A visualization tool for energy disaggregation in commercial buildings

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Abstract

This paper introduces a novel visualization tool that uses supervised and unsupervised disaggregation methods to present energy data estimated at the building and system levels and allows end-users to interact with the visualization to gain insights that can be used to improve building energy performance. The features of the visualization tool are demonstrated through a case study that utilizes data collected from air handling units (AHUs) and bulk energy meters located in a commercial building in Ottawa, Canada. The data are used to feed into multiple linear regression models to estimate the heating and cooling energy use by the AHUs and time series decomposition models to disaggregate major end uses. End-users can interact with the visualization tool to identify any energy anomalies to assist in building operational decisions. The potential of the visualization tool for improving building energy performance and assisting decision-making processes is discussed through illustrative examples.

Introduction

Disaggregation techniques play an important role in optimizing energy consumption in buildings. These techniques, categorized into supervised and unsupervised, offer valuable alternatives for different data availability scenarios. In supervised methods, optimization algorithms are utilized, but their main drawback is the requirement of a labeled dataset (e.g., refrigerator, air conditioner, washing machine). Acquiring labeled data can increase the setup costs of non-intrusive load monitoring (NILM) systems, making unsupervised methods more favorable in some cases (García et al. (2018)). Using an unsupervised disaggregation method, García et al. (2018) presented an interactive web tool for exploring NILM results. Using non-negative matrix factorization (NMF) methods, it analyzes power demand data from a hospital complex. The tool integrates user knowledge through visual analytics, allowing expert users to interpret NMF components and identify demand patterns and inefficiencies. In a previous study presented by Brucke et al. (2020), a fully unsupervised approach using particle swarm optimization was introduced for energy disaggregation. However, its application was limited to power data from two industrial consumers, making comparisons with other research challenging.

Efficient visualization of energy data plays a crucial role in enhancing the understanding of energy consumption dynamics and supporting decision-making processes in building operations. By utilizing data obtained from sensing and metering networks, it becomes possible to create visual representations of energy flows within the critical components of commercial buildings, particularly in the realm of heating, ventilation, and air conditioning (HVAC). These visualizations enable building stakeholders to interact with graphical depictions of energy usage, providing them with valuable insights to support decision-making and enhance the overall energy performance of the building. However, the full potential of the available data is often underutilized in existing building automation systems (BASs) due to a lack of effective visualization techniques capable of transforming energy data into meaningful visual representations. Consequently, there is a need for a visualization tool that effectively leverages the data from BASs, creating informative visualizations and allowing end-users to interact with these visualizations to gain insights into their operational tasks. Such a tool would greatly contribute to the comprehension of energy flow within buildings, enabling stakeholders to gain insights that facilitate operational decisions, optimize energy efficiency, and improve maintenance scheduling of HVAC equipment, ultimately enhancing overall building performance. Through visual representations, users can easily spot anomalous values, detect malfunctioning or poorly commissioned systems, and observe energy consumption patterns, enabling them to make informed decisions and visually compare the energy consumption of similar systems. This visualization-based approach enhances the ability to analyze and interpret energy data, enabling more effective decision-making and interventions to optimize energy usage within buildings (Meyers et al. (1996)). Despite recent efforts to develop

novel NILM systems, only a few have explored their application within the visual analytics (VA) paradigm. NILM techniques prove to be suitable analysis tools for VA since the disaggregated consumption reveals temporal patterns, offering valuable insights when represented through appropriate data visualizations, such as a week or calendar heat maps (Yarbrough et al. (2015)). Darwazeh et al. (2023) developed a virtual metering visualization tool that utilizes inverse grey-box models trained with operational data from a commercial building. Virtual meters estimate heat contributions from AHUs and zone-level radiant heaters. Also, Markus et al. (2022) presented a multi-source, data-driven building energy management software application incorporating established data-driven inverse energy modeling, fault detection and diagnosis, load disaggregation, and occupancy and occupant complaint analytic methods. In the field of home energy management, Ramadan et al. (2022) presented the FHMM to disaggregate power consumption in smart homes. They introduced the ThingSpeak platform to aid customers in reducing power consumption, with Twitter used to send appliance data outputs. Additionally, customer behavior is analyzed to shift power-intensive appliances from peak to off-peak hours based on the time of use (ToU) rate, aiming to save money and reduce grid load during peak periods.

