Building Energy Management and Optimization

BLDG 5301F

Canal Building Performance Report

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Abstract

The following report seeks to identify the energy use and operational anomalies of Canal Building at Carleton University. The investigation is based on Weather, Air Handling Unit (AHU), and Energy Use Data for the 2017 calendar year. Recommendations are provided based on analysis using inverse modelling, energy use benchmarking through submetering, and fault and anomaly detection of soft and hard faults.

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Data Preprocessing and Cleaning:

The script performs data preprocessing and cleaning for the datasets, addressing issues related to timestamps. Data from energy use, air handling units (AHU1 and AHU2), and weather conditions were loaded and cleaned based on their timestamps. No deficiencies were found in the datasets, except for the data corresponding to the last day of the year. Although linear interpolation could be used to estimate the missing data for the final day, it was deemed unnecessary as it would not significantly affect the confidence of the analysis. The cleaned datasets have been saved for subsequent analysis and modeling.

Data Aggregation:

The cleaned energy use file was loaded and aggregated to provide energy use data for heating (AHU1 + AHU2), cooling (Chiller 1 + Chiller 2), plug loads, and lighting. The consolidated file contains five columns representing timestamps and the total energy usage for each category: Chiller, AHU, plugs, and lighting.

The script then processed this data to create a .xlsx file, including heating and cooling energy use corresponding to their respective timestamps.

- **Creating the Heating Column:**
  The script identifies periods where:
  - Total Chiller is 0 (indicating no cooling activity).
  - Total AHU is greater than 0 (indicating heating activity).

For rows meeting these conditions, the value of Total AHU is assigned to the Heating column. Otherwise, the value is set to 0.

- **Creating the Cooling Column:**
  Similarly, the script identifies periods where:
  - Total Chiller is greater than 0 (indicating cooling activity).
  - Total AHU is greater than 0.

For rows meeting these conditions, the value of Total AHU is assigned to the Cooling column. Otherwise, the value is set to 0.

Inverse Modelling

Three-Parameter Change-Point Model:

The relationship between energy use (heating and cooling separately) and outdoor temperature was modeled using a three-parameter change-point model.

Heating:

The three parameters were structured as $(x<b, a\cdot(x-b)+c, c)$, and a fitted curve was overlaid on the scatter plot (see Figure 1). The trend aligns with expected HVAC system behavior, with heating energy use stabilizing near zero during the summer months. However, there are significant outliers, suggesting potential faults in the system.

The model's performance was evaluated by calculating residuals and computing performance metrics, including RMSE, CV(RMSE), and NMBE. While the model is unbiased (NMBE ≈ 0%), the predictions exhibit high variability (CV(RMSE) = 155%), indicating that the change-point model captures the general trend but fails to explain the variability in heating energy use. This suggests that the model is oversimplified and does not account for other influencing factors.

Note: The total heating energy use is calculated by aggregating the AHU values from the energy use file under the condition Chiller ≤ 0 and AHU > 0. Perimeter heating energy use was not considered.

