Unsupervised Energy Disaggregation Using Time Series Decomposition for Commercial Buildings

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Abstract

"We can't manage what we don't measure." Understanding energy flow and end-uses within a building is essential for energy management. Although submetering is very important, many buildings still do not have adequate submetering for their major end-uses due to cost and practical issues. Energy disaggregation approaches can break down the bulkmeter energy signal into specific end-uses to gain insight into consumption patterns. With high-quality building automation system (BAS) trend data, unmeasured energy flow can be captured at high accuracy using disaggregation techniques. However, it remains an untackled challenge to disaggregate end-uses without high-resolution, reliable BAS trend data. This paper explores the time-series decomposition-based method to disaggregate major energy end-uses without BAS trend data. The proposed decomposition model uses data from an office building in Ottawa, Canada, to break down the total energy use into three major end-uses: lighting and plug loads and cooling and heating energy use. The disaggregation result was then compared with actual submeter data for validation purposes. The proposed method's promising performance points to its potential application in quick and low-cost auditing of commercial buildings.

CCS Concepts: • **Computing methodologies** → **Model verification and validation**; **Model verification and validation**; • **Applied computing** → **Engineering**.

Keywords: unsupervised disaggregation, major end-uses, time-series decomposition

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1 Introduction

Understanding major end-uses and the energy flow in large buildings is very important for energy management due to the high demand in this sector. Having high-resolution energy data in commercial buildings is challenging since they have many variable load devices, such as fans, valves, and pumps, while many occupants interact with lighting and plug loads. Submetering from large end-uses to device level would be ideal, but implementing them in existing buildings is complicated for special building types such as hospitals and historic ones. Adding submeters may require mechanical and electrical system modifications in most cases. NSTC [10] reported several case studies to understand the complexity and economic aspects of using submeters in energy management. Zhai and Salazar [14] also investigated the depth and cost of submetering for 21 case studies and analyzed the energy saving and cost-effectiveness of different metering levels.

Non-intrusive load monitoring (NILM) algorithms and disaggregation techniques represent great opportunities to avoid deploying physical submeters. Energy disaggregation aims to provide detailed information on energy use and building energy flow into end-uses, which can further be analyzed for energy systems development. Disaggregation approaches are mostly implemented in residential sector; however, several studies focus on commercial buildings [4, 7, 12]. BAS trend data also can provide contextual information about the operating status of major end-uses for disaggregation purposes. For instance, using BAS data, Gunay et al. [4] demonstrated that electricity energy use can be disaggregated into lighting and plug loads, air distribution systems, and chillers. Zaeri et al. [12] extended this approach to thermal energy by disaggregating heating and cooling loads per each AHU heating, cooling coils, and perimeter heating device. They also investigated [13] the effect of submeter density and configuration on the performance of the disaggregation strategy using BAS trend data.

Although BAS trend data-based disaggregation has been receiving greater attention due to its potential for reducing energy consumption, there are still buildings that do not have available BAS data. Energy disaggregation analysis without BAS data opens another challenge to understanding the energy flow without any prior information. Birt et al. [3] developed a method for residential buildings that plots hourly electricity use data for an individual household vs. ambient temperature to partially disaggregate loads into five end-uses: base load, activity load, heating season gradient, cooling season gradient, and lowest ambient temperature at which air-conditioning is used. Furthermore, when BAS data is unavailable, time-series analysis of building energy use data could provide insightful information about major end-uses, energy use patterns, building operations, and characteristics. Time-series analysis is often useful to identify the underlying patterns of signal and better understand the contribution of multiple components, including trend, seasonality, and residual, for forecasting and anomaly detection [8, 9]. Time-series decomposition has been used in many other fields, but with very limited application to energy disaggregation and buildings, [2]. For example, Ghelardoni et al. [5], and Tascikaraoglu et al.[11] used classical time-series decomposition to develop building energy demand and forecasting models. Pickering et al.[9] used time-series decomposition techniques for building electricity consumption and weather data for six commercial buildings. Their results from time-series decomposition and suggested rescheduling introduce significant energy savings. A time-series decomposition-based disaggregation method for commercial building end-uses has not been developed. In this paper, a time-series decomposition-based load disaggregation method is deployed by using data from a government office building in Ottawa, Canada. The proposed disaggregation method breaks down the total electricity use into three major end-uses (lighting and plug loads, heating and cooling). The results and the accuracy of applying this time-series decomposition approach with actual metered data have been discussed.

