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A statistically-based fault detection approach for environmental and energy management in buildings

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Abstract

Commercial buildings during operation are dynamic environments where changes to control strategies and space usage regularly occur. As a result of these and other issues, a performance gap between design intent and actual building performance emerges. This paper seeks to address the operational performance gap and enhance operational building performance through statistically-based fault detection. Additionally, this paper seeks to remedy the knowledge gap building managers face in the identification of key building faults based on minimal quantities and streams of time-series building data. A new methodology is presented that incorporates simulation and breakout detection to address these issues. Residual based Exponentially Weighted Moving Average (EWMA) charts and Shewhart charts are compared against a breakout detection algorithm to identify shifts or faults in building performance data. Artificial faults are introduced into the measured time-series data to test the validity of the chosen statistical techniques. Statistical metric sensitivity and precision are calculated to quantify the performance of the new methodology. A summary of results demonstrate that the breakout detection algorithm was the most effective method in detecting meaningful faults in building performance data, followed by residual based EWMA and Shewhart models.

Building owners and operators stand to gain considerably from the greater certainty around performance prediction and measurement.

Keywords: performance gap, fault detection, building performance, data analysis, changepoint analysis, statistical analysis, breakout detection.

Nomenclature

λ Lambda

τ Tau

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θ	Theta
c	Critical Value
H_0	Null Hypothesis
H_1	Alternative Hypothesis
i	Model Instance
m	Measured Data
n	Number of Data Points
p	Probability
s	Simulated Data
t	Time
y	Incoming Data

1. Introduction

Buildings consume 40% of global energy, 25% of global water, 40% of global resources and emit 33% of global GHG emissions [1]. It is widely recognised that not all buildings perform efficiently, with European and American legislators commissioning directives such as the Energy Performance of Buildings Directive (2002/91/EC) (recast 2010) [2] and ASHRAE Standard 90.1 [3] to combat the issue. In spite of these directives, indoor environmental needs of occupants are not always satisfied. Overall, typical commercial buildings do not perform adequately in terms of environmental performance and associated energy consumption [4]. A solution to commercial building performance inefficiency may lie within the vast quantities of data now being produced by buildings [5].

Buildings are becoming more intelligent. By 2020, an estimated 20% of the global building stock will be "Smart Buildings" containing 50 billion devices connected to the Internet of Things [6]. Commercial building managers are beginning to see the merit in analysing this building performance data to inform decision making [7]. This analysis typically takes the form of visualisations, where building managers attempt to spot trends in time-series data [8, 9]. Additionally, building managers are generally not equipped with the correct tools and skills to generate insight from building performance data [10]. Building managers are generally limited in terms of time and resources, with their focus on dealing with the next problem that arises in building operation. This reactive process forces the building manager to deal with the highest priority problem first, resulting in many problems being left unsolved [11].

Therefore, accurate and timely information is needed for building managers to make actionable decisions. A number of statistically-based data mining techniques have been used to generate information for building managers, for example decision trees and clustering have been used to discover occupancy patterns within buildings [12, 13]. However, these techniques may be beyond the skills of a typical building manager and with global data production increasing at a rate of 40% annually, traditional visual detection of performance problems by building managers is not feasible [14].

A number of automated analytical processes can aid building managers in the detection of performance problems. One such approach is the breakout detection algorithm which can identify problems caused by unintended shifts in building performance. Breakout detection is a form of changepoint detection that identifies when the probability distribution of a time-series changes [15]. Statistical Process Control (SPC) techniques such as EWMA and Shewhart control charts can also be used to detect shifts in building performance data, enabling the identification of statistically-meaningful performance problems. SPC is applied in a wide variety of industries to monitor and control a process, thus ensuring the monitored process operates to its full potential. Breakout detection and the SPC control chart described above are univariate techniques, applied to a single time-series, and therefore can be used to monitor specific analysis contexts from an energy perspective (e.g. HVAC energy consumption) and from an indoor environmental perspective (e.g. zone dry bulb temperature).

This paper seeks to address the knowledge gap building managers face in the identification of key building faults based on minimal quantities and streams of time-series building data. The objective of this paper is to minimise the operational performance gap and enhance operational building performance through fault detection. In the context of this paper, the operational performance gap can be viewed as the environmental and energy performance gap that exists between 1) measured operational building data and 2) predicted performance as quantified by a building performance simulation model, data driven model or other. In this paper we reference a calibrated simulation model.

This work introduces a new statistically-robust methodology that incorporates simulation and breakout detection to achieve these objectives.

The methodology uses short-term forecasts of building performance, represented by prediction model output data, to reset and guide operation once a shift in building performance has been identified by the chosen statistical technique. Through this methodology, statistically-significant faults can be correctly identified for building managers. Predictive models can be simulation or statistically-based and provide a prediction of future performance for a particular analysis context.

The breakout detection algorithm achieves the best performance when compared against a number of other statistically-based fault detection techniques in the detection of meaningful faults in building performance data, followed by residual based EWMA and Shewhart models. The effectiveness of the breakout detection methodology is demonstrated by means of a case study that analyses relative humidity time-series data from a swimming pool hall.

The state-of-the-art in relation to fault detection in buildings and the merits of a number of statistically-based fault detection techniques in comparison to the breakout detection technique used in this paper are reviewed in Section 2. The statistically robust methodology is presented in Section 3 to identify statistically-significant faults for building managers. An evaluation of breakout detection in buildings is presented in Section 4, while the applicability of the breakout detection methodology is demonstrated by means of a case study of indoor environmental conditions within a swimming pool hall in Section 5.

2. State-of-the-Art

Building Management Systems (BMSs) often have pre-programmed alarm notifications for important criteria such as room temperature, room humidity etc. If room temperature, for example, goes outside a specified pre-programmed range an alarm notification is triggered in the BMS for the building manager to check. Building managers normally operate within resource constrained environments and are typically overrun by alarms, ensuring that many building problems continue indefinitely. A building manager's focus is not optimal operation but simply keeping the building operational [11]. Many methods exist for Fault Detection and Diagnosis (FDD) in operational buildings, fault detection can be achieved "manually" through visual inspection of charts or trend analysis. Another method to detect faults in buildings is through rule-based methods.

Rule-based methods can be broadly categorised as first-principle qualitative models, where qualitative relationships or "rules" are generated from knowledge of underlying system operation [16]. House et al. (2001) developed a rule-based fault detection method for Air Handling Units (AHUs) and tested it using simulation and field data [17]. This work was extended by [18] with the development of a fault detection tool underpinned by a set of expert rules in the assessment of Air Handling Unit (AHU) performance. The developed tool was referred to as AHU Performance Assessment Rules (APAR), which uses occupancy information in conjunction with control signals to define operational modes of AHUs, thereby identifying a subset of rules that specify temperature relationships for specific AHU operational modes. Bruton et al. (2014) undertook extensive field testing of the APAR system in order to prove its effectiveness [19]. This work also developed an automated fault detection and diagnosis expert system for AHUs, which was shown to outperform the APAR with both simulated and actual field data. Additionally, Bruton et al. (2013), undertook an extensive review of automated fault detection and diagnostic tools in AHUs [20]. Statistical-based methods to detect faults in buildings will be reviewed in Section 3.5.