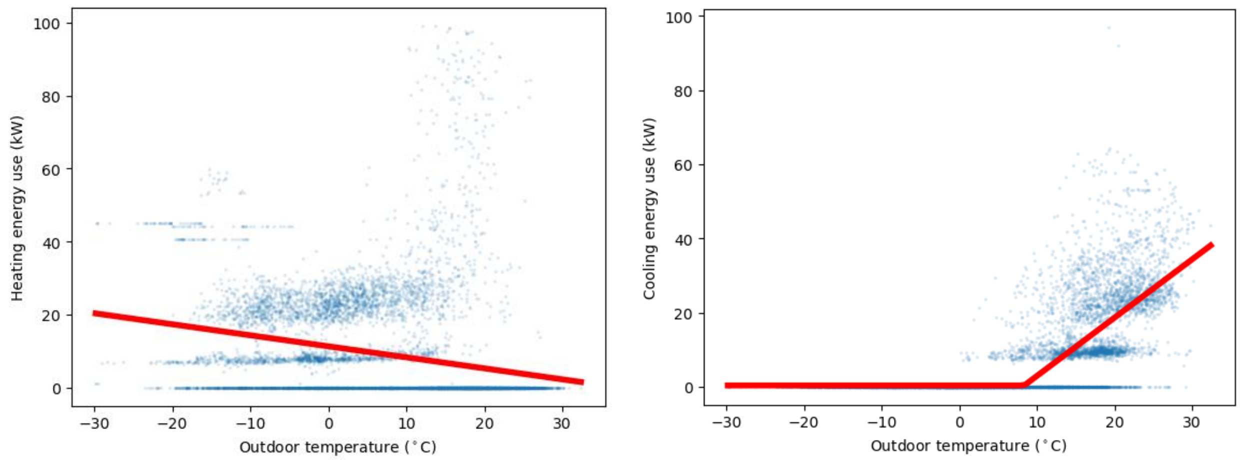


Figure 1: Relation between Energy use and Outdoor temperatures

Cooling:

For cooling, the three parameters were structured as (x>b,a·(x−b)+c,c) and a fitted curve was overlaid on the scatter plot (see Figure 2).The trend shows a predictive pattern with most data points falling within the summer months, as expected, and only a few outliers.

The performance metrics for cooling energy use indicate significant discrepancies between the predicted and observed values, with a CV(RMSE) of 195%, suggesting that the model is not adequately capturing the complexity of cooling demand. Additionally, the NMBE value of 23% indicates that the model consistently over-predicts cooling energy use. This over-prediction could be due to overly simplistic assumptions or missing variables that affect cooling demand.

Load Analysis with Submetering

An analysis of different loads was conducted using the canal energy use data. Below are plots highlighting the annual electricity use of AHU's 1 and 2 and Chiller's 1 and 2.

