Tightening the Constraints Faster: A Statistical Process Control Approach to Commissioning in Buildings.

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ABSTRACT

Statistical Process control is a technique often used in manufacturing in order to determine whether a process is changing based upon most recent measurements. This paper will outline a preliminary methodology for determining when building operation parameters have changed, attempt to identify them, and suggest solutions, given a top-down monitoring methodology combined with a bottom-up fault diagnostics approach. The approach in this paper will combine the use of free open-source graphical analytic tools with whole building interval energy consumption data for the development of control charts. This technique leverages advancements in computing and smart grid technology along with industrial process quality control methods to facilitate fault detection and diagnostics in commercial buildings. This technique will be discussed, from technical requirements to implementation, with special attention paid to the progress of a test case deployment.

Introduction

Buildings consume roughly 40% of energy in the United States, with 19% of that energy being in the commercial sector. In addition to being a major contributor to energy consumption, commercial buildings are projected to be the fastest growing energy consuming sector in the next 25 years. (EIA 2013). In order to manage the energy consumption of existing buildings, retrocommissioning (RCx)- tuning buildings to consume less energy, is employed. In the process of retrocommissioning, building energy consumption is reduced on average by 16% at a cost of $0.30 per square food, producing an average payback of 1.1 years. These savings persist for roughly 3-5 years, and if each building commissioned every 5 years, it would lead to a future industry that has revenues of $4 billion dollars per year - up from a 2009 industry of $200M a year (LBNL 2009). The length of time that it takes for 50% of retrocommissioning measures to fail is known as the expected usable life (EUL). Utilities have different definitions of what the EUL of RCx measures are, with PG&E stating that control changes have an EUL of 3 years, equipment repair has an EUL of 8 years, and equipment replacement has an EUL of 12 years (Roberts and Bing 2010). In order to combat this loss of energy savings experienced by failing efficiency measures, there has been a research and development drive in "Monitoring Based Commissioning (MBCx) programs. MBCx combines permanent building monitoring systems with RCx protocols in order to produce lasting savings in buildings (Brown 2006).

When an industry goes from making one-off items to massive, repeated production of a good or service, it must create a means for ensuring the quality and specificity of its wares. In the Total Quality Revolution of the 1950s, Edward Deming developed and helped implement a statistical quality improvement system in Japan's auto industry. Deming's work built upon the work of Walter Shewart, who introduced control charts as a statistical approach to improving manufacturing at Bell Labs (Devore, Chang, and Sutherland, 2006). Previous work has looked at how to attach metrics to building energy use that are chartable, but not necessarily statistically derived in a process control framework (Price et al, 2011). The building commissioning industry is at the point where it needs both a mass production method and a quality assurance procedure such as that explored in this paper. We present the beginnings of a method of statistical process control (SPC) that offers the basis of these requirements for a commercial deployment of SPC technology on buildings.

Regression based SPC is a technique for monitoring and improving temporally auto-correlated processes in industrial processes (Apley 2002). For this procedure, at every time point, a processes' outcome is predicted by some means that properly accounts for time-series effects, and then compared to the result acquired when the process is measured at that time step. In order to measure the statistical significance of the prediction deviating from the actual measurements, a control chart methodology is applied to this problem. In our case, we use a moving average control chart because it can highlight trends faster than some other kinds of control charts. In addition, we use a rolling window outlier detection scheme that is similar to a classical control chart in order to highlight points in a building's interval electricity consumption data that are difficult to predict. (Devore, Chang, and Sutherland, 2006).

Methods

All of the data in this paper were analyzed using R - a free software environment for statistical computing. Building power use data for this paper are stored on the sMAP repository at (new.openbms.org). sMAP is an open source standard for communicating sensor data, similar to how HTTP is a standard for internet communications. More information on sMAP can be found at (http://www.cs.berkeley.edu/~stevedh/smap2/). More information on R can be found at (http://www.r-project.org/)

Data was gathered from two commercial buildings in different locations: for the purpose of anonymity, the buildings will only be referred to by a name and number. Table 1 gives the building names and a brief description of their characteristics.

