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Disaggregation of commercial building end-uses with automation system data

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ABSTRACT

While understanding end-uses and their flow within a building is essential for energy management, many existing buildings still do not have adequate submetering for important end-uses such as heating, cooling, air distribution, lighting and plug loads. To this end, this paper presents a new end-use disaggregation method for commercial buildings. Unlike previous disaggregation methods which mainly rely on standalone devices to sample power draw at high frequencies, we used common building automation system (BAS) data types which indicate the operational state of fans and pumps to disaggregate low-frequency electricity data into three major end-uses: lighting and plug loads, distribution, and chillers. The method employs regression models that associate BAS data with related end-uses – e.g., variable speed air handling unit (AHU) fan state and fan electricity use. The model parameters are estimated by the genetic algorithm minimizing the misfit between the predicted and metered electricity use subject to several practical constraints. The accuracy of the method is evaluated by using a dataset from an office building with high-resolution submetering. Six different disaggregation scenarios representing various model forms are used in this investigation. The results indicate that the method can accurately disaggregate hourly building-level electricity use into three end-use categories for lighting and plug loads, distribution, and chillers with the contextual information provided by a few common BAS data types.

1. Introduction

Understanding end-uses and their flow within a building is essential for energy management. Recognizing the importance of high-resolution end-use monitoring, modern energy codes, standards, and certification programs have begun to prescribe minimum metering requirements. For example, ASHRAE Standard 90.1 [1] recommends building-level electricity submeters for heating, ventilation, and air-conditioning (HVAC), lighting, and receptacles for buildings larger than 2500 m^2. In addition, it recommends archiving utility meter data for at least 36 months. Similarly, California Title 24 [2] requires submetering and data collection for any electrical service rated more than 50 kVA. LEED V4 BD + C [3] offers an advanced energy metering point for submetering all end-uses that represent 10% or more of the total annual consumption.

Despite these new policies, meter infrastructure and data collection practices in many existing commercial buildings are inadequate to understand energy use patterns, identify anomalies, and perform on-going commissioning [4,5]. The initial cost to install meters in all eligible commercial spaces remains a tangible barrier. Furthermore, major retrofits may be required to accommodate meter installations, such as refitting pipes, rewiring, etc. Methods to disaggregate end-uses from existing meter infrastructure in commercial buildings can enable or improve the energy data analytics capabilities.

1.1. Background and previous work

A load disaggregation (i.e., non-intrusive load monitoring) method was first introduced by Hart [6] for residential appliances. Hart's method first employs an edge detection algorithm to identify changes in the steady-state power draw levels; subsequently, it clusters the changes in real and reactive power levels. Lastly, it associates these clusters to consumption levels of known appliances. The association step requires either a one-time training for each new application (by systematically turning on/off individual appliances) or historical electricity use data collected from similar appliances. While Hart's method was suitable to detect on-off appliances, it could not detect multi-state or variable load appliances. Further, appliances of similar real and reactive power

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characteristics could be misclassified. To correctly isolate steady-state power draw effects of individual devices, reactive and real power data must be collected at high frequencies (typically 1 Hz or higher) – which require the deployment of a standalone data acquisition system.

Several papers introduced methods to disaggregate residential appliance electricity use by looking at real power at low sampling frequencies – one measurement per 16 seconds [7,8] to 15 minutes [9]. These methods were overall successful at detecting the power draw by large appliances such as air conditioners, refrigerators, water heaters, and clothes dryers. Baranski et al. [10,11] employed the genetic algorithm to fit the measured data by using a discrete number of steady-state power draw change levels associated with the appliances present. They also used only real power, albeit collected at 1 Hz frequency.

Associating a detected change in the power draw levels to a unique appliance requires a detailed a priori knowledge of appliance characteristics from each building – which can be time-consuming if load signature of each appliance is unavailable [12]. Caminola et al. [12] attempted to tackle the need to acquire a priori knowledge by developing a semi-supervised load disaggregation method in which appliance-level information is retrieved from occupant energy use diaries (collected over a short period) and meter data. They demonstrated the method with major household appliances by using one-minute interval data with hidden Markov models and subsequence dynamic time warping. Similarly, Berges et al. [13] proposed a user-centred load disaggregation technique that requests user input to improve the association accuracy of detected power level change events to a specific appliance. Similar to the original load disaggregation method proposed by Hart [6], Berges et al. [13]'s method used high frequency (20 Hz to 60 Hz) real and reactive power measurements to disaggregate the power draw from typical home appliances.

While most existing load disaggregation methods rely on event detection algorithms to identify instances of appliance state change, Basu et al. [14] present a non-event-based approach that disaggregates each timestep into a set of fixed steady-state power levels representing each household appliance. This non-event-based load disaggregation approach is more suitable when high-frequency power draw data are not available. Birt et al. [15] developed change-point models to disaggregate hourly residential electricity use data into four broad end-use categories: baseload (representing non-HVAC loads that do not depend on occupant activities), activity load (representing electricity use due to occupant activities), and heating and cooling energy use. While the temporal resolution of data was not suitable for traditional appliance-level load disaggregation, this analysis provided insights into the end-use patterns – which can be used in performance benchmarking and energy use anomaly detection through cross-sectional comparisons with other homes.

Methods for appliance-level load disaggregation for residential buildings are widely studied and adopted by the industry. Recent review articles [16–18] identified over 50 different methods that attempt to improve the accuracy and practicality of load disaggregation methods in home energy management. Mayhorn et al. [19] reported over 18 active companies with commercially available or advanced prototype devices for load disaggregation in the residential sector. In contrast, the disaggregation of loads in commercial buildings is considerably more challenging and relatively understudied [20]. In large commercial and institutional buildings, there are many multi-stage and variable load devices such as variable frequency drive (VFD) fans, pumps, motors that serve air and hot/chilled water distribution systems and the plant equipment – while hundreds of occupants interacting with lighting and plug-in office equipment in a stochastic fashion. In addition, unlike residential buildings, energy systems in commercial buildings are operated in a tightly regulated control sequence whereby individual pieces of equipment turn on/off or ramp up/down simultaneously. For example, in a building with an air-based cooling system, only when at least one of the AHU fans are scheduled to start, the chillers turn on – also triggering the chilled water pump, cooling tower fans, etc. This functional causality leads to near-simultaneous changes in the energy consumption of different equipment and exacerbates the difficulty of discerning individual effects [21]. However, arguably, the benefits of load disaggregation for energy management in commercial buildings are at least as important as they are for residential buildings. Currently, operations staff of large commercial buildings with limited submetering work blindly without knowing how the energy is used and distributed.

Norford and Leeb [22] were the first to look at the load disaggregation problem in commercial buildings; they developed a prototype load disaggregation device for commercial buildings, which is intended to distinguish simultaneously scheduled equipment as well as devices with similar power levels. The device used high frequency reactive and real power measurements and tested in a laboratory setting under a few scenarios in the presence of fluorescent lamps and induction motors. Shao et al. [21] proposed a temporal motif mining-based load disaggregation method. Their method employs clustering to discover a discrete number of power levels and identifies the periodic occurrence patterns of these power levels. They demonstrated the method with ten-second interval data gathered individually from a pump, two fans, a blower, and an elevator.

Batra et al. [20] evaluated a combinatorial optimization-based disaggregation algorithm which represented AHUs as a two-state (on/off) load. While the algorithm was successful at disaggregating loads at the floor-level, it failed to capture the continuously varying loads by multiple AHUs for whole-building. Thus, they demonstrated that a disaggregation algorithm's accuracy is dependent on the number, diversity, and power draw characteristics of equipment present. In another study, a Fourier series model-based method to accurately disaggregate hourly lighting and plug load data from HVAC energy use in commercial buildings was developed [4]. Along with the studies that try to disaggregate the HVAC energy use in commercial buildings, Rogriguez et al. [23] and Doherty and Trenbath [24] investigated disaggregation of plug-in office equipment loads. They both submetered a small number of typical office equipment such as monitors, desktop computers, laptop computers, photocopiers, microwave oven, etc. They analyzed the correlation as well as the cross-correlation of their steady-state power draw patterns and explored the viability to disaggregate their effects. Rafsanjani et al. [25,26] developed a load disaggregation method to isolate the impact of occupant activities on aggregate electricity use data. They utilized WiFi-based occupancy detections and a density-based clustering approach to associate arrival and departure events to the changes in the power draw level. Through two case studies with eleven occupants, their method demonstrated the importance of external data sources that provide context (e.g., WiFi) to achieve high disaggregation accuracy.

Emerging practice to collect long-term HVAC control system data has led to another approach to gain insights into unmetered energy end-uses and flows in commercial buildings: virtual metering. Virtual meters are inverse models trained with HVAC control system data to estimate unmeasured quantities. Unlike load disaggregation, virtual metering is a bottom-up approach largely relying on HVAC control system data. For example, Darwazeh et al. [27] developed a virtual meter to compute the heat injected or extracted by an AHU's heating and cooling coils, respectively. By using supply, return, and outdoor air temperatures, supply airflow rate, outdoor air damper position, and heating and cooling coil valve position, the virtual meter estimates the energy supplied by the heating and cooling coils. A few other examples of virtual meters for building energy systems are those that monitor energy use in AHUs [28,29] and electricity use by evaporator and condenser fans and compressors by using sensor and actuator data and equipment nameplate information [28,30]. Note that while in modern buildings, a BAS may include HVAC, energy meter, lighting, and access control networks, etc., the role of a BAS in many existing buildings is still largely limited to HVAC controls. In many buildings, energy metering devices communicate via a different protocol (e.g., Modbus) than HVAC control devices (e.g., BACnet) [31]. Thus, in this paper, we used the terms HVAC control system data and BAS data interchangeably.

