Virtual energy metering of whole building cooling load from both airside and waterside measurements

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Abstract

Sub-hourly data from buildings are becoming increasingly available and represent an untapped opportunity to better manage and operate buildings. To complement the available data, soft sensors and virtual meters could be developed to infer important variables (most notably, energy numbers) that are typically not measured. While research has mainly focussed on virtual meters at the local component level, this paper presents data-driven virtual energy meters to estimate cooling load at the whole building level. These virtual meters rely on measurements, as well as energy and mass balance equations from: 1) the chilled water plant, 2) the air handling units and 3) the variable air volume boxes and thermostats. Cooling load estimations were compared for a large Canadian commercial building, and the merits of each method are discussed in terms of uncertainty, ease of implementation and applications.

Introduction

Data acquisition systems have become increasingly available in buildings and allow the collection of operational data at sub-hourly intervals e.g., at every five minutes. Common metering devices, such as temperature, pressure and relative humidity sensors, flow meters, valve openings and power readings, expand from the central plant system to the Heating, Ventilation and Air Conditioning (HVAC) systems, and then to room thermostats. These devices are installed mainly for local controls and Fault Detection and Diagnostics (FDD) purposes. The vast amount of data from these metering devices represents an untapped opportunity for many other applications, for instance, to better track building energy performance and improve its operational efficiency. However, not all key variables for performance tracking are directly measured or readily available. Installing new meters for those specific variables could be costly and bring practical issues. Virtual metering could be a potential solution to overcome those issues by estimating the required variables based on the available data and physical principles.

Existing research has mainly focussed on inferring unmeasured variables for specific system components within a building. Li et al. (2011) performed a literature review of virtual sensing technologies applied to building systems. They highlighted the role of virtual sensors to further support FDD and optimal controls, as well as the importance of correcting inefficient operations, which are often ignored as long as thermal comfort is satisfied. They investigated virtual sensors to infer a wide range of variables such as pressure, humidity, compressor efficiency, heat loss coefficient and valve leakage in various HVAC systems such as vapour compression air-conditioners, chillers, heat pumps, cooling and heating coils. McDonald & Zmeureanu (2015) developed a virtual flow meter to monitor the performance of a cooling plant; more specifically, they calculated chilled and condenser water mass flow rates mainly from water and refrigerant temperatures and pressures. Similar virtual flow meters were developed by Song et al. (2013) for chilled water flow rate while Yu et al. (2011) investigated supply airflow rate and Ahamed et al. (2020) supply air temperature in air handling units. Cheung and Braun (2014) focussed on rooftop units and developed virtual sensors for the cooling capacity and evaporator fan power consumption based on internal operating conditions (pressure, temperature, etc.). At the zone level, Darwazeh et al. (2021) investigated virtual metering methods to estimate perimeter heater energy supply based on steady-state, transient and load disaggregation models as well as measurements for outdoor air temperature, zone temperature, discharged air flow rate and valve position. The authors mentioned that the approach selection depends on the available measured data.

As investigated by Darwazeh et al. (2021), the disaggregation of energy consumption has also been recently investigated and could be used for virtual energy metering. In such a field, black-box models and Machine Learning techniques such as artificial neural networks and random forests (Xiao, Fan, et al., 2021) could be of great interest. Xiao, Gang et al. (2021) performed cooling load disaggregation and identified four sub-loads: equipment, occupant, fresh air and envelope. They tested two approaches depending on available weather data and discussed the practical implementation of each approach. Gunay et al. (2020) introduced a new disaggregation approach for commercial building end-uses based on building automation system data. Identified load categories are chillers, AHU, plug loads and lighting. Similarly, disaggregation of electricity and heating consumption of commercial buildings have been performed by Zaeri et al. (2022) where various subcategories were used for electricity (occupant-controlled loads such as lighting and plug loads, and AHU electric power) and heating (AHU heating coils, perimeter heating devices).