In order to predict the behavior of a building an hour ahead for each time step, a seasonal-trend-loess (STL) model was trained on six months of previous data in order to predict one hour ahead at each step. The entire prediction is then moved one hour, so that at each step in the procedure, one hour of data is predicted. An hour ahead was chosen because the power of the predictive method chosen decays quickly as the prediction horizon extends. The STL method, first presented in (Cleveland, Cleveland and McRae 1990) decomposes time series into three parts: a seasonal component, a trend component, and a remainder. The particular STL model used in this paper took as input only previous power use of the building and outside air temperature.

Table 1. Building names and Descriptions

Building Name	Description
Building 1	100,000 sq.ft 1990's vintage office building in California thermal zone 3. This building is a high tech sector 3-story office building with significant lab loads. The building is primarily a VAV Reheat system, with additional cooling via fan coils serving high load areas.
Building 2	200,000 sq.ft 1980's vintage office building near Chicago, IL. The 12-story all-electric office building is mostly tenant occupied office space with a detached non-enclosed three-level parking garage.

We believe that it is a necessary but not sufficient condition for a building to be predictable in order for it to be well tuned. This is in line with the literature on statistical process control for time series methods (Roberts and Alwan, 1988). In order to test this theory, a residual based control chart technique was employed. Following this predictive method, each hour of prediction is subtracted from the actual power use to yield the residual power use, or error in prediction. This error term, denotes how far off at each hour our prediction is from the actual behavior of the building. This information of error is then fed into our control chart methodology, which allows us to diagnose buildings at an accelerated rate.

In this case, we use three control charts - a moving average (MA) control chart, a rolling outlier (RO) control chart, and a dual measure control chart - combining the metrics of the MA and RO charts. The moving average control (figure of merit designated as: Mt), assumes that at the start of the process, the mean of the process should be stationary and computes the mean of the prediction process residual (actual – predicted) as a two week rolling average - This is updated as the process moves along, and each point in the control chart is then developed using a two-week (336 hour) rolling window. In SPC, upper and lower control limits (UCL and LCL, respectively) are designated to specify when a process is "out of control" - for the MA chart, the control limits that we use are:

$$\text{UCL} / \text{LCL} = \text{Process mean} +/- \frac{3\sigma}{\sqrt{n * w}}$$

Where σ is the standard deviation of the process up to time within window w, n is the number of samples averaged at each time point, and w is the total number of samples in the rolling window. For the purposes of this examination, we used n=4 and w = 336, with measurements in hours. The RO chart is constructed in a manner that allows us to see which points are hard to predict on a weekly basis. For every hour in the data set after the first week, the 99% percentile of residuals in the preceding week is calculated. Following this calculation, a point is flagged as "hard to predict" if it's residual is above the 99% percentile for the previous week, giving us the hardest points to predict in each week's rolling window. In short, the MA chart shows us when the mean of the prediction process shifts, and the RO chart shows us when it produces extreme outlier. We view the construction of control charts as a convenient method for data mining. The two charts previously constructed are therefore combined to allow for a "vote" on when the building is malfunctioning. The combined chart is a dual measure (DM) chart, which tells us when the prediction process is producing outliers at the same time that the prediction process mean shifts. This methodology could be extended to any number of possible rule sets, but we only demonstrate this one here as a means of data mining the prediction process.

Experimental Design

The analysis of this data was done through a two-phase process - automated data analysis and manual examination of flagged points for errors. It was important to test whether the data analysis methodology presented in this paper could identify faults with only whole building interval power data and local weather data. Building energy interval data was transmitted to the sMAP repository where it was retrieved for analysis. No identifying information was sent about the building except for identifying the nearest weather station.   The buildings chosen were two that are currently undergoing retrocommissioning work at the time of the final draft of this paper.

Results were reviewed by engineers with familiarity with the buildings to explore what information the control charts exposed and examine whether the flagged points appeared to be errors. This review consisted of first looking at the control charts generated by the automated analysis. Flagged timestamps corresponding with known building events were filtered out to focus on timestamps where potential faults were identified. Heatmap charts of daily peak kW and total kW for periods surrounding the remaining flagged timestamps were reviewed to identify suspicious variations in peak load and daily energy consumption. Finally building load profiles were reviewed for days and times where flags were identified.

