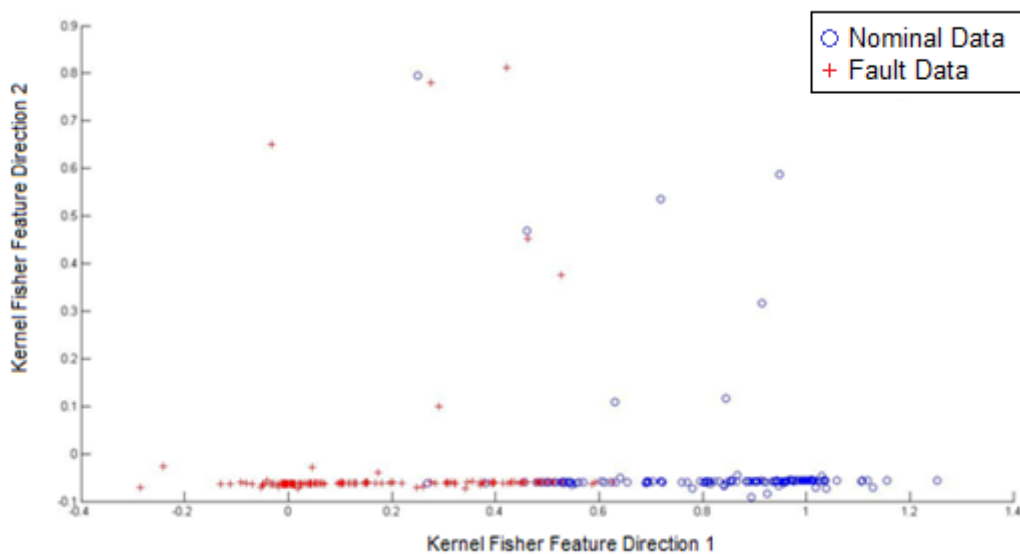


Figure 7.44 – Nominal and test case 4 KFDA scatter

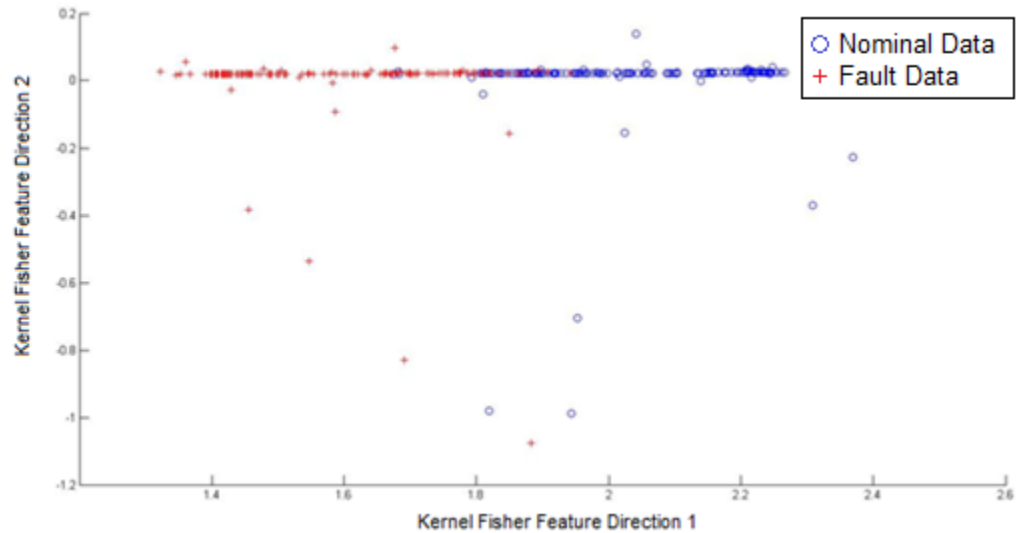


Figure 7.45 – Nominal and test case 5 KFDA scatter

Unlike the previous test cases there are no distinct lines of separation along the first Fisher feature direction. Furthermore there is an overlap occurring where the two clusters meet. Given that fault case 4 & 5 showed similar T score scatter in the 2<sup>nd</sup> and 3<sup>rd</sup> principal components it is not surprising that there are similarities between the KFDA results as well. These similarities can be attributed to the fact that both test cases have varying fault symptoms that move both up and down with the nominal variance as opposed to an abrupt step change or an incipient divergence.

In order to perform fault diagnosis the generalised form of KFDA was used in which separation of multiple classes was performed. Multi way KFDA was applied to the 6 fault groups and the nominal T-score data. Fault test 2 was omitted as the similarities with fault test 1 would obscure the classification process. The clusters from test case 4 and 5 were far closer to the nominal case than the other test cases which led to the separation between these classes becoming obscured when all fault classes were plotted simultaneously. Hence two separate plots of the multiclass KFDA are shown. Figure 7.46 shows the nominal case and the three test 1 cases and test case 3. Figure 7.47 shows the nominal case and test case 4 and 5. It should be noted that whilst the KFDA plots are presented separately, the clusters were computed simultaneously for use by the KNN algorithms.

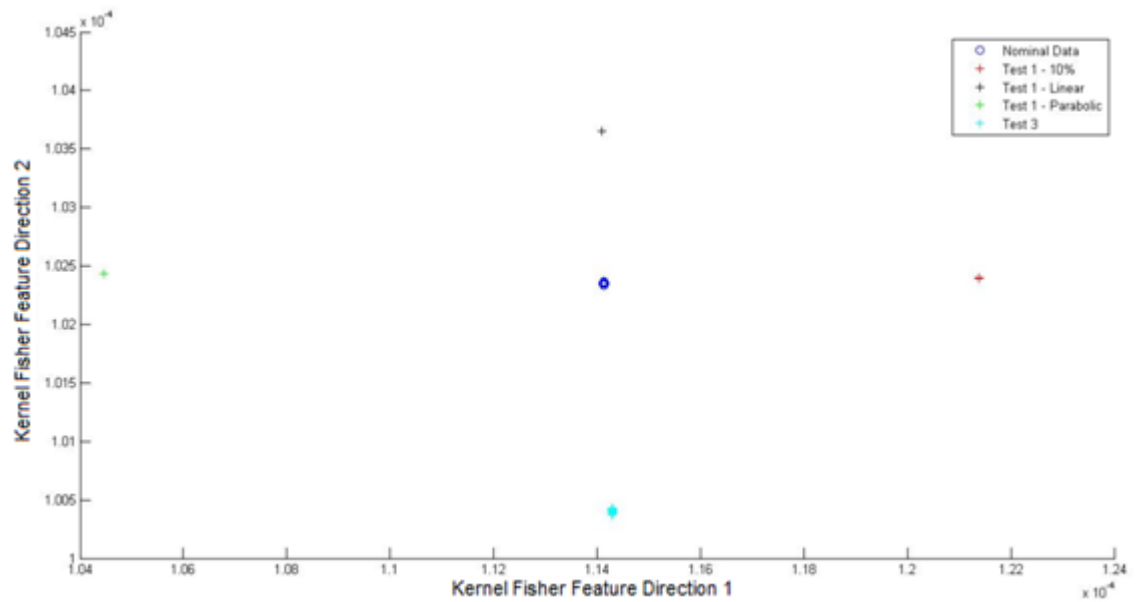


Figure 7.46 – February multi way KFDA scatter

Figure 7.46 shows a proficient level of separation between the different fault types and the fault profiles for the test 1 cases and test case 3. The fault classes for tests 4 and 5 are shown along with the nominal case in Figure 7.47.

