TLC Building Study

Path to Zero Net Energy

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Executive Summary

Our team has been working on a Teaching and Learning Complex (TLC) building study. We collaborate with the UC Davis Energy Conservation Office. The TLC is a new building on campus and is designed to be a low energy intensity building. However, it needs to be determined if the TLC is living up to its promises. To answer this question we compared data from a simulation that was performed in the design phase of this building to data from the operation of the building. We tried to explain the differences between the modeled and real world data and derive possible actions to improve the energy performance of the TLC building.

Project Background

The Teaching and Learning Complex (TLC) is the newest building on the UC Davis campus. The 101,000 square foot structure is designed to be energy efficient, incorporating systems such as ceiling fans, radiant ceiling panels, and a dedicated outdoor air system with heat recovery. Some of its features include group study areas, interactive learning classrooms, collaborative spaces, and a canopy of solar panels that shade an outdoor seating area. The UC Davis Energy Conservation Office (ECO), the client for this project, has been tracking its hourly energy consumption since its opening in 2022 but now seeks to determine if the building is living up to its energy-efficient design.

Buildings account for approximately 40% of primary energy consumption in the United States, with roughly half of that associated with space heating and cooling (Luo et al., 2022). Research has shown that a building's actual energy consumption can be as high as 2.5 times the simulated or predicted energy consumption (De Wilde, 2014). Energy performance gap (EPG) analysis is therefore critical for identifying opportunities for energy conservation and improving a building's efficiency. Several studies have shown that EPG, that is, the difference between the simulated or modeled building consumption and actual consumption, is a crucial challenge to achieving energy-efficient goals (Cozza et al., 2021; Jain et al., 2020; Liang et al., 2019).

Liang et al. (2019) highlight and analyze the driving factors (technical, behavioral and organizational) for building energy performance gaps. They collect data from different facility managers across the United States using completed surveys. Three chief reasons for building energy performance gaps are more occupants than originally designed, occupants using more energy than designed, and energy-efficient technology failures. The authors recommend giving incentives to facility managers, incorporating behavioral changes into energy management practices, and continuous monitoring of energy performance as some of the ways to mitigate energy performance gaps.

Fathi & Srinivasan (2016) assess the energy performance of two buildings at the University of Florida (UF) and evaluate the effects of some Energy Efficiency Measures (EEM) on their energy performance. The authors use DesignBuilder v 3.2 to determine the monthly and annual energy consumption of the buildings in terms of heating, cooling, electricity, and lighting. Coefficient of Variation (CV) of the Root Mean Squared Error (RMSE) is calculated to compare differences between actual data and modeled data based on standard calibration protocols. Results suggest that EEMs such as natural ventilation, heating, and cooling setpoint temperatures, and sensible heat recovery systems can reduce the energy consumption of buildings with potential energy savings.

Project Scope

The TLC Building project therefore seeks to answer the question: Is the TLC living up to its energy promise? Thus, this project is a first step in answering this question, as it will show where and how the model inputs need to be adjusted (or calibrated) to reflect actual building operations. These inputs include occupancy level/pattern, lighting or plug load level/pattern, weather data, etc. Outdoor temperatures, occupancy schedules, and building age are factors that influence the energy consumption of campus buildings (Khoshbakht et al., 2018). However, this project only considers the effect of outside air temperatures (OAT) on the energy consumption of TLC. Other simulation inputs were not considered since there was no access to the simulation software.

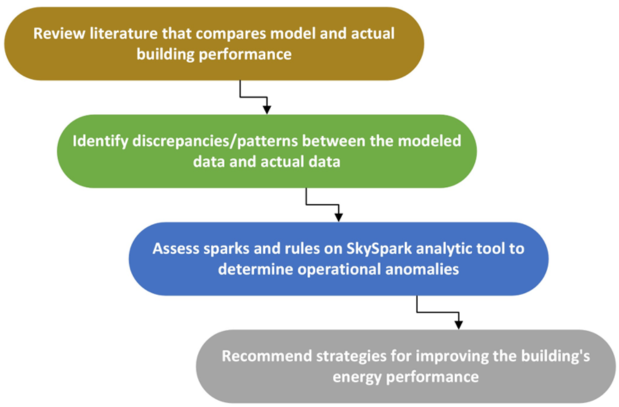

Figure 1: Final Scope of Work

The initial project scope included investigating the building's thermal comfort by checking the temperature and CO_2 concentration levels of rooms with complaint tickets to determine if they were at appropriate levels. It also included using WiFi connection data to propose a new schedule for the building. However, after consultation with the client, it was recommended that the project focus on comparing the simulation's actual performance with actual performance while also identifying operational shortcomings of the buildings using the SkySpark analytic tool. Figure 1 presents the final project scope. Therefore, the outcome of this project presents the building's actual versus expected performance and possible suggestions for operational improvement.