Results

For each of the two buildings presented here, the mean absolute percent error (MAPE) is presented as a function of time from the forecast horizon in figure 1. We examine the case of a building with low error and one with high error, each of which yields different information. . For the purposes of analyzing results, it should be noted that the hour ahead forecasts are most reliable, so the horizon was trimmed there for purposes of this analysis. The MAPE for hour-ahead predictions in building 1 was 4.94%, while the MAPE in building 2 was 19.2% for hour-ahead predictions. Error is defined as actual minus predicted value in this case.

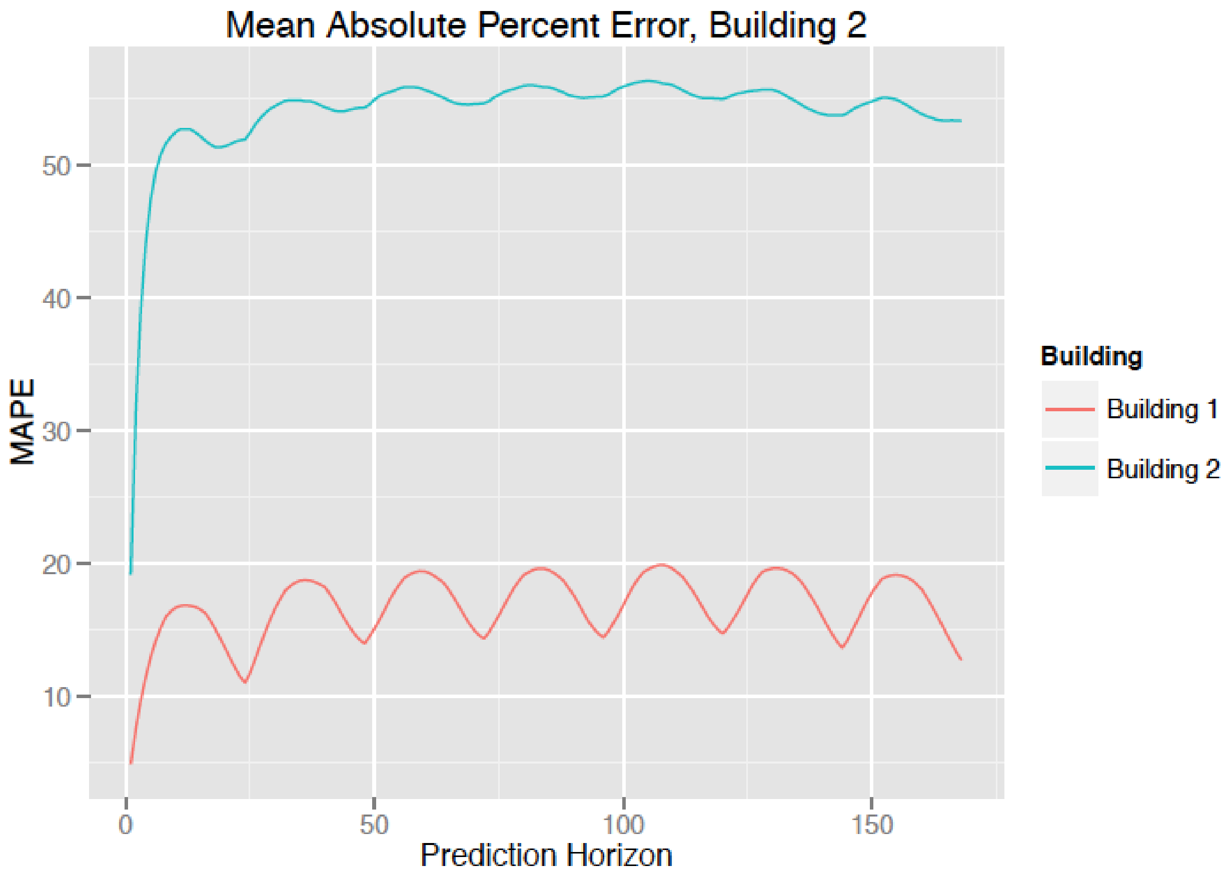

Figure 1. Mean Absolute Percent Error for both buildings over a 168 hour prediction frame. Because predictability decays with time, we used 1 hour ahead predictions for the following work

RESIDUAL BASED CONTROL CHARTS

Here we present the control charts for the buildings in our analysis. It should be noted that this is an example of a technique that can be used for any building, but for this application, due to time constraints, only the two buildings in our data set were analyzed.