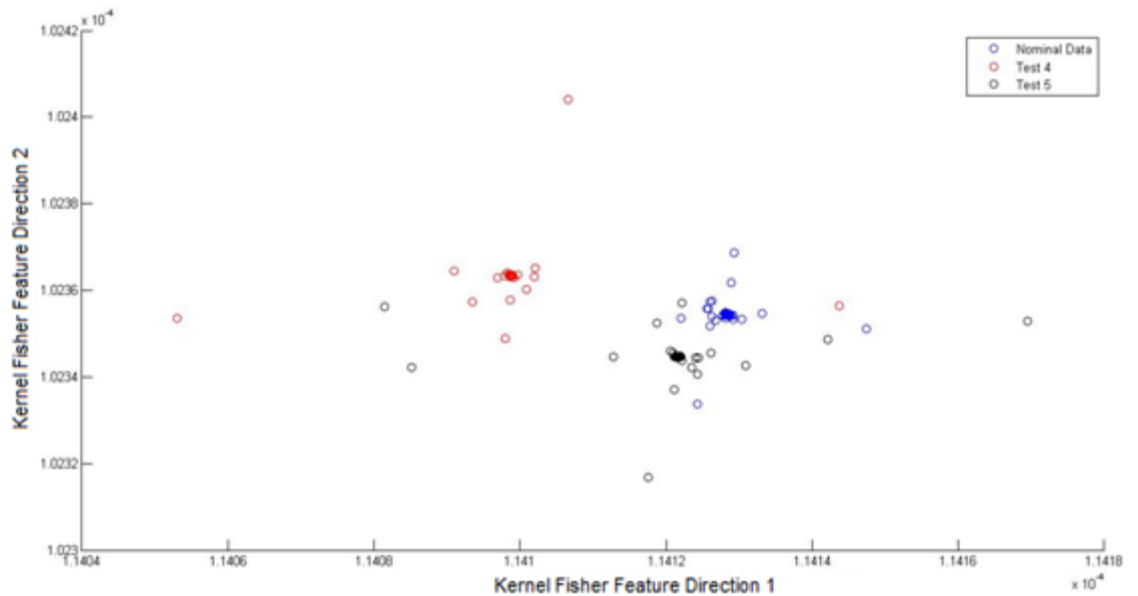


Figure 7.47 – February multi way KFDA scatter (Test 4 and 5)

Comparatively, the fault classes are far closer together reflecting the similarities shown in the Figure 7.44 and 7.45. Test 5 shows a particularly closeness to the nominal case. The sample fault cases were then introduced. Using the KNN algorithms the distance between the sample cluster and the closest class was determined. The results of which are given in Table 7.4.

Table 7.4 – Sample classification results (February)

<i>Class</i>	<i>Sample 1</i>	<i>Sample 2</i>	<i>Sample 3</i>
Nominal	0	0	0
Test 1 – 10%	100%	0	0
Test 1 – Linear	0	0	0
Test 1 – Parabolic	0	0	0
Test 3	0	83.66%	0
Test 4	0	1.96%	76.92%
Test 5	0	14.38%	23.08%

It should be noted that whilst the samples are approximating a fault test they were not identical to it hence as is shown in Samples 2 and 3 the classification rate may not be 100%. Sample 1 does have a 100% classification but was this due fault sample 1 sharing nearly all the same characteristics as fault case 1. As a result fault sample 1 only has one nearest neighbour the fault test 1 cluster. The classification rate for Februarys fault samples was satisfactory. However, the diagnosis of the fault samples for May performed poorly by comparison. Figure 7.48 shows the increased level of scatter for May.

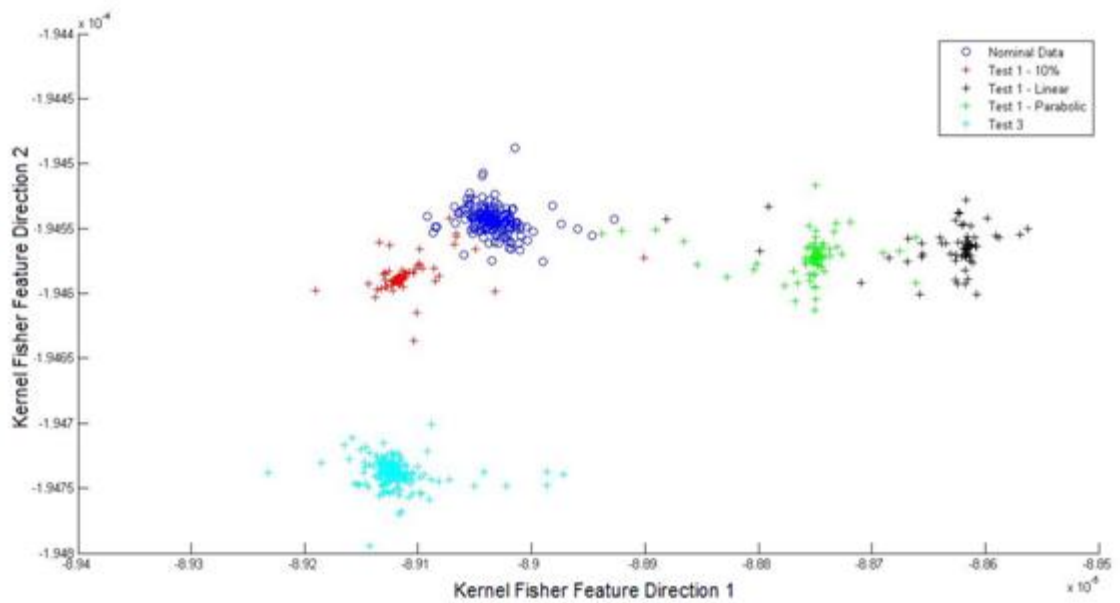


Figure 7.48 – May multi way KFDA scatter

The classes were significantly closer together; as a result there is an observable level of scatter amongst the classes. The KFDA was unable to separate test case 4 from the nominal case as is seen in Figure 7.49.

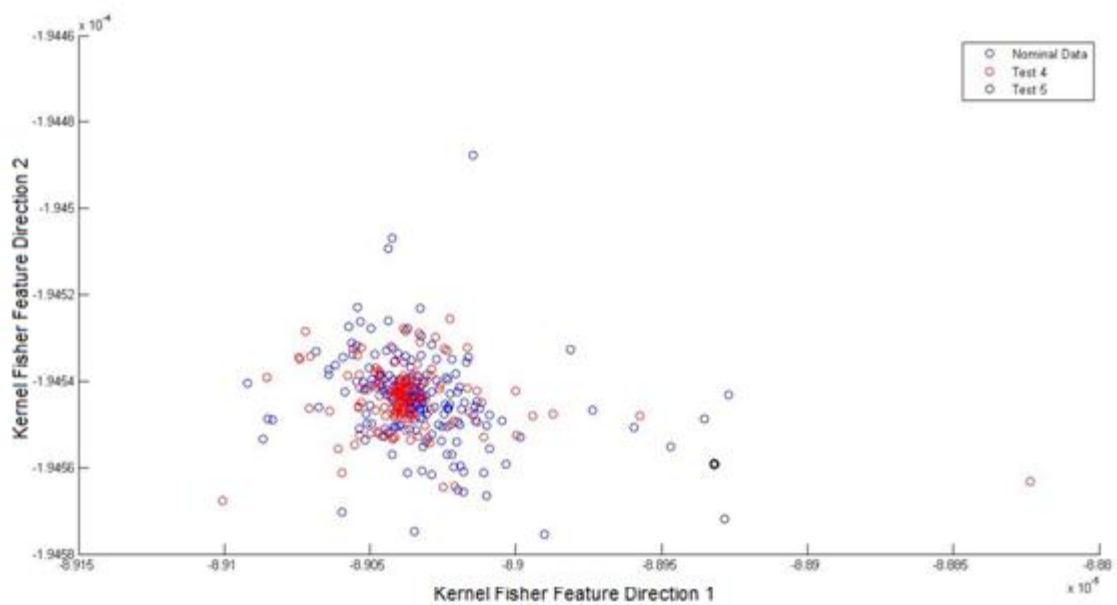


Figure 7.49 – May multi way KFDA scatter (Test 4 and 5)

The classification for the month of May was far less successful given that the clusters are closer together and that fault 4 was overlapping with nominal data with a huge spread of projected data. Thus the results shown in Table 7.5 display a poorer classification rate.