Project Objectives

The major goal of the study is to determine if the TLC is living up to its energy-efficient design. The specific objectives of this study are to:

- compare energy use intensity (EUI), electricity, cold water and hot water demand of simulated and actual data.
- investigate effects of outside air temperature (OAT) on energy consumption
- recommend strategies for improving TLC’s actual performance, and reducing its operating cost

Methodology

Data Collection and Analysis

Figure 2 shows all the steps performed to achieve the above-mentioned objectives. First, all the data sets used for the analysis for both model and actual data were collected from the clients (ECO Office). The 1-hour timeframe data on energy consumption comprises variables that include timestamp, total electricity demand (KBtu), hot water demand (KBtu), chilled water demand (KBtu), occupancy (Wi-Fi count), and outside air temperature. The model data had no occupancy input. Data cleaning was thereafter done for the interval exploratory analysis, that is, visually comparing base loads, peak loads, electricity, cold water, and hot water demand of both model and actual data.

The ECO office recommended using the Energy Charting and Metrics Tool (ECAM) for analyzing load profiles at a weekly and monthly scale. ECAM is a tool that facilitates the analysis, summarization, and charting of energy use and point-level data from building automation systems and utility meters (Koran, 2016). ECAM was also used in this project to get load profiles by day type (weekends, weekdays, seasons, and holidays) and point history charts for electricity, cold water, and hot water demand. Operational analysis was done on the SkySpark Analytic tool to track key performance indicators (KPIs) such as air handling unit (AHU) valve hunting and AHU MAT and OAT sensor matching. SkySpark was adopted to identify abnormalities in equipment, such as setpoints not changing with the schedule.

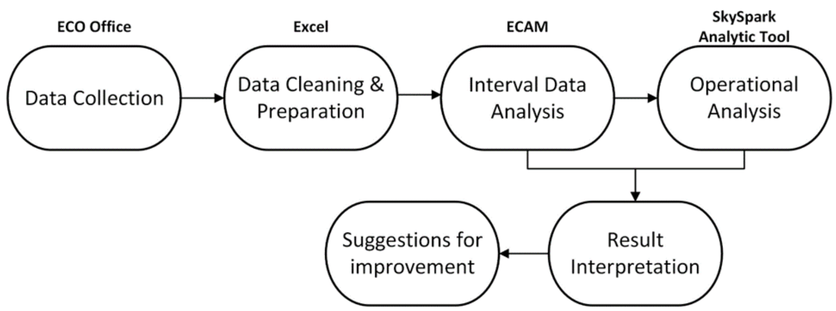

Figure 2: Flowchart showing step by step methodology for this study

Finally, the results obtained from the analysis were interpreted based on visual representation and are presented in the next section.

Equity and Energy Justice

New, renovated, and remodeled buildings are required to factor in building equity and energy justice, i.e., provide every user with equal access to comfortable occupying spaces and reliable inclusive energy solutions. TLC is not an exception, as it incorporates energy-efficient systems that promote the comfort of its occupants as students, staff, and faculty members. Additionally, everyone can give feedback on the thermal comfort of the TLC building through the energy feedback website. The UC Davis ECO office adjusts the temperature or CO_2 levels of the building to address the feedback received. The adjustment is usually based on the number of people who make the same or related queries or complaints. Therefore, it helps improve energy equity as the concerns and needs of all individuals are considered.

Results & Discussion

Model Input

Before comparing the results from the simulation and reality, the various boundary conditions must first be clarified. First, it should be mentioned that the real data of the TLC building is from April 2022 to April 2023. Therefore, in the upcoming figures comparing consumption over the year, January, February, and March were taken from 2023 and inserted before April and the rest of 2022. The fact that the year shown is from January to December makes the comparison much easier.

The model is based on a temperature curve that corresponds to an average over multiple years. This is shown in red in Figure 3. The actual outside air temperature (OAT) in 2022 to 2023 corresponds to the blue temperature in the graph. In comparison, it can be seen that July, August, and September in particular were warmer in 2022 than the average. January, February and March, on the other hand, were colder. This comparison of OAT is especially important when comparing absolute values later in this text. In order to extract the influence of the OAT, graphs with the OAT on the x-axis were also compared.