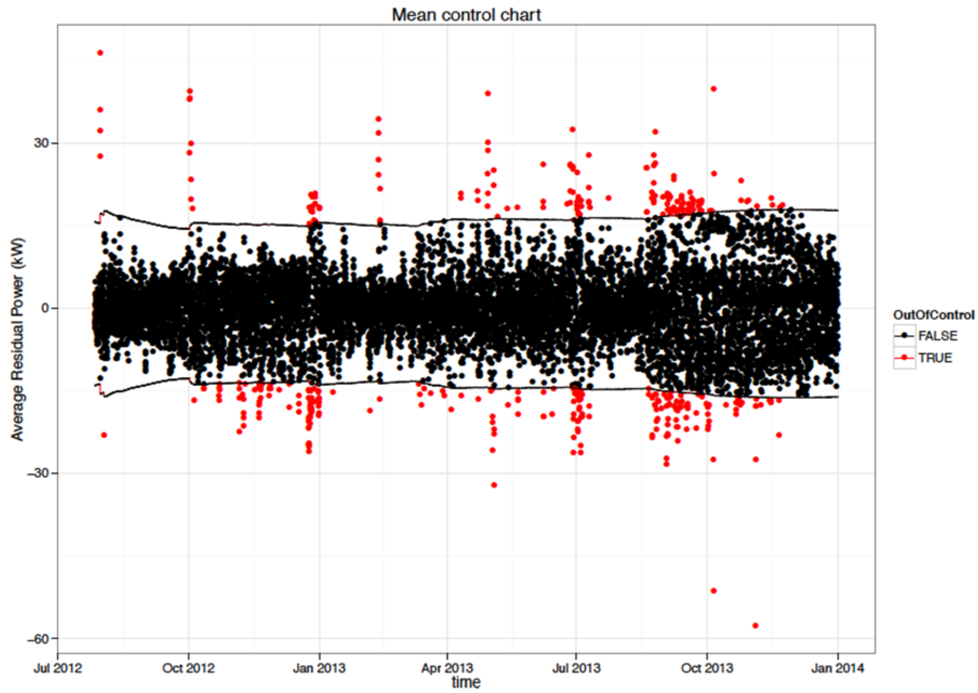

Figure 2. Moving Average Chart for Building 1 – The points on this chart represent a 4 hour moving average of the distance that the predicted values are from the actual values. The lines on the graph are the upper and lower control limits (UCL, LCL). Note the "cone" toward the end of the graph – this corresponds to a major retrofit.

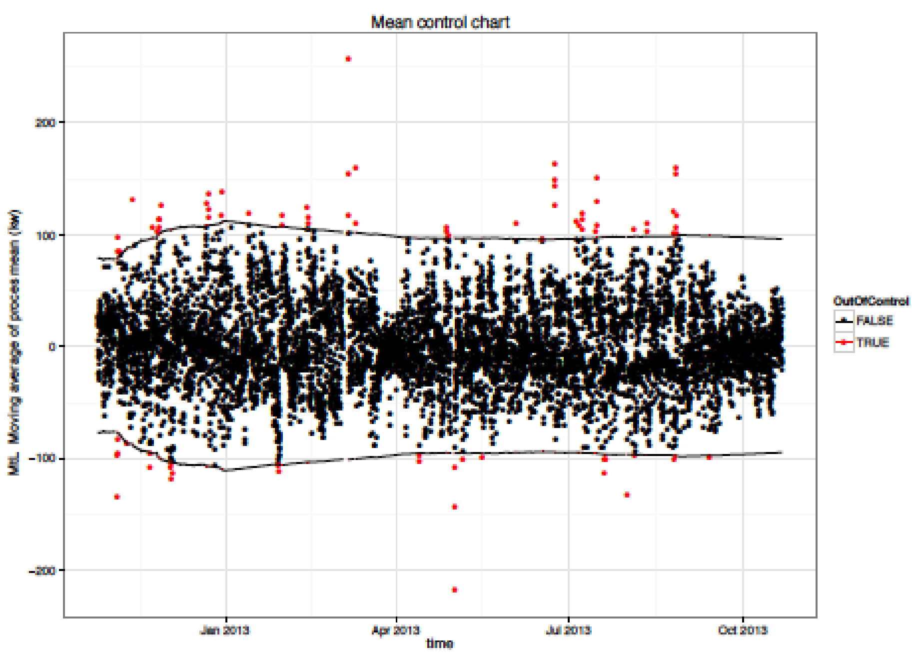

Figure 3. Similar to above, The points on this chart represent a 4 hour moving average of the distance that the predicted values are from the actual values. The points outside of the black lines are "out of control".