This study focuses on the development of virtual energy meters (VEMs) to estimate building energy use at different system levels; this multi-level virtual metering has not been tackled in the past for real buildings to the best of our knowledge. More specifically, we intend to estimate the cooling load of a large commercial building based on available airside and waterside measurements. The novelty of the proposed approach also lies in the applications to improve the operation of real buildings. Benefits of such an approach include energy performance tracking at various levels (whole building, system, and room), estimation of the nature of the load (sensible and/or latent heat load) for modelling purposes, and energy flow mapping at room level, which could be easily coupled with occupancy data to track energy usage in relation to the actual needs.

Methods: development of virtual energy meters

In this work, we investigate VEMs for a cooling system commonly seen in a large commercial and institutional building: the Variable Air Volume (VAV) system with a chilled water network. Specifically, we investigate three types of virtual energy meters at three different levels: 1) the chilled water plant, denoted as VEM #1, 2) the AHU, denoted as VEM #2 and 3) the room level, denoted as VEM #3. Note that the same methods would apply for a VAV system with a hot water network heating system. Figure 1 presents a simplified schematic of a cooling system with system boundaries and indicative locations of the studied VEM. In general, we develop the VEM based on available measurements, mass and energy balance equations. We explain the method below in detail on the development of the VEM.

It is worth mentioning that all the virtual energy meters are quasi steady-state models. Therefore, there is negligible mass and energy accumulation with time while temperature and relative humidity change slowly within the calculation time-step.

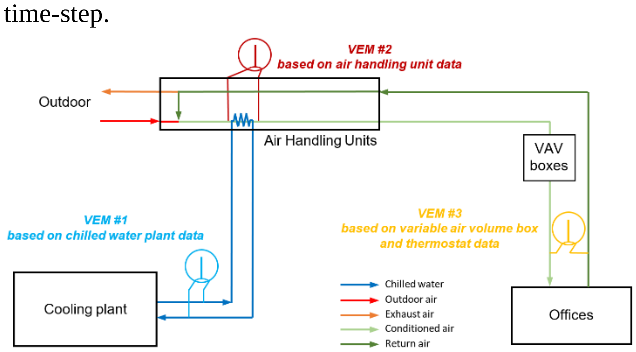

Figure 1: A simplified schematic of a cooling system with system boundaries and indicative locations of VEM.

Virtual energy meter #1: based on chilled water plant data

The VEM #1 estimates the cooling load based on the chilled water plan measurements. We use data from water flow rate ($\dot{m}_w$), specific heat of water ($c_{p,w}$), supply and return water temperatures ($T_{w,\text{supply}}$ and $T_{w,\text{return}}$) in the chilled water network. Eq. (1) shows the equation within this VEM. This meter requires only three measured variables, which are usually available. It allows the calculation of total building cooling load easily from the supply side. The uncertainty associated to this calculation might also be relatively low, especially if the system does not operate at very low flow rate and if the temperature difference is large enough.

$$\dot{Q}_{\text{cool,w}} = \dot{m}_w c_{p,w}\left(T_{w,\text{return}} - T_{w,\text{supply}}\right) \tag{1}$$

Virtual energy meter #2: based on air handling unit data

The VEM #2 estimates the cooling load based on airside measurements in the AHUs. This meter aims to evaluate the total building cooling load at the HVAC system level. Eq. (2) shows how the VEM #2 estimates the total coil cooling load within the AHU. Based on temperature, relative humidity and flowrate measurements, it allows to estimate the separate contributions of sensible (Eq. 3) and latent heat (Eq. 4) to the total load. Note that these equations consider the case with water condensation within the coil, i.e., the outlet temperature $T_{\text{coil,i,out}}$ is lower than the inlet air dew point. In the case without water condensation, the equations will be simplified with cooling only.