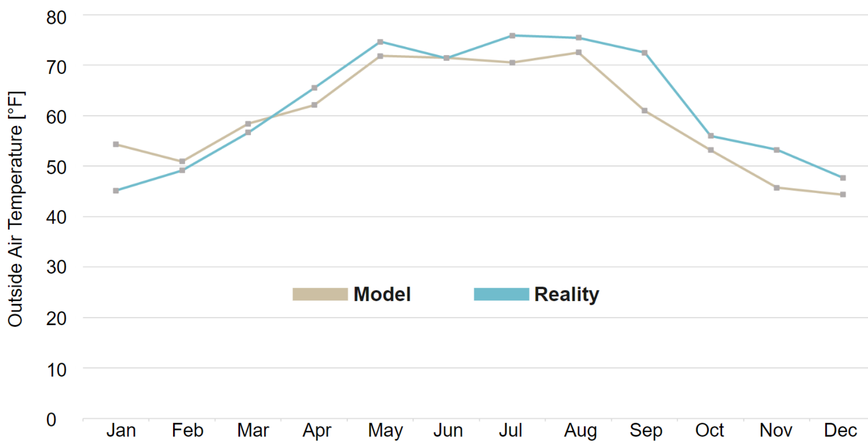

Figure 3: Comparison between model input OAT and real OAT

Total Energy Consumption

For the Comparison of the model and the real life data, first it is looked into the total annual energy consumption. For this, first the Energy Usage Intensity (EUI) is calculated, which indicates the annual energy consumption per area. The model predicted an EUI of 35 [kBtu/sq.ft], in reality this is slightly higher at 40 [kBtu/sq.ft]. An average classroom building here at UC Davis has an EUI of about 75 [kBtu/sq.ft]. Thus, in reality, the total building consumption is about 14.3% greater than the model predicted. However, the TLC is still a very energy efficient building compared to other classroom buildings.

Comparing the individual forms of energy consumed by the building, it is noticeable that the building consumes all forms of energy more than predicted. Overall, the least energy is used for the hot water, the difference between prediction and reality is 40%. The difference is smaller for the cold water consumption. Here the difference is about 26%. For the electricity consumption the value is about 12%. The absolute values are shown in Figure 4.

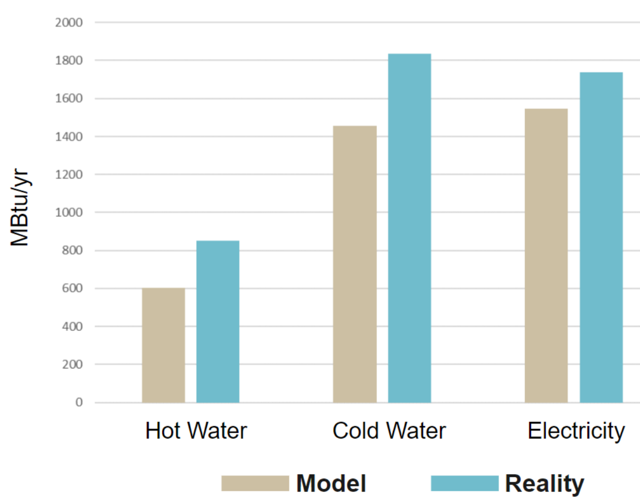

Figure 4: Comparison of total yearly energy consumption

Hot Water Consumption

As discussed in the previous section the total hot water consumption predicted by the model was around 40% lower than the actual one. If one compares the data over the whole year, one can quickly see that this occurs mainly during the winter months and the individual peaks during the day. The maximum consumption of hot water was strongly underestimated in the model. During the summer months it can be seen that the consumption was estimated relatively well, but not much hot water was consumed.

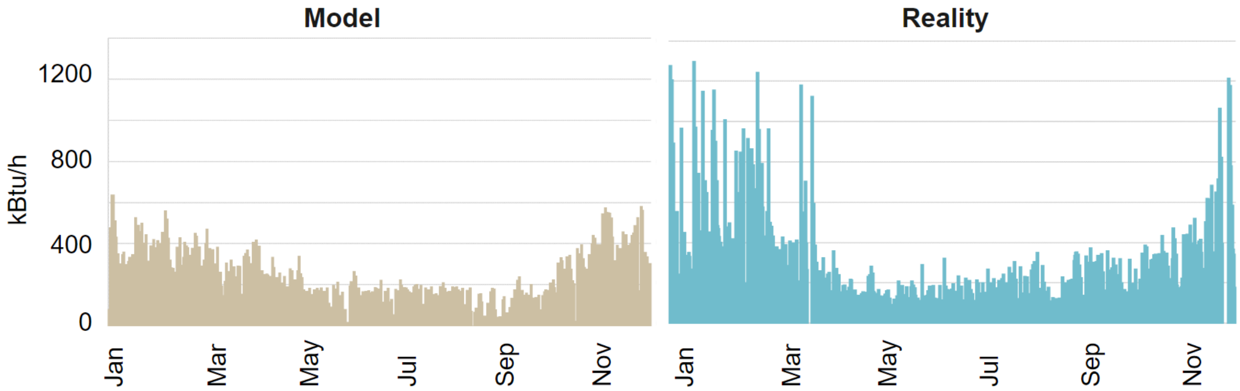

Figure 5: Yearly hot water consumption

In order to calculate the dependence of the energy consumption on the outside air temperature, the hot water consumption in Figure 6 was plotted over the outside air temperature. It can be seen that especially at colder temperatures below 60 °F, as they occur in winter, the hot water consumption in reality is significantly higher than in the model. However, it can also be seen that the consumption at high temperatures in reality is slightly below the predictions. Furthermore, in the data from the model for slightly higher temperatures a high, a medium and a low cluster can be seen. These correspond to the consumption on weekdays, Saturdays and Sundays. In the data from reality, such a tripartite clustering is not seen.