Table 7.5 – Sample classification results (May)

<i>Class</i>	<i>Sample 1</i>	<i>Sample 2</i>	<i>Sample 3</i>
Nominal	26.5%	21.5%	36.5%
Test 1 – 10%	35.5%	4	0.5%
Test 1 – Linear	1%	0	0
Test 1 – Parabolic	7.5%	0	0.5%
Test 3	9%	51.5%	17.5%
Test 4	20.5%	23%	44.5%
Test 5	0	0	0.5%

Removal of fault case 4 from the fault classes resulted a 53% successful classification rate for fault sample 1. This demonstrated the weakness of KFDA in that multiple classifications that were inseparable can entirely disrupt the classification process with nominal data being classified as faulty and vice versa. Despite the greater levels of scatter, all 3 fault samples had the highest level of association attributed to their approximated fault cases.

### 7.3 Summary

The aim of applying multivariate statistics to the building process parameters was to capture the variance expressed in the data and thereby capture the building operation state. The KPCA method was successful in reducing the dimensionality of the data so that the fault detection statistic ( $T^2$ ) was able to differentiate between nominal and abnormal conditions. The  $T^2$  detection method was sufficient at detecting all but the intermittent fault profiles. However, with further training data the  $T^2$  limit threshold could be altered to increase the detection rate. The main drawback of altering the  $T^2$  limit is that acceptable deviations such as extended operating hours could increase the number of false alarms. The KFDA and KNN algorithms would be better suited to ensuring acceptable deviations are

accounted for. The acceptable deviations would be allocated their own class under a non-fault label similar to fault case classes. Monitoring the energy consumption during these non-fault deviations would allow for allocating an energy value to each non-fault class. The energy value could then be used as a means of adjusting the dynamic targets. The drawback of using classification techniques is that unless the T-score projections onto the Fisher feature space are significantly different to the other classes there will inevitably be an overlap as was seen for the May test cases. Management of the classification database would be required to ensure that there were no overlaps in the classification clusters; however this could mean certain faults would need to be disregarded. In the practical application of the system there would be a finite number of classifications that could be stored and used without compromising the abilities of the KNN algorithm to diagnose the faults. Hence the fault types that are representative of the greatest energy costs would need to be retained along with the non-fault acceptable deviations. Lesser faults or the faults that obscure the classification process would require an alternative means of detection and diagnosis.

# CHAPTER 8

## 8. HVAC FDD Results and Discussion

The automated expert system was tested via the 4 AES Fault Cases/events described in Chapter 6. Each fault event had an equivalent fault rule. The fault rules described the state of the relevant parameters when the fault was present. In order to develop the fault events and fault rules the nominal relationships were first determined. Details of the nominal case for each fault event are given in the next section.

### 8.1 Nominal Case

The 1<sup>st</sup> and 2<sup>nd</sup> fault events used the boiler flow and return temperatures and the radiant heating flow temperature. The nominal relationship for the parameters was not easily identifiable; hence there were difficulties in altering the parameters to replicate a specific fault. However, this problem was circumnavigated by changing the process parameter data to emulate a fault profile rather than a specific fault. Two separate fault profiles were implemented for fault event 1 and 2 in which the fault symptoms were identical. This provided the opportunity to test the AESs ability to differentiate between an incipient and intermittent fault profile. Figure 8.1 shows the nominal relationship for the parameters used for fault events 1 and 2.

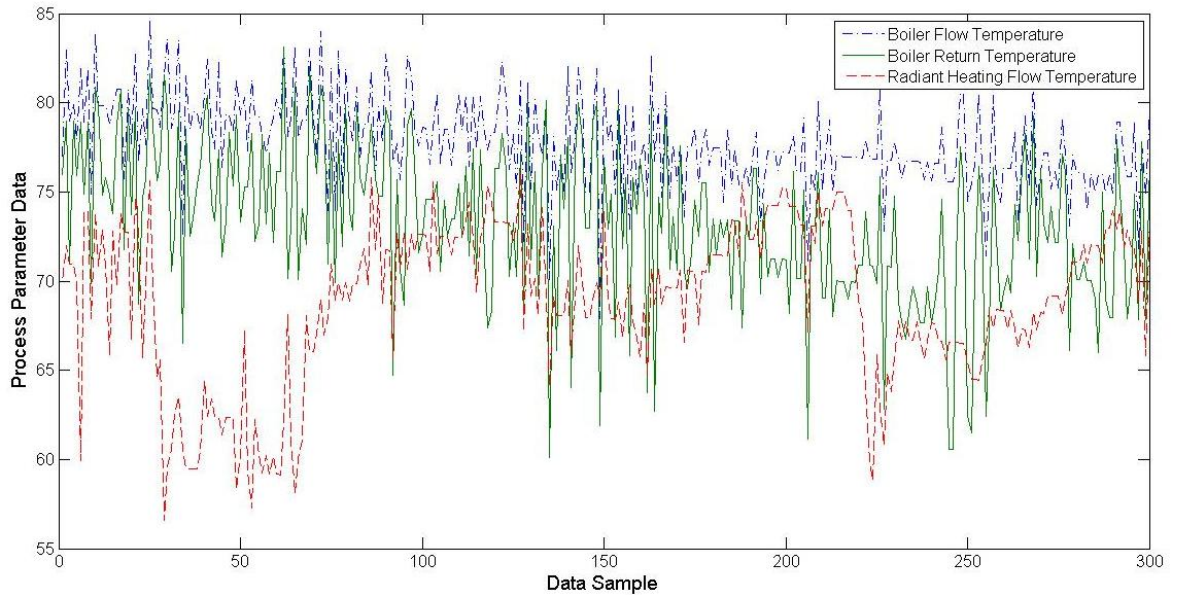


Figure 8.1 – Nominal relationship for fault event 1 and 2 parameters

The 3<sup>rd</sup> fault event modified the radiant panel valve and temperature parameters for the multi-conference room to replicate an abrupt fault with the valve. Under nominal operating conditions the valve position closes when the temperature is 22°C or above. The opening condition for the valve was at a radiant panel temperature of 20°C. Figure 8.2 shows the relationship between the two parameters.

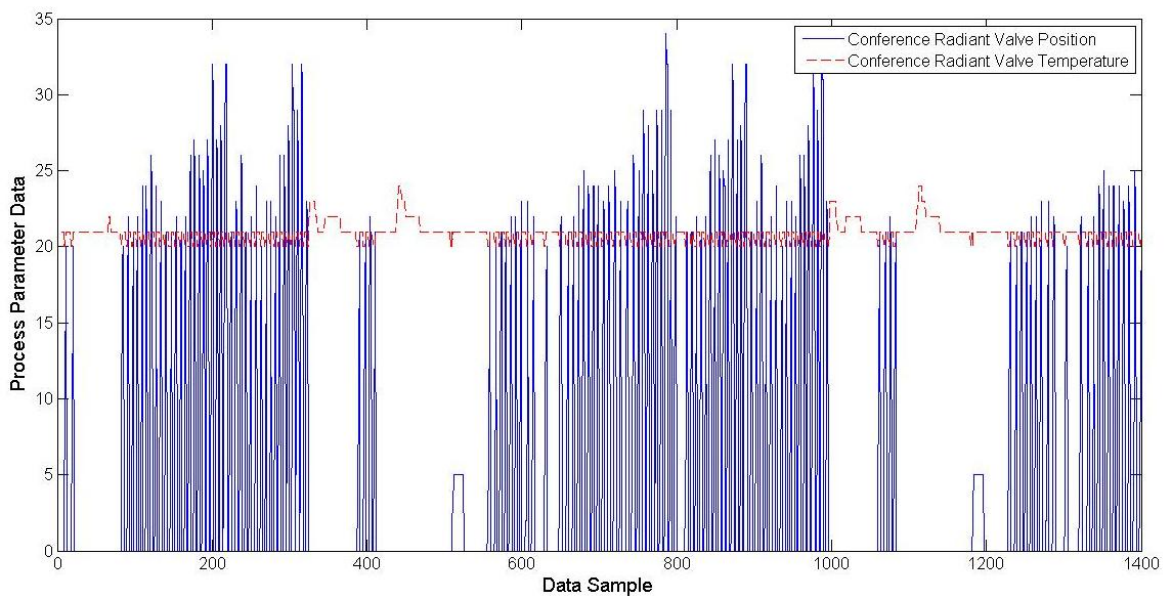


Figure 8.2 – Nominal relationship for fault event 3 Parameters

The 4<sup>th</sup> test case altered the window opening positions for the atrium chimney. The atrium windows open when the atrium vent temperature surpasses 24°C; once the windows were opened they did not close until the vent temperature fell to 21°C. Figure 8.3 shows the nominal relationship between the atrium vent temperature and the window positions.