$$\dot{Q}_{\text{cool,AHU}} = \sum_i \left(\begin{array}{l} \dot{m}_{a,AHU_i} \left(\begin{array}{l} h_a\left(T_{\text{coil,i,in}}, \omega_{\text{coil,i,in}}\right) \\ -h_a\left(T_{\text{coil,i,out}}, \omega_{\text{coil,i,out}}\right) \end{array} \right) \\ -\dot{m}_{w,AHU_i} h_w\left(T_{\text{coil,i,out}}, x=0\right) \end{array} \right) \tag{2}$$

$$\dot{Q}_{\text{cool,AHU,sensible}} = \sum_i \left(\dot{m}_{a,AHU_i} \left(\begin{array}{l} h_a\left(T_{\text{coil,i,in}}, \omega_{\text{coil,i,out}}\right) \\ -h_a\left(T_{\text{coil,i,out}}, \omega_{\text{coil,i,out}}\right) \end{array} \right) \right) \tag{3}$$

$$\dot{Q}_{\text{cool,AHU,latent}} = \sum_i \left(\begin{array}{l} \dot{m}_{a,AHU_i} \left(\begin{array}{l} h_a\left(T_{\text{coil,i,in}}, \omega_{\text{coil,i,in}}\right) \\ -h_a\left(T_{\text{coil,i,in}}, \omega_{\text{coil,i,out}}\right) \end{array} \right) \\ -\dot{m}_{w,AHU_i} h_w\left(T_{\text{coil,i,out}}, x=0\right) \end{array} \right) \tag{4}$$

where $\dot{m}_{a,AHU_i}$ is mass flow rate of air in AHU_i and $\dot{m}_{w,AHU_i}$ is mass flow rate of condensation water, indices *coil,i,in* and *coil,i,out* refer to cooling coil inlet and outlet of AHU_i, h_w is enthalpy of water and x is vapor quality.

The humidity ratio (ω) in Eq. (5) is a function of temperature (T), relative humidity (RH) and atmospheric pressure (P_{atm}) and depends on saturated pressure of water ($P_{sat,w}$). The enthalpy of humid air (h_a) is calculated in Eq.

(6) as a function of air specific heat ($c_{p,a}$) and abovementioned variables, as follows:

$$\omega = 0.622 \frac{RH \times P_{sat,w}(T)}{P_{atm} - RH \times P_{sat,w}(T)} \quad (5)$$

$$h_a(T,\omega) = c_{p,a}(T, P_{atm})T + \omega h_w(T, x=1) \quad (6)$$

When compared to the VEM #1, this approach requires more measurements, which might not always be available. Virtual sensors could be developed to infer some of the missing variables. It also requires airside temperature, relative humidity and flow rate measurements, which might make this approach more prone to uncertainty overall.

Virtual energy meter #3: based on variable air volume box and thermostat data

The VEM #3 estimates the cooling load at the room level. It uses airside measurements from the VAV terminal boxes and thermostats. As shown in Eq. (7), it depends on air flow rate ($\dot{m}_{a,\text{VAV}_i}$) in each VAV box, as well as supply air enthalpy ($h_{a,\text{supply,VAV}_i}$), and average air enthalpy of all rooms supplied by the i^{th} VAV ($\bar{h}_{\text{room,i}}$).

The advantage of this virtual meter is that it estimates the building cooling load at the room level and thus gives high spatial granularity on the distribution of the load. Similar to the first virtual energy meter, the same arguments apply to the calculation uncertainty, which is expected to be low.

$$\dot{Q}_{\text{cool,VAV}} = \sum_i \left(\dot{m}_{a,\text{VAV}_i} \left(\bar{h}_{\text{room,i}} - h_{a,\text{supply,VAV}_i} \right) \right) \quad (7)$$