1.2. Motivation and objectives

HVAC control network setpoints, schedules, sensors, and actuators provide plenty of contextual information regarding the operational state of building energy systems. Thus, the use of HVAC control system data in tandem with meter data can improve the accuracy and scalability of load disaggregation solutions for commercial buildings. They may also alleviate the need for high-frequency electricity data in load disaggregation. As an example implementation of this approach, Bansal and Schmidt [32] used three-minute interval data for chiller flow rate, condenser supply and return temperatures, and chilled water supply and return temperatures to disaggregate the electricity use of three large chillers. While the potential of blending HVAC control system data with meter data has been recognized by other researchers [13,22], a disaggregation method exploiting this at the whole-building level has yet to be developed. In load disaggregation, HVAC control and meter data have been treated as two disparate data sources. Researchers developing methods to estimate unmeasured energy end-uses and flows have largely relied on either HVAC control system data to develop *virtual meter* algorithms or meter data to develop *load disaggregation* algorithms.

This paper explores the potential of load disaggregation algorithms that utilize archived HVAC control data in large commercial and institutional buildings. To this end, we selected a case study building with submeters for the following end-uses: occupant-controlled loads (lighting and plug loads), scheduled distribution loads (AHU fans), and cooling loads (chillers). While developing load disaggregation algorithms, we superimposed two or more of these three end-uses and then tried to differentiate them from one another. In addition to hourly superimposed end-use data, variations of the tested load disaggregation algorithms used a subset of the following common BAS data types: AHU on/off operating schedule, AHU fan VFD state, AHU supply air pressure, chilled water supply pump VFD state, and outdoor air temperature.

The contribution of this paper is to demonstrate the potential of blending traditionally disparate operational data sources – *BAS (HVAC controls) and meter data* – for load disaggregation. We developed a suite of load disaggregation algorithms leveraging commonly available low-frequency data streams and demonstrated the potential as well as the limitations by using data gathered from a real building. Further, new application venues for the proposed load disaggregation approach, such as predictive controls and anomaly detection – not only for electricity but also for other energy end-uses and flows – are identified, and future work recommendations are developed.

2. Methodology

The proposed method is intended to disaggregate building-level electricity use from a single meter into three categories: (a) occupant-controlled loads (lighting and plug loads), (b) scheduled distribution loads (fans and pumps), and (c) cooling loads (chillers). As illustrated in Fig. 1, this is equivalent to extracting Tier 3 level metering information from a building with only a Tier 1 level metering. In addition, for buildings in which the cooling loads are directly measured (e.g., buildings with dedicated submeters for chillers or chilled water energy meters), the electricity use is disaggregated in two categories: occupant-controlled loads (lighting and plug loads) and (b) scheduled distribution loads (fans and pumps). This is equivalent to extracting Tier 3 level metering information from a building with a Tier 2 level metering (see Fig. 1). Note that the term fans and pumps in the Fig. broadly refer to the electricity used for the distribution of heat/coolth inside a building. This includes the electricity used by the AHU supply and return fans as well as the secondary pumps that circulate hot/chilled water to the heating and cooling coils and the reheat coils/radiators. The term chillers represents the electricity used by the compressor motor as well as the fans and pumps serving the refrigeration, condenser, and cooling tower loops.

2.1. End-use disaggregation models

Table 1 lists the six end-use disaggregation scenarios investigated in this study. Three of them are intended for buildings with Tier 1 level metering, and the rest are intended for buildings with Tier 2 level metering. These methods hypothesize that total electricity use can be represented by superimposing individual end-uses predicted by their corresponding regression models shown in Fig. 2. Simply put, we superimposed three data records (i.e., electricity use by lighting and plug loads, fans and pumps, and chillers) and developed algorithms to disaggregate them – by looking at BAS data representing the operation of various energy systems. Note that we did not include other electricity uses such as elevators and exterior lighting. Thus, the method may not be directly used for buildings in which such end-uses account for a significant fraction of the electricity use. In those situations, other data types representing the operation of unaccounted energy systems such as elevator states or exterior lighting schedules can be incorporated in disaggregation algorithms. It is recommended that the dominant electrical end-uses of a building are estimated first before disaggregation can be applied. Note that the scenarios listed in Table 1 represent the use of different BAS data based on their availability. Table 1 also summarizes the models used to disaggregate the end-uses for each scenario. Fig. 2 schematically illustrates these load disaggregation models. Table 1 and Fig. 2 show only the proposed qualitative relationships that will be developed in the following sections by using data from the case study building.

Fig. 2(a) presents the model used to disaggregate lighting and plug loads. The lighting and plug load disaggregation model is built

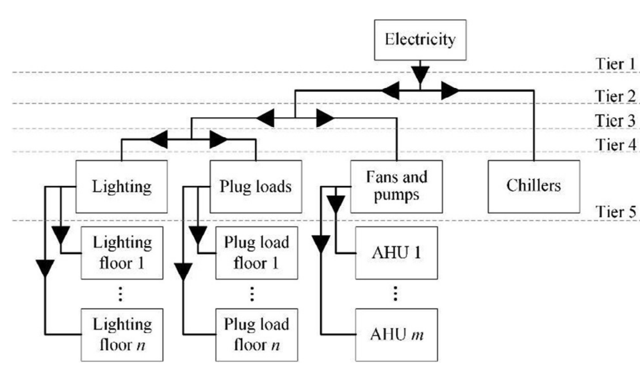

Fig. 1. A schematic illustrating the flow of electricity in a commercial building. The tiers indicate the levels of metering present from a single bulk meter for the whole building Tier 1 to floor-level and system-level submetering Tier 5.

Table 1
End-use disaggregation scenarios. The table lists the lighting and plug loads, distribution, and cooling electricity use models and their parameters used in disaggregation. The table also lists meter and BAS data needed to train these disaggregation models for each scenario.

Disaggregation Scenario	Meter data	BAS data	Models		
			Lighting and plug loads	Distribution	Cooling
Tier 1a Tier 1b Tier 1c	Electricity meter for chillers, fans, pumps, plug loads, and lighting	AHU schedule Outdoor temperature AHU fan state Chiller pump state AHU supply air pressure Chiller pump state	Fig 2(a) $f\left(x_{1to4}, y_1, y_{2,\mathrm{wkdy}}, y_{2,\mathrm{wknd}}\right)$	Fig 2(b) $f(y_3, y_4)$ Fig 2(c) $f(y_5)$ Fig 2(d) $f(y_6)$	Fig 2(e) $f(y_7, y_8, s_1, s_2, T_b)$ Fig 2(f) $f(y_9)$
Tier 2a Tier 2b Tier 2c	Electricity meter for fans, pumps, plug loads, and lighting	AHU schedule AHU fan state AHU supply air pressure		Fig 2(b) $f(y_3, y_4)$ Fig 2(c) $f(y_5)$ Fig 2(d) $f(y_6)$	–

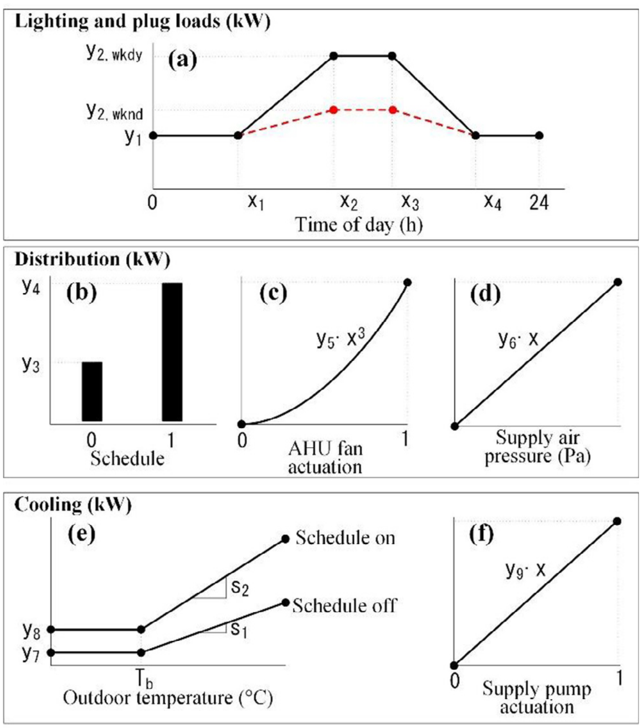

Fig. 2. Illustration of the end-use disaggregation models for (a) lighting and plug loads; fans by using hourly (b) availability schedule, (c) feedback from VFDs, (d) supply air pressure sensors; cooling by employing (e) a five-parameter univariate change point model and (f) feedback from a chilled water supply pump.