2.1. Statistical Learning Based Methods for Fault Detection

Analytics of time-series building data is emerging, with a variety of techniques and potential application cases. Machine learning models have been used extensively to predict building energy consumption [21, 22]. By feeding time series building data to statistical techniques such as linear regression, neural networks, support vector machines etc., predictions of future building performance can be generated. These statistical approaches do not explicitly model the buildings' physical systems, but instead use a number of carefully selected variables such as outside air temperature, historical building performance data, occupancy etc. to predict correlated outputs such as the energy consumption of a building [23]. However, these statistical models need to be trained and tested on extensive quantities of time-series data, in the region of two year's worth, to produce meaningful performance predictions [21, 24]. Additionally, this quantity of time-series data is needed for each input (e.g. occupancy level) of the statistical model.

Machine learning models have also been used in a number of analysis contexts for FDD in buildings. West et al. (2011) developed a FDD approach for HVAC subsystems based on statistical machine learning and information theory [25]. A genetic algorithm in tandem with cumulative sum analysis was used to detect faults in control loops by Wang et al. [26]. An automated building HVAC fault detection approach was developed by [27] that uses a recursive least-squares-based algorithm to detect faults in HVAC operation. The advantage of this approach is that it does not require a detailed physics-based model of the building to function successfully.

Principal Components Analysis (PCA) was used in conjunction with joint angle analysis by [28] to detect both fixed and drifting biases of sensors in variable air volume systems. PCA was again used in conjunction with an expert rule system to detect sensor faults in typical AHUs by [29].

Support Vector Machines (SVM) were used in tandem with a genetic algorithm with parameter tuning for FDD in chillers by [30]. Parameter tuning was then used to select the best parameters to optimise SVM performance while additionally simplifying the detection and diagnosis process. The number of parameters used in SVM was reduced from 64 to 8 by parameter tuning.

When reviewing the methods described above, the combined use of a number of statistically-based techniques is needed to detect and diagnose performance problems in buildings. Generally, the use of multiple statistical techniques in tandem is necessary to simplify the fault detection process. These techniques can be complicated to implement, time consuming to optimise and computationally intensive.

2.2. Statistical Process Control Techniques

Simpler statistical approaches, that work with a single time-series and do not require the same quantity of data as machine learning models to run effectively can be used to identify building performance problems. Statistical Process Control (SPC) techniques such as Shewhart and EWMA are statistical techniques that are employed to monitor and control a process. These techniques can be applied to building performance data to identify if HVAC equipment is operating optimally or not [31]. An SPC technique that has the ability to detect parameter shifts in the variable of interest will now be discussed.

Shewhart charts are a form of SPC chart used to monitor and control a process of interest. Shewhart charts are sensitive to detecting relatively large shifts in the process mean (i.e. of the order of 1.5σ or above) [32]. Shewhart charts only use the last data sample from a process and do not retain any historical data. This potentially makes Shewhart charts less useful in monitoring processes where issues occur in relation to small to moderate mean shifts. Residual based Shewhart control charts were used by [33] within a web-based platform to evaluate the quality of HVAC systems in buildings. The capacity to detect small parameter shifts in the variable of interest can be enhanced by using a technique that integrates information from current samples in addition to past samples such as EWMA.

EWMA control-based monitoring calculates a moving average through the multiplication of all historical observations by a weight that decays exponentially over time [34]. Essentially, EWMA gives less weight to data as they are further removed in time. EWMA control-based monitoring is effective in detecting small shifts in the process mean (i.e. of less than 1.5σ). By regulating the value of the weighting factor λ, the EWMA control procedure can be made sensitive to small or gradual shifts in the process. Cumulative Sum (CUSUM) charts can also be used to detect small shifts in the process mean, but as EWMA uses a weighted average of all observations it is less sensitive to violating the normality assumption [35]. Additionally, CUSUM is relatively slow in responding to large shifts in the process mean. EWMA control charts were also used by [36] for early detection of fouling of heat recovery systems. Residual based EWMA control charts were used for FDD in air-conditioning systems in tandem with an expert rule system by [37].

Again a combination of techniques was necessary to simplify the identification and diagnosis of key building faults by [37]. The development of an expert rule system may be beyond the scope of the skills of a typically building manager and time consuming to implement across all building systems and processes. A more scalable technique is now discussed in Section 2.3.

2.3. Breakout Detection

Breakout detection is another univariate statistical analysis technique that will be used in this paper to identify problems caused by unintended shifts in building performance. Breakout detection is a form of changepoint detection that identifies when the probability distribution of a time-series changes and does not require the same quantity of data as machine learning algorithms to run effectively. Breakout detection does not require a combination of techniques to accurately identify building performance problems.

A breakout is characterised by either a mean shift or a ramp up from one steady state to another in a given time-series (Figure 1) [15]. Since breakout detection is run using a single time-series the detection of the performance problem is much easier, with methods such as parameter tuning unnecessary.

From a building performance perspective, the breakout detection algorithm has only been used once previously in a model calibration context [38]. The algorithm was used to identify macro-level changes in eight years of historical power meter time-series data. The algorithm's focus was to determine continuous areas of performance that are similar and transition performance periods, with a minimum time-span of six months allowed between the detection of subsequent breakouts.

This paper leverages the E-Divisive with Medians (EDM) breakout detection technique, developed by [39]. EDM uses a modified variant of energy statistics that is more resilient to anomalies through the use of robust statistics such as the median. The concept of energy statistics is to compare the distances of means of two random variables contained within a larger time-series. However, the presence of outliers or anomalies would limit the effectiveness of using the mean in this process as a single outlier can have a significant effect on the mean of a time-series. To that end, the EDM technique is built on the more robust median. EDM has shown to outperform other existing breakout detection approaches based on the

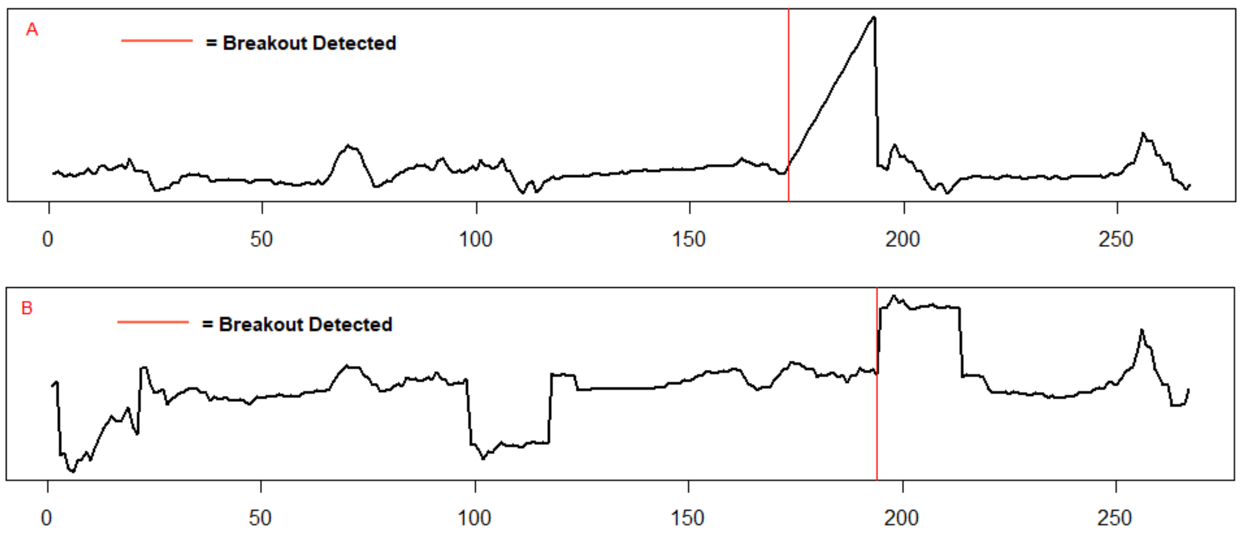

Figure 1: Figure 1 (A) illustrates detection of a ramp-up in the time-series by the breakout algorithm. Figure 1 (B) illustrates detection of a shift in the time-series by the breakout algorithm.