Wu et al. (2023) also proposed a visual analysis approach to explore energy consumption time series at multiple spatiotemporal scales. Unlike conventional data-driven methods, their approach utilizes visual charts that enhance data understanding and allow interactive exploration for better insights. Their proposed visual analysis framework includes data storage in a relational database, three analytic models for variability, segmentation, and demand shift patterns, and a user-friendly web application for data visualization and interactions. Users can add new models through standardized APIs. The iterative knowledge discovery process involves users formulating business questions, exploring analytical views, and refining model parameters for deeper insights, fostering an interactive loop between users and data analysis.

Using energy disaggregation methods and visualization techniques together can bring several advantages where only bulk meters are available. In the absence of a metering network, energy disaggregation can serve as an alternative to submetering instead of installing submeters for each end-use or thermal zone. An energy disaggregation-based visualization tool helps building owners engage with occupants regarding their energy usage. By providing transparent information about tenant energy consumption, occupants become more aware of their energy behaviours. This knowledge fosters a sense of responsibility and encourages energy-saving actions, leading to reduced energy waste and lower utility bills.

This paper presents a novel energy disaggregation-based visualization tool that can be used to improve building energy performance and allow end-users to interact with the visualizations to gain insights into operational decisions. The visualization tool's use is demonstrated through illustrative examples using data collected from a commercial building. To this end, multiple linear regression and time series decomposition models are developed using operational data from an office building in Ottawa, Canada. Model parameters estimate system and building-level end-uses, including the heating and cooling energy added by AHUs and the heat added by perimeter radiant heaters and cooling added by unmonitored devices. The proposed web application results are presented through a novel visualization tool that allows end users to interact with the virtual metered energy and gain insights that facilitate decision-making processes.

Methodology

The development of the proposed disaggregation visualization tool involves the following stages: a) data collection and processing, b) modelling and parameter estimation, and c) developing a web application tool. These stages are further described in the following subsections.

Data collection and processing

Data was collected from multiple AHU systems in a commercial building located in Ottawa, Canada. The building, constructed in 1979, boasts a gross area of 70,970 m^2 and comprises 13 stories. The data collection spanned from January to December, 2018, with measurements taken at 15-minute intervals. The AHU-level data consisted of readings from heating and cooling valve positions, as well as outdoor air temperature, obtained from the BAS. Additionally, heating and cooling data were collected from building-level energy meters. To illustrate the effectiveness of the application for cases where BAS data is unavailable, the total electricity usage for thermal loads, lighting, and plug loads was recorded. The BAS and meter data described in this section serve as a case study for demonstrating both supervised and unsupervised disaggregation models, along with the utilization of the web application discussed in the subsequent subsections.

Load disaggregation models

Supervised model using BAS data

Two regression models have been developed for each of the two energy meters, namely cooling and heating

energy by Zaeri et al. (2022).

Major end uses for office buildings can be found for both cooling and heating energy use as introduced in Equations (1) and (3); where $E_{H_{ahu_n}}(kW)$, $E_{PH}(kW)$, and E_{other} (kW) are the heating loads for AHU_n, perimeter heating devices, and other heating devices energy use, respectively, which are represented in Equation (3). The cooling and heating energy use are calculated using Equations (2) and (4) as E_C (kW) and E_H (kW), respectively. $E_{C_{ahu_i}}(kW)$, and E_{um} (kW) are the AHUs cooling energy use and the unmonitored cooling loads such as radiant cooling, data center cooling systems, etc in the investigated building. The $X_{cc,ahu_i}(\%)$, $X_{hc,ahu_i}(\%)$ and $T_{oa}(C)$ represent the AHUs cooling coil valve position, AHUs heating coil valve position, and outdoor air temperature, respectively. The regression coefficients representing the heating energy use are shown as c_i for the AHUs, and d_1, d_2 are the parameters representing the heat from the perimeter heaters. The intercept term d_3 represents the heating energy used for hot water. For cooling energy use, the regression coefficients a_i represent the AHUs cooling energy use, and f_1 and b_1 are the change point temperature and the slope of the cooling model to capture the energy used by unmonitored cooling devices. The error terms e_c and e_h account for measurement errors in the heating and cooling disaggregation models and any unmeasured heating or cooling loads.