on a commonly used steady periodicity assumption with two daily profiles – one for weekdays and one for weekends. It has seven unknown parameters that need to be estimated. Of them, four divide each day into five periods: before first arrivals ($t < x_1$), arrival period ($x_1 \leq t < x_2$), occupancy period ($x_2 \leq t < x_3$), departure period ($x_3 \leq t < x_4$), and after last departures ($x_4 \leq t$). The remaining parameters define three steady-state power levels: y_1 (kW) for afterhours, and $y_{2,\mathrm{wknd}}$ (kW) and $y_{2,\mathrm{wkdy}}$ (kW) for weekend and weekday occupancy periods, respectively. It is assumed that power-level linearly changes during arrival and departure periods. The model was defined with two practical constraints: arrival, occupancy, and departure periods cannot be less than two hours; and, the steady-state power level for occupancy should be greater than the power-level afterhours. Note that while these constraints can be tuned for each building, having such constraints are critical as they help an optimization algorithm distinguish one end-use from another. For example, in a large building, occupants' arrivals and departures are processes that extend over several hours [33,34]; thus, their impact on electricity use is expected to be a slow ramp-up/-down due to their use of lighting and plug-in equipment. In contrast, the impact of scheduled HVAC equipment (e.g., AHU fans) is expected to happen much more rapidly. It is also important to note the model was designed to capture only the basic shape of the lighting and plug load profiles. This basic load shape was previously used by O'Brien et al. [35] to model tenant-level lighting and plug load profiles. The number of parameters estimated was kept as low as possible to avoid overfitting; consequently, details such as changes in power draw during lunchtime or arrival/departure times on different days of the week were disregarded.

Fig. 2 also presents three different models used in disaggregating the electricity by the distribution system. One of the models use the binary availability schedule of the AHU fans as a predictor and simply represents the AHU electricity use in two steady-state power levels: power draw when the schedule is off y_3 and on y_4 (see Fig. 2(b)), respectively. While this model may not be suitable for a building with substantial diurnal variations in supply airflow rates, it can be sufficient for a building with stable loads. As illustrated in Fig. 2(c) and (d), the second and third models propose a cubic relationship between the feedback signals from individual VFD fans and electricity use (y_5), and a linear relationship between the supply air pressure and electricity use (y_6), respectively [36].

The electricity use of the chillers is represented by two different models. One of them is a five-parameter change point model shown in Fig. 2(e) – a commonly used inverse model form described in ASHRAE Guideline 14 [37]. The model proposes a linear relationship between the outdoor temperature and the electricity use by the chillers above a change point temperature (T_b (°C)). This relationship is defined with two parameters: s_1 (kW/°C) and s_2 (kW/°C) when the binary availability schedule of the AHU fans is off and on, respectively. The model assumes that the electricity use below the change point temperature is constant and can be defined with two parameters: y_7 (kW) and y_8 (kW) when the binary availability schedule of the AHU fans is off and on, respectively. It is worth noting that the assumption to train two separate cooling change-point models (as schematically illustrated in Fig. 2(e)) is valid only in buildings with a single daily operating schedule for all AHUs and chillers. As shown in Fig. 2(f), the second model is built simply assuming a linear relationship between the VFD chilled water pump state and the electricity use. While we recognize more complex models with other predictors could improve the accuracy of a chiller model when its electricity use is submetered, we refrained relying on complex relationships between BAS data and energy use to ensure the transferability of the methods to many buildings and to avoid overfitting.

Recall that the purpose of these models is to represent different end-uses. The unknown parameters of these models are estimated such that the misfit between the sum of their predictions and a bulk meter data record is minimized. Consider bulk meter data that account for the combined effect of lighting and plug loads, distribution, and cooling loads. Here, we argue that the individual end-uses can be disaggregated by estimating the unknown parameters of the models shown in Fig. 2(a) for lighting and plug loads and Fig. 2(b) or (c) or (d) for distribution and Fig. 2(e) or (f) for cooling. In this paper, we are assessing the suitability of different combinations of these models to disaggregate the aforementioned end-uses. The relationships proposed with these models are demonstrated with data from the case study building in Section 2.3.

2.2. Parameter estimation and assessment of accuracy

The genetic algorithm is used to estimate the parameters of each of the six end-use disaggregation scenarios listed in Table 1. For example, 14 parameters ($x_{1\ \mathrm{to}\ 4}$, y_1, $y_{2,wkdy}$, and $y_{2,wknd}$ for the lighting and plug load model (Fig. 2(a)), y_3 and y_4 for the distribution model (Fig. 2(b)), y_7, y_8, s_1, s_2, and T_b for the chiller model (Fig. 2(e))) are estimated to disaggregate Tier 1 level meter data by using the AHU schedule and outdoor temperature data (see scenario Tier 1a in Table 1). Recall that once trained with archived electricity use data, each disaggregation model in Fig. 2 is expected to estimate the end-use patterns by looking at a small amount of BAS data.

The genetic algorithm minimized the root mean square error (RMSE) between the measured and predicted electricity use subject to the constraints shown in Table 2. The lower and upper limits of each parameter can be determined by considering practical limits (e.g., office occupants are expected to start arriving between 6 am and 12 pm), through visual inspection of the electricity use data or by extracting relevant nameplate information. In addition to these upper and lower limits, we defined seven inequality constraints. The hyperparameters of the genetic algorithm are determined through a sensitivity analysis. In this study, the population size, the maximum number of generations, and the crossover fraction were set to 5000, 40, and 0.5, respectively. The optimization process was terminated if the parameter estimates providing the lowest RMSE did not change for five consecutive generations, or the maximum number of generations was reached. Note that in the implementation of these methods to new buildings, if the range between lower and upper bounds can be reduced based on a priori information, the population size and the maximum number of generations can be lowered. On the contrary, if the range between lower and upper bounds were greater, we may have had to increase the population size and the maximum number of generations. Recall that this prior knowledge can come from a preliminary inspection of the aggregate energy use data, nameplate information about the major equipment of a building, and expert knowledge to determine a reasonable range of plausible load densities.

The accuracy and appropriateness of the six end-use disaggregation scenarios are assessed in two different ways. First, we compared the disaggregated end-use models with the same model form trained using submeter data for each end-use. Simply put, how much better can we characterize each end-use if we train the models shown in Fig. 2 with submeters dedicated for each end-use in lieu of using the genetic algorithm to disassociate them from a single meter? Second, we assessed the RMSE of the models relative to the magnitude and variation of the end-uses that they disaggregate. RMSE of each model was normalized with the difference between the maximum and minimum (i.e., min-max normalization) as well as the mean of each corresponding end-use.

Table 2
The constraints used in estimating the parameters of the models in Fig. 2.

	Lighting and plug loads							AHUs				Chillers					
	x_1 (h)	x_2 (h)	x_3 (h)	x_4 (h)	y_1 (kW)	$y_{2,wknd}$ (kW)	$y_{2,wkdy}$ (kW)	y_3 (kW)	y_4 (kW)	y_5 (kW)	y_6 (kW/Pa)	y_7 (kW)	y_8 (kW)	T_b (°C)	s_1 (kW/°C)	s_2 (kW/°C)	y_9 (kW)
Lower limit	6	9	12	16	0	0	0	0	0	0	0	0	0	5	0	0	0
Upper limit	9	12	17	22	50†	50†	50†	100†	100†	100†	1†	20†	20†	18	15†	15†	150†
Inequality constraints	$y_1 < y_{2,wknd} < y_{2,wkdy}$; $x_2 - x_1 > 2$; $y_3 < y_4$ $y_7 < s_1 < s_2$ $x_3 - x_2 > 2$; $x_4 - x_3 > 2$																

† The upper bounds for these parameters should be determined after manually inspecting the electricity use data or from nameplate information in each building. The values shown are the ones that we used in our case study building.

2.3. Case study building and dataset

The end-use disaggregation methods are demonstrated on a dataset gathered from an academic office building in Ottawa, Canada. The six-storey building has an area of ~ 6000 m^2, and it was completed in 2011. While heating is supplied from a district plant, cooling is generated by two identical chillers located in the building. The chillers were sequenced such that if one of the chillers can meet the cooling load, only one of them operated. At loads that exceed the capacity of chillers individually, they worked in parallel. The facility monitored the electricity used by the chillers together as well as the chilled water supply to the building. The heating and cooling are distributed to the building by two AHUs with VFD return and supply fans, as well as hydronic perimeter heaters and reheat VAV coils in thermal zones. The building is instrumented with submeters monitoring the electricity flow at the floor-level. Average hourly data from each submeter are stored in the energy management system. In this study, we used the data collected in 2017. The building had an annual electricity use intensity of 89 kWh/m^2 – of that 47% was used by plug-in equipment and lighting, 26% was used by the fans of the two AHUs (distribution), and 27% was consumed by the chillers (including the electricity use by the pumps). Fig. 3 presents the breakdown of total electricity use as well as the flow of electricity to subsystems and floors in the building. When training the load disaggregation models for Tier 1a-c (see Table 1), only the main electricity meter data were used. When the load disaggregation models for Tier 2a-c (see Table 1) were trained, only the combined power draw by the AHUs and plug loads and lighting was assumed available. To assess the disaggregation results, three separate time-series were used for hourly electricity use by the AHUs, plug loads and lighting, and chillers. Fig. 4 presents these three major end-uses that we attempt to disaggregate in this study. Some visible characteristics of these end-uses highlight three challenges for the disaggregation method. First, aside from the weekly steady-periodicity assumed in Fig. 2 (a), lighting and plug loads appear to be slightly lower during the summer months than the rest of the year. Second, the power use characteristics of the AHUs changed drastically in June. The authors later discovered that both the supply and return fans in one of the AHUs were stuck on due to an unintended change in the controls program. This is anticipated to detrimentally affect the representativeness of the disaggregation model shown in