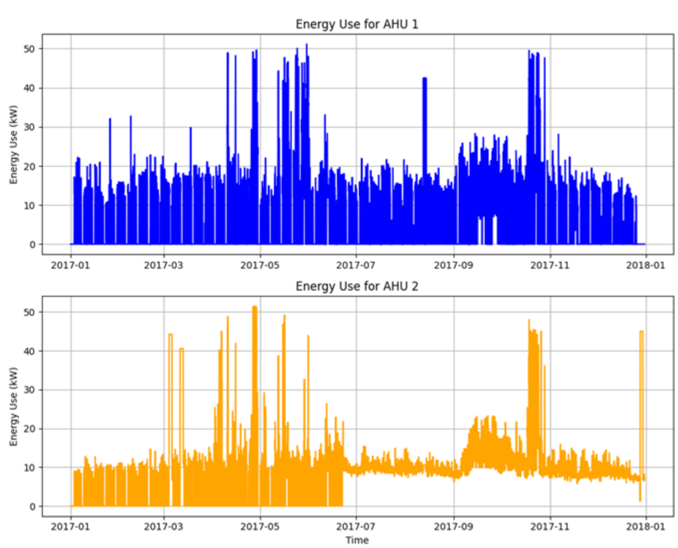


Figure 2: AHU Electricity Use for 2017

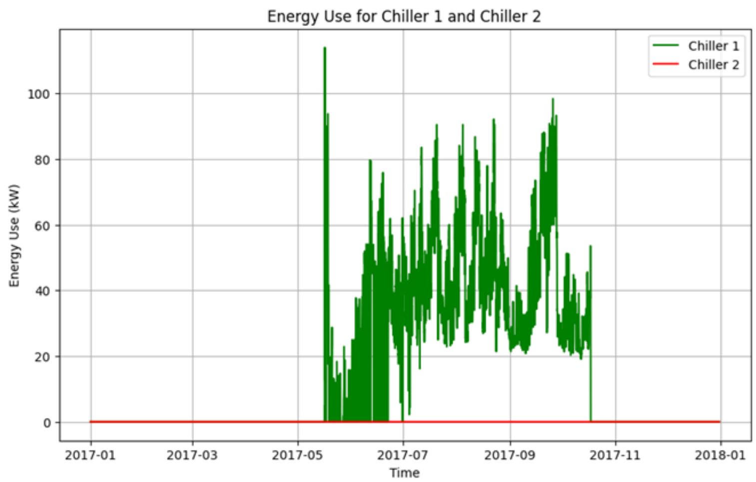


Figure 3: Chiller Electricity Use for 2017

From the plots, we note that Chiller 2 is not operational. For optimization, it may prove useful to building management to utilize Chiller 2 in combination with Chiller 1 to reduce total energy consumption. It is also noteworthy that from July onwards, AHU 2 does not turn off. This may be due to differences in control strategy. E.g., servicing spaces that require 24/7 operation, such as a server room. It would be advised that building management inspect schedules or implement different algorithms to avoid unnecessary operation if this is not the case.

The energy use vs supply air pressure was monitored for both AHU's. The outliers, shown in red, are values which deviate from Q1 and Q3 based on the interquartile range (IQR) method [1] for AHU 2.

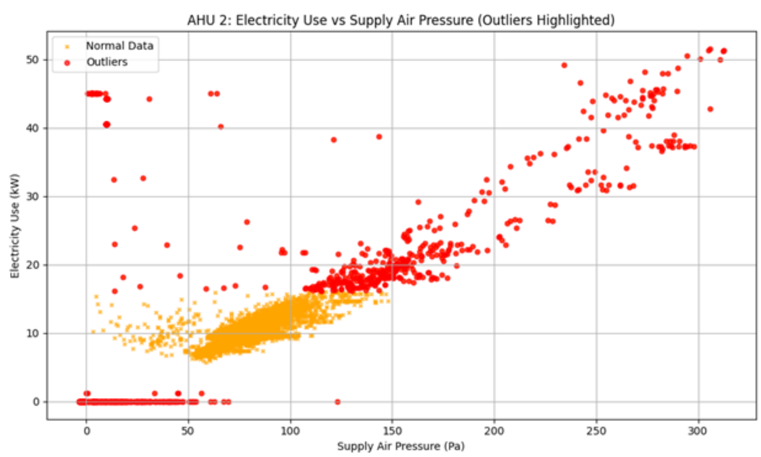


Figure 4: AHU 2 Electricity Use vs Supply Air Pressure

Occurrences of outliers below 50 Pa were recorded in the chart below. Many of these outliers occur in March. If we examine the energy use figure, we notice similar spikes in March. These outliers may be examined to check for sensor faults, overridden controls, or abnormal operational conditions.

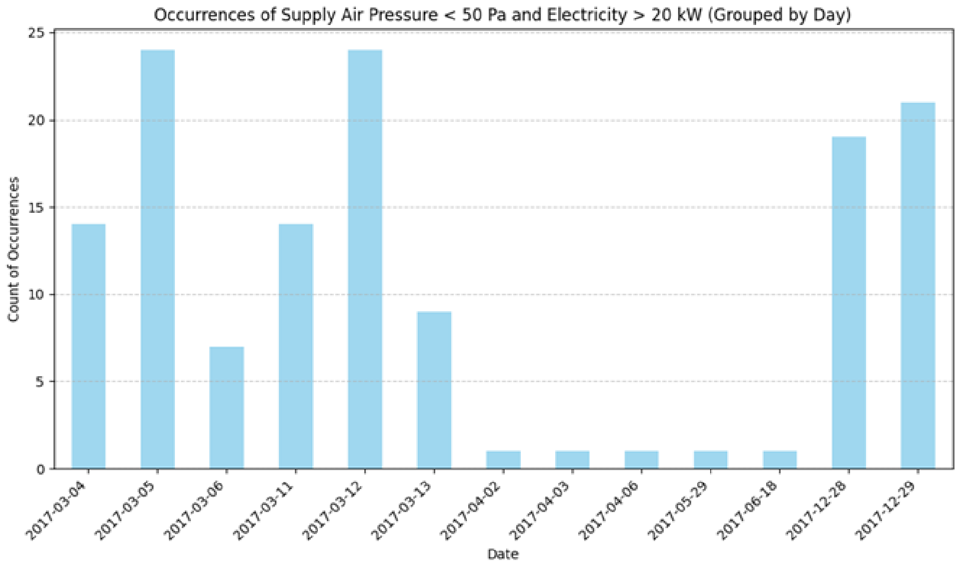


Figure 5: Occurrences of Anomalies

Findings from Submetering Analysis

Outliers in AHU 2 Operations:
There are periods when AHU 2 consumes significantly higher electricity at unusually low supply pressures, indicating inefficiencies or faults.