$$E_C = \sum_{i=1}^{n} E_{C_{ahu_i}} + E_{um} + e_c \tag{1}$$

$$E_C = \sum_{i=1}^{n} a_i \cdot X_{cc,ahu_i} + (T_{oa} - f_1)^+ \cdot b_1 + e_c \tag{2}$$

$$E_H = \sum_{i=1}^{n} E_{H_{ahu_i}} + E_{PH} + E_{hotwater} + e_h \tag{3}$$

$$E_H = \sum_{i=1}^{n} c_i \cdot X_{hc,ahu_i} + (T_{oa} - d_1)^- \cdot d_2 + d_3 + e_h \tag{4}$$

Time series decomposition model

For the unsupervised disaggregation model, a multiplicative model is used to capture the seasonal and trend components of the total energy use. The total electricity consumption breaks down to three end-uses as shown in Equation (5) where E_{LP}, E_C and E_H represent electricity used by lighting and plug loads, cooling and heating, respectively. The methodology is described in more detail by Zaeri et al. (2023) to generate the decomposition results. To separate the electricity used by lighting and plug loads from the total energy consumption, the weekly seasonality of total electricity usage (S_t) and the minimum trend component (T_t) are utilized to adjust the amplitude of disaggregated signals when cooling and heating are not needed in the building (see Equation 6). Throughout the year, the trend for lighting and plug loads remains relatively constant, with a slight decrease during the cooling season due to increased daylight from solar radiation. Next, the change point detection technique along with the climate zone is used to identify the cooling and heating seasons. As shown in Equation 7, for cooling electricity usage, we multiply the trend component during cooling operation (T_{t_c}) with the weekly seasonality (S_{t_c}) and residuals (R_{t_c}). Then, the calculated energy use for lighting and plug loads from the previous step is subtracted from this signal. Similarly, for heating electricity usage as presented in Equation 8, we multiply the trend component during the heating season (T_{t_h}) with the weekly seasonality (S_{t_h}) and residuals (R_{t_h}), and then subtract this from the energy use for lighting and plug loads calculated during the heating season from the previous step. These steps allow us to effectively disaggregate and analyze energy consumption patterns for lighting and plug loads, cooling, and heating in the building. Also, t_c and t_h show the cooling and heating operation time respectively.

$$E_t = E_{LP} + E_C + E_H \tag{5}$$

$$E_{LP} = min(T_t) \times S_t \tag{6}$$

$$E_C = S_{t_c} \times T_{t_c} \times R_{t_c} - E_{LP} \tag{7}$$

$$E_H = S_{t_h} \times T_{t_h} \times R_{t_h} - E_{LP} \tag{8}$$

Web interface

An integrated web application is developed using Streamlit and compiled in Python. The application offers a user-friendly platform for energy disaggregation analysis. The application is stored in a public GitHub repository (Zaeri (2023)), facilitating access and collaboration among researchers and practitioners. The application comprises three pages that enable users to analyze energy consumption patterns and optimize energy usage.

Manual data upload in supervised disaggregation with bulk meter and BAS data

The first page of the web application enables users to manually upload BAS and meter data for energy disaggregation analysis. This feature enhances the flexibility of the application, allowing users to perform energy consumption analysis even when direct access to BAS data is unavailable. By inputting the necessary data, users can obtain a comprehensive view of energy consumption attributed to various components within the