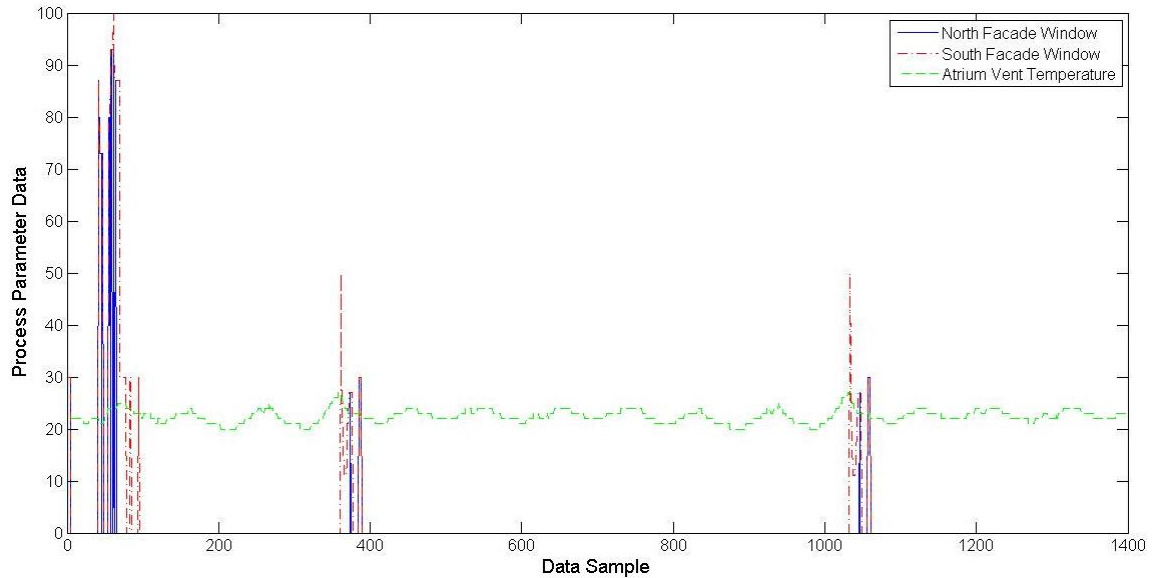


Figure 8.3 – Nominal relationship for fault event 4 Parameters

As can be seen in Figure 8.3 there only 3 occurrences where the windows were required to open. The sporadic utilisation of the chimney windows reduces the number of occasion in which the fault would manifest.

## 8.2 Fault Cases

Once the nominal operating relationship between the parameters for each fault event was established the process data was then altered to simulate a fault or a fault profile. The 1<sup>st</sup> fault event was a slow developing fault in which the boiler output was reduced leading to a lower boiler flow and return temperature and a lower radiant heating flow temperature. As was detailed in the previous section there was no clearly identifiable relationship hence a linear reduction was applied to all three parameters. Figure 8.4 shows the effect of the fault profile on the parameter data.

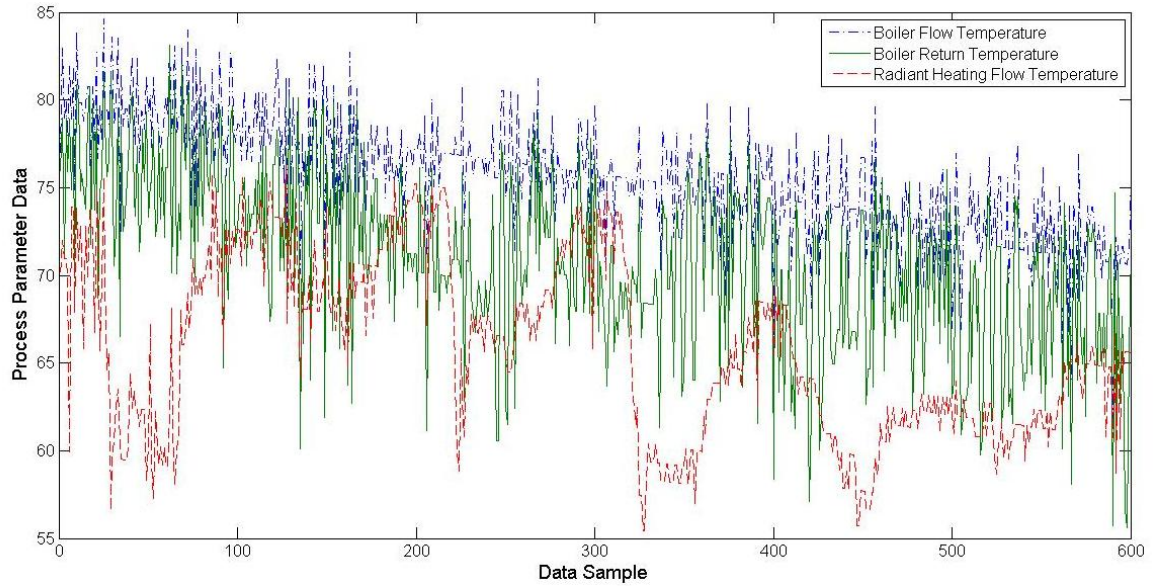


Figure 8.4 – Parameter modifications for fault event 1

In fault event 2 the reduction in boiler output occurred intermittently. The fault was designed to manifest on 3 occasions. On the first two occasions the duration of the intermittent fault was less than the value of  $E_1$  in the fault rule. The time period between the faults occurring was less than  $E_2$ . The symptoms of the intermittent fault on the process data can be seen in Figure 8.5, where the faults occur at the 98<sup>th</sup>, 125<sup>th</sup> and 160<sup>th</sup> samples.