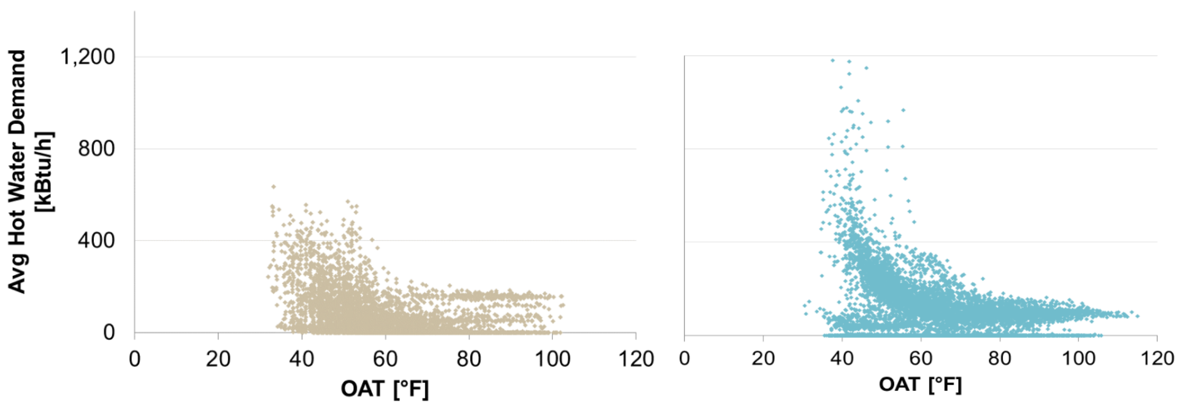

Figure 6: Hot Water consumption vs OAT

Cold Water Consumption

As seen in Figure 8, the cold water consumption has been modeled with a peak during the summer. This is an indication that the model did not take into account the schedule of the building. During the summer session, the OAT is very high, but only a few rooms of the building are used. The peak in the 2022 data was therefore at the beginning of the fall quarter, a period when the building was heavily used and temperatures were still very high. The height of the peak was also greater than the model predicted. It is also noticeable that the baseload in reality was 15 kBtu/h, which is slightly higher than the modeled value of 5 kBtu/h. However, this value is still comparatively small compared to other baseloads, as we will see in the further course.

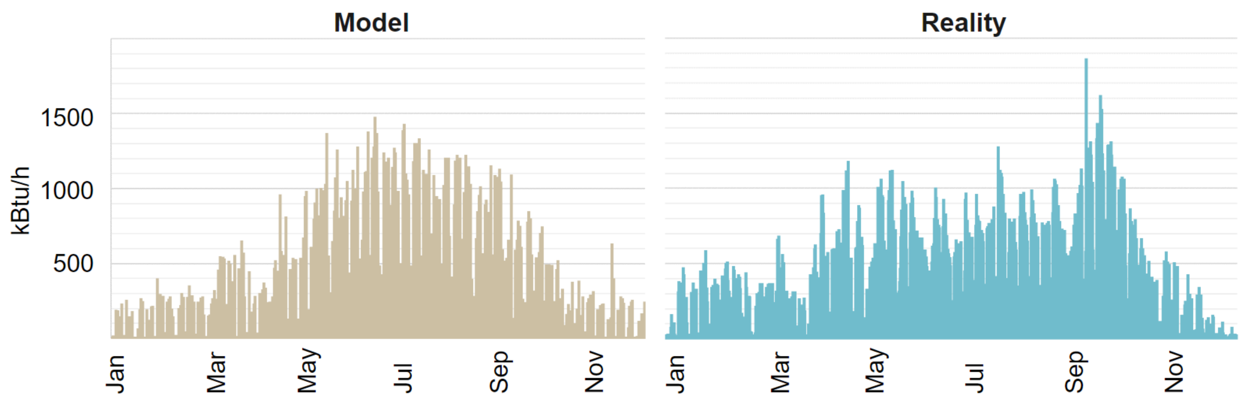

Figure 8: Yearly cold water consumption

The cold water consumption was also plotted against the OAT in Figure 9. It can be seen that the basic consumption in reality is very similar to the modeled data except for some peaks. In the point cloud from the actual data, a cluster at high temperatures and a consumption of about 400 kBtu/h can be seen. However, we could not find any correlation in our analysis, it does not seem to be a certain day of the week, nor a certain time of the day.