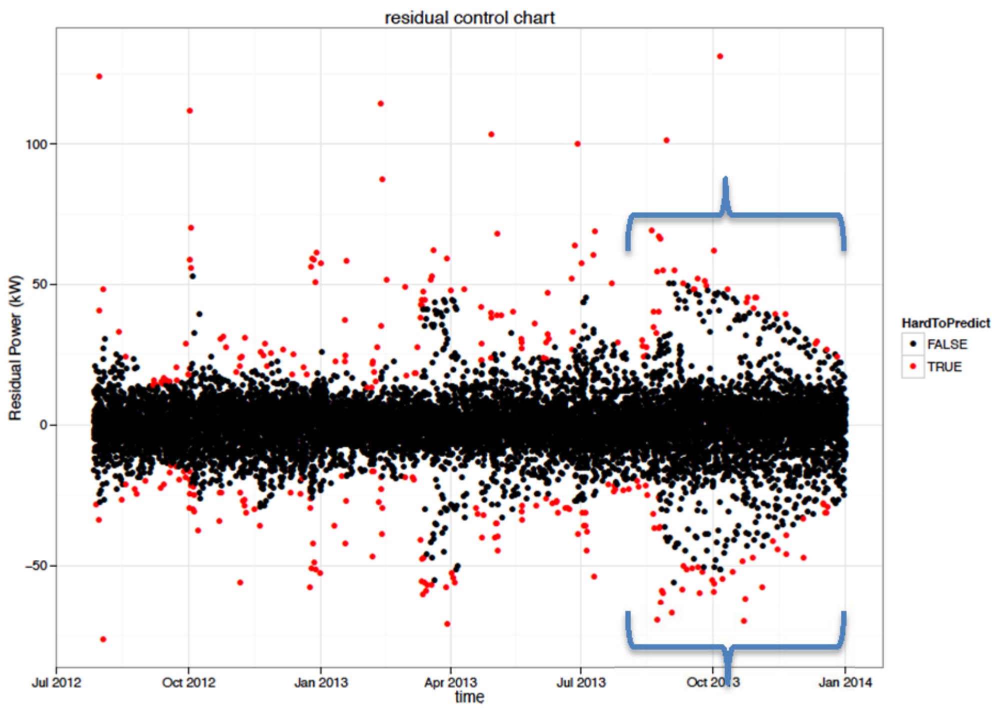

Figure 3. Rolling outlier chart for residuals of power prediction in building 1. This chart demonstrates how the rolling outlier technique picks out points that are harder to predict than 99% of points in the previous week. There is a "cone" that is noted in this graph, and this was a point when there was a major retrofit in this building.