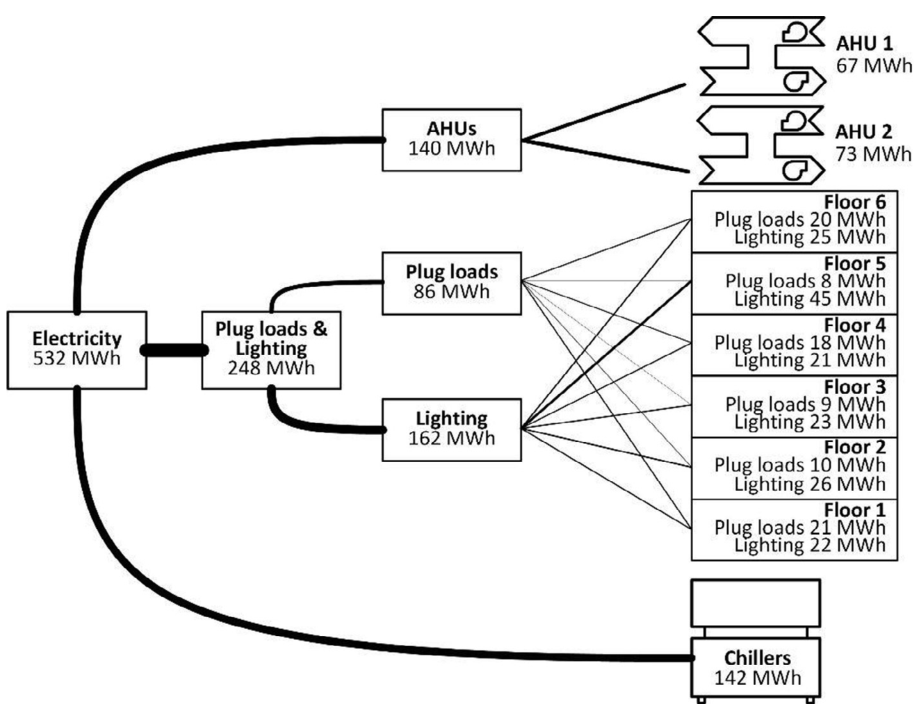

Fig. 3. The annual breakdown and flow of electricity in the case study building. The thickness of each line is proportional to the electricity consumption.

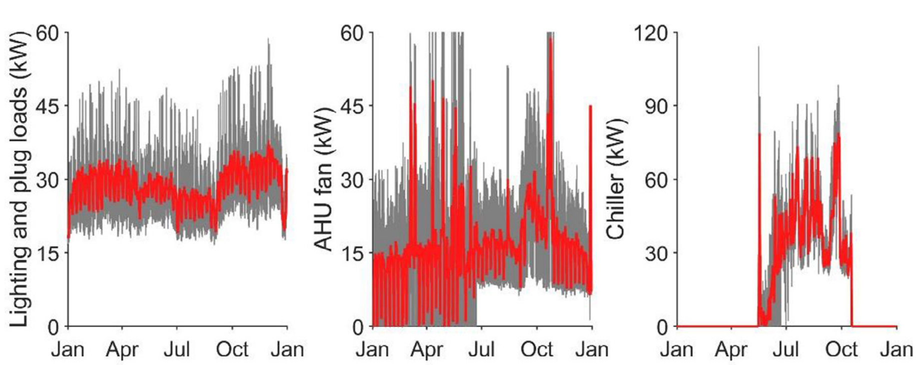

Fig. 4. The hourly time-series for the three major end-uses investigated in this paper. The thick red lines indicate the mean daily running average.

Fig. 2(b). Third, the abrupt increase in the cooling-related electricity load in May is caused due to a late switchover to cooling. As the building's thermal mass reached elevated indoor temperatures due to a delayed seasonal switchover, electricity use by the chillers was unexpectedly high irrespective of the outdoor temperature. This anomaly and the fact that one of the two AHUs stuck on without following the binary availability schedule is expected to detrimentally influence the accuracy of the model shown in Fig. 2(e).

In addition to the meter data, five BAS data types were extracted for the same period: outdoor temperature, binary availability schedule of the AHU fans, the supply fan states for each AHU, supply air pressure of each AHU, and the chilled water supply pump state. As shown in Fig. 5, the mean power draw by the AHUs was 28 kW when the schedule was on, and it was 8 kW when the schedule was off. The bimodal behaviour of the AHU power draw when the schedule was off can be attributed to the AHU override in June, causing one of the two AHUs not to follow the scheduled off command. In addition, Fig. 5 presents the cubic relationship proposed in Fig. 2(c) between the AHU VFD states and AHU electricity use, the linear relationship proposed in Fig. 2(d) between the AHU supply air pressure and the AHU electricity use, and the linear relationship proposed in Fig. 2(f) between the chilled water supply pump state (primary pump) and the chiller electricity use.

3. Results and discussion

In this section, we will investigate two different aspects of the disaggregation models: (1) How accurate is the disaggregation approach in replicating the models trained directly using submeter data? (2) How accurate are these models in representing the end-uses? In addition, the limitations of the proposed method are identified, and future work recommendations are developed. Note that the disaggregation scenarios did not have access to the submetered end-use data. They used only the bulkmetered electricity use data and the BAS data indicating the operational state of electricity using equipment (see Table 1). The accuracy was assessed by comparing the models trained through disaggregation and directly with the submetered data. In other words, the submeter data were used only for the assessment of the trained disaggregation models – they were not used during the model training phase.

3.1. Disaggregating occupant, distribution, and cooling loads

Fig. 6 presents the results for the end-use disaggregation scenario Tier 1a (see Table 1). In the Fig., measured hourly electricity use was presented in terms of box and whisker plots for lighting and plug loads and distribution and with scatter plots for chillers. The models trained through disaggregation by the genetic algorithm and those directly trained with the submetered end-use data were overlaid on the measured electricity end-uses. Recall that in this scenario, the disaggregation approach inputs hourly electricity meter data (for lighting and plug loads, distribution, and chillers), outdoor temperature, and the binary availability schedule of the AHU fans.

The genetic algorithm subject to several practical constraints (explained in Section 2.2) estimates the unknown parameters of the three disaggregation models given these data. As a reference, the models were trained again with the same algorithm and con-

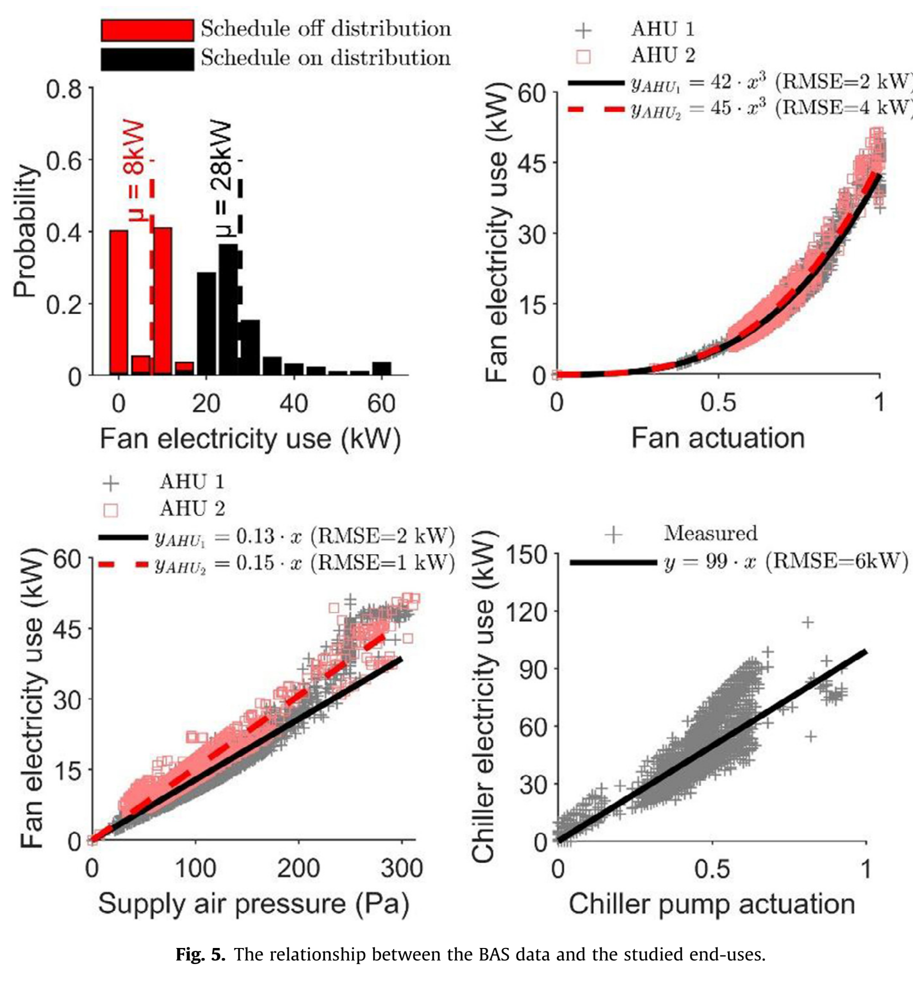

Fig. 5. The relationship between the BAS data and the studied end-uses.