Temporal Correlations:
Outliers are not randomly distributed but occur during specific periods, suggesting operational, environmental, or system-specific events.

Efficiency Concerns:
AHU 2 operates less efficiently than AHU 1 overall, with higher and more erratic energy use patterns. This could be related to:

- Suboptimal control strategies
- Faulty components (e.g., fans, dampers, or sensors)
- Differences in zones served or demand profiles

Fault Detection and Diagnostics

The mixing box dampers, heating coil, and cooling coil dampers in AHU 1 and AHU 2 are examined to compare the actual performance of the system with the expected state of operations.

The black dots represent the faulty timesteps that do not meet either cooling, heating, economizer, and economizer with cooling mode. As can be seen in the figure below, both AHU 1 and AHU 2 do not have heating and cooling states except for two hours in AHU 1. This is an indication of a clear fault.

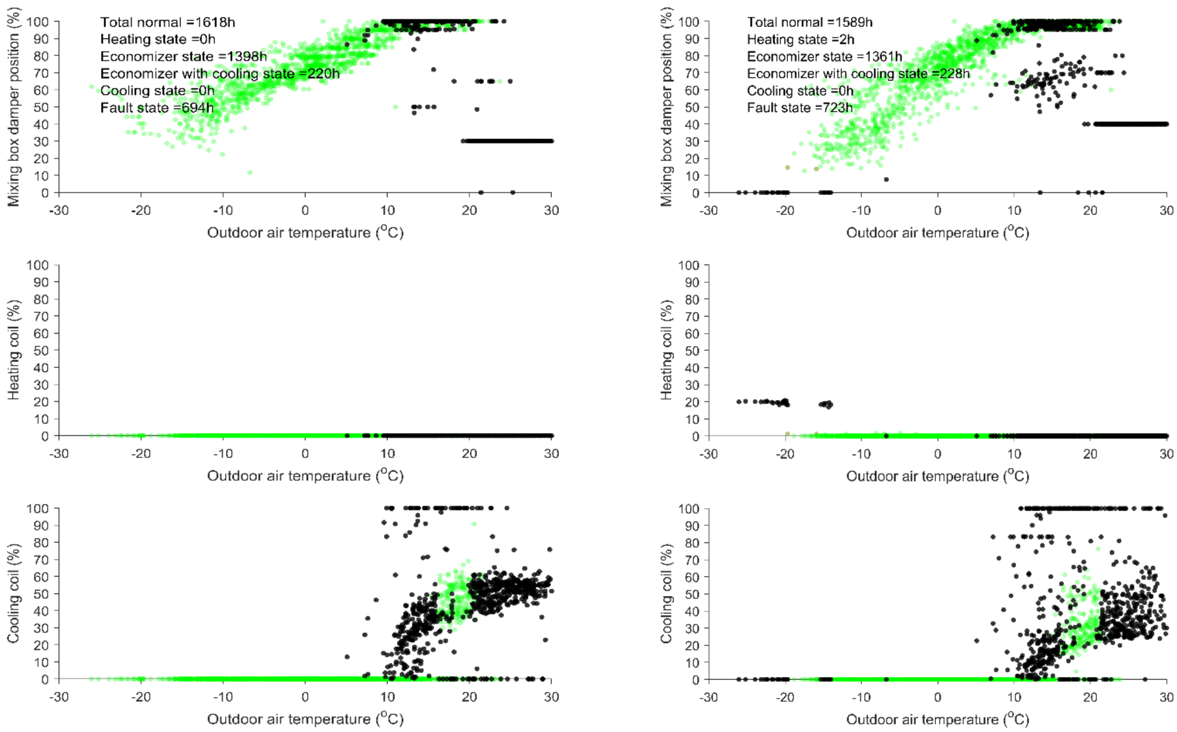


Figure 6: Expected and measured states of operation in AHU 1 and AHU2

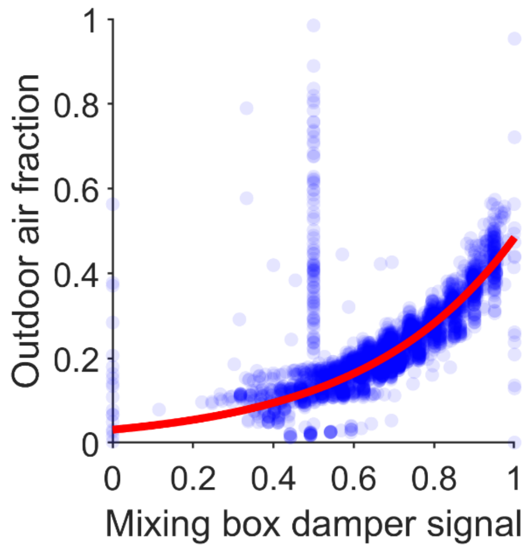
After analyzing the Excel sheet, it is found that in the most time steps either the heating or cooling valve is open, the fan state damper position is zero or the outdoor air damper position is too high which does not meet the expected condition in the code. There are also several time steps in the heating season, where the heating valve is closed, and the same behavior is observed in the data for the cooling season.