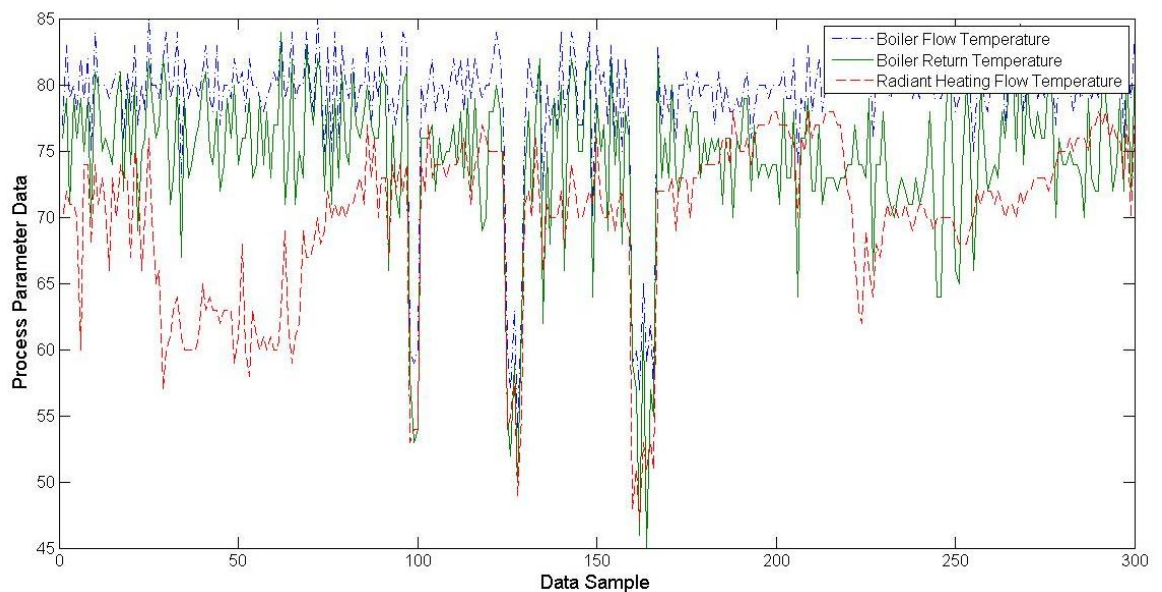


Figure 8.5 – Parameter modifications for fault event 2

For the 3<sup>rd</sup> fault case the changes to the process data was applied at the 600<sup>th</sup> sample. As can be seen from Figure 8.6 the valve position was set to close with the radiant panel temperature falling to 10°C. The abrupt nature of the fault was reflected in the step change in the process parameter data.

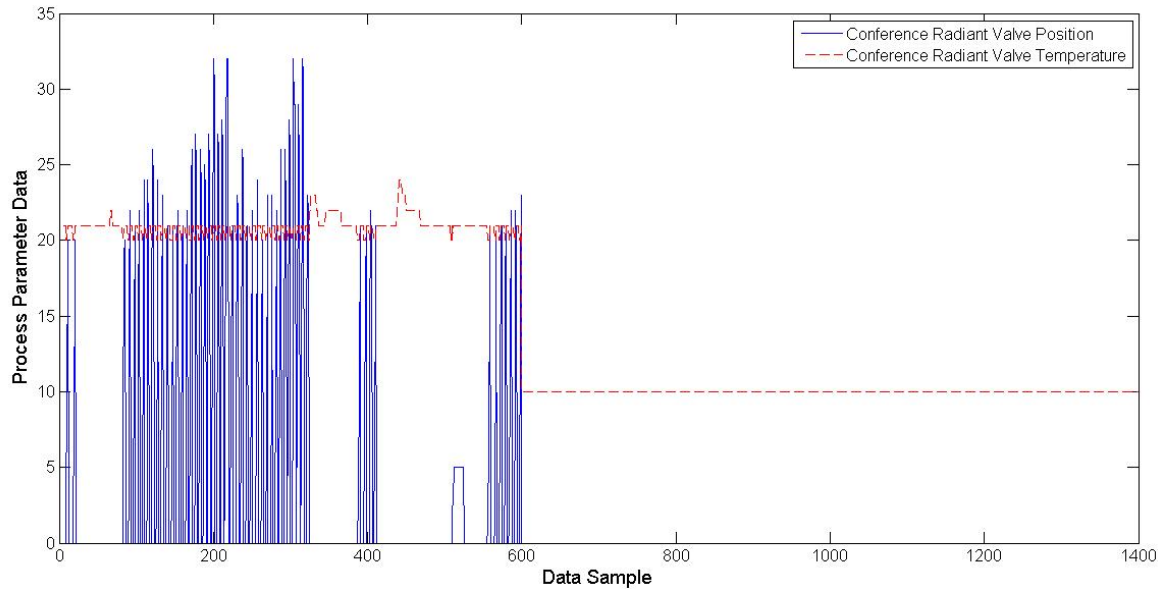


Figure 8.6 – Parameter modifications for fault event 3

In order to emulate a slow developing fault with the atrium chimney actuators a linear reduction in the maximum opening position was applied for fault event 4. Hence as the vent temperature rose above 24°C the window position was unable to open to the nominal amount as time passed. By the 1100<sup>th</sup> sample the windows are unable to open more than 15% of the normal capacity as is shown in Figure 8.7.

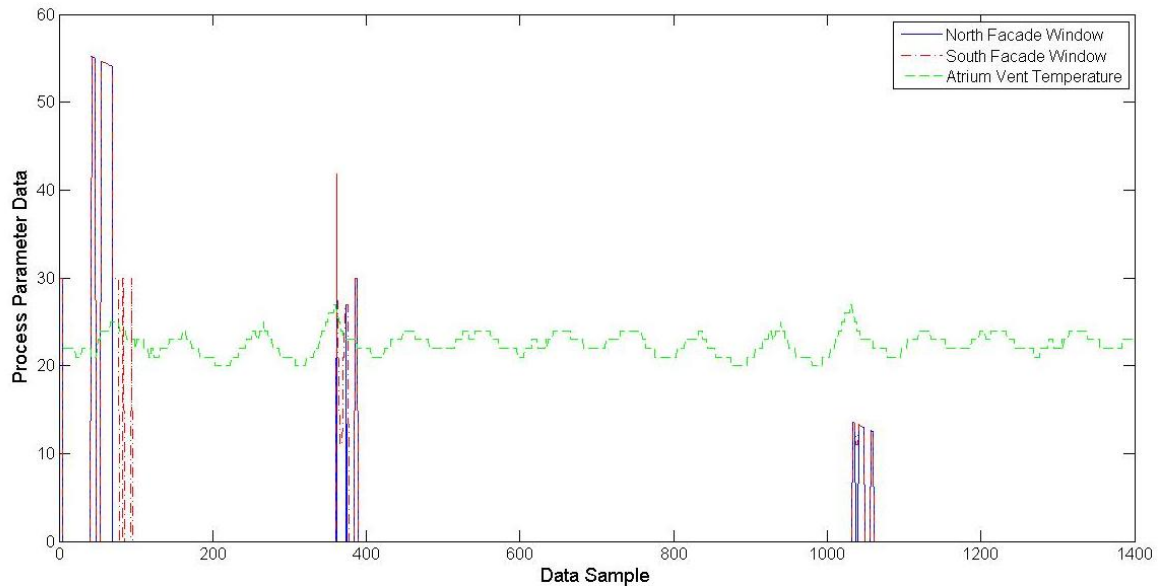


Figure 8.7 – Parameter modifications for fault event 4

### 8.3 Detection, Diagnosis and Decision Confidence

In the automated expert system the fault rules were used to detect whether a fault event had occurred. Given that the fault rules each described a specific fault event the activation of a fault rule not only provided fault detection but also simultaneous diagnosis. However, diagnosis through the use of heuristic knowledge representation is subjective and will therefore always contain imprecision. To prevent the inherent imprecision leading to poor decisions being made, a decision confidence algorithm was implemented in which the level of supporting evidence determined the confidence of the output.

The first two fault events had identical fault symptoms but differing fault profiles. The ability of the ES to distinguish between the two fault profiles had mixed results. In fault event 1 the slow developing reduction of the boiler output lead to both fault rules 1 and 2 being triggered as can be seen in Figure 8.8.