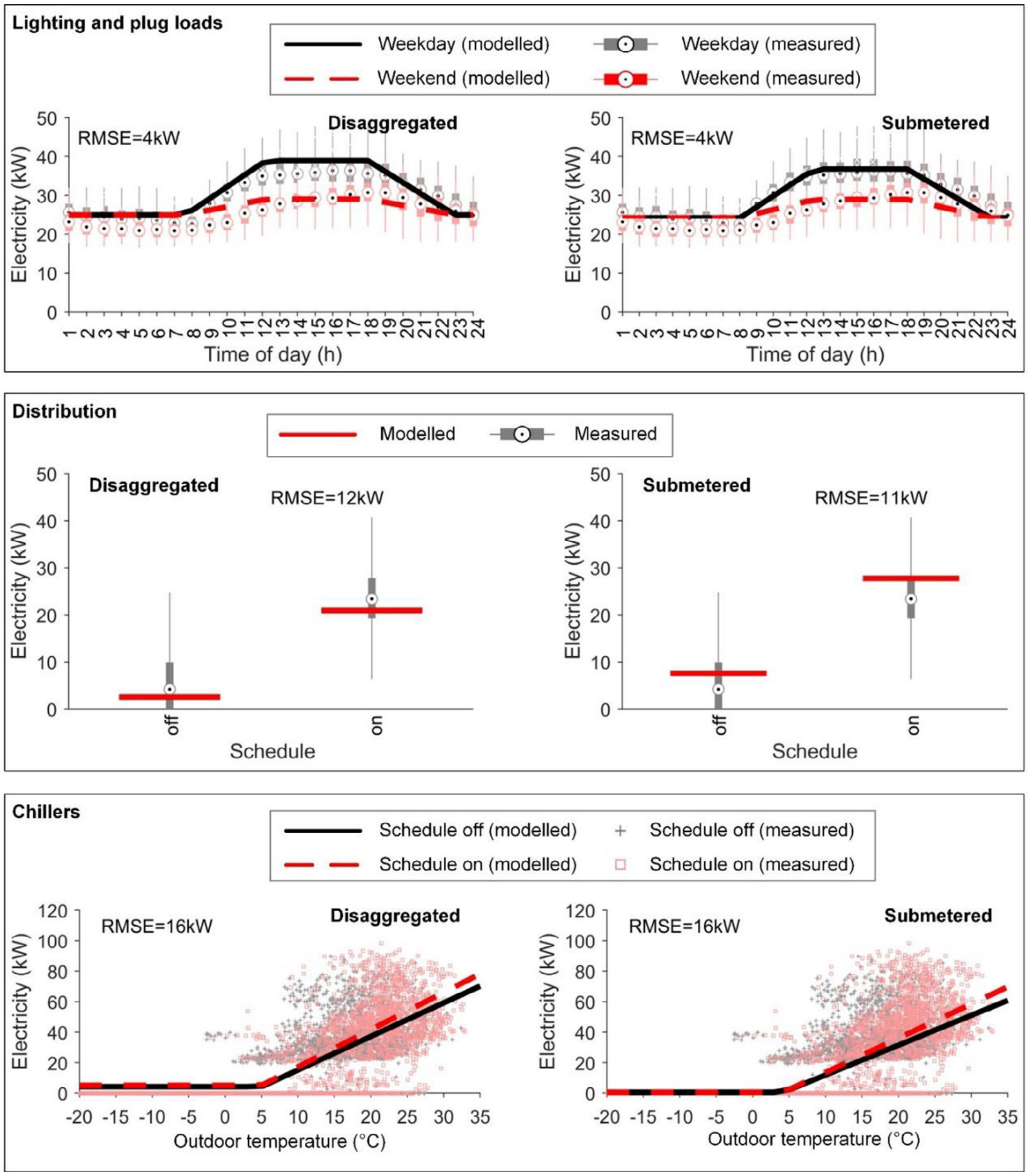

Fig. 6. A comparison of the models trained with load disaggregation and directly with the submeter data. The load disaggregation approach inputs Tier 1 meter data, binary availability of the AHU fans, and the outdoor temperature as shown in Table 1.

straints, albeit directly with submeter data for each end-use. The results indicate that the disaggregation approach was able to achieve nearly the same RMSE as the models trained directly with the submeter data for each of the three end-uses. While this was a promising observation, RMSE values of the models for the AHUs and chillers were considerably large – 12 kW and 16 kW, respectively. In part, this can be explained by the fact that the fans of one of the AHUs were stuck on in about half of the dataset. Thus, the fans did not follow the binary availability schedule of the AHUs. In a building with forced-air-based cooling under normal circumstances, when the AHU fan is scheduled to be off, cooling energy use should be negligible. Simply put, without airflow, no thermal energy should be extracted across the AHU cooling coils. However, the continuous operation of the fans led to substantial electricity use by the chillers even when the schedule was off. Further, the airflow rate of the building exhibited substantial day-to-day variations, which prevented us from characterizing their electricity use with two simple steady-state power levels. In brief, in buildings with similar faults, this disaggregation method (which uses the binary availability schedule as a predictor) may not be appropriate to represent the end-uses. However, as an indirect benefit, this method may help identify the presence of such faults, when submeters to isolate the cause of energy use anomalies are unavailable. Note that the lighting and plug loads during weekdays were, on average, 24 kW before 8 am and after 10 pm. Mean weekday lighting and plug loads increased linearly from 24 kW at 8 am to 37 kW at noon and decreased linearly from 37 kW at 5 pm to 24 kW at 10 pm. This can be interpreted as that the arrival and departure periods of the occupants extend over a four- to five-hour window in this academic office building. These patterns were nearly identically revealed by models trained with the disaggregation algorithm and the submeter data.

Fig. 7 presents the results for disaggregation scenario Tier 1b (see Table 1). Recall that this scenario is identical to Tier 1a except that instead of the binary availability schedule of AHU fans and the outdoor temperature, it uses the feedback from the VFD fans and

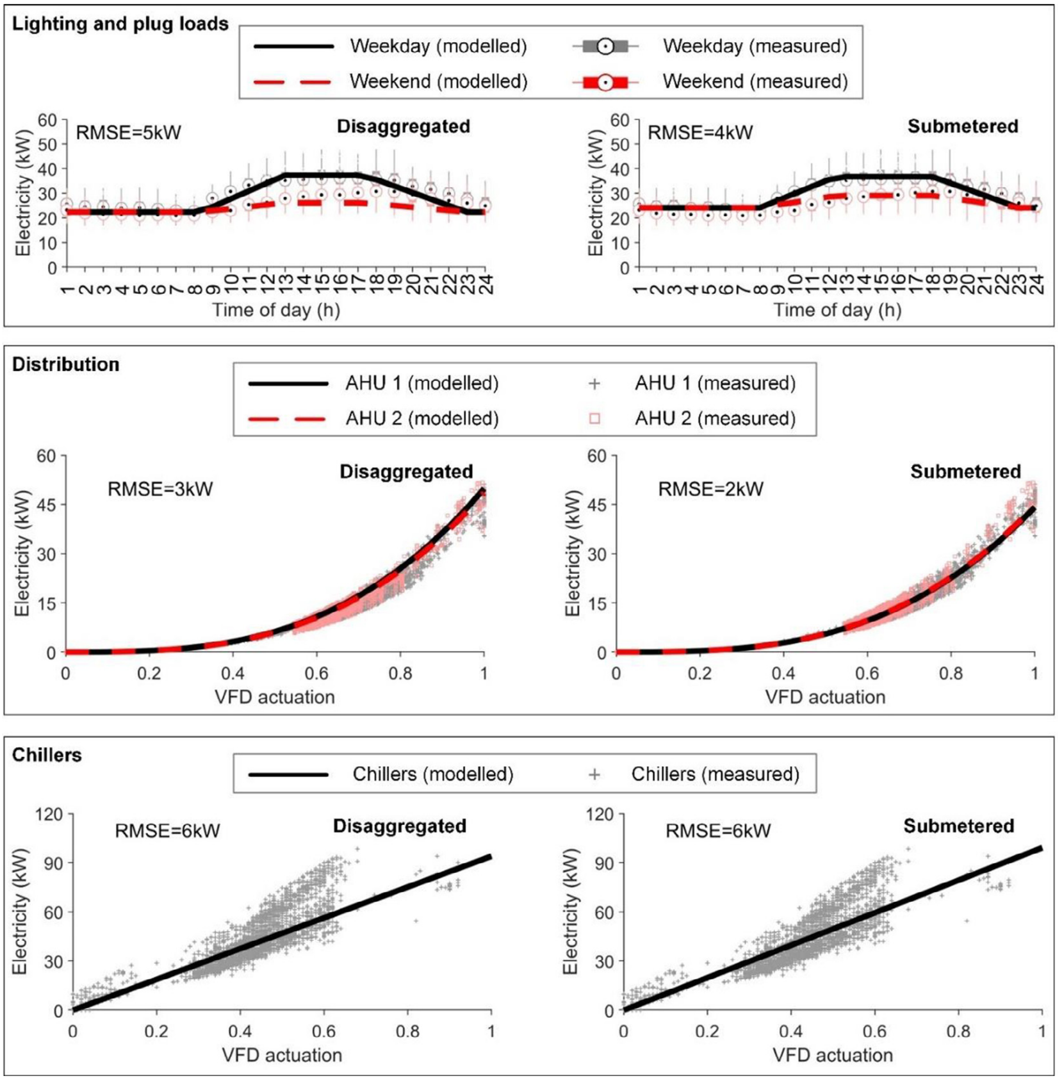

Fig. 7. A comparison of the models trained with load disaggregation and directly with the submeter data. The load disaggregation approach inputs Tier 1 meter data, AHU fan VFD states, and chilled water VFD pump state, as shown in Table 1.