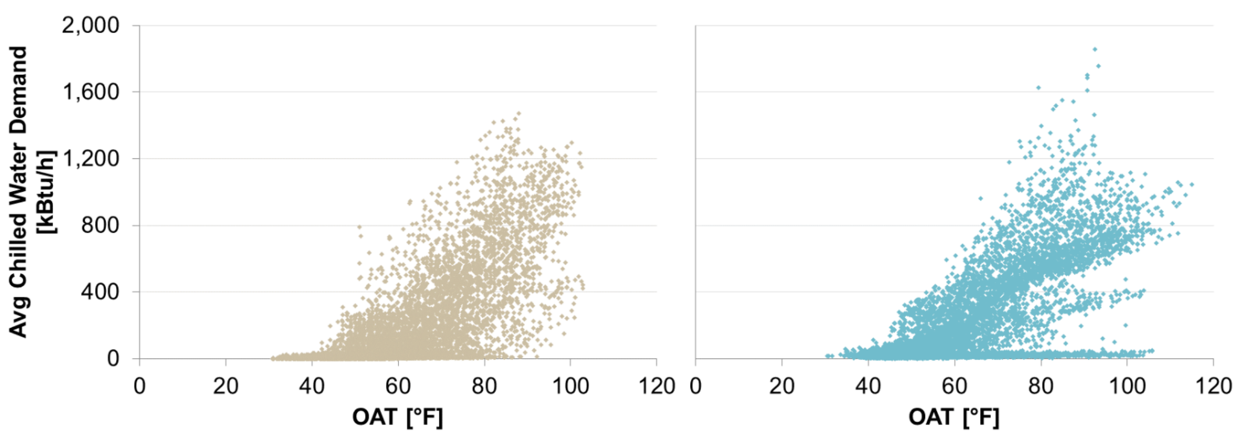

Figure 9: Yearly cold water consumption vs OAT

Electricity consumption

The data of Electricity consumption is the most different from all forms of energy supply. In the data of the model it can be seen in Figure 10, that the model has assumed a constant electricity demand throughout the year. However, the reality is very different. Each quarter can be seen very precisely, so it can be assumed that the electricity consumption is strongly dependent on the use of the building. In the summer session and in the breaks between fall and winter and winter and spring quarter it is therefore lowest. The highest electricity consumption occurs at the beginning of the fall quarter, since the building is heavily used here. In addition, it was still very warm at this time, which meant that the large classrooms also had to be cooled considerably. Since these are not cooled by radiator plates like the smaller rooms, but air has to be moved, the greater the demand for cooling, the greater the electricity consumption, since the fans use more power.

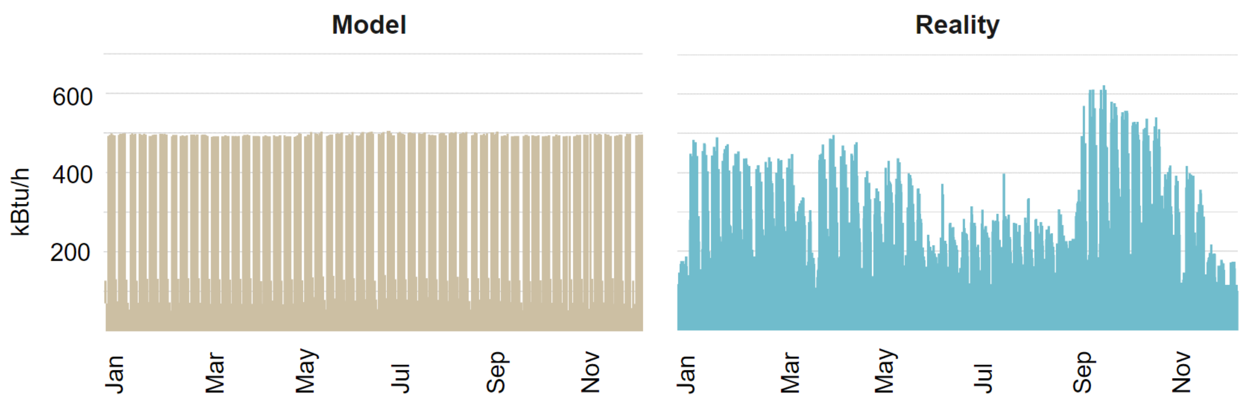

Figure 10: Yearly electricity consumption

In Figure 11 from the model (left), it is clear that the model has calculated a constant consumption for every time of the year. The individual horizontal lines therefore represent specific hours for which the electricity consumption is constant over the entire year. The reality is very different, as new plug loads are constantly being plugged in and unplugged. No cluster is formed at all and it can be seen that the power demand only increases slightly with the temperature. Another important finding from the comparison of these two graphs is that the baseload in reality, at 110 kBtu/h, is significantly greater than in the model, where it is around 30 kBtu/h.