Eq. (7) relies on relative humidity measurements, which might not be readily available. In this case, latent heat could be neglected and VEM #3 can be simplified as follows by introducing specific heat of air ($c_{p,a}$), supply air temperature ($T_{a,\text{supply,VAV}_i}$) in each VAV box, and average air temperature of all rooms supplied by the i^{th} VAV ($\bar{T}_{\text{room,i}}$); in this case, VEM #3 calculates sensible cooling load only:

$$\dot{Q}_{\text{cool,VAV}} = \sum_i \left(\dot{m}_{a,\text{VAV}_i} c_{p,a} \left(\bar{T}_{\text{room,i}} - T_{a,\text{supply,VAV}_i} \right) \right) \quad (8)$$

Case study: large commercial building

Building description

We applied the three types of VEM to an office building located in Montreal, Quebec. The building has 11 floors with a total floor area of 36,000 m^2. The cooling system has three chillers with air condensers and water towers. It produces chilled water to the cooling coils in the AHUs located from the 2nd to the 11th floor via a chilled-water network. Unlike a typical AHU system, the studied system includes a fresh air pre-treatment unit, a heat recovery wheel and secondary cooling coils, as shown in Figure 2. The gas burner is only activated in winter to avoid cold fresh air directly entering the system. Similarly, the humidifier is only activated when the outdoor air is too dry in winter. The heat recovery wheel is used to recycle part of the heat or coolness in the exhaust air depending on the heating or cooling season. After being precooled, the fresh air is then mixed with return air, further cooled down if required and discharged to rooms through single- or dual-duct systems. Note that for dual-duct systems, part of the cooled air is bypassed from the secondary cooling coils via the hot deck and then mixed again with the cold deck, either in the ducts or through dual-duct VAV boxes. Within this building, there are 2 fresh air pre-treatment units and 22 secondary cooling coil units (called fan coils below because each coil always comes with a supply fan). The fan coils are then connected to 519 terminal boxes, each of which is controlled by a corresponding thermostat located at each room or controlled thermal zone.

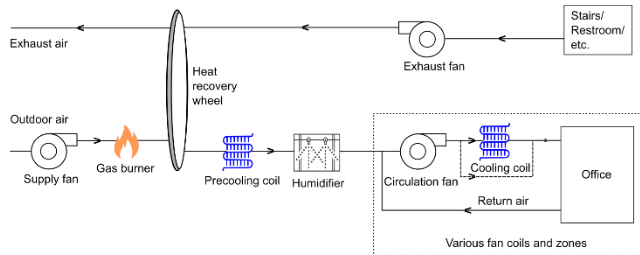

Figure 2: Air Handling Unit system diagram of the large commercial building under study.

Data preprocessing and calculation assumptions

Building operational data (over 6,000 variables) are recorded every 5 minutes and include many control points such as temperature, relative humidity, pressure, flow rates or valve openings at key locations in the system.

- In the chilled-water network, measurements are available for supply water flow rate, supply and return water temperature; they are used for VEM #1.
- In the fresh air pre-treatment units, flow rate, temperature and relative humidity are recorded and used to develop VEM #2 (precooling coil in Figure 2).
- In VAV boxes, discharged air flow rate and temperature, and room air temperature are collected and used to calculate VEM #3. Since relative humidity measurements are not available, Eq. (8) was used and VEM #3 calculates total sensible cooling load.

In the fan coil units, some – but not all – flow rate, temperature and relative humidity are measured and used for VEM #2 (cooling coil in Figure 2). For variables that are not measured, assumptions were made, and specific virtual sensors were developed based on mass and energy balance equations and used as proxy values. It includes:

- Relative humidity of return air and the air after the cooling coil is assumed equal to that of exhaust air.
- Return air temperature when not available is assumed equal to room temperature.
- Return air flow rate is calculated from discharged air flow rates and fresh air flow rates (mass balance equation).

- The air flow rate going through the cooling coil is estimated from discharged air flow rates and damper openings.
- Relative humidity of air before the cooling coil is calculated from both mass and energy balance equations.
- The enthalpy rise due to the fan was estimated from energy balance equation.