2 Methodology

The proposed method disaggregates building-level electricity energy from the bulkmeter into three categories: lighting and plug loads and cooling and heating energy in an office building.

2.1 time-series Decomposition-based Load Disaggregation Model

The time-series decomposition is a statistical method that breaks down a time-series into several components. The trend component represents the signal's long-term progression. The seasonal component represents periodic (in this case weekly) fluctuation of time-series. Unexplained events must also be assessed to fully represent the behavior of the data as described by a residual term [6]. Mathematically, the time-series decomposition is described as Equation 1:

$$Y_t = f(T_t, S_t, R_t) \tag{1}$$

where Y_t is the observed time-series data, T_t is the trend component, S_t is the seasonal component, and R_t is the residual component.

The additive decomposition model is most appropriate if the magnitude of the seasonal fluctuations or the variation around the trend does not vary with the level of time-series. In this study, a multiplicative model is selected since the variation in the seasonal pattern, or the variation around the trend cycle appears to be proportional to the level of the time-series. The multiplicative model, is used to capture the seasonal and trend components of the total energy use (see Equation 2).

$$Y_t = S_t \times T_t \times R_t \tag{2}$$

The seasonal-trend decomposition using LOESS (STL) method uses locally fitted regression models to decompose a time-series into trend, seasonal, and residual components. The total electricity consumption breaks down to three end-uses as shown in Equation 3 which, E_{LP}, E_C and E_H represent electricity used by lighting and plug loads, cooling and heating, respectively.

Figure 1 shows the energy consumption pattern seen over a year and how energy use varies during heating, cooling, and transition season for lighting and plug loads, heating, and cooling energy use. According to the climate and type of building, energy usage fell into three phases: cooling, heating, and transition. Transition season usually identifies the minimum level of monthly energy consumption. The lowest trend values in Figure 1 represent the minimum energy level in a transition season. The maximum level of lighting and plug can be found when a building does not require any cooling or heating. Firstly, to disaggregate the electricity used by lighting and plug loads from total energy use, we start by multiplying the weekly seasonality of the total electricity use ,S_t, with the minimum trend component ,T_t, to adjust the amplitude of disaggregated signals when no heating and cooling is required in the building. As the typical yearly energy use by lighting and plug loads shows, the trend stays constant over a year with only a slight decrease during the cooling season due to solar radiation and daylight increase. Second, the trend component, T, is used to identify the cooling and heating seasons using the change point detector technique [1]. Based on the signal change point detector and climate zone, the cooling season in this study includes the months of June through September, while the heating season includes November till April. The transition season includes May and October. The trend component during cooling operation,

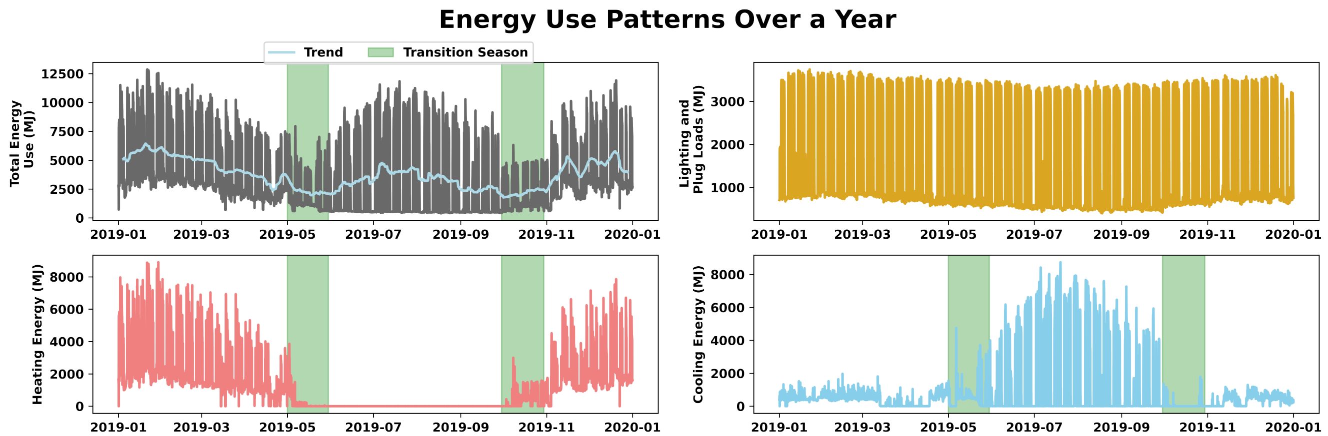

Figure 1. Energy consumption pattern of a building over a year for major end-uses: Total energy use, lighting and plug loads, heating and cooling energy use.