pumps to disaggregate the three end-uses. Again, the disaggregated models and models developed on direct submeter data performed very similarly, meaning that the genetic algorithm was overall successful at discerning the differences between the end-uses by using these BAS data and the constraints listed in Table 2. Further, the results indicate that the feedback from VFD fans and pumps are much more suitable to disaggregate the end-uses than the binary availability schedules and the outdoor temperature. RMSE of the models for the AHUs and chillers were only 3 kW and 6 kW, respectively. Note that beyond disaggregating the total electricity use for distribution, we were able to estimate the power draw by each AHU. Thus, an additional benefit of using the feedback from individual VFD fans was the ability to disaggregate the power draw by individual AHUs. This observation can lead to a research question: By blending equipment/device-level BAS data (e.g., feedback from various actuators), can we develop disaggregation algorithms that characterize the energy flows within a large building?

Fig. 8 presents the results for the disaggregation scenario Tier 1c shown in Table 1. This scenario is the same as Tier 1b except that AHU supply air pressure sensor data, instead of the feedback from the VFDs of AHU fans, were used as a predictor. The disaggregation accuracy for each end-use was similar to Tier 1b. Thus, not only feedback from actuators but also sensors indicating the operational state of a system can be used in the load disaggregation problem. Future work should investigate the use of multiple data streams with similar information in load disaggregation. For example, supply air pressure and VFD fan state data together can improve the robustness of the disaggregation method in case of a fault in either data streams.

3.2. Disaggregating occupant and distribution loads

Fig. 9 presents the results for the disaggregation scenario Tier 2a (see Table 1). Recall that the disaggregation scenario Tier 2a is the same as the scenario Tier 1a except that in Tier 2a we are trying to disaggregate the electricity use for lighting and plug loads and distribution only. Scenarios Tier 2a-c are applicable to buildings in which cooling is submetered. The results indicate that the accuracy of the models disaggregated by the genetic algorithm was overall comparable to the end-use models developed directly by using submeters. However, it is worth noting that the disaggregated

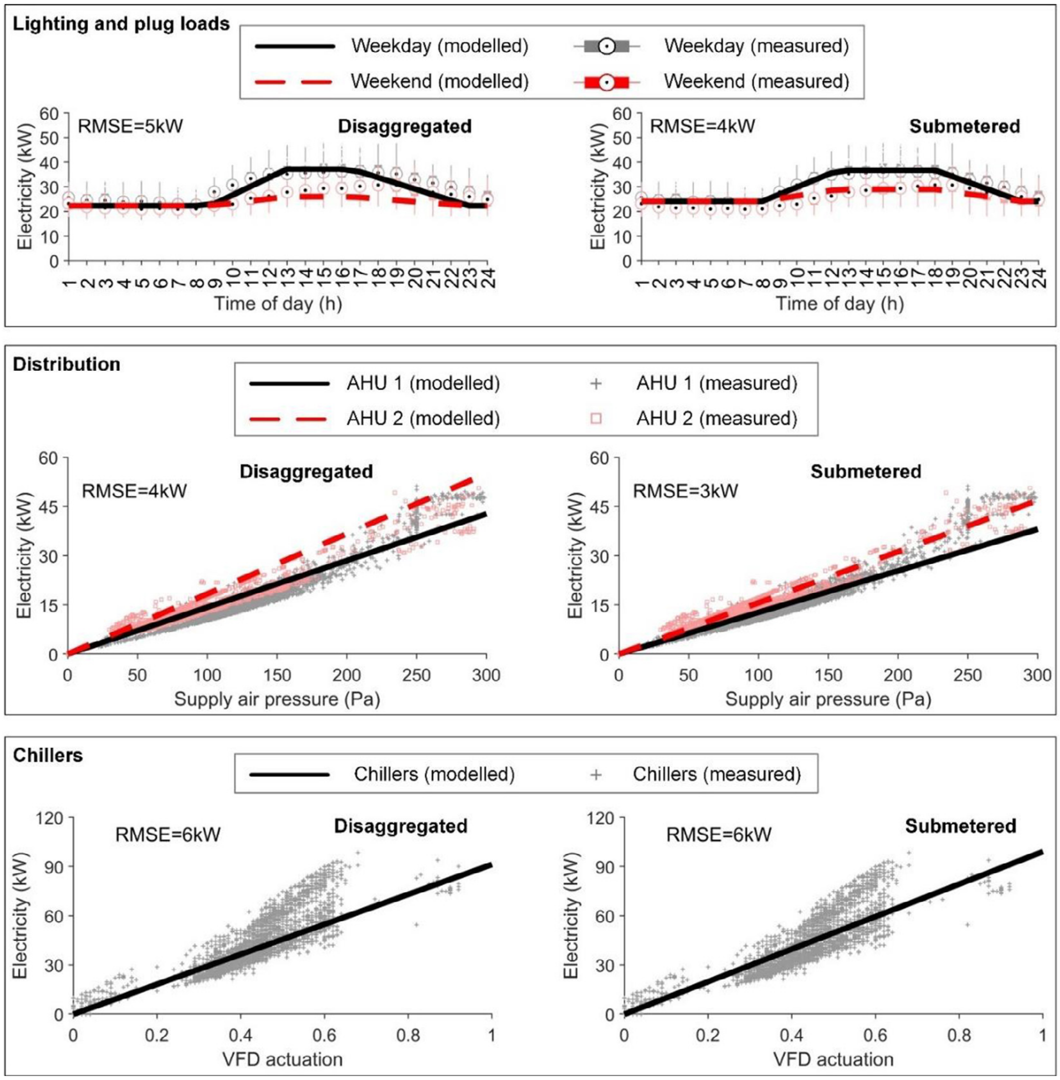

Fig. 8. A comparison of the models trained with load disaggregation and directly with the submeter data. The load disaggregation approach inputs Tier 1 meter data, AHU supply air pressure sensor data, and chilled water VFD pump state, as shown in Table 1.

models tend to overestimate lighting and plug loads during the occupancy periods on weekends and weekdays ($y_{2,\mathrm{wkdy}}$ and $y_{2,\mathrm{wknd}}$in Fig. 2). Further, this disaggregation approach suffered from the aforementioned fan stuck on fault in one of the AHUs as well as large day-to-day variations in electricity use rates. Both through disaggregation and using submeter data, RMSE of representing the fan electricity use with only two steady-state power levels (one for schedule on and one for schedule off) was 11 kW. Recall that the research was conducted in an academic office building with more than typical variations in occupant-driven loads throughout the year between semesters, during spring/fall breaks and exam periods. While this load disaggregation scenario did not perform well in this building, it may perform remarkably better in other buildings with relatively constant in-service airflow rates, functional AHU schedules, and a more steady-periodic occupancy. Thus, future research should further investigate these end-use disaggregation scenarios with data from other buildings.

Fig. 10 presents the results for the disaggregation scenario Tier 2b (see Table 1). This scenario is the same as Tier 2a except that it uses the feedback from the AHU fans instead of the binary availability schedule as a predictor. The results indicate that the disaggregation approach was able to discern the differences between the two end-uses accurately. The models estimated by genetic algorithm-based disaggregation and directly with submeter data were nearly identical. RMSEs of the disaggregated models were 5 kW and 2 kW for lighting and plug loads and distribution, respectively.

Fig. 11 presents the results for the disaggregation scenario Tier 2c (see Table 1). This scenario is the same as Tier 2b, with the exception that instead of the feedback from the VFD fan states, it inputs the supply air pressure from each AHU. The results were again promising that the disaggregated models were largely able to replicate those estimated using the submeter data. RMSE of the lighting and plug loads and AHU models disaggregated from a single Tier 2 electricity meter was 4 kW and 3 kW, respectively. Like scenarios Tier 1b and 1c, beyond disaggregating the total electricity use for distribution, the scenarios Tier 2b and 2c allowed us to disaggregate the electricity use by the two AHUs individually.