Measurements from June 19^{th}, 2020 to September 1^{st}, 2020 were used to develop and validate the proposed virtual energy meters. Measured operation conditions (temperature, relative humidity) from a given floor (4^{th}) were used to develop the VEM and were extrapolated to the other floors; discharged air flow rates were adjusted to account for load variability among floors and AHUs. Since each floor may have a specific schedule, results for VEM #2 and #3 were not calculated at night. Operational data were synchronized, outliers and missing values were removed based on statistical means and expert knowledge. VEM requiring more calculations might show more missing values; they were left as blanks. Calculations were performed using data at 5-minute intervals.

- In VEM #2, virtual sensors used to infer missing variables might have led to non-physical values (e.g., negative flow rates), which were removed from the analysis.
- In VEM #3, the cooling load is the summation of all zone cooling loads; a few missing zone data might affect results and cooling load was not reported if there were missing data for one VAV box or more.

Results: comparison of cooling load estimations

Cooling load estimations

Figure 3 shows the statistical distributions for each cooling load calculation obtained for the 3-month period, when the data was available for all VEM. Figure 4 shows the virtual energy meter estimations along with the outdoor air conditions for a one-week period.

We can notice significant differences among the three virtual energy meters, especially for VEM #2. These differences could be explained by several factors:

- The uncertainty associated to each sensor or meter used for the calculations
- The nature of the load
- The extrapolation of operational conditions to other floors
- Thermal inertia and operation under transient conditions

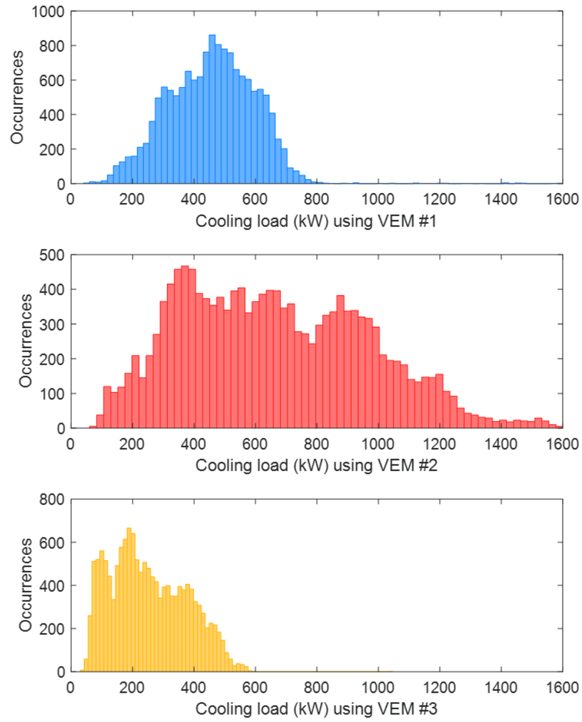

Figure 3: Statistical distribution of the building cooling load using: VEM #1 (top), VEM #2 (middle), VEM #3 (bottom).

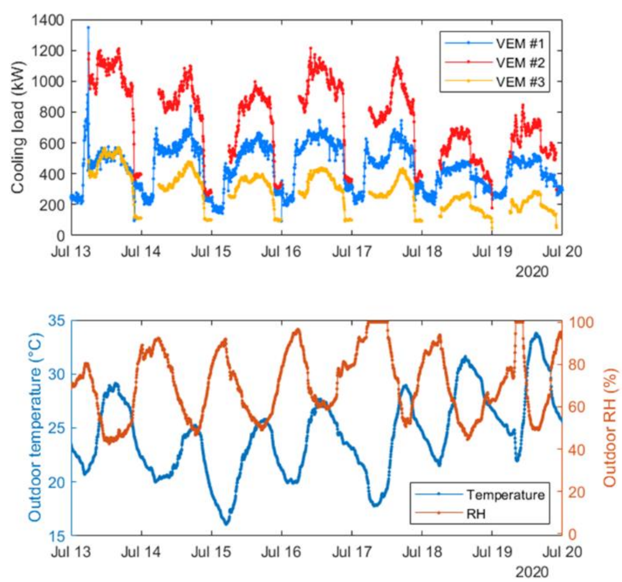

Figure 4: Building cooling load (top) and outdoor conditions (bottom) profiles for a week in July.