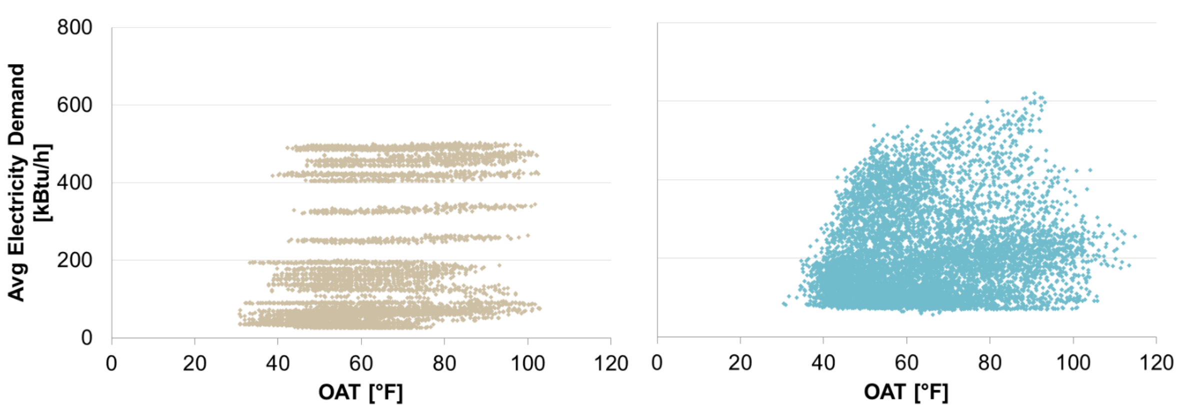

Figure 11: Yearly electricity consumption vs OAT

This high baseload can also be seen in the hourly comparison over the day in Figure 12. Furthermore, it can be seen that the peak of electricity consumption in the model is slightly higher than in reality. In reality, however, the consumption is more spread over the day. Overall, the higher baseload leads to an overall higher electricity consumption.

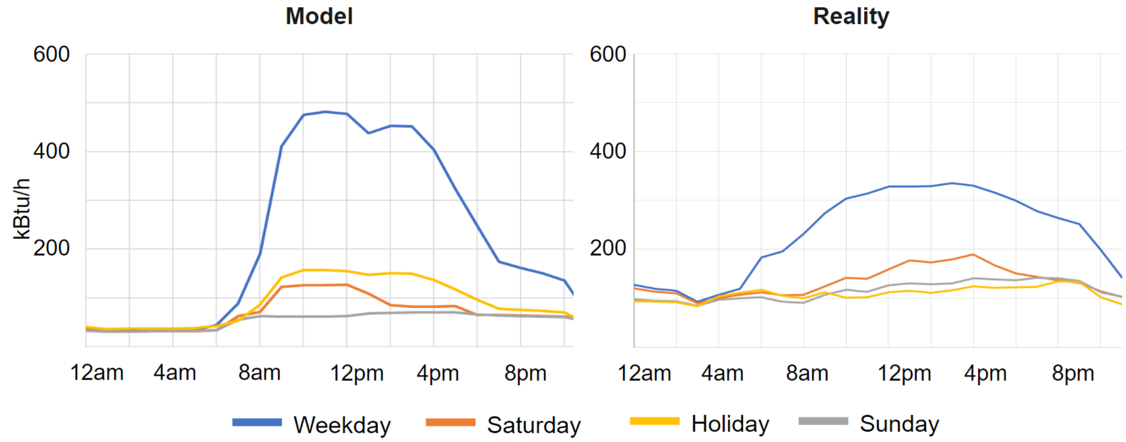

Figure 12: Hourly electricity consumption

Recommendations & Conclusions

Problem 1: High electricity Baseload

Since the electricity baseload in reality was many times higher than predicted by the model, this field was looked at first. A high electricity baseload can occur when lights are left on overnight, plug loads such as media systems in the classrooms are not turned off, or when pumps and fans for the HVAC system are running unnecessarily. Since there is no data on the individual plug loads, we focused mainly on the HVAC system and after a short search found a cold water pump that continuously pumps a little water (Figure 13). This is not a big load, but it is wasted energy, which is easily avoidable.

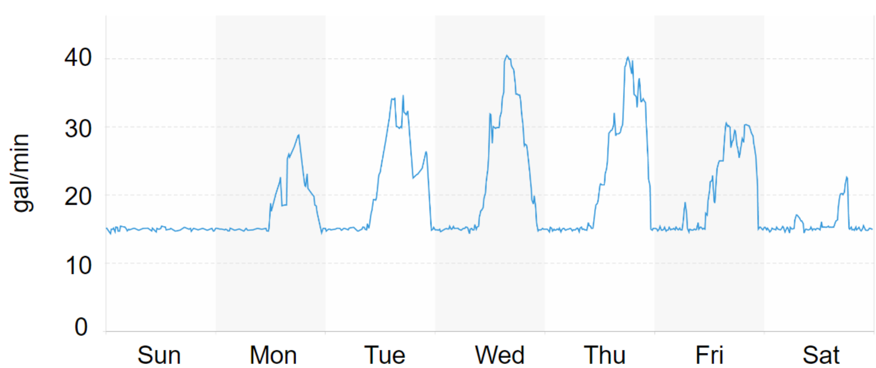

Figure 13: Volume flow of a cold water pump

Problem 2: Non-optimal Operating Point of HVAC System

In the current HVAC system, the outside air to be added to the system always goes through the heat exchanger with the exhaust air. This makes sense because theoretically the exhaust air temperature is close to the setpoint for the temperatures. After the heat exchanger, the air is then cooled or warmed up until the setpoint temperature is reached. During operation, however, there is sometimes an operating point where the outside air is heated up in the heat exchanger and then has to be cooled down again. This leads to a waste of energy, exactly at the level of the outside air in front of the heat exchanger and behind the heat exchanger. To calculate the amount of lost energy, we took the data from Skyspark from mid-December 2022 to April 2023 and calculated this lost energy. The result puts the energy loss at about 10286 kBtu/month. Since the energy form is mainly cold water, this energy loss costs about 53 $/month. A solution to this problem is a bypass around the heat exchanger, which would be activated exactly at the times of this unfavorable operating point. However, since this would have to be very large and the cost savings are comparatively small, it is expected that the payback time for this change in the system would be very high.