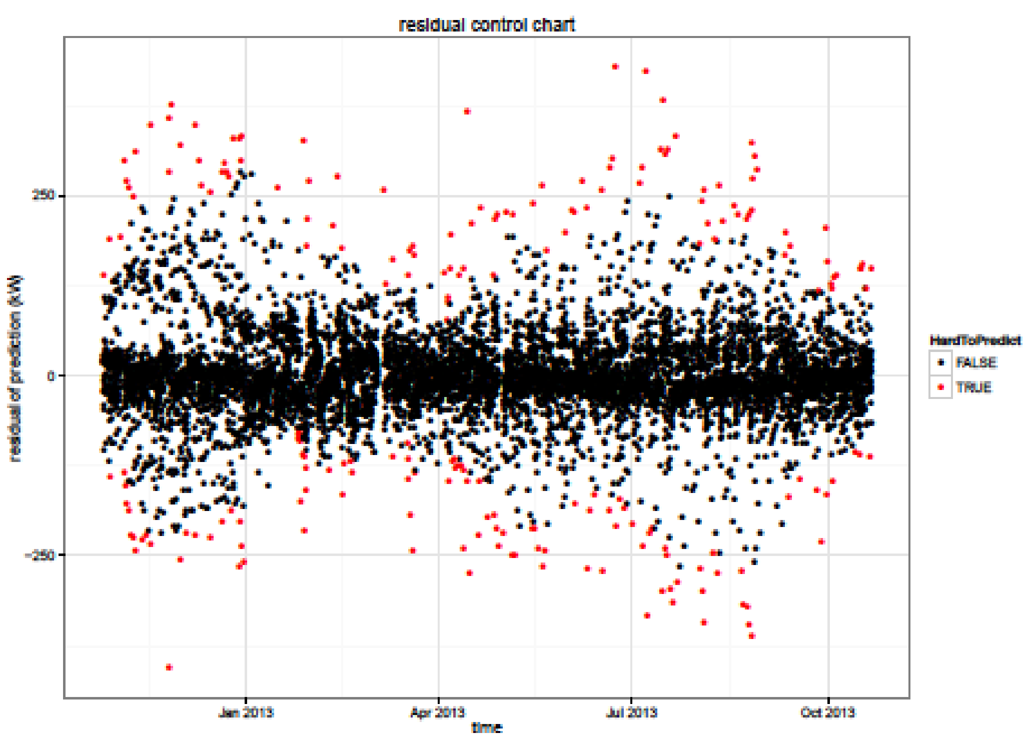

Figure 4. Rolling Outlier chart for building 2: the red points mark data points that are outside of the 99th percentile of errors over a one week rolling window.

The "cone" that we see in the charts for figure 4 correspond to a point where the chiller in that building was replaced and subsequently commissioned. As the commissioning goes on, the predictability of the building changes. For reference, Figures 6 and 7 show the power use of each building with both Hard to Predict and Out of Control points embedded in the graphs.

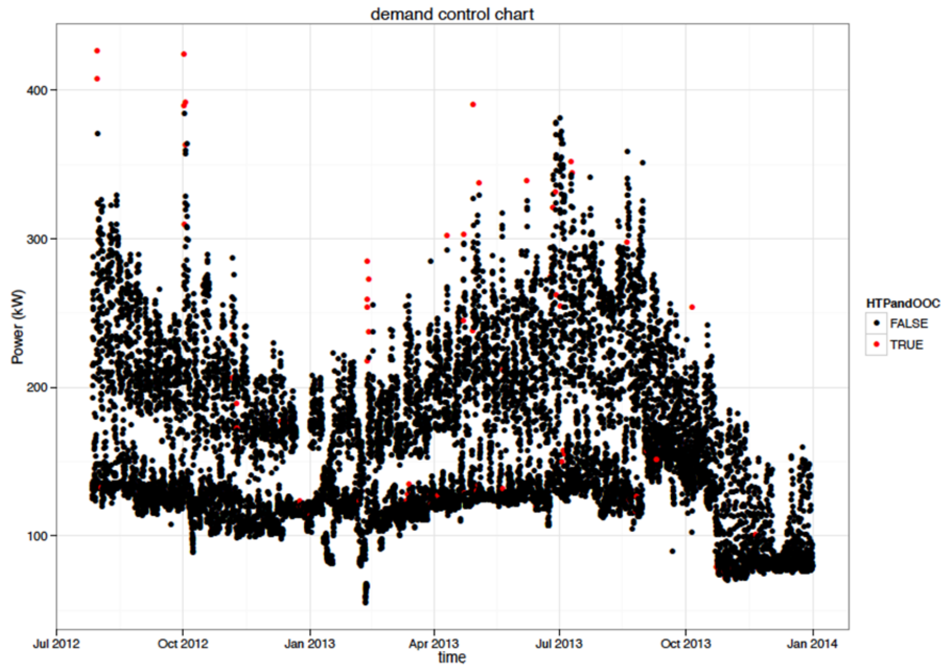

Figure 5: Power use in building 1 with red points being out of control and hard to predict, as described in the graphs above.