VEM #1 and VEM #2 include both sensible and latent heat, but VEM #2 might come with higher uncertainty due to the higher number of required variables, the inferred missing variables and sensor uncertainty (airside temperature, relative humidity, flow rate). VEM #2 and #3 are based on operational conditions of the 4th floor, which were extrapolated to the other floors; such meters might thus be more prone to errors. In this case study, VEM #3 only considers sensible heat (Eq. 8) and eventually underestimates building cooling load when latent heat contribution is significant, especially when outdoor air temperature and relative humidity are high. Finally, the operation might occur under transient conditions and there might be some energy supply delays due to system thermal inertia.

Sensible heat ratio

VEM #1 (based on chilled water plant data) could be considered as the *most probable cooling load*, since it relies on the fewest number of variables, which in addition may not be too affected by uncertainties. However, VEM #2 and #3 can still provide useful information about the building performance. Figure 5 shows the sensible heat ratio which can be estimated from VEM #2 (where sensible and latent heat contributions can be separated) or by calculating results from the ratio between VEM #3 (sensible cooling load) and VEM #1 (total cooling load). If VEM #3 was estimated using Eq. (7), sensible and latent heat contributions could have been calculated similarly to VEM #2.

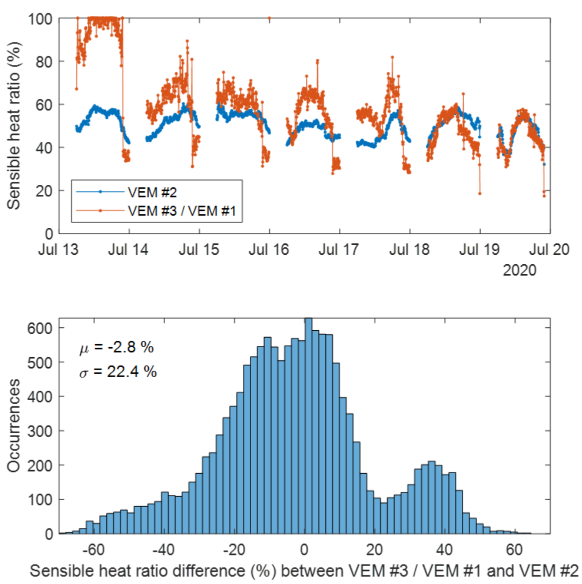

Figure 5: Sensible heat ratio for a week in July (top) and statistical distribution of the difference between sensible heat ratios calculated using two different methods (bottom).

We can notice that trends are somewhat similar, although there are some differences in absolute values (see Figure 5). The difference between both methods is in average –2.8% and shows a standard deviation of 22.4%. VEM #2 calculations might again come with higher uncertainty; however, it provides higher granularity by calculating sensible and latent heat load for each fan coil units, which could be of interest for a better understanding of building energy usage.

Cooling load per zone

Figure 6 shows the cooling load distribution in a given floor and more specifically, the four zones serviced by the four dedicated AHU (e.g. zone #1 serviced by AHU #1). AHUs measurements (VEM #2) and VAV box and thermostat measurements (VEM #3) were used for the calculations. This figure shows relatively similar distribution of the cooling load: zones #1 and #3 account for around 75% of the floor cooling load while zone #2 is quite low. Zone #4 load appears slightly higher with VEM #3 (around 25%) than with VEM #2 (around 15%) and zone #2 shows negligible load with VEM #3. These differences could be explained by the VEM location (VEM #3 excludes fresh air pre-treatment; see Figure 1) and the nature of the load (i.e., VEM #3 only considers sensible heat in this case study).