"time-to-detect" a breakout and precision [15]. The mathematical background behind EDM breakout detection technique is presented in Appendix A.

Certain situations exist where the EDM algorithm may be limited in terms of performance. Situations where building systems or components are cycling on/off constantly throughout the course of the day may induce false positives in the EDM algorithm. EDM may view the data points produced from cycle on/off as anomalies.

The statistically-robust breakout detection methodology is now presented in Section 3 that enables the automated detection of faults using building time-series data.

3. Methodology

The methodology presented in this paper combines: 1) measured time-series data used in a statistically-based analysis technique to identify unintended changes in building performance and 2) short term forecasts of building performance, represented by prediction model output data, to reset and guide operational performance (Figure 2). The methodology's key contribution is an improvement in building performance through the identification of key building faults for building managers, thereby reducing in the environmental and energy performance gap.

The choice of analysis context is the key input that underpins the methodology. The methodology can be implemented over a range of analysis contexts (i.e. building, system, component level and zonal level) [40] if time-series data exists, for that particular analysis context. The breakout detection methodology is illustrated through the use of a worked example that uses Air Cooled Chiller (ACC) electricity time-series data. The 'R' programming language was used to implement the methodology and subsequent analysis.

The breakout detection methodology comprises three key stages once a particular analysis context has been selected (Figure 2):

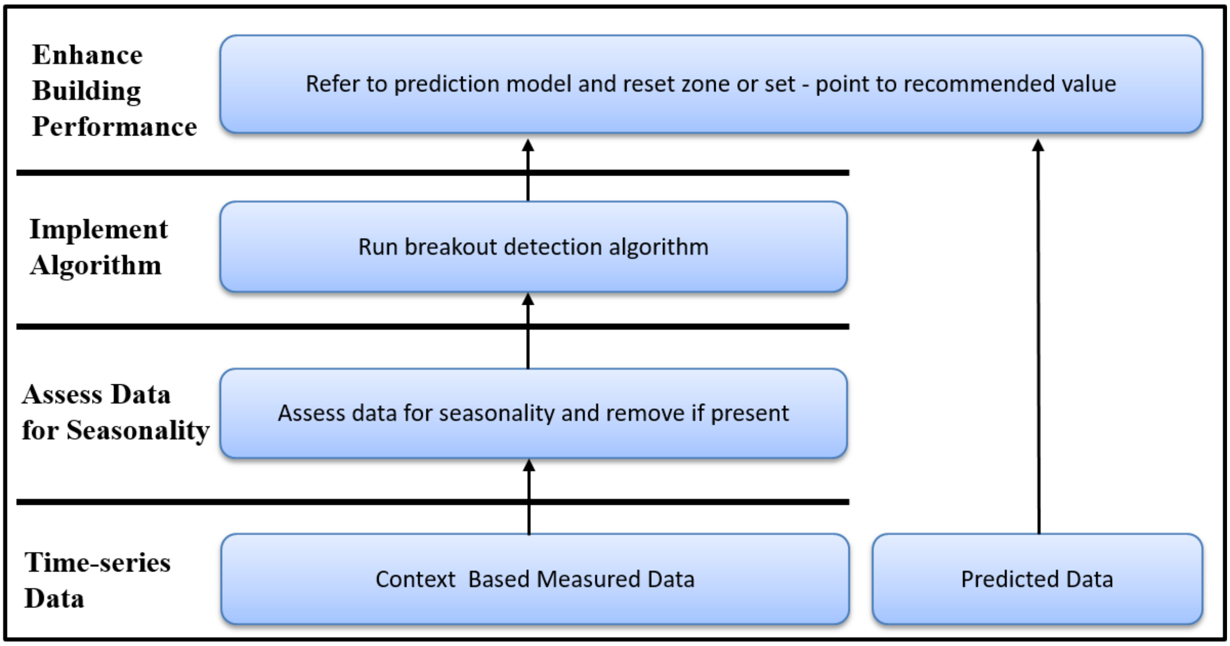

Figure 2: Methodology that combines measured time-series data used in a scalable breakout detection algorithm to identify unintended shifts in building performance and prediction model output data, as a reference to guide operational performance.

1. Assessment of the existence of seasonality in the data (Section 3.1)
2. Implementation of EDM breakout algorithm on the data (Section 3.2)
3. Enhancement in building performance (Section 3.3)

3.1. Assessment of the Existence of Seasonality in the data

A seasonal pattern exists in a time-series if it is influenced by seasonal factors such as the month of the year, or the day of the week. For instance, office energy consumption is usually higher on weekdays than on weekends. This is a seasonality of 7 days. The EDM algorithm has shown to be more susceptible to false positives when seasonality exists in time-series data [41]. A false positive can be thought as a false alarm. That is, identification of a breakout by the EDM algorithm when in fact no breakout has occurred. Therefore, the data has to be tested for seasonality, and if present, such seasonality removed or mitigated.

The identification of a seasonal pattern within a time-series is achieved mathematically through the seasonal Trend Decomposition using the Loess (STL) [42] algorithm that decomposes the original time-series into three separate components, namely: seasonal, trend and remainder:

1. Seasonal: the pattern that repeats with a fixed period of time.
2. Trend: the underlying trend of the metric. For example, Air Cooled Chiller (ACC) electricity consumption may peak in the summer months. So the time-series of ACC electricity consumption will trend upwards from March to September and decline from October to March.