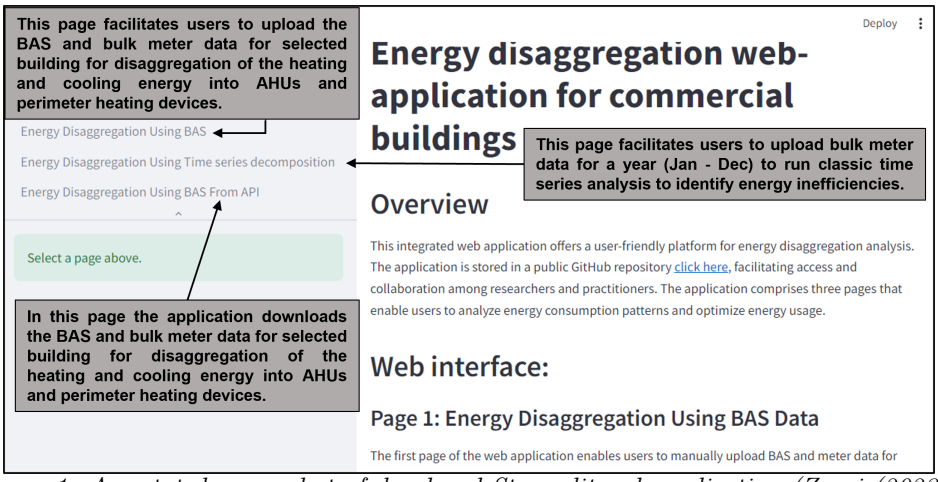

Figure 1: Annotated screenshot of developed Streamlit web application (Zaeri (2023)).

building, including AHUs, perimeter heating devices, and unmonitored cooling energy usage, such as radiant cooling, data center cooling systems, etc.

Unsupervised disaggregation analysis using bulk meter data

In scenarios where only bulk meter data is available, the second page of the web application utilizes unsupervised disaggregation techniques, specifically time series decomposition. This approach disaggregates the electricity consumption into major end-uses such as heating, cooling, lighting and plug loads. Users can identify energy anomalies, such as after-hour or overnight energy waste, and assess the need for rescheduling. The application provides weekly and daily classic time series analysis, enabling users to gain insights into energy consumption patterns.

Supervised disaggregation using bulk meter and BAS data from API

The third page of the web application focuses on energy disaggregation analysis using BAS data. By accessing BAS data and integrating an API for retrieving information from bulk steam and chilled water meters, the application employs a multiple linear regression model. This model incorporates the outdoor air temperature to calculate the contribution of each AHU, perimeter heating device, and hot water to the total heating loads. The outputs of this analysis provide users with detailed insights into the energy consumption patterns of individual components (see Figure 1). Pie charts and Sankey diagrams in Figure 4 are also generated to demonstrate the distribution of the energy flow into AHUs, perimeter heating devices, and cooling devices.

Detection of energy use anomalies

For the BAS-based disaggregation analysis, a comprehensive set of metrics is employed to identify energy use anomalies, comprising the perimeter heating to total heating ratio, outlier AHU detection for heating energy use, outlier AHU detection for cooling energy use, schedule effectiveness, and afterhours energy use ratios (Gunay et al. (2019)). The list of possible energy anomalies and the corresponding calculated metrics are presented in the below Table 1. Outlier AHU detection for heating involves assessing if the heating consumption (H_i) of a specific AHU_x exceeds three times the median absolute deviation (MAD) heating consumption (H_{MAD}) observed among other AHUs in the building. Outlier AHU detection for cooling employs a similar approach, where C_i represents the cooling consumption of AHU_x, and C_{MAD} is the MAD cooling consumption observed among other AHUs in the building. For schedule effectiveness, the metric gauges the disparity between the slopes of the work-hours energy use line and the after-hours energy use line.

$$Y_{htg} = \begin{cases} x_{1,htg} + x_{2,htg}(T_{oa} - x_{3,htg})^-, & \text{Work hours,} \\ x_{4,htg} + x_{5,htg}(T_{oa} - x_{6,htg})^-, & \text{After hours.} \end{cases} \quad (9)$$

$$Y_{clg} = \begin{cases} x_{1,clg} + x_{2,clg}(T_{oa} - x_{3,clg})^+, & \text{Work hours,} \\ x_{4,clg} + x_{5,clg}(T_{oa} - x_{6,clg})^+, & \text{After hours.} \end{cases} \quad (10)$$