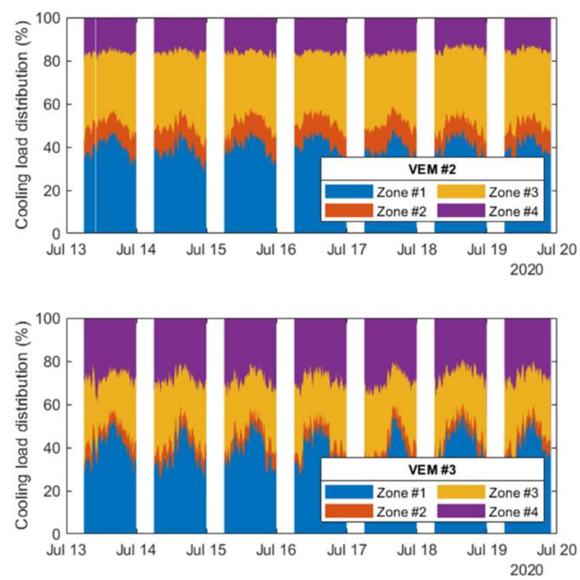

Figure 6: Cooling load per zone in a given floor using VEM #2 (top) and VEM #3 (bottom) for a week in July.

Cooling load per room

One of the main benefits of VEM #3 is also the possibility to obtain a high granularity of the cooling load for each zone, targeting energy flow mapping in the building. The cooling load could be estimated per room and used along with occupancy data to ensure that rooms are appropriately conditioned, and that this conditioning takes place only when required. Figure 7 shows the cooling load per room in a given floor for a week in July and the statistical distribution of the cooling usage during a work week (from Monday to Friday).

Most of the rooms show a relatively constant load during business hours but some of them show slightly different behaviours (schedules different than business hours, peaks in the middle of the day, etc.), which could be further investigated. In terms of overall energy usage, there are three groups: 3 rooms show high cooling load (more than 250 kWh), 24 rooms show intermediate load (between 45 and 170 kWh) while the other 57 rooms are below 45 kWh. Such pieces of information could be very useful to identify overcooling in specific zones and to match energy demand with occupation. Cooling per room was given in kWh but these numbers could be normalized using floor area if available (kWh/m^2); nonetheless, absolute values could still provide insights on energy usage with regards to occupancy needs (e.g., kWh/occupant).

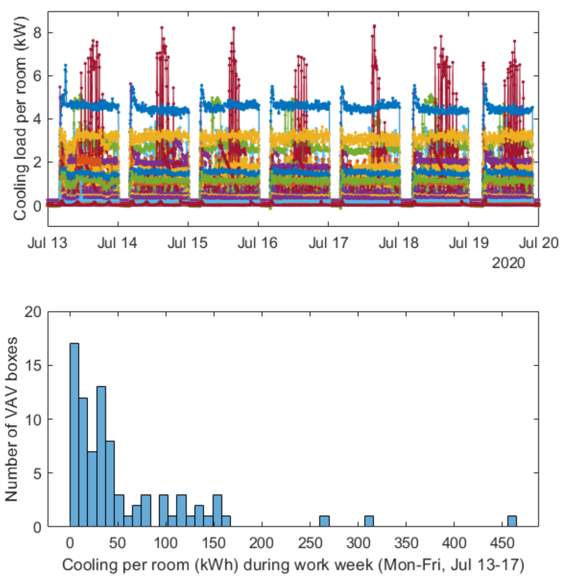

Figure 7: Cooling load per room (x 84) within a given floor for a week in July (top) and statistical distribution of cooling usage during a work week, Mon-Fri (bottom).

Discussion: virtual energy meters merits and applications

The proposed three VEM allow to evaluate whole building cooling load from three different perspectives and show results, which could be quite different from each other. Merits of each method, applications and future work are detailed in this section.