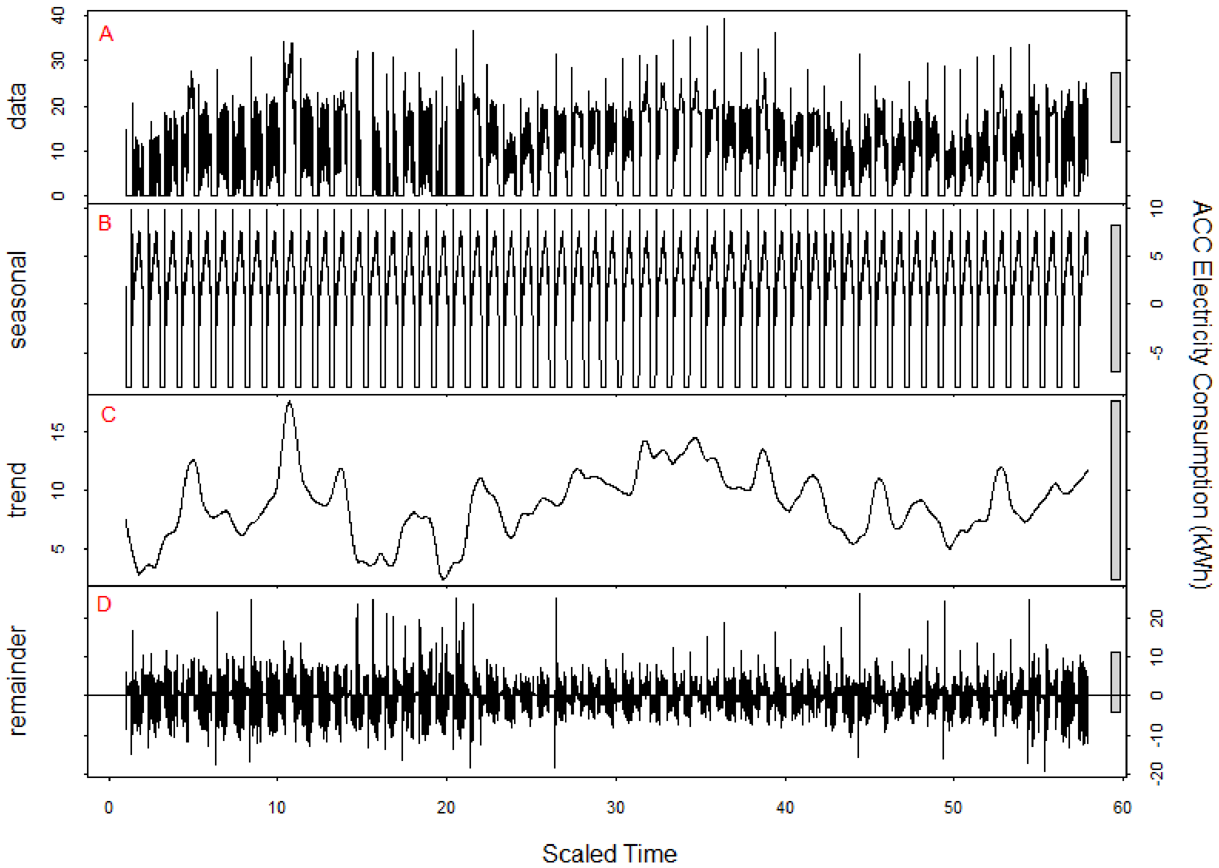

Figure 3: Output from STL algorithm implemented on ACC electricity consumption data. The STL algorithm divided the original time-series into three components. With a seasonality of one day clearly seen in the ACC electricity time-series (Component B).

3. Remainder: the remainder of the time-series after allocation into the seasonal and trend time-series. The remainder can be viewed as noise in the time-series.

Once seasonality has been identified in the time-series it is then subtracted from the original time-series. Two periods of data are needed to perform decomposition. Given that the data used in the Figure 3 is in 15 minute resolution, four data points will be logged each hour in relation to ACC electricity consumption. A seasonality of one day is clearly seen in the ACC electricity time-series in Figure 3 (Component B).

3.2. Implementation of EDM Breakout Algorithm on the Data

The EDM algorithm is now run on the ACC electricity consumption time-series data to identify whether a breakout has occurred, i.e., if the ACC performance has shifted from one performance state to another or experienced a ramp up. When applying the EDM algorithm to building performance data, the EDM algorithm should be set to detect a single changepoint in a time-series due to the real nature of the analysis performed.

3.3. Enhancement in Building Performance

If the breakout detection algorithm deems the difference in the ACC time-series to be statistically-significant, a breakout will be identified. This breakout algorithm can identify either a mean shift or a ramp up from one steady state to another in a given time-series. Once a breakout is identified, the output data from the prediction model is referred to. This enables identification of the correct operational value, for the ACC, at that particular moment in time.

The performance gap is addressed through the provision of statistically meaningful and actionable information to building manager. In this case the building manager can examine the air cooled chiller and identify the root cause of the problem. He/she can subsequently adjust the operation of the air cooled chiller until the recommended value from the calibrated simulation model is obtained. Through this process, the performance gap is minimised through the realignment of the measured operational building performance with simulated performance.

A number of components that underpin the methodology will now be discussed in Sections 3.4, 3.5 and 3.6.

3.4. Simulation Model Use and Development

In the first years of a building's operation it undergoes a period of 'sea trials' [43], where occupation levels are increasing and all seasonal modes of operation occur. Therefore, calibrated dynamic building energy models such as EnergyPlus can act as a tool in the assessment of building performance and quantification of efficiency improvements in early operational stage of the Building Life Cycle (BLC) [44].

For the purpose of this work we need a benchmark from which non-standard performance can be compared. Calibrated prediction models provide a representation of normal operational building behaviour. Different modelling solutions exist at different scales within buildings, in this paper for example, the whole building energy simulation model was developed in EnergyPlus, while the HVAC and control system of UCD swimming pool were developed in Modelica. Calibrated prediction models can therefore represent a whole BEPS or a detailed system or component level model, depending on the analysis context.

Building Performance Simulation Models (BEPS) are best used to quantify differences between alternatives during the design process. When considering buildings and prediction models during operation:

- the nature of change can be considered stochastic for buildings as opposed to deterministic in the most commonly used BEPS software,
- the sequence of change in buildings is continuous whereas BEPS software typically considered changes in discrete time-steps and
- when calculating changes in the status buildings can be considered event oriented and typical BEPS software uses uniform time units.

In addition, the largest factor in the performance gap can be the modellers themselves due to the number of subjective decisions and work-arounds to software limitations that are made during model development.

Once a breakout is detected in time-series building data as per the methodology detailed in Section 3, a calibrated simulation model is referred to and the building system or zone set-point is reset to the recommended value.

The validation of dynamic building energy simulation models against measured building performance data is currently based on a simulation model's compliance to standard statistical indices such as the Mean Bias Error (MBE). MBE is a measure of overall bias error or systematic error. It is non-dimensional, usually written as a percentage error. MBE is an acceptable gauge of bias in the simulation model. It gives an indication of the mean difference between measured and simulated data, where m_i and s_i are the measured and simulated data points for each model instance 'i', and n is the number of data points.

$$MBE = \frac{\sum_{i=1}^{n}(m_i - s_i)}{\sum_{i=1}^{n}(m_i)} \tag{1}$$

The International Performance Measurement and Verification Protocol (IMVP), provided validation criteria for simulation models to be calibrated to hourly building data, with a 5% difference between measured and simulated deemed acceptable [45]. Other validation criteria exist based on whether the simulation model is calibrated to monthly measured building data [46, 47]. Given the real-time nature of this analysis, the acceptable difference between measured and simulated data is 5% based on the validation criteria provided by IMVP.

3.5. Statistical Model Development

In order to achieve real-time simulation modelling, continuous re-calibration of a dynamic building energy model is required. This is quite a time consuming and laborious task as specific values are assigned to a large number of input parameters such as expected occupancy for each re-calibration of the simulation model. Alternative, statistical approaches exist to provide a representation of the operational performance of a building and its systems. This approach is widely known as machine learning and has previously been discussed above in Section 2.

Once the building is settled and has completed its period of 'sea trials', statistical models can act as a substitute for dynamic building energy simulation models. Sufficient time-series data must also exist to train and run the machine learning models for each analysis context, in the region of two years worth. These machine learning models can provide a representation of correct performance for building systems and components throughout the operational phase of the BLC once the building has settled. The production of machine learning models to predict future building performance is computationally inexpensive relative to the re-calibration of a dynamic simulation model on a real-time basis.

3.6. Ideal Data Resolution

A data resolution of minimum 15 minutes is recommended for building and zonal level building analysis contexts. The ideal data resolution for building and zonal level building analysis contexts is one minute, to facilitate real-time performance analysis.