Table 3 presents a summary of the normalized RMSE for the six disaggregation scenarios. Recall that the RMSE values were computed based on the residuals between the measured submetered end-uses and those predicted through disaggregation models. Note

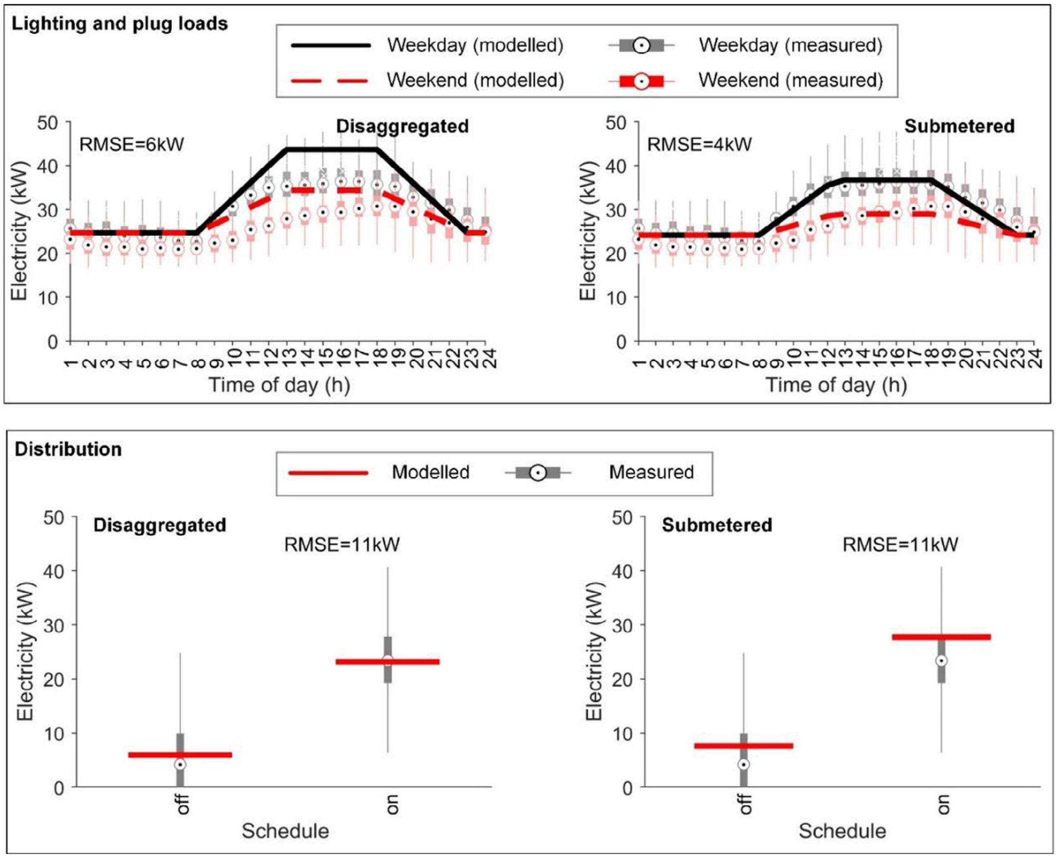

Fig. 9. A comparison of the models trained with load disaggregation and directly with the submeter data. The load disaggregation approach inputs Tier 2 meter data and binary availability of the AHU fans, as shown in Table 1.

that RMSE was normalized in two different ways – with the range of data and the mean of data that the model predicts (i.e., CV (RMSE)). A comparison of scenarios Tier 1a-c with scenarios Tier 2a-c indicates that disaggregating three end-uses instead of two end-uses only slightly reduced the predictive accuracy. A comparison of scenarios Tier 1b and 1c and Tier 2b and 2c indicates that models with AHU fan VFD and supply air pressure performed similarly. These two predictors were much better than the binary AHU fan availability schedule in isolating the impact of AHU operation from the hourly electricity use data. A comparison between scenarios Tier 1a and Tier 1b highlights that the chilled water pump VFD was significantly better at isolating the effect of chiller electricity use than the five-parameter change-point model. It is important to note that normalizing the RMSE for the chillers with the mean resulted in drastically larger values than normalizing it with the min-max range. This is because the chillers were off for most of the year – causing the min-max range to be about eight times larger than the mean. While the disaggregation process was able to retrieve the overall shape and magnitude of the mean daily lighting and plug load profiles, the normalized RMSE values were between 9% and 21%. However, we should acknowledge that occupancy and lighting and plug load use in the case study building [33] is much lower than typical office buildings [38,39]. Mean lighting and plug load power intensity was 6.5 W/m^2 during occupancy periods and 4 W/m^2 overnight. Arguably, lighting and plug load disaggregation accuracy will be higher in office buildings with more predictable and higher occupancy levels. It is important to note that the normalized RMSE and CV(RMSE) values shown in Table 3 are computed for disaggregation accuracies in making predictions at hourly intervals. If the objective in load disaggregation is to estimate these end-uses on a daily basis or on a monthly basis, the disaggregation accuracies will be substantially better than those reported in Table 3. This is because hourly variations in residuals are expected to cancel each other out over daily or monthly intervals.

3.3. Discussion

The case study results indicate that the operational context provided by HVAC control system data is invaluable in disaggregating electricity end-uses. In this paper, this operational context was provided by the following trend logs: operating schedules of the AHU fans, VFD feedback from the AHU fans and chiller pumps, and AHU supply air pressures. The use of these HVAC control system data eliminated the need for high-frequency power draw sampling devices and non-intrusive load monitoring algorithms found in the literature – many of which were deemed incompatible to large commercial and institutional buildings. Considering the emerging practice of collecting subhourly HVAC control system data from commercial buildings, future research, building on the methodology presented in this paper, can investigate practical load disaggregation solutions. However, the method presented in this paper should be considered as a first attempt to test the viability of using HVAC control system data in the load disaggregation problem. There are several unresolved issues that we left for future work:

- The end-use disaggregation method was presented with data from a single academic office building with unique electricity use characteristics. Accuracy and transferability of the method should be investigated in other commercial buildings.

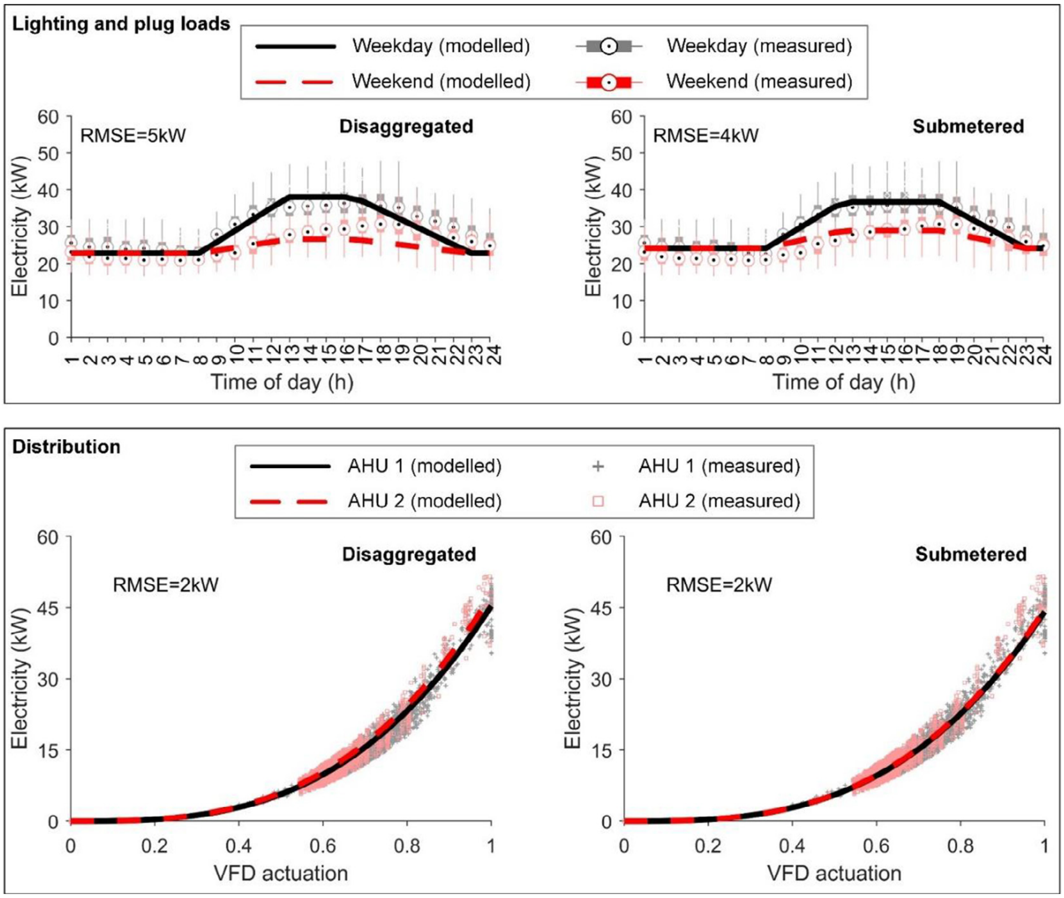

Fig. 10. A comparison of the models trained with load disaggregation and directly with the submeter data. The load disaggregation approach inputs Tier 2 meter data and AHU fan VFD states, as shown in Table 1.