Merits of each method

Table 1 shows benefits and drawbacks for each method. Although VEM #1 may provide the most probable cooling load, this calculation is limited to the building level. On the other hand, VEM #3 provides the highest granularity level by estimating the load at zone level; however, its main drawbacks are that it measures sensible heat only if relative humidity measurements are not available. This is not uncommon when room-level data are from thermostats. VEM #3 may also have privacy concerns related to monitoring the usage at such a high granularity (single occupant usage in some cases). VEM #2 provides a relatively high granularity (AHU level), but this approach requires variables (or sensors) which are not necessarily measured or often recalibrated, which is also the case for VEM #3. VEM #2 is also more prone to uncertainty, compared to VEM #1 and #3. As Figure 5 shows, both VEM #1 and VEM #3 (Eq. 8) could be coupled to estimate the dehumidification load, which is the main contribution of VEM #2, but it will be calculated at the building level and not necessarily at the AHU level, as VEM #2 does.

Table 1: Merits of each virtual energy flow meter.

VEM	Pros	Cons
#1	+ Few variables required, usually available + Easy to calculate + Low uncertainty	- Building-level granularity - Sensible & latent heat not known
#2	+ AHU-level granularity + Calculates sensible & latent heat	- More prone to uncertainty - More difficult to calculate - More variables required, not necessarily available
#3	+ Zone-level granularity + Energy flow mapping; links to occupancy, space utilization + Low to medium uncertainty + Variables usually available + Easy to calculate	- Latent heat could be neglected - More variables required

Application to real buildings

Performance tracking: the VEM discussed in this work could be used for performance tracking at the building (VEM #1), the AHU (VEM #2) and the zone level (VEM #3). Key Performance Indicators (KPI) could be built based on these VEM estimations to better evaluate whole building performance as well as the type of load (sensible, latent) and the energy distribution within it. More specifically, a dedicated KPI such as sensible heat ratio (calculated either from VEM #2 or VEM #1 and VEM #3) could help identify conditions such as a too low supply air temperature, which might cause excessive dehumidification requirements. In this case, VEM #2 could even help identify problematic fan coil units.

Energy use mapping: VEM #3 could be the foundation of an energy mapping tool aiming at better matching energy usage and actual needs. This tool could be used along with occupancy data to track if each occupied room is appropriately conditioned while other non-occupied rooms could be less conditioned. It could eventually be used along with space utilization; for instance, a building operator could identify excessive cooling loads or overcooled rooms to investigate usage requirements (i.e., energy usage vs. occupants needs) and adjust indoor air conditions accordingly (e.g. reduce cooling) or suggest retrofits measures (e.g., window replacement).

Operation optimization: the estimated cooling load by the VEM could be used for load forecasting with the aim of optimizing central cooling plant operation (e.g., chiller sequencing). The estimation of sensible and latent heat contributions could further help develop dedicated models for sensible heat only (e.g., Resistance-Capacitance model to estimate the air temperature of a zone or a building). This approach would allow to develop load management strategies via model-based controls or model-based predictive controls (e.g., precooling strategy).

Application in building performance simulation tools

The applications to real buildings discussed in the above section could also be applied in building performance simulation (BPS) tools, either to track building performance (KPI to track performance at building, AHU and zone level; sensible and latent cooling loads; energy flow mapping along with occupancy data) or to optimize building operation (load forecasting and advanced controls). Performance tracking could be used to support BPS model calibration and ensure for example typical distribution between sensible and latent cooling loads. Operation optimization could be performed directly using BPS tool capabilities or using co-simulation platforms. For instance, synthetic data could be generated from BPS tools, be fed to a simplified control-oriented model for calibration purposes, which will optimize control strategies and test them back in the BPS environment. Occupant-centric controls for improving building performance could be directly incorporated and evaluated within BPS tools.

Future work

This work is a first step towards a building energy performance tracking tool to further improve building operation. The analysis could be refined to consider each floor individually, rather than extrapolating a given floor operation to the others. The proposed work focuses on 2020 operational