When analysing the performance of system and component level building analysis contexts such as a control loop, a shorter time interval of one second may be used [48]. For example, the entire short cycling period associated has been shown to be approximately two minutes [49]. This higher resolution data will enable the identification of building systems and components that are malfunctioning, that would not be possible with lower resolution data.

The time-series building data that is fed into the chosen statistical technique and prediction model output data must have the same resolution (e.g. 1 second, 1 minute, 15 minute etc.). This ensures that the measured data resolution and the predicted model output data align, when the prediction model is referred to.

4. Evaluation of Breakout Detection in Buildings

In order to evaluate the performance of the EDM breakout detection technique it is compared against a number of SPC techniques, discussed in Section 2.2. The EDM technique is compared against residual based EWMA control charts and residual based Shewhart control charts. The chosen SPC techniques work with a single time-series and are able to detect shifts in the process of interest, similar to breakout detection. Additionally, residual based EWMA control charts is a state-of-the-art technique that has been recently used by [37] to detect faults using building performance time-series data.

The key idea behind residual based control charts is to fit a time-series model to subtract the autocorrelation in the data. Autocorrelation quantifies the linear relationship between lagged values of a time-series. The existence of autocorrelation in a time-series used in a SPC technique can induce false positives in the SPC technique. Typically an ARMA time-series model is fitted to the data to subtract the autocorrelation in the data as discussed in detail by [37]. The chosen SPC is then used to monitor the statistically independent residuals of the ARMA time-series model. Through this process, the chosen SPC technique can identify if the analysis context is "in-control" or "out-of-control". A process is "in-control" if its data lies between the Upper Control Limit (UCL) and Lower Control Limit (LCL) of the chosen SPC technique. A process is "out-of-control" if its data lies outside the UCL and LCL of the chosen SPC technique. For the EWMA control chart a value of 0.05 was chosen for the weighting factor λ, to enable the identification of small shifts in a time-series. λ is generally chosen between 0.05 and 0.25 [31] for EWMA control charts and the value chosen is dependent on the monitored process. When $\lambda = 1$, the EWMA resorts to a Shewhart chart that is focused on large shifts in the monitored process. A value of $\lambda = 1$ will be used to develop the Shewhart control charts in this paper.

The performance of the residual based EWMA control charts, residual based Shewhart control charts and breakout detection are now compared and validated through the identification of faults in building performance data. Two metrics are used to compare the performance of the three techniques: i) Sensitivity and ii) Precision.

- Sensitivity: For those data that are truly faults, how many were identified as faults by the statistical technique?. Sensitivity is the ratio of True Positives (TPs) over the sum of TPs and False Negatives (FNs).
- Precision: For those data points that are identified as faults by the statistical technique, how many were truly faults?. Precision is the ratio of TPs over the sum of TPs and FPs.

A number of artificial faults are introduced to measured building time-series data that have been operating under normal conditions for a period of two days. These artificial faults are simulated in seven building time-series at varying degrees of severity to test the performance of the three statistical techniques. The artificial faults are simulated in system level performance data and zonal level indoor environmental data.

4.1. Example: Abrupt Change in AHU Supply Temperature

For this example, measured operational data was obtained from an AHU within University College Dublin (UCD) sports centre at 15 minute resolution. An artificial fault in the form of an abrupt increase in the AHU supply temperature time-series was introduced at data point 196 approximately. The artificial fault lasted for 17 data points, finishing at data point 213 in the time-series. The AHU supply temperature fault represents a system level fault within the building [40]. The performance of the AHU directly impacts the indoor environmental conditions of the occupants that reside in the zone the AHU maintains. It is therefore of paramount importance that the AHU operates correctly with minimal faults.

The residual based EWMA control chart correctly identifies the artificial fault from points 196-213 (Figure 4) as the data rises above the UCL. However, the residual based EWMA control chart also incorrectly classifies a number of points at data point 1, 100 and 182 as being "out-of-control" as the data falls below the LCL when in fact the points are "in-control".

The residual based shewhart control chart was also implement on the AHU supply temperature containing an artificial fault from points 196-213. The residual based shewhart control chart also identifies that the AHU supply temperature also experiences an abrupt shift at point 196 (Figure 5), however as the residual based shewhart only use the last data sample from the process and does not retain any historical data it fails to classify the rest of the artificial fault from 197-213 correctly as faulty data. The residual based shewhart control chart also incorrectly classifies a number of points as being "out-of-control" when in fact the points are "in-control".

The EDM algorithm correctly identified the abrupt increase in AHU supply temperature using the methodology discussed in detail in Section 3 (Figure 6). The EDM algorithm correctly identified the location of the change in the time-series and also identified the increase in AHU supply temperature in a timely fashion, at data point 196 approximately.

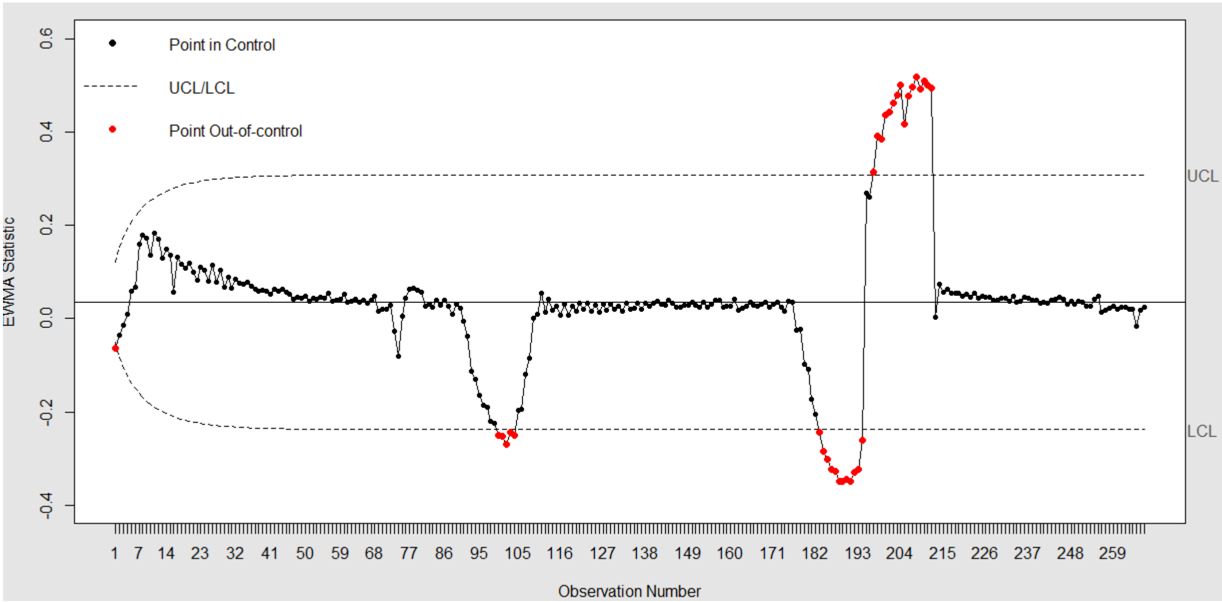

Figure 4: Output from residual based EWMA control chart implemented on AHU supply temperature data. Although the residual based EWMA control chart detects the artificial fault from points 196-213, a number of false alarms also occur, represented by the red dots.