- The six load disaggregation scenarios were formulated by using only five common BAS data types such as AHU fan state, chilled water pump state, AHU supply air pressure, binary AHU availability schedule, and outdoor temperature. Only six different model forms were used to characterize the relationship between these BAS data types and end-uses for lighting and plug loads, distribution, and chillers. The models' parameters were estimated by the genetic algorithm subject to several practical constraints. Future research should investigate the potential of other model forms, predictors, and parameter estimation techniques. In addition, the qualities of BAS data required to train accurate disaggregation models should be investigated. What is the minimum length of necessary data (e.g., several weeks, months, years)? To what extent can BAS data abnormalities be tolerated (e.g., faulty actuators, sensors)?
- It is important to note that the six disaggregation models shown in Fig. 2 are classic regression models – thus, when they predict the instantaneous breakdown of electricity use as end-use categories, there may be some residuals. For example, once the models are trained with archived meter and BAS data for a building, at any given instance, one can predict the lighting and plug loads, AHU power draw, and chiller electricity use. However, the sum of these predicted end-uses may be slightly more or less than the instantaneous power draw. For the real-time implementation of the approach, one may allocate these residuals proportional to the expected accuracy of each end-use model. For example, for disaggregation scenarios Tier 2b and c, we are much more confident about our predictions of the AHU electricity use than the lighting and plug load electricity use. Thus, much of the residuals (amounts instantaneously unaccounted for by the models) can be attributed to lighting and plug loads. Future research is needed to account for these disaggregation residuals. Regardless, the classic regression models used in this study are likely adequate for most energy managers and operators to understand the energy use patterns in large commercial buildings.
- While the method presented in this paper focusses only on electricity-based end-use disaggregation, the contextual information provided by BAS data could be used to disaggregate energy flows beyond electricity. For example, valve positions for the AHU heating coils, terminal device reheat coils, and perimeter heaters may be used to disaggregate the submetered heating energy use of a building at the zone-level. Similarly, valve positions for the AHU cooling coils and terminal device airflow rates may be used to disaggregate the submetered cooling energy use of a building at the zone-level. This disaggregation approach may rely on greybox models associating a carefully selected set of predictors to submetered heating/cooling energy use or machine learning models associating BAS data to the meter data through dimensionality reduction and feature selection. Application of disaggregation models that connect meter data to BAS actuators includes zone-level energy use anomaly detection and interpretation and predictive controllers minimizing energy use by treating BAS actuators as predictors and sensors as controlled variables. In brief, future research should investigate BAS data-based disaggregation methods for non-electricity energy flows.

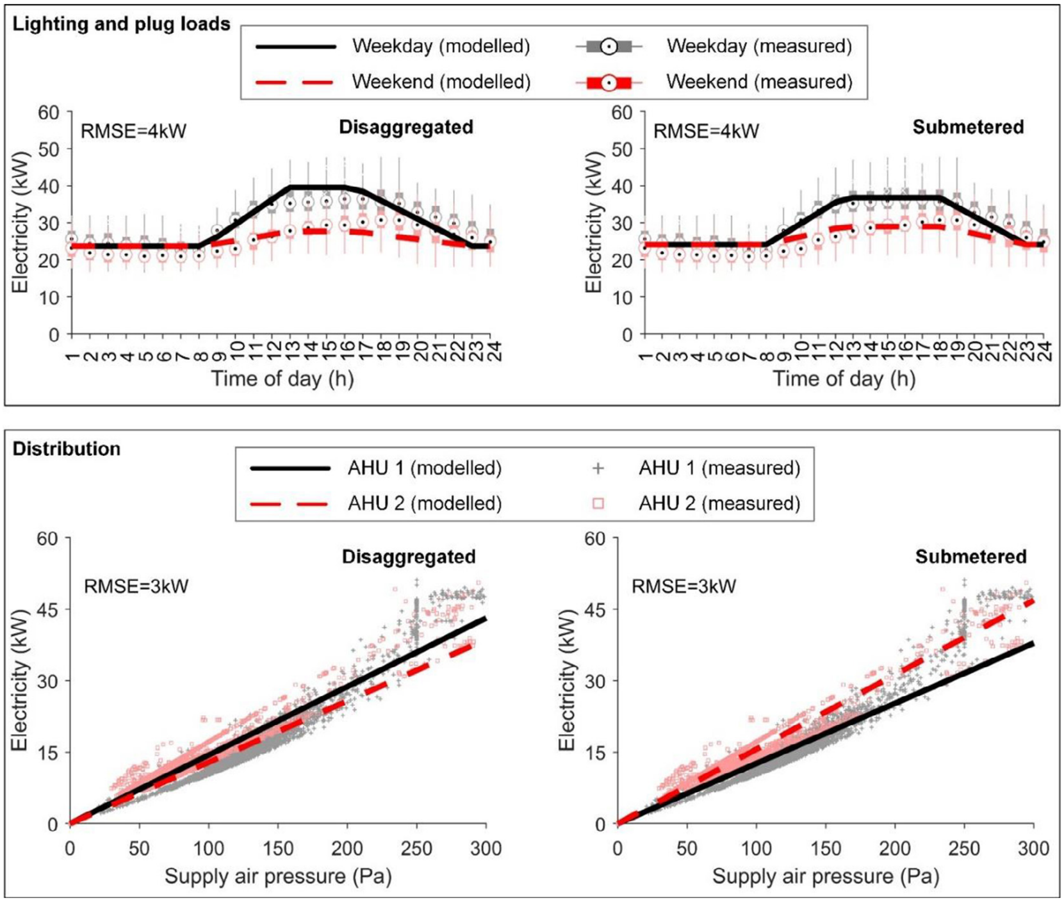

Fig. 11. A comparison of the models trained with load disaggregation and directly with the submeter data. The load disaggregation approach inputs Tier 2 meter data and AHU supply air pressure sensor data, as shown in Table 1.

Table 3
Summary of normalized RMSE values for the six disaggregation scenarios.

Disaggregation Scenario	$\frac{RMSE}{(y_{max}-y_{min})}$			$\frac{RMSE}{y_{avg}}$		
	Lighting and plug loads	Distribution	Chillers	Lighting and plug loads	Distribution	Chillers
Tier 1a	0.09	0.12	0.14	0.14	0.72	1.05
Tier 1b	0.11	0.03	0.05	0.17	0.18	0.39
Tier 1c	0.11	0.04	0.05	0.17	0.24	0.39
Tier 2a	0.14	0.11	–	0.21	0.66	–
Tier 2b	0.11	0.02	–	0.17	0.12	–
Tier 2c	0.09	0.03	–	0.14	0.18	–

4. Conclusions

An electricity end-use disaggregation method was developed and demonstrated using data from an academic office building. Unlike previous end-use disaggregation approaches, it utilizes BAS data from the operational state of equipment to disaggregate low-frequency electricity data into major commercial building end-uses. The method blends common BAS data streams (e.g., AHU fan state, chilled water pump state, AHU binary availability schedule, AHU supply air temperature, and outdoor temperature) and hourly meter data to train simple regression models. The model parameters are estimated by the genetic algorithm minimizing the misfit between the measured and predicted electricity use subject to several practical constraints.

The method was assessed with six different load disaggregation scenarios. Of these methods, three were looking to disaggregate three major end-uses: lighting and plug loads, distribution, and chillers. The other three were intended for buildings in which cooling is submetered, and they were looking to disaggregate two end-uses: lighting and plug loads and distribution. In these scenarios, the power drawn by the chillers was represented in two different ways: with a five-parameter univariate change point model and by assuming a linear relationship with the chilled water pump state. The power drawn by the AHUs was represented in three different ways: with two steady-state power draw levels for the on and off stages of the AHU availability schedule, by assuming a cubic relationship with the AHU VFD fan state, and by assuming a linear relationship with the AHU supply air pressure.

The findings from this study were promising that low-frequency meter data could be disaggregated at a reasonable accuracy with the contextual information provided by the BAS data. The lowest normalized RMSEs for lighting and plug loads were 9% and 14% when the RMSEs were normalized with the min-max range and the mean of the data record, respectively. The lowest normalized RMSEs for distribution were 2% and 12% with min-max and mean normalization, respectively. This was achieved when the AHU VFD fan state was used as a predictor. Lastly, the lowest normalized RMSEs for the chillers were obtained when the chilled water pump state was used as a predictor; and they were 5% and 39% with min-max and mean normalization, respectively.

Future research will extend the findings of this study to disaggregate the heating and cooling energy flows by using BAS data. Building on the method presented in this paper, submetered heating and cooling energy use will be disaggregated at the system- and zone-levels by using archived BAS data for heating/cooling/reheat coil and perimeter heater valve states as predictors.

CRediT authorship contribution statement

H. Burak Gunay: Conceptualization, Methodology, Investigation. **Zixiao Shi:** Data curation, Formal analysis, Writing - original draft. **Ian Wilton:** Funding acquisition, Writing - review & editing. **Jayson Bursill:** Visualization, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2020.110222.

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