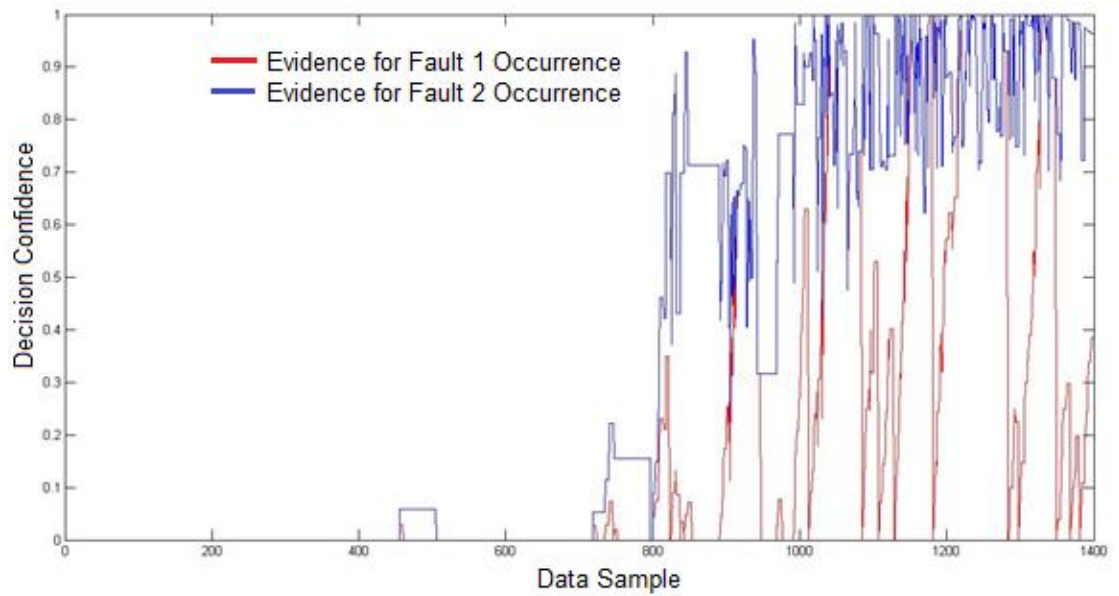


Figure 8.8 – Decision confidence for fault event 1

The structure of the fault rules was such that intermittent faults needed fewer occurrences for confirmation ( $E_1$ ) and a longer period of clear operation before the fault counter was reset ( $E_2$ ) when compared to incipient fault rules. This was to ensure that intermittent faults that occurred for short periods of time and had large intervals between occurrences could be detected. Whilst these properties may have resulted in the incorrect diagnosis for the incipient fault the converse does not apply. Figure 8.9 shows that the intermittent fault is successfully detected by fault rule 2 and has a higher level of confidence than fault event 1.

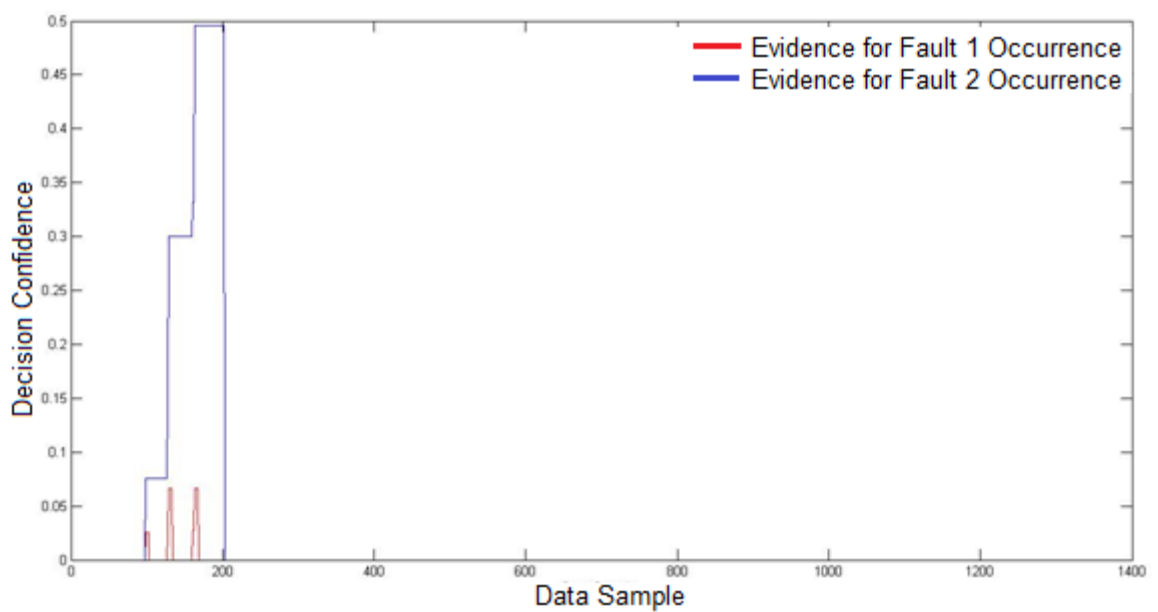


Figure 8.9 – Decision confidence for fault event 2

The stepped increase in the decision confidence is attributed to the three occurrences of the intermittent fault which was sufficiently captured by the fault rule. Figure 8.9 also shows that the ES has ability to diagnose intermittent deviations more accurately than incipient faults. This characteristic could be used to separate the two fault profiles by using semantic relations on the decision confidence output. For example, if the decision confidence values indicated that there was evidence for both fault events 1 and 2 then it would be possible to infer that fault 1 had likely occurred from the evidence shown in Figures 8.8 and 8.9. Furthermore, the likelihood of fault event 2 occurring was if the majority of evidence indicated it. Additionally, the characteristics of the process parameters also influenced the effectiveness of the detection methodology. Parameters that possessed a wide operating range in which the values of the parameters changed quickly over time had far greater chance of being misdiagnosed especially if the fault rule monitored for subtle or incipient changes to the process data.

The ability of the AES to detect the step change (abrupt) fault profile is optimal. Step changes are simpler to detect if the range and operating trend of the parameters are predictable under normal operating conditions. Figure 8.10 shows the change in decision confidence after the introduction of the fault symptoms at sample 600.

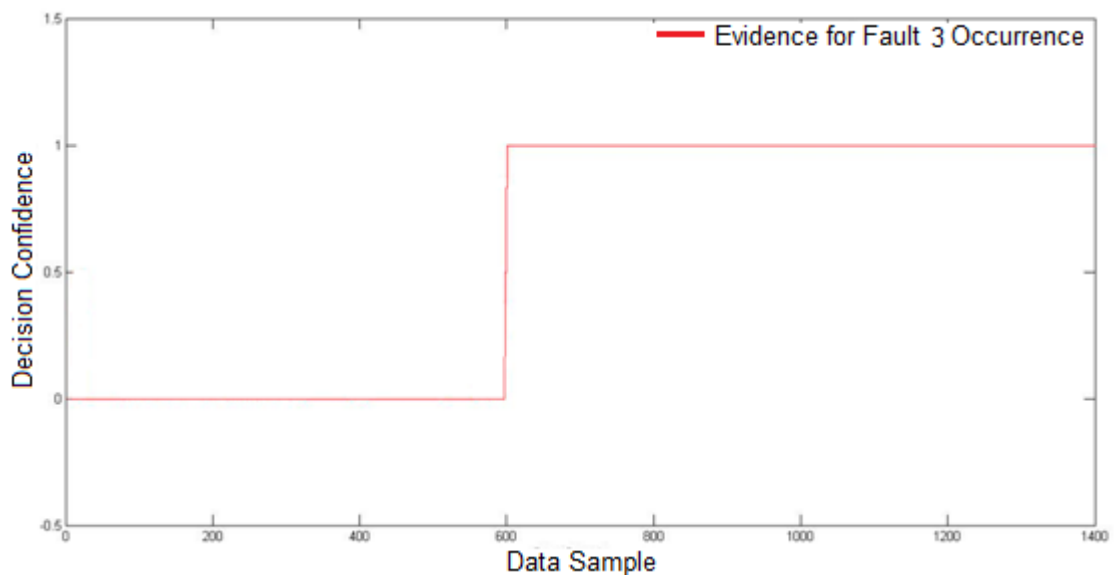


Figure 8.10 – Decision confidence for fault event 3

The change in decision confidence was not an instantaneous step change from 0 to 1 due to the fault confirmation process which required 4 occurrences of fault event 3 in order for the fault counter to equate to element  $E_1$  of the fault rule. For abrupt faults the value of  $E_1$  can be kept to a relatively small value as long as the magnitude of the step change in the process data is distinguishable from normal operation patterns.