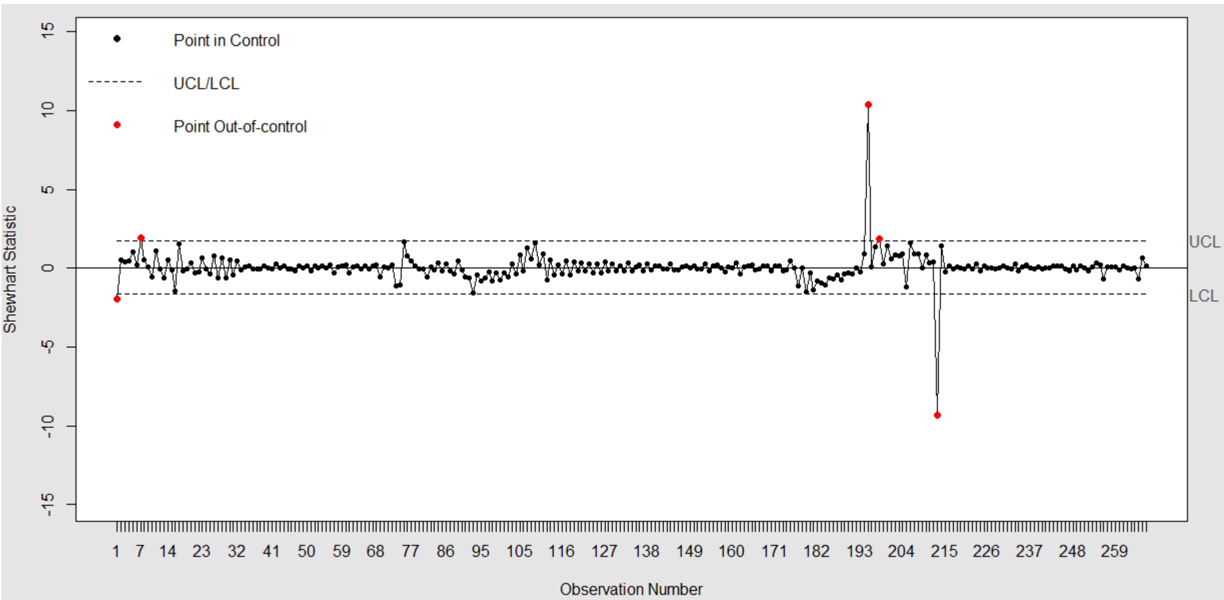

Figure 5: Output from residual based shewhart control chart implemented on AHU supply temperature data. Although the residual based shewhart control chart detects the artificial fault at point 196, a number of false alarms are also seen represented by the red dots.

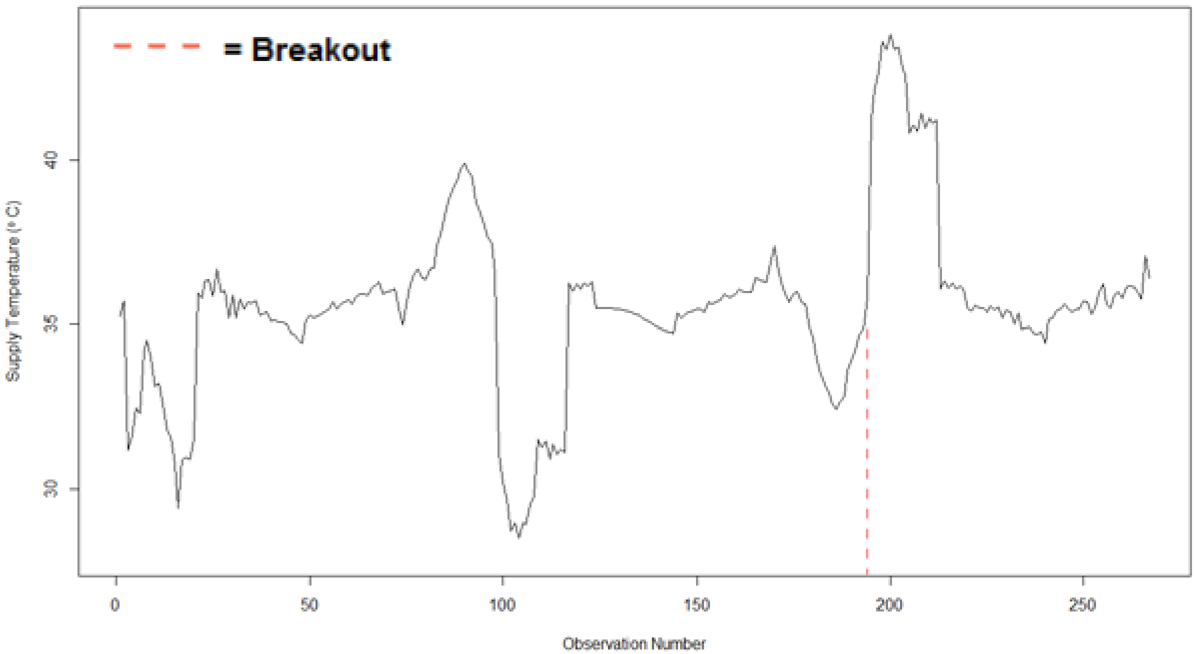

Figure 6: Output from the breakout detection algorithm implemented on AHU supply temperature data. The breakout detection algorithm correctly identifies the abrupt increase in AHU supply temperature.

At observation number 90 in Figure 6, the EDM algorithm did not deem the drop in supply temperature statistically-significant. Seasonality has been extracted from the original time-series as per the methodology discussed in Section 3 resulting in the EDM algorithm correctly identifying the abnormal change in the time-series as a fault at data point 196.

A summary of results is now presented in Section 4.2.

4.2. Summary of Results

As seen in Table 1 the breakout detection technique achieves the best performance, followed by residual based EWMA control chart and finally the residual based shewhart control chart. The EDM algorithm has a sensitivity of 0.857, meaning that it will correctly identify faulty data 85.7% of the time. The residual based EWMA control chart has a similar performance when correctly identifying faulty data with its sensitivity standing at 80.8%. The residual based shewhart control chart has the worst performance of the three techniques when identifying faulty data with its sensitivity standing at 47.7%.

The EDM algorithm again outperforms the residual based EWMA and shewhart control charts in terms of precision. The breakout detection algorithm has a precision of 0.857, meaning of the data points identified as faults by breakout detection, 85.7% of the time these data are actually faults. The residual based EWMA control chart has the next best performance with its precision standing at 63.3%. The residual based shewhart control chart has the worst performance of the three techniques when identifying faulty data with its precision standing at 29.2%.

A case study will now be presented using time-series data from the UCD sports hall

Table 1: The sensitivity and precision are reported for residual based EWMA control charts, residual based shewhart control charts and breakout detection in Table 1

Statistical Technique	Sensitivity	Precision
EWMA	0.808	0.633
Shewhart	0.477	0.292
Breakout Detection	0.857	0.857

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and the breakout detection methodology discussed in detail in Section 2.3 will be used to illustrate the case study.

5. Case Study

The case study analysed Relative Humidity (RH) time-series data from the sports centre within the UCD swimming pool hall in 2015. The pool air is typically kept at 30°C and relative humidity kept in the region of 50%-70%. With this air temperature and the warm temperature of the water (29-30°C), there will be a lot of evaporation from the pool. Humidity can rise quickly and if humidity levels in the swimming pool hall rise above 70%, chemicals from the pool water become airborne. These chemicals can rapidly corrode the walls and other surfaces within the pool hall over time. If excessive humidity levels within a swimming pool hall are countered by increased dehumidification, pool water evaporation will further increase, increasing the demand on energy and water for refilling. Additionally, high humidity above 70% provides uncomfortable indoor environmental conditions for occupants.

Traditionally, an alarm notification would have been set off in the building management system, notifying the building manager if RH levels exceeded 70%. This is the case, as illustrated by the RH time-series venturing above 70% RH (represented by the dashed blue line) multiple times in Figure 7. Given that the RH data is at a resolution of 15 minutes over a hundred alarms would have been triggered in the BMS for the building manager to review. Due to the volume triggered in the BMS the building manager will more than likely deem the alarms redundant and move onto the latest problem or fire that needs to be dealt with in the building. Alternatively, she/he would have spent considerable time and resources checking the environmental conditions within the pool hall and HVAC system settings to ensure everything was satisfactory.

Therefore the context based time-series data analysed is RH data of 15 minute resolution from the sports centre within the UCD swimming pool hall. Seasonality is then removed from the time-series as per the methodology in Section 3. The removal of seasonality from the time-series will mitigate the effect of external air moisture content and solar gain on pool humidity levels. Once seasonality is removed, the EDM breakout detection algorithm is then run on the RH time-series data.

A breakout was detected (represented by the dashed red line) by the breakout detection algorithm on the 14th of May in Figure 7. In this instance, pool hall RH levels experienced a steady state shift in RH from 62% to 73%. This new steady state is operating above 70%.

The building manager should then refer to the output data from the calibrated simulation

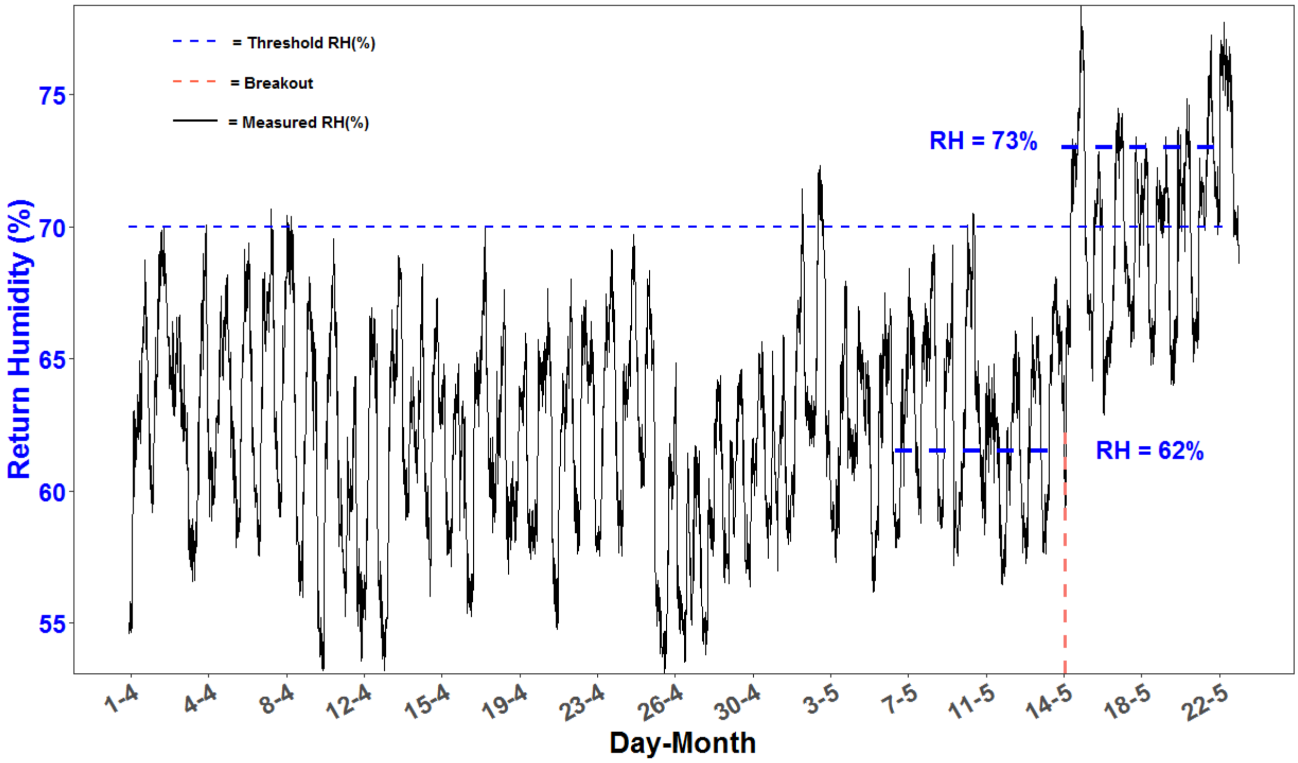

Figure 7: Breakout detection algorithm illustrating the detection of a steady state shift in RH above an acceptable value of 70%.

model as per the methodology in Section 3. The mean value of the new steady state of 73% is compared with the mean value from the calibrated simulation model.

As the breakout was detected on the 14th of May, a two-day average is taken of the output from the calibrated simulation model from the 13th to 15th of May. This process is to ensure a representative value of RH is obtained, reducing the bias associated with single point measurement taken from the calibrated simulation model to represent normal operational swimming pool RH. The two-day average value from the 13th to 15 to May for RH from the calibrated simulation model is approximately 60%, illustrated by the solid red line intersecting the dashed blue line in Figure 8. Additionally, the maximum value of RH from the calibrated simulation model over the seven week period analysed was 65.7%, well below the maximum limit for swimming pool halls of 70% RH for swimming pool halls. Maintaining RH below 70% reduces condensation on the swimming pool halls internal structure and provides comfortable conditions for occupants.

The building manager would then reset the operating conditions within the HVAC system that maintain the environmental conditions within the pool hall until correct operating conditions are reached. In this instance 60% RH. Maintaining RH below 70% reduces condensation on the swimming pool hall internal structure and provides comfortable conditions for occupants. Alternatively, the detected breakout in Figure 7 could signify that a piece of HVAC equipment has broken or developed a fault.

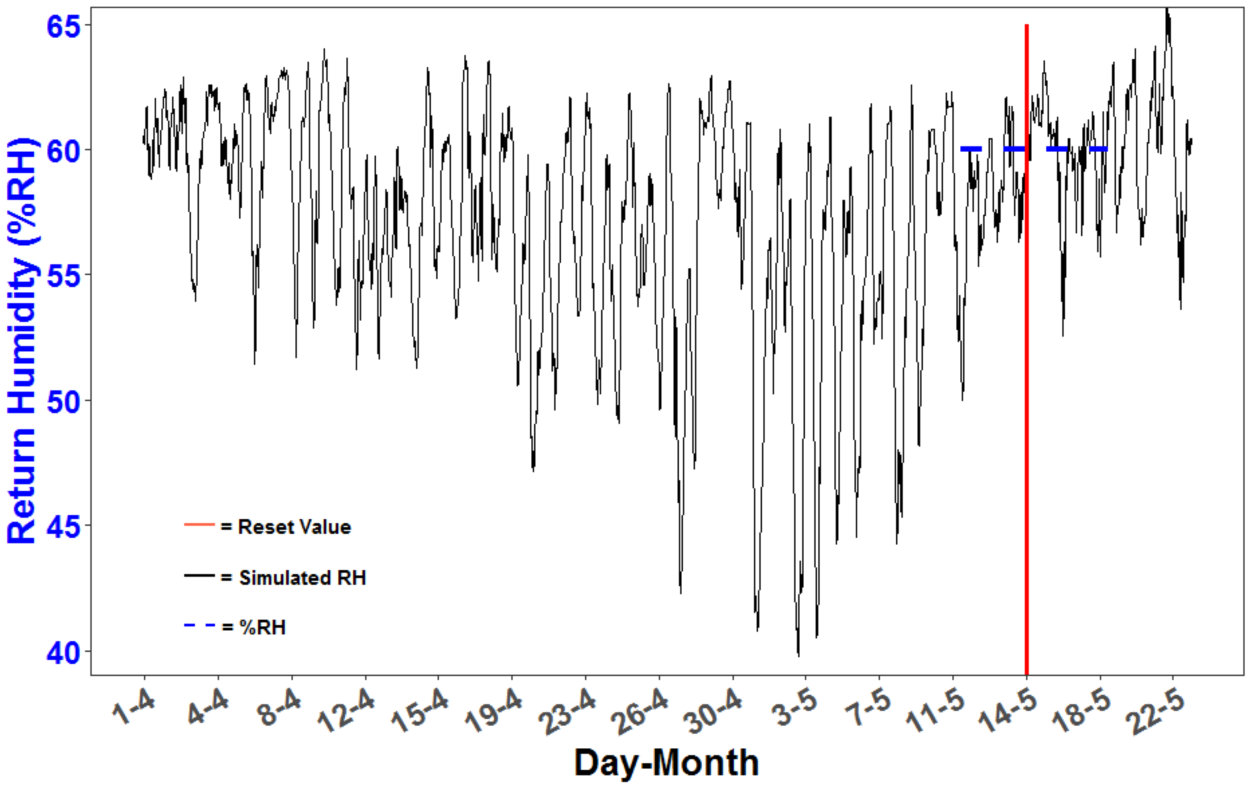

Figure 8: The calibrated simulation output data is referred to, enabling identification of the correct value of pool hall RH at that particular moment in time. In this instance it is approximately 60% RH.

It should be noted that EDM does not provide significance values for each breakout detected. EDM automatically detects based on a significance value of 5%.

When an unintended shift in building performance was detected (e.g. RH), actual time-series data from the UCD pool hall are compared with output data from a prediction model, in this instance a simulation model. The combined use of the breakout detection algorithm and calibrated simulation model output data ensures the building manager is not overrun by non-significant alarms, enabling him/her to do more work with available resources.

6. Conclusion and Future Work

This paper proposes the idea that data analysis and simulation can be used in tandem to improve building performance and reduce the environmental and energy performance gaps in buildings.

This work presents a novel combined approach to address the performance gap. A scalable methodology is implemented that identify shifts in building performance, with calibrated simulation used to reset and guide operational performance. The engineering value of this process is that it can be run in real-time, as time-series data is produced, to identify shifts in performance and reduce the performance gap.

The combined approach can be viewed as a tool to improve building performance and reduce the environmental and energy performance gap, in the face of increased regulation and specifications regarding building performance.

These methodology can be applied generally to any building context, as long as time-series data is produced and a prediction model exists related to the context in question. Specifically, this context based analysis approach generates efficiencies within the building performance sector, by enabling building managers to identify the root cause of the problem within the building and rectify it. This is of paramount importance as building management is a reactive process akin to fire fighting where the next emergency is dealt with first.

Results demonstrate that the breakout detection algorithm was the most effective method in detecting meaningful faults in building performance data, followed by residual based EWMA and Shewhart models.

Dependent on the analysis context in question, this will result in an improvement in indoor environmental conditions or a reduction in building energy consumption. The energy performance gap between measured and simulated energy consumption will narrow, as measured building performance is aligned with simulated building performance.

This work automates the manual visual detection of performance problems that is currently undertaken by building managers through trend analysis. Thus enabling building managers to do more work with the resources available to them. This approach is scalable across the building stock, once the building has gone through its period of settlement and time-series data exists to train and run statistical-based performance prediction models.

Future work in this research process will look into context based analysis of building performance. These models will use measured time-series building performance data to produce context based performance prediction models. The delivered outcome from this process will be the production of statistically-based prediction models to represent building performance.

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Appendix A. Mathematical Background of EDM

This section describes the mathematical background of the chosen EDM technique implemented in Section 3.

A hypothesis test is used to determine if this difference in state is statistically-significant. Specifically, within the EDM technique used in this paper, the hypothesis test seeks to determine if a significant changepoint exists or not in the time-series. In this paper, the EDM technique was set to detect a single changepoint in a time-series.

The null hypothesis (H_0) is that no changepoint exists in the time-series. The alternative hypothesis (H_1) is that a significant changepoint exists in the time-series. The EDM technique is based on Maximum Log-likelihood Estimation (MLE) (Eq. A.1). Likelihood is a measure of how good the hypothesis is, essentially the probability of observing the data contained in the time-series are true. The alternative (H_1) hypothesis is true and changepoint exists at time $\mathrm{t} = \tau$, dependent on the data in the time-series. The incoming data (e.g. ACC electricity consumption) supplied to the EDM algorithm is represented $\mathrm{y}_{1:\mathrm{n}} \in (y_1, ..., y_\mathrm{n})$.

Each continuous random variable or data point in the time-series is assumed to be drawn from some Probability Density Function (PDF), described by p. The maximum likelihood estimate of the parameters is represented by θ. A PDF is a function whose value at a given sample point, in a sample space (i.e. set of possible values the random variable can take) provides a relative likelihood that the value of the random variable would equal that sample. For a model with a changepoint at τ_1 where $\tau_1 \in (1, 2, ...n-1)$, the MLE is the PDF of θ, the parameter of interest.

$$MLE(\tau_1) = ln(p)(y_1 : \tau_1|\hat{\theta_1}) + ln(p)(y(\tau_1 + 1 : n|\hat{\theta_2}) \tag{A.1}$$

At some point in the time-series and precisely between t = τ and t = $\tau + 1$, a changepoint is detected. The changepoint location is unknown, therefore the likelihood for each changepoint location is calculated with the most likely value taken as the hypothesised changepoint location. This likelihood and location is then tested to check if the changepoint is significant by comparing the test statistic λ (Eq. A.2), to a 'critical value' c. If $\lambda >$ c, the null hypothesis is rejected and a changepoint is identified. $maxML(\tau_1)$ and $ln(p)(y_1 + 1 : n|\hat{\theta})$ represent the alternative and null hypothesises in (Eq. A.2).

$$\lambda = 2[maxML(\tau_1) - ln(p)(y_1 + 1 : n|\hat{\theta})] \tag{A.2}$$

The calculation of a precise critical value to test the hypothesis requires knowledge of the underlying distribution, which is generally unknown. Therefore, a permutation test is used to determine if the distance between the means of the two random variables is statistically-significant. Data from the two time-series is permuted a finite or limited number of times to ensure the process of comparing permuted time-series computationally manageable. The appropriate value for the critical value 'c' is still an open research question with several authors devising p values and other criteria under different types of changes.