Problem 3: AHU Mixed Air Temperature and Outside Air Temperature Sensors not matching at 100% Outside Air Damper

The case study showed that the energy performance and thermal comfort of a multi-zone commercial building were affected by the sensor error (Li et al. 3).

The “Sensor impacts on building and HVAC controls: A critical review for building energy performance” article is a literature review on sensor type, impact of sensors on the HVAC system, collective data from sensors, control of sensors, and location. In addition, this article contains interviews with experts in the relative field about their experience on how sensors are applied for each situation, the selection of sensor components, and the improvement of sensor implementation. In the article, experts were interviewed to select the strategy for improving sensor performance (Bae et al. 1). Bae et al. mentioned the top three strategies are the following (11-12):

1. Adding extra sensor kits
2. Using new or updated sensor systems
3. Adjusting sensor configuration

The first strategy is adding extra sensor kits. Additional sensors should be installed in the poor sensor coverage area. Installing extra sensors helps execute self-calibration and for better reliability. Wireless sensors are recommended because sensor data that is collected from wireless sensors do not need to be monitored constantly during installation. In addition, the wireless sensor is more cost-effective. Before installing more sensors in the system, it needs to ensure that the result after adding sensors is profitable in an economical aspect. The second strategy is using new or updated sensor systems. Examples of new sensor systems are advanced imaging sensors, advanced data-driven analytics, and local thermal imaging. The last strategy is adjusting sensor configuration. The sensor configuration should be uncomplicated and designed based on how sensor data will be used. Sensors should be routinely calibrated. Sensor labels need to be correct (Bae et al. 11).

Problem 4: AHU Valve Hunting

AHU valve hunting has a consequence in decreasing the efficiency of HVAC systems and setpoint trackings, occupant discomfort, and increasing energy and operation cost (Price et al. 1, 19).

Price et al. demonstrated that applying Cascaded control loops reduces valve hunting in three campus buildings. Those three buildings are Building 1497, 0474, and 1600 at Texas A&M University. A cascaded control loop was implemented into Building Energy Management (BEM) software. The cascaded control loop algorithm was applied to the AHU discharge air temperature control. The chilled water supply valves were adjusted by the AHU discharge air temperature control (1, 5). Price et al. explained that Cascaded control implementation has two following methods (4-5):

1. Cascaded control implementation with two LOOPs

Algorithm 1 Cascaded control implementation with two LOOPs

```
C Point Name Abbreviations
DEFINE(X,"AH01.")
DEFINE(Y,"DATLOOP1.")
DEFINE(Y,"DATLOOP2.")
C Outer Loop Anti-Windup
IF("%X%CCV" .GT. 1 .AND. "%X%CCV" .LT. 99) THEN SET(0,SECND2)
IF(SECND2 .GT. "DISABLE.TIMER") THEN DISABL(110) ELSE ENABLE(110)
C Inner Loop Control
LOOP(128,"%X%DAT","%Y%ILSP","%X%DAT.S","%Y%P","%Y%I",0,"%Y%TIME","%Y%BIAS",50,70,0)
C Outer Loop Control
LOOP(0,"%X%DAT","%X%CCV","%Y%ILSP","%Z%P",0,0,"%Z%TIME","%Z%BIAS",50,70,0)
```

Figure 14: The Cascaded control with two LOOPs algorithm

2. Simplified cascaded control implementation with one LOOP

Algorithm 2 Simplified cascaded control implementation with one LOOP

```
C Point Name Abbreviation
DEFINE(X,"AH01.")
C Bias Term Calculation
$LOC1 = "%X%BIAS" + "%X%KL"*"%X%DAT"
C Cascaded Control
LOOP(0,"%X%DAT","%X%CCV","%X%DAT.S","%X%P","%X%I",0,"%X%TIME",$LOC1,0,100,0)
```

Figure 15: The Simplified cascaded control with one LOOP algorithm

The simplified cascaded control with one LOOP does not require the additional intermediate virtual point. It is a more simplified and shorter code. However, outer and inner loops have the same sampling times (Price et al. 4-5).

The result of implementing the cascaded control on three buildings at Texas A&M University is decreasing hunting behavior, improving setpoint tracking performance, reducing actuation frequency, and gaining 2.2 – 4.4% of energy cost saving (Price et al. 19).