Detection of the 4<sup>th</sup> fault event displayed a confident output from the AES about the occurrence of the window actuator fault as can be seen in Figure 8.11.

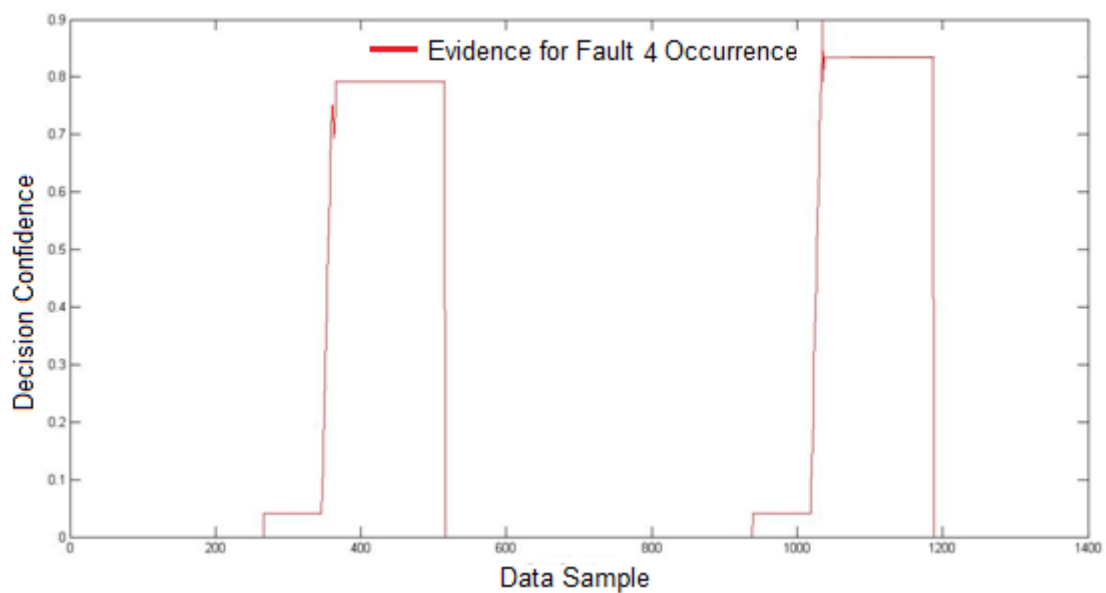


Figure 8.11 – Decision confidence for fault event 4

Whilst the AES was able to diagnose the fault with a decision confidence value of higher than 0.8, the fault was only identified when the atrium chimney window was not able to open. Condition monitoring predominantly relies upon a change in feature to detect faults however, for parameters which are utilised sporadically or infrequently it is not possible to determine the change when the system is not in use. Degradation could occur in-between the time periods where the system is activated during which the fault would be undetectable until the system is called upon. In such cases planned preventative maintenance practices would be a more effective means of ensuring the optimal operation of the system.

## 8.4 Summary

There has been considerable research performed in applying expert systems to the process of detecting and diagnosing faults for the HVAC systems. The majority of the work has focussed on a single HVAC system. A possible explanation for this is that in order to fully describe a complex fault the fault rule may consist of multiple qualifying or conditional statements. A system with a number of complex fault paths would require substantial amounts of programming to sufficiently depict the fault in a robust manner. Whilst proper maintenance of the HVAC is necessary to ensure minimal energy wastage, the level of programming required when considering several HVAC systems can be time and cost prohibitive. An alternative approach would be to use the expert system to focus exclusively on the identification of the faults that had the largest energy penalties if left uncorrected. In the case of the research performed in this thesis it is far easier to classify new data clusters as faults using the statistical methodologies than it is to build a comprehensive fault rule describing that fault. The focus of the HVAC expert system would be as a means of confirming the occurrence of a fault and to compensate for the weaknesses of the data driven methodologies such as the identification of intermittent fault profiles. In doing so, it would provide a practical means of tackling the bottom-up maintenance and top-down whole building assessment requirements for use in the energy evaluation process.

The fault events developed to test the AES were deterministic and simple in order to illustrate the decision confidence algorithm which presented a novel manner in which to handle the imprecision of the fuzzy knowledge representation. The structure of the fault rule was designed to differentiate between the fault profiles and with the exception of incipient faults this was successfully achieved. It was also determined that faults that involved parameters with irregular or sporadic change of features were more effectively handled by planned preventative maintenance.

# CHAPTER 9

## 9. Commercial Implications

This chapter shall cover the commercial implications of the research detailed in this thesis. The development of a holistic and comprehensive means of evaluating building energy performance has been investigated in both academic and commercially commissioned research. There are a number of participants for whom developments in the field of energy assessment would have important implications, namely those involved in the design, construction and operation of buildings. These shareholders are wide ranging from architects and building services engineers to the owners and operators of buildings to name a few. The response of these participants to the particular research performed in this project would depend on several drivers. As with most industries the financial implications typically take precedence over other factors, these financial drivers are discussed in the following section.

### 9.1 Financial Drivers

The increasing levels of globalisation within the world markets has meant that companies need to lower operational costs in order to remain competitive and protect profit margins. Additionally, the rising cost of energy commodities has meant that there is now a greater emphasis placed upon energy savings. Cost effective means of energy reduction are now more likely to be implemented by the owner/occupants of buildings than in previous years in order to achieve lower operational costs. The financial incentives for implementing the methodologies in this thesis can be summarised within the following bullet points:

- Greater visibility of energy performance
- Differentiation between energy wastage and energy efficient behaviour irrespective of past consumption
- Greater levels of energy accountability by relating non-fault deviations to an energy cost
- Proactive cost reduction through the use of targeting inefficient HVAC systems

- Active monitoring and budgeting of energy consumption

The last point is especially pertinent given implementation of carbon monitoring schemes such as the Carbon Reduction Commitment in which there are penalties for poor energy management.

The financial viability of investing money and resources in new technologies is generally determined by the payback period. Payback periods of 5 years or less are generally considered to be acceptable investments. Assuming that the methodologies in this project have been fully developed and a product released to market the payback period of implementing the product would depend on several factors. The maintenance practices of the Facilities Management (FM) would play an integral role, FM teams that are more likely to act upon the feedback would see greater returns in a shorter period of time. Additionally, the operation efficiency of the building before the system was implemented would also be a significant factor; buildings that were performing poorly previously would likely see greater benefits than a building that is already operating in an efficient manner. The research within this thesis did not extend to actual building prototype testing as was first envisaged. And as such cannot provide any data on payback periods. However, given that 15-30% of energy wastage occurs in the HVAC, a reduction in that figure by only 30-40% would account for a sizeable cost saving and provide an attractive financial incentive for investment.

## **9.2 Commercial Adoption**

Despite the potential commercial benefits of implementing condition monitoring techniques and real time assessment to the building sector, commercial uptake would largely be dependent on the attitudes of the participants engaged in designing and constructing buildings. Construction firms, architects, building services engineers and controls companies would all need to share the belief that adoption of a new energy evaluation method would be more beneficial than continuing with the current *modus operandi*. Whilst significant research has already been performed within the building sector relating to the implementation of FDD for HVAC systems there has been very few commercial applications (Katipamula and Brambley 2005b). This is largely attributed to

the inertia associated with construction firms and architects in adopting novel solutions for fear of increasing costs and the associated liabilities that may be incurred. Given that the construction companies do not directly benefit as a result of energy savings, other incentives must be provided in order for these companies to share in the vision of improving energy consumption. Sadly the evidence so far has indicated that legislative enforcement is needed in order to enact any real changes in the building industry. However, it should be noted that impetus to improve energy efficiency has translated into real changes in how buildings are now designed and constructed via the legislative amendments to Part L. Whilst the current legislative requirements have already been discussed in Chapter 2, the implementation and enforcement of the higher standards within the building sector can be viewed as the Government taking its commitment on improving efficiency in the building sector seriously. The underlying motivation can be seen in the manner in which the improvement targets are set. Each iteration of Part L post 2006 requires better emissions performance than the previous version. With this in mind there is the distinct possibility that future energy evaluation methodologies such as the one made reference to in the EPBD would eventually stipulate some form of real time energy evaluation. Ultimately, without legislative enforcement it would be the client who would need to demand and be willing shoulder the costs of investing in new energy evaluation methodologies.