Possible reasons:

1. Faulty heating and cooling damper valve
2. The damper mix box position is continuously open during the expected heating and cooling state.
3. Faulty sensors that do not properly capture data from the mentioned dampers.

The graphs below show the relationship between the outdoor air fraction and the mixing box damper position. The line shows the expected mixing damper valve position to bring a certain fraction of air into the air handling unit. Blue dots indicate the measured outdoor air fraction and mixing box damper position in each time step.

The left and right graphs illustrate AHU 2 and AHU 1, respectively. As can be seen in AHU 1, there are many time steps where the outdoor air fraction is from 0.15 to 0.18 while the damper position is closed. Moreover, in AHU 2, in the time steps that the mixing box damper is around 0.5, the outdoor air fraction is higher than the value we expected. It can be deduced that the mixing box damper valve sensor has sent some faulty signals during operation.



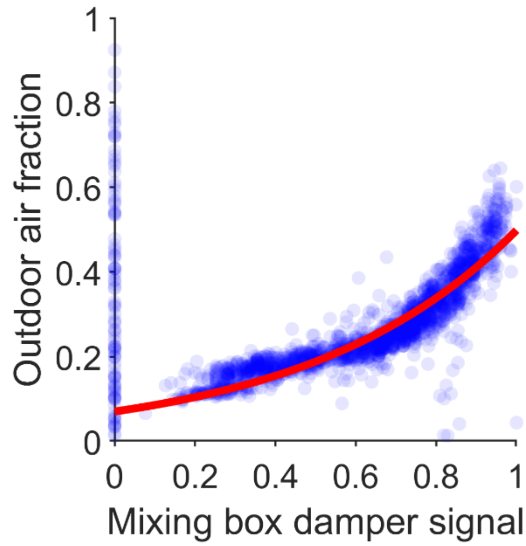
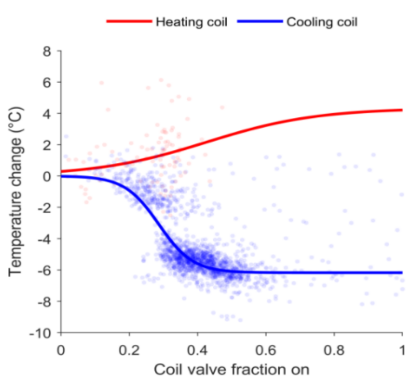


Figure 7: Mixing box damper position in AHU 2 *Figure 8: Mixing box damper position in AHU 1*