Positive values indicate a steeper work-hours slope, while negative values suggest a steeper after-hours slope. A higher positive value is desirable, indicating an effective reduction in energy use rates during afterhours. The application generates change point models for cooling and heating energy use with outdoor air temperature to estimate the slopes as defined in Gunay et al. (2019). The parameters of the change point models defined by Afroz et al. (2021) for building heating and cooling energy use are as follows (see Equations 9 & 10): The $x_{1,htg}$ and $x_{1,clg}$, representing y-intercept values at the change point model for work hours, and $x_{4,htg}$ and $x_{4,clg}$ are intercepts values for afterhours.

Table 1: Possible energy inefficiencies

Energy anomalies	Metrics
Perimeter heating to total heating ratio: Calculate the percentage of perimeter heating energy use by dividing the energy consumed by perimeter heating devices by the total heating energy consumption. A ratio exceeding 50% suggests a significant allocation of HVAC energy to perimeter heating.	$\sum_{i=1}^{8760} \frac{E_{PH}}{E_H} = \sum_{i=1}^{8760} \frac{(T_{oa}-d_1)^- \cdot d_2}{E_H}$ (see Equation 4)
Schedule effectiveness energy use ratios: Optimal results are indicated by values close to 1, signifying that the schedule is highly effective in minimizing energy consumption during non-working hours. Conversely, values nearing 0 or in the negative range suggest poor performance. (R_s below 30%)	$1 - \frac{x_{5,htg}}{x_{2,htg}}$ (see Equation 9) $1 - \frac{x_{5,clg}}{x_{2,clg}}$ (see Equation 10)
Afterhours energy use ratios: The after-hours energy use ratio represents the proportion of energy consumed during afterhours relative to the total energy use. A higher ratio denotes a larger portion of total energy consumption occurring during afterhours. Hence, a lower ratio is considered desirable. (R_a above 60%)	$\sum_{i=1}^{8760} \frac{x_{4,htg}+x_{5,htg}(T_{oa,i}-x_{6,htg})^-}{Y_{htg,i}}$ $\sum_{i=1}^{8760} \frac{x_{4,clg}+x_{5,clg}(T_{oa,i}-x_{6,clg})^+}{Y_{clg,i}}$
Outlier AHU detection for heating/cooling: The condition for identifying AHU_x with heating/cooling consumption exceeding three times the median absolute deviation heating/cooling consumption.	$E_{H,ahu_i} > 3 \times H_{MAD}$ $E_{C,ahu_i} > 3 \times C_{MAD}$

The $x_{2,htg}$ and $x_{2,clg}$ are the slope of models for work hours and $x_{5,htg}$ and $x_{5,clg}$ representing the slope of the models during afterhours. Also, $x_{3,htg}$ and $x_{3,clg}$ represent the change point temperature of the model during work hours. Similarly, $x_{6,htg}$ and $x_{6,clg}$ indicate the change point temperature of the model but during afterhours. It is recommended to carefully examine any ratios below 30% for a more thorough assessment (R_s) according to the tool developed by Markus et al. (2022) for schedule effectiveness ratio. The afterhours energy use ratio represents the proportion of energy consumed during afterhours relative to the total energy use. A higher ratio denotes a larger portion of total energy consumption occurring during after hours, making a lower ratio more desirable. It is advisable (Markus et al. (2022)) to notify users when the afterhours ratio exceeding 60% serves as a threshold (R_a). In essence, these metrics for BAS-based disaggregation form a robust toolkit to thoroughly examine and identify anomalies in energy usage patterns. The incorporation of schedule effectiveness and afterhours energy use ratios enhances the evaluation of the disaggregation process, contributing to a comprehensive assessment of its performance in capturing and distinguishing between different operational patterns during distinct periods. The incorporation of these metrics into the unsupervised disaggregation framework ensures a robust evaluation of heating and cooling energy consumption behaviors. By analyzing schedule effectiveness and after-hours energy use ratios, the methodology gains the capability to detect patterns and anomalies in energy usage, contributing to the optimization of the disaggregation process. These metrics serve as valuable tools for assessing the accuracy and reliability of unsupervised disaggregation methods, thereby facilitating informed decision-making in building operations and energy management.