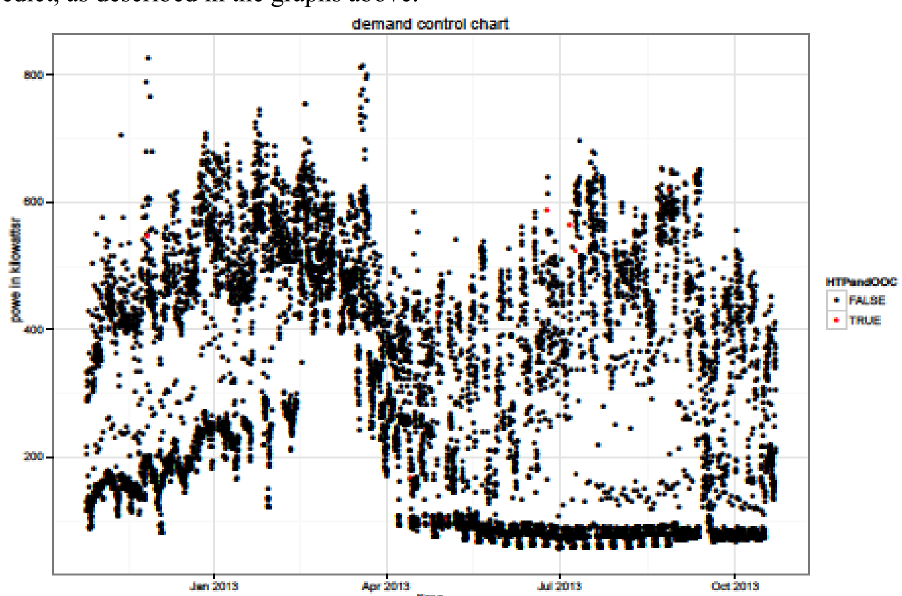

Figure 6. Power use in building 2 with red points being out of control and hard to predict, as described in the graphs above.

Example Root Cause Analysis

Upon analysis, scheduling errors and equipment commissioning problems were able to be picked out of the data by being flagged and then zoomed in on with deeper interval data analysis around the flagged timestamp. This would normally take an engineer a large amount of time examining time series of HVAC systems. An example point that was flagged by the algorithm on Saturday, Nov 2, 2013 in building 1 turned out to be equipment cycling overnight because of a control problem during commissioning. A graph of the power use on days in question is presented in Figure 8:

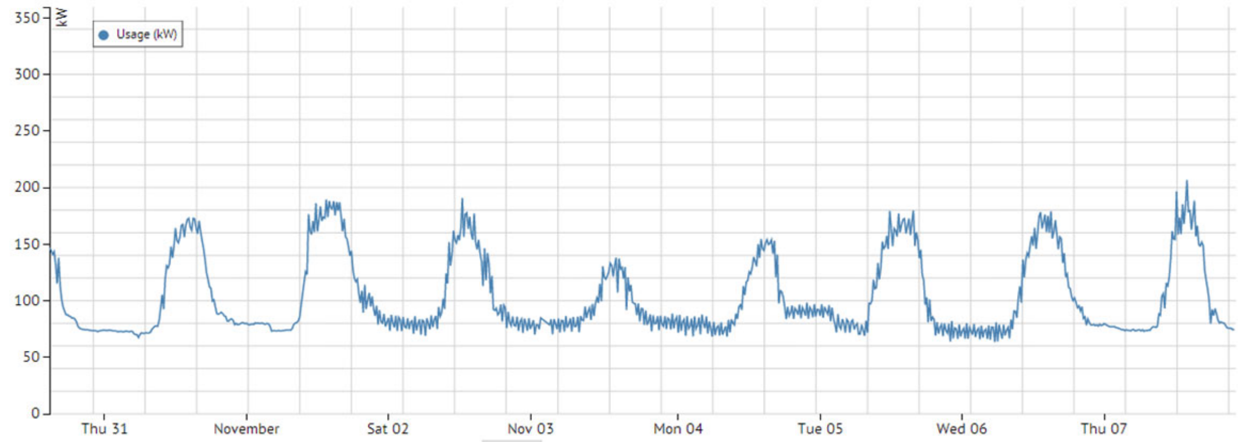

Figure 7. Our method picked up cycling at night over this week, when shown to the engineer, they stated that they had not seen it before we employed this tool.

The application can also find errors that are more apparent but also time consuming to find, such as anomalous nighttime power usage. In normal applications of RCx, the engineer would sift through the data looking for these points. With our method, it shows up as one of several suspect points on a graph and is simply investigated that way in a speedy fashion. Figure 9 shows a period in which building 2 used an unexplained amount of power in the time period of Thursday, September 12 at night, when the building failed to power down correctly.

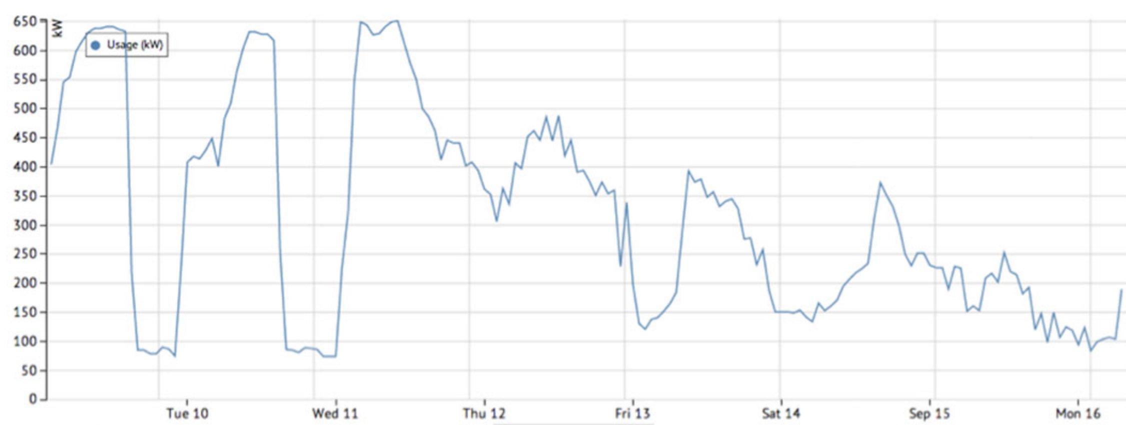

Figure 8. Our method picked up unexplained nighttime power quickly and effectively in a much shorter time than an engineer combing data would take.

Future Work

There is significant work to be done in the area of applying statistical process control to buildings. In addition to charting metrics and mining predicted power use data so that we can identify faults in buildings faster, there is value in looking at examples of derived metrics that stem from the experience of building commissioning agents. It is the authors' opinion that much information is to be gained through careful construction and charting of informative metrics in buildings that are being or have been commissioned. This information can be presented in the form of graphical interfaces that can be interpreted by engineers working in the buildings or by a computer program that synthesizes the information and presents it to the engineer. Further, these algorithms should be tested out with sub-metered data and with more finely tuned algorithms. In addition to this, one of the referees suggested plotting the residuals as the relative error (residual over actual usage). Upon examination, this method of error detection might be viable, but is not applicable to this method due to the underlying statistical assumptions that would be needed in order to do so.

In the case of building 2, it is very difficult to predict the power use of the building an hour ahead using our model. Upon inspection, is has become clear that this building has all electronic heating systems, which we hypothesize caused the models to perform poorly because they seek to fit into a longer seasonal pattern. It should be examined whether this is a recurring pattern or something else is responsible for this level of unpredictability.

Application to Persistence in Monitoring Based Commissioning

As buildings are retrocommissioned, their behavior should become more predictable, and thus more in control, according to our algorithms. In the case of building 1 – we can see the building becoming more predictable toward the end of the "cone" that is illustrated – this is a chiller replacement. This could have applications for the persistence of RCx measures - once a building is tuned, to continue monitoring that building in a manner that does not require human intervention at every step, and could provide automatic notification of building drift.

Conclusions

It is possible to determine when some energy efficiency flaws are happening in a building by using statistical process control methods. Using these early stage methods, we have managed to find errors in a building that would take an engineer many hours to pull out by hand. We have also demonstrated a method for determining if there are scheduling faults in a building by simply running a predictive algorithm on whole building meter data. This is promising and points to a good future for the development of these algorithms. This is just the start of predictive analytics based commissioning.

Overall, there were more alert flags than errors that could be ascertained. The system could benefit from a rule based expert systems approach to eliminating possible false flags, and this can be added in as additional buildings are analyzed. While these present technical challenges, the overall analysis of these methods indicates that they are sound and can be examined for deployment at scale. This is a promising new direction for building commissioning as an industry and represents the power of bringing new computational methods to bear on a problem that has been studied in as a manual procedure in the past.

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