In the next step, the heating and cooling coil dampers are examined. This analysis shows the variation in the difference between the mixed air temperature and the supply air temperature as the coil valve fraction increases. Based on the figure and its formula, we expect a similar trend: as the coil valve fraction increases, the temperature difference in heating increases, while in the cooling coil, the temperature difference decreases.



$$T_{sa} - T_{ma} = \frac{x_{3,hc/cc}}{exp\left(x_{1,hc/cc} \cdot s_{hc/cc} + x_{2,hc/cc}\right)}$$

Figure 9: Expected behavior [2]

The opposite trend is observed in AHU 1 and AHU 2, indicating that the heating and cooling valves are malfunctioning. The heating valve in both air handling units, represented by the red color, shows no temperature difference between the mixed air and supply air temperatures as the valve position increases.

Additionally, the cooling coil, represented by the blue line, shows an increasing trend in temperature difference as the cooling coil valve opens, which deviates from the expected behavior based on the previously discussed formula and graph.

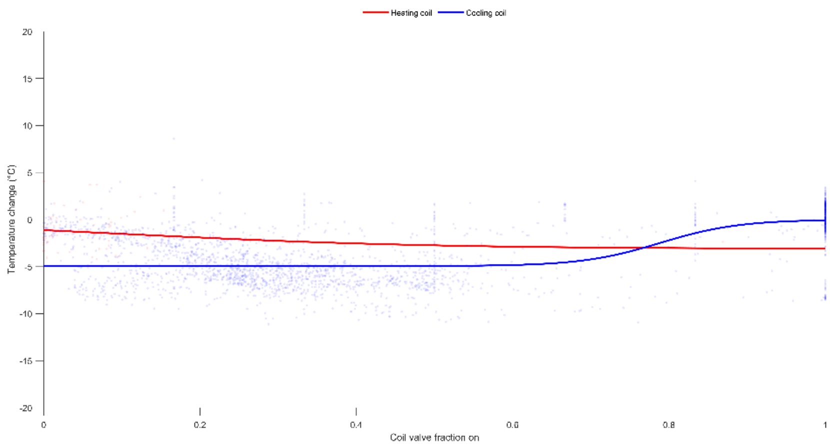


Figure 10: AHU 1

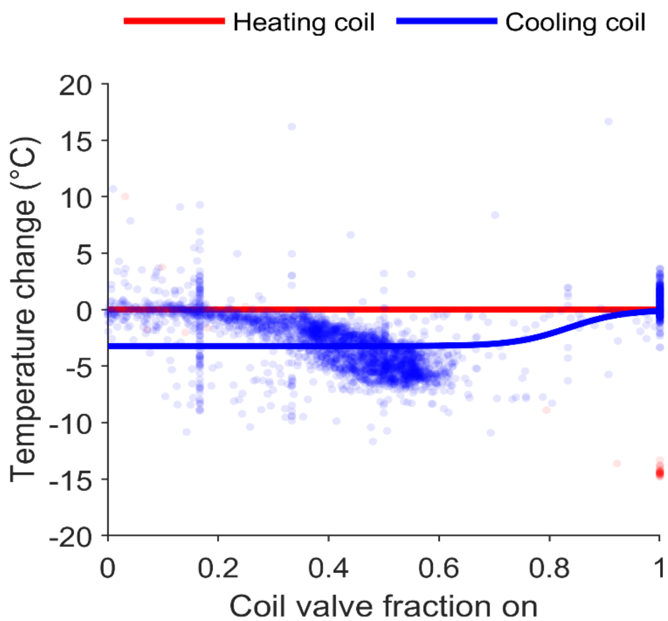


Figure 11: AHU 1

References

[1] PennState Eberly College of Science, “3.2 - Identifying Outliers: IQR Method | STAT 200,” *PennState: Statistics Online Courses*. https://online.stat.psu.edu/stat200/lesson/3/3.2

[2] B. Gunay. (2024). Fault detection and diagnostics - hard faults [PDF document]. Available: https://brightspace.carleton.ca/d2l/le/content/287558/viewContent/3972126/view