Results and discussion

Utilizing data extracted through API downloads from both the BAS and bulk meter, our analysis centers on an office building situated in Ottawa. The outcomes are showcased in the radar graph (Figure 2), serving as a valuable visualization tool. This graph aids decision-making processes involving multiple criteria, providing a comprehensive view of the analyzed data. This graph reveals the following insights into health indices including schedule effectiveness and work-hours energy use ratio, AHUs heating ratios (the percentage of energy used by AHUs), and non-outlier AHUs for cooling and heating systems (The percentage of the number of non-outlier AHUs). For cooling, schedule effectiveness of 59% indicates a reduction in energy use during afterhours, as the work-hours energy use slope is steeper than that of after-hours. This positive outcome underscores an effective strategy for managing and reducing cooling energy consumption during non-work hours. One potential reason for this success could be the implementation of after-hours AHU on-off and temperature setback schedules, optimizing the cooling system's efficiency when the building is not in active use. Additionally, the after-hours energy use ratio of 22% further supports the efficiency of energy utilization, signifying a relatively smaller proportion of total energy consumption during after-hours. In contrast, the results for heating show a schedule effectiveness of 12%,

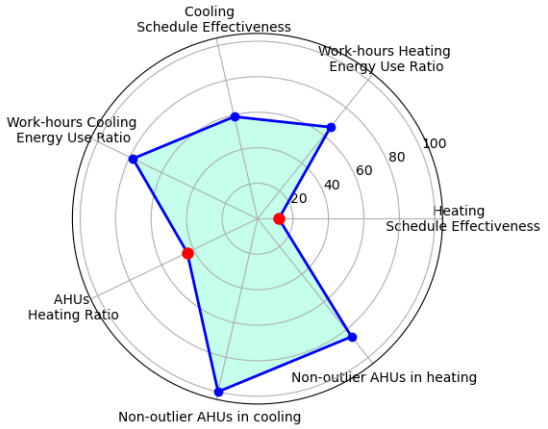

Figure 2: Radar chart based on energy anomalies metrics generated by the web application.

denoting a moderate reduction in energy use during after-hours. One potential reason for this could also be attributed to the after-hours AHU on-off and temperature setback schedules, although the impact might be less pronounced compared to the cooling system. While this indicates efforts to optimize heating energy consumption outside of regular work hours, the after-hours energy use ratio of 34% suggests a larger share of total energy consumption during after-hours, leaving room for further improvements in energy efficiency. These findings, coupled with the potential influence of AHU schedules, provide valuable insights for optimizing energy consumption patterns, with a focus on enhancing after-hours efficiency for both cooling and heating systems. The perimeter heating to total heating ratio of 56% for the selected time suggests a significant allocation of heating energy to perimeter heating devices which could be related to faulty HVAC equipment, inappropriate controls programming, undersized HVAC systems or weather conditions that need to be identified by energy managers. Also, $AHU_{2,4}$ are identified as outliers during the heating season due to the exceeded MAD values which could be related to faulty, equipment, sequence of operation or control programming (see Figure 4). Utilizing a time series decomposition disaggregation approach, this study investigated the energy consumption dynamics of an office building in Ottawa, Canada, relying only on data from the bulk electricity meter under the assumption that BAS data is unavailable. The decomposition results generated by the web application are shown in Figures 3 and 5. The analysis revealed distinct patterns for cooling and heating energy use. For cooling, the schedule effectiveness is calculated at 57%, indicating a considerable reduction in energy use during after-hours, as the work-hours energy use slope surpasses that of after-hours. Furthermore, the after-hours energy use ratio stands at 30%, reflecting a relatively moderate proportion of total energy consumption during non-working hours. In the case of heating, the schedule effectiveness registers at -7%, implying a steeper after-hours energy use slope compared to work hours. While these values denote a less effective reduction in heating energy use during after-hours as compared to cooling energy use, the after-hours energy use ratio is found to be 40%, highlighting a substantial share of total energy consumption occurring after regular work hours. These results showcase the potential for optimizing energy efficiency even without BAS data, using disaggregated bulk electricity meter data and time series decomposition techniques. This analysis aids energy managers in detecting inefficiencies during weekdays and weekends, identifying peak energy usage, and detecting abnormalities during or after working hours. Once energy deficiencies are identified, adjustments such as rescheduling turn-on/off events and setting point changes on weekdays and weekends can lead to significant energy savings. Before developing the proposed web application, the disaggregated signals (such as lighting and plug loads, heating, and cooling) were determined to match the submetered data. This is important for conducting further classical time-series analysis. By analyzing energy usage, it becomes possible to better understand a building's daily operational signature for three major end-uses. As presented in Figure 5 the selected building shows consistent operational patterns across cooling and lighting and plug loads components on different days of the week. The clear distinction between energy usage patterns on working days and weekends suggests efficient building operations. For heating load, the building does not show a significantly lower usage during weekends and non-working hours compared to working days. This is an unusual pattern for office buildings and may require the building manager's attention. The study introduces an integrated web application designed for comprehensive energy disaggregation analysis in commercial buildings, utilizing various data sources and advanced techniques. Leveraging BAS data and bulk meter data, the application employs multiple linear regression and unsupervised disaggregation methods to provide detailed insights into energy consumption patterns. The first page of the web application allows manual data upload in scenarios without direct BAS access, providing flexibility in application use. The second page, designed for situations with only bulk meter data, utilizes unsupervised disaggregation techniques like time series decomposition to identify major end-uses of electricity consumption, aiding in anomaly detection and trend analysis. The third page of the application utilizes BAS data for a thorough analysis, calculating contributions from various components like AHUs and perimeter heating devices. Schedule effec-