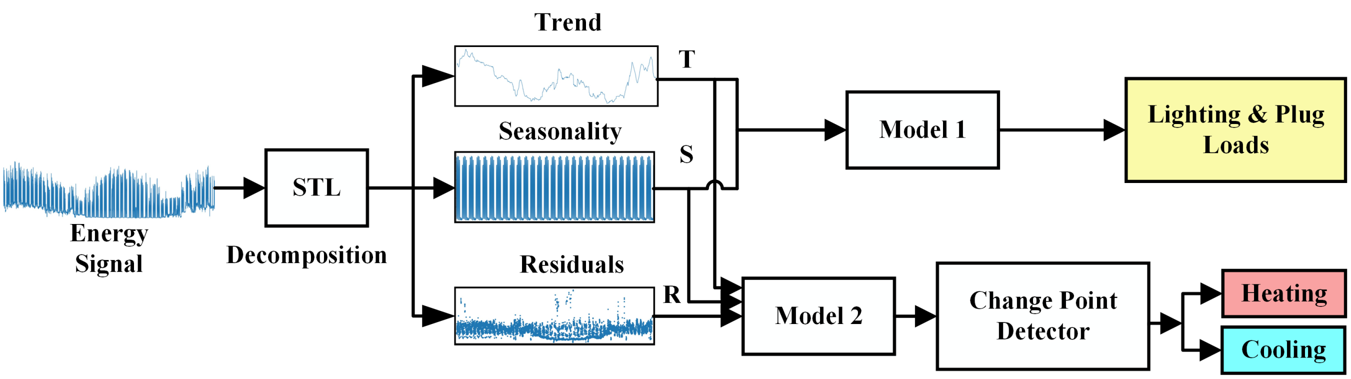

Figure 2. The disaggregation model is based on the time-series decomposition model for total energy use to its subcategories: lighting and plug loads, heating, and cooling electricity use of an office building over a year.

T_{t_c},is multiplied by weekly seasonality, S_{t_c}, and residuals, R_{t_c}, for cooling electricity use. Then the lighting and plug loads energy use calculated from the first step is subtracted from the signal as shown in Equations 4 and 6. For heating electricity use, the trend component during the heating season, T_{t_h}, is multiplied by weekly seasonality, S_{t_h}, and residuals, R_{t_h}, and then subtracted from the lighting and plug loads energy use calculated from the first step during the heating season as shown in Equation 5. Equation 4 represents the Model 1, and Equation 5 and 6 represent the Model 2 in block-diagram shown in Figure 2. Also, t_c and t_h show the cooling and heating operation time respectively. A changepoint detector is applied to the trend component to separate the heating and cooling operation.

$$E_t = E_{LP} + E_C + E_H \tag{3}$$

$$E_{LP} = min(T_t) \times S_t \tag{4}$$

$$E_H = S_{t_h} \times T_{t_h} \times R_{t_h} - E_{LP} \tag{5}$$

$$E_C = S_{t_c} \times T_{t_c} \times R_{t_c} - E_{LP} \tag{6}$$

2.2 Case Study

The proposed decomposition method is implemented on hourly data collected from an office building located in Ottawa, Canada. The building has a floor area of 38,472 m^2, it was constructed in 1969, and the submeter data was captured for the whole year of 2019. Some assumptions are considered to validate the results of the proposed decomposition method due to unavailable submetered data from electricity use-only buildings. The submeter data (electricity, steam, and chilled water) are superimposed from this building to create bulkmeter data. Then the bulkmeter was used to propose the disaggregation method and the disaggregated energy use components compared to submeter data for evaluation purposes.