Problem 5: AHU Supply Static Pressure Setpoint Not Met and AHU Supply End of Line Static Pressure Setpoint Not Met

The energy consumption of heating and cooling will increase If the system cannot maintain the static pressure at the setpoint level. Because this condition makes fans in the system need to operate intensely ("Building Re-Tuning Training Guide: AHU Static Pressure Control." 1).

The “Energy Savings from Robust Control of Static Pressure Based upon Zonal Occupancy for Multiple-Zone VAV Systems” article demonstrates an implementation of a proposed algorithm on the Building Automation System (BAS) of a multiple zone building that has one AHU, 20 VAV terminal zones and serves 12,000 ft^2 of floor area (Tukur et al. 1, 7). This algorithm has three key following steps (Tukur et al. 3):

1. Resetting the minimum zone airflow based on the CO_2 value in the zone
2. Detecting rogue zones in the system by performing FDD
3. Resetting duct static pressure based on the damper positions of the critical zones

*Rogue zones are zones that always require high static pressure because of undersized or failed VAV, or dysfunctional thermostats. FDD stands for Fault Detection and Diagnostics (Tukur et al. 2, 4).

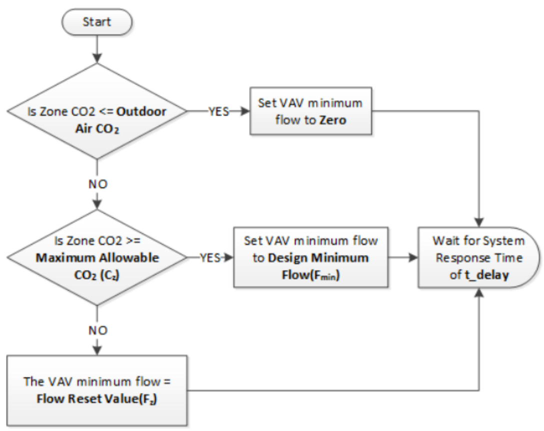

Figure 16: Logic diagram of resetting the minimum zone airflow based on the CO2 value in the zone

Resetting the minimum zone airflow based on the CO2 value in the zone: This step must have a time delay during running the loop to prevent too much resetting. According to this step diagram in Figure 16, If the CO2 concentration of the zone is more than the outside CO2 concentration but less than the maximum allowable CO2. The VAV minimum airflow needs to be reset (Tukur et al. 3-4).

Detecting rogue zones in the system by performing FDD: The FDD algorithm applies to VAV boxes and thermostats (Tukur et al. 5). The FDD algorithm has two rules to detect failures of VAV boxes. These two rules are listed below (Tukur et al. 6):

1. Rule 1 - VAV box communication error
2. Rule 2 - Stuck damper position

The FDD algorithm has three following rules to detect rogue zones (Tukur et al. 5):

1. Rule 1 - Thermostat communication error
2. Rule 2 - Thermostat reporting a continuous zero value
3. Rule 3 - Thermostat reporting a stale value

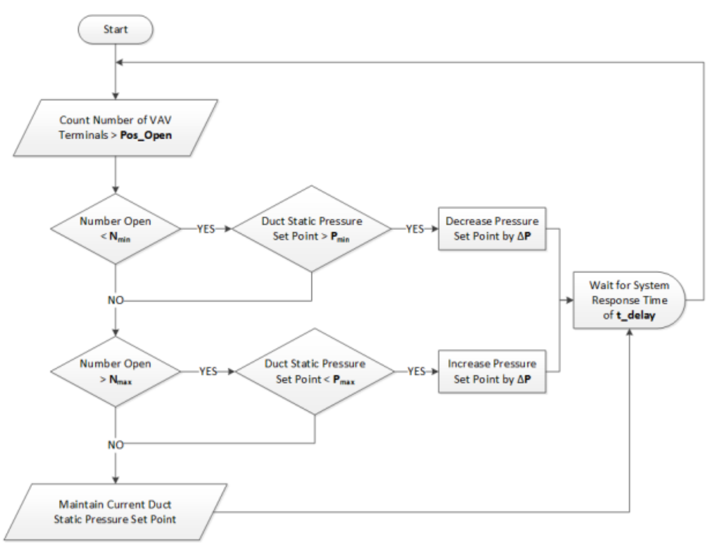

Figure 17: Logic diagram of the resetting duct static pressure based on the damper positions of the critical zones

Resetting duct static pressure based on the damper positions of the critical zones: This step is to reset the static pressure setpoint depending on the number of opening VAV terminals. Figure 17 is the logic diagram of this step. When the number of opening VAV terminals is more than the limited minimum number of opening VAV terminals, the static pressure setpoint must increase. When the number of opening VAV terminals is less than the limited minimum number of opening VAV terminals, the static pressure setpoint must decrease (Tukur et al. 6).

After implementing these three steps, ventilation setpoints are maintained, VAV energy efficiency is improved, and gaining 25% of fan energy savings (Tukur et al. 11).

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