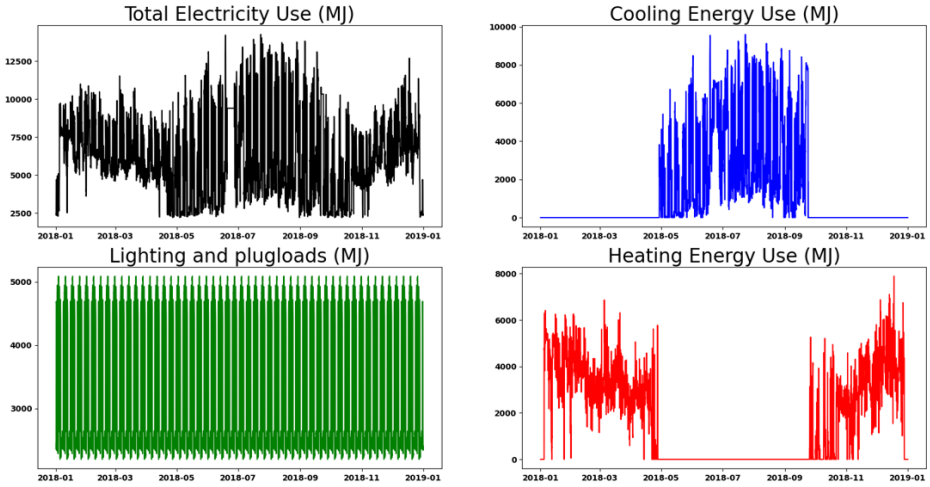

Figure 3: Time series decomposition results generated by the web application for uploaded bulk electricity meter data.