### **9.3 System Development**

The methodologies detailed in this thesis use a limited number process parameters and fault test cases for the purposes of demonstrating the capabilities of the CM methodologies. The use of stochastic fault cases would allow for robust testing of the methods presented here and would determine the operating limits of the CM systems. Greater levels of investment are needed for the commercial development of a holistic real time energy evaluation tool; the use of a dedicated test case construction would be beneficial to validate the methodology and to develop a database of fault states. The long term objective of which would be the development of a modular ‘plug and play’ system. However, in order for this to happen, further integration of the HVAC systems is required and a standardised approach to building feature representation within BEMSs.

Given that the real time evaluation tool uses relatively simple calculations, integration of this methodology into a BEMS would not be problematic. It would require a token level of data storage space to hold the DTM data and some simple math functions for degree day adjustment. Open source BEMS software platforms such as BACnet offer substantial flexibility in programming the HVAC systems and thus include a number of programmable functions. This would also allow for the integration of knowledge based models which use standard programming syntax. However the integration of data driven condition monitoring methodologies would be a more difficult task requiring higher levels computational effort and the use of mathematically complex functions that are not available within BEMSs. This could be overcome with cross-licensing agreements between BEMS software developers and computational software companies such as Mathworks, the developers of the Matlab programming environment. A stand alone piece of software would overcome this problem, however the costs surrounding the development of such a system would be considerable, hence work in this field is most likely to be driven by changes in legislation rather than through commercial exploitation.

## **9.4 Industrial Contribution**

The performance and maintenance systems that have been developed for this research project not only address a gap in knowledge with respects to the project hypothesis but also deliver an industrial contribution. The development and application of the data driven Condition Monitoring system is novel within the building sector. As was previously highlighted, the majority of industrial systems rely upon limit thresholds and therefore lack the ability to capture the state of complex, multivariate systems such as large commercial buildings. The state evaluation techniques have the ability to not only capture the characteristics of a building but are able to do so without intensive programming. Furthermore, the dynamic benchmark (TCR) would be of significant commercial benefit to building owners and facilities management teams who wish to achieve greater control over operational costs. Further development of these novel systems could potentially lead to a commercial product in which intelligent real time evaluation and building performance representation is delivered, thus providing an alternative to current monitoring and targeting software. As with monitoring and targeting software, the system would be integrated within the BEMS. The system would be capable of not only providing analysis

on energy performance but additionally would be able to target areas of poor performance and their causes as well as maintenance faults. The development of the prognostic features would allow for extrapolation of future trends for improved long term performance and remediation of maintenance faults before they fully propagate. These innovative features would differentiate this product from commercial competitors and allow for the formation of the next generation of performance evaluation software within the building sector.

## CHAPTER 10

### 10. Conclusions & Future Recommendations

The primary aim of this research project was to apply condition monitoring strategies for the evaluation of building performance and maintenance practices. A literature survey of the current methods of energy evaluation in commercial building revealed that there was a lack real time energy assessment outside of monitoring and targeting software. The nonlinear and dynamic nature of building operation resulted in many evaluation methods simply using annualised benchmarks that did not take into account the actual features of the building under question. Furthermore, it was determined that the fair appraisal of building performance necessitates that the parameters that affect energy consumption are accounted for. Evaluating energy deviations in isolation was not enough to infer the state of the building. In addition to this, genuine improvements in building performance can only be attained by ensuring that inefficiencies, faults with HVAC and poor operation of the building are identified and remedied.

Three individual techniques were developed aimed at addressing the current shortfalls in building performance evaluation. These methods provided a real time energy performance indicator measuring the actual energy consumption against the design consumption and two condition monitoring strategies targeting building state evaluation and HVAC fault detection and diagnosis.

The real time evaluation methodology provided a basis from which actual energy performance could be measured against. There was a need to calibrate the off peak load which illustrated that it would be highly unlikely that the model output and the actual energy consumption will be completely the same. This can largely be attributed to the fact that variations in building control strategies cannot fully be accounted for using the NCM profiles. Furthermore, variations in the occupancy were not explained by the energy performance indicators. Additionally, permitted or acceptable increases in consumption would negatively impact on the performance rating and conversely, unpermitted reductions in energy consumption as a result of a fault or breakdown would show an improvement.

The key deficiency in the real time evaluation methodology was that it could not differentiate between the various states of operation and therefore could not in isolation fairly appraise the performance of the building. To overcome these deficiencies condition monitoring techniques were employed that would work in tandem with the real time energy tool to provide fair assessment.

The building state evaluation methods had the capability to identify the faulty states of building operation regardless of whether it resulted in an increase or decrease in energy consumption. The state evaluation system required the use of a nonlinear kernel function to accurately represent the building processes. The KPCA method lacked the ability to trace the parameters responsible for the threshold breaches back to the input space for fault isolation. Evaluation of the fault test cases revealed that the KPCA method had the ability to detect the three main fault profiles effectively, with further improvements possible by adjustment of the  $T^2$  threshold limit and sufficient training data. The use of the KFDA and KNN algorithms for fault diagnosis provided a means of establishing classes or groupings of operating states. Supervised training would be required for diagnosis to ensure various building states are accurately classified. Distinguishing between fault events and permitted deviations in energy consumption could be achieved with creation of a separate non-fault class to ensure that acceptable deviations to the nominal case do not result in false alarms. By attributing an energy cost with each classification group the benchmark could be adjusted appropriately to ensure a fair appraisal of building performance. Aside from intermittent faults the statistical based methods were able to successfully detect and diagnose the abrupt and incipient fault cases.

The knowledge models had the ability to detect the intermittent fault profiles far more effectively than the data driven methodology, however, it lacked the versatility to easily adapt to novel situations without the creation of new rules. Introduction of new rules to the rule base would require examination of the process parameters and robust testing to ensure the fault rules did not coincide with other normal operating conditions. It was concluded that the expert system would perform more effectively as a complement to the data driven systems in targeting the fault types that the statistical methods were ineffective at diagnosing, namely intermittent faults. By compensating for the weaknesses of each system, a comprehensive solution to state evaluation was found that could be used to provide the real time energy evaluation tool with the necessary adjustments to ensure fair

evaluation. Additionally, the condition monitoring methodologies would be able to provide feedback to the building user on the faults that were impacting on energy efficiency.

## **10.1 Future Recommendations**

The research performed within this thesis has largely focussed on the effects of individual faults occurring in isolation. Consideration of multiple faults would be an important area of investigation in the process of developing a robust methodology of building state evaluation. The development of a fault classification database would also be a valuable tool in characterising the features of both fault and non-fault events. This in turn would provide a means of determining a relationship between the successful classification rate and the number of classifications held in the database for both fault and non fault parameter changes.

The migration of the fault samples from the nominal data cluster has been mentioned previously. This phenomenon provides a means of fault detection but more importantly by examination of the direction the data samples migrate in also allow for a potential means of prognostics. Work looking into fault paths and fault propagation would offer the means to develop an early warning system for less energy wastage.

Finally, investigations into the limiting factors in the development of a plug and play evaluation system would be useful for identifying the areas in which further research and development is required to progress the field of building performance evaluation.

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