3 Results and Discussion

The disaggregation model using time-series decomposition is implemented in a case study to identify if the disaggregated signals, including lighting, plug loads, and heating

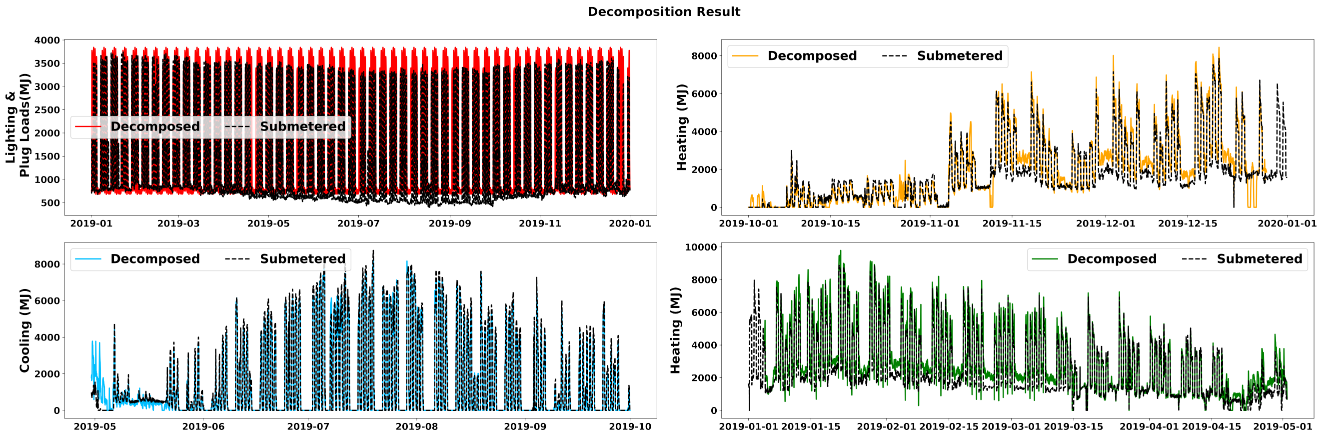

Figure 3. Disaggregation result based on time-series components for the case study over 2019.

and cooling, match the submetered data for further classical time-series analysis. Electricity energy use can be analyzed to illustrate a building's daily operational signature. The hourly time-series disaggregation result for the building and their corresponding submetered data are illustrated in Figure 3. For lighting and plug loads, the seasonality of the signal has been captured accurately. However, the trend values during the cooling season are estimated to be higher than actual submetered values due to daylight increases. The proposed model estimated higher trend values during weekends and after working hours compared to real submeter data for heating energy. The seasonality components for the heating season captured better than trend values. For cooling energy, the decomposition model captures the seasonality and trend estimation better than the heating season. As shown in Figure 3 the only period the cooling is not captured accurately is in May when the submeter measures some cooling energy, but the decomposition model could not estimate it properly since during transition season; we usually do not see much cooling energy use in the office buildings.

3.1 Accuracy of Decomposition Model

RMSE values were calculated for the building for decomposed end-use electricity consumption to assess the disaggregation accuracy of the data. Since the electrical energy used by lighting and plug loads, heating, and cooling were of different scales, the RMSE was normalized (NRMSE) by the range of the submetered data and expressed as a percentage as shown in Equation 7:

$$NRMSE\% = \frac{RMSE}{(y_{max} - y_{min})} \times 100 \tag{7}$$

According to the NRMSE result, the proposed method can disaggregate the total electrical energy use into subcategories with high accuracy. The NRMSE values for lighting and plug loads and heating and cooling energy use were calculated as 13%, 5%, and 7%, respectively. The disaggregation model on thermal loads shows better accuracy than lighting and plug loads. Due to the proposed model's high accuracy, further classic time-series analysis can be applied to the case study, such as hourly, daily, and weekly energy use signatures. This analysis can help energy managers identify any inefficiency during weekdays and weekends. Peak time energy use and abnormality during or after working hours could also be recognized. After identifying the energy loss, rescheduling the turn-on/off events and set point changes during weekdays and weekends would result in more energy savings.

4 Conclusion

The decomposition model for electricity energy use disaggregation provides significant insights about the building only by having a single meter without any prior information. Three end-uses are identified using the multiplicative decomposition model and their time-series components. The decomposition model was introduced based on the energy use pattern during the heating and cooling season and electricity use for lighting and plug loads. The minimum level of energy consumption has been identified from the trend component to calculate the non-thermal load. Then the lighting and plug loads energy use are subtracted from the total energy signal. The heating and cooling energy use are then estimated using the trend, residual, and seasonality during the heating and cooling season. Then the disaggregated result is compared with submetered data for evaluation. A comprehensive understanding of a building's energy flow and operation can easily be obtained through decomposition analysis when submetering is unavailable. Time-series decomposition can be further refined for specific cases, such as different building archetypes and climate zones. The result of this study and similar works can be used to provide inexpensive, rapid, and intuitive insights into the end-uses patterns in large commercial buildings.

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