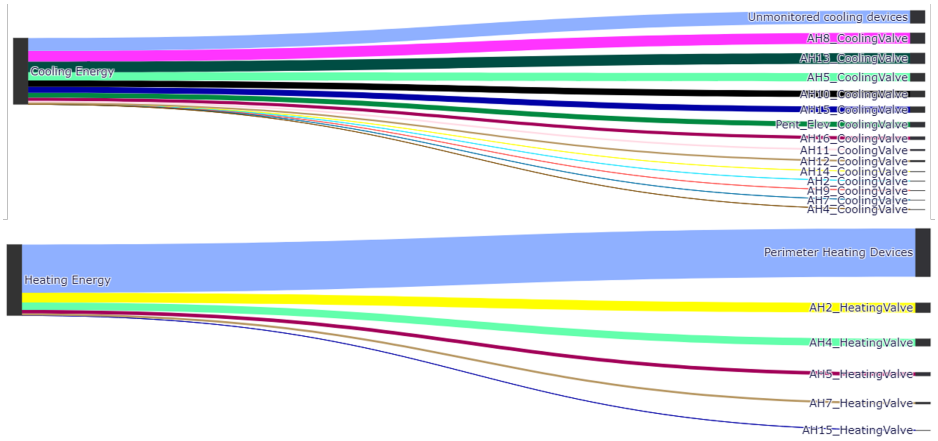

Figure 4: A Sankey diagram visualizing the heating and cooling energy use distribution.

tiveness and after-hours energy use ratios are separately calculated for cooling energy use, offering valuable information for energy optimization. The web application serves as a user-friendly platform for building managers and energy professionals, promoting transparency and collaboration through its public GitHub(Zaeri (2023)) repository. While acknowledging the application's capabilities, the study highlights the importance of data quality and assumptions made in the models. Future research could explore expanding the application's capabilities by incorporating additional data sources and machine-learning techniques. In conclusion, the web application demonstrates the potential of Streamlit and Python for energy disaggregation analysis, offering a valuable tool for optimizing energy consumption and enhancing sustainability in commercial buildings.

Conclusion

The integrated web application developed in this study offers a comprehensive solution for energy disaggregation analysis in commercial buildings. By leveraging BAS data, bulk meter data, multiple linear regression models, and unsupervised disaggregation techniques, the application enables users to optimize energy consumption. The three pages provide a user-friendly interface for analyzing energy usage patterns, identifying specific end-uses, and detecting energy anomalies. The public GitHub repository ensures easy accessibility and promotes collaboration among researchers and practitioners. Future work aims to add functions enabling users to download a report file. The results obtained for the office building will be thoroughly discussed with building stakeholders. This validation process will involve soliciting feedback and insights from relevant parties to ensure the reliability of the obtained results. Feedback from interviews with professionals will be used to improve the report's content and presentation in the web application. To enhance the web application's capabilities, there is a plan to expand the features to include recommendations for the minimum number of thermal submetering installations based on BAS data and bulk meter data. Future research will also focus on expanding datasets to different climate zones, estimating performance and financial impacts better, and addressing web application limitations.

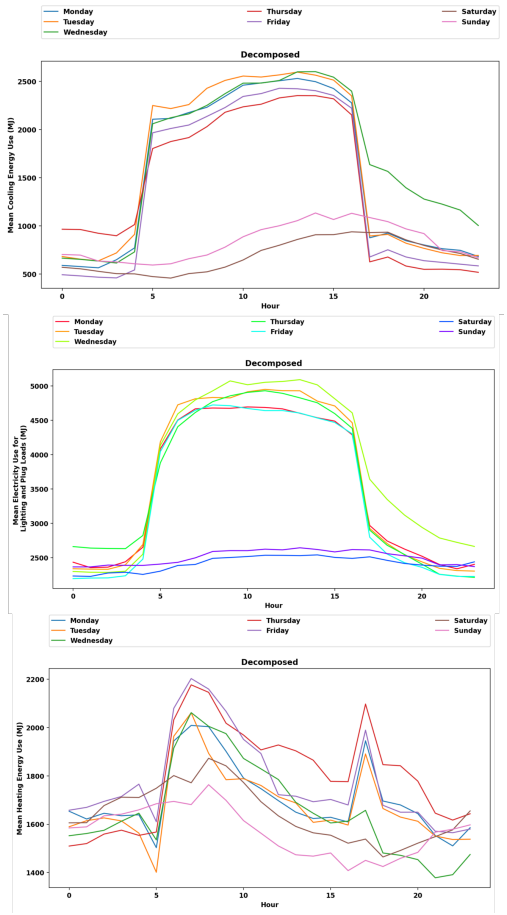

Figure 5: Decomposed lighting and plug loads, cooling, and heating daily operational signatures generated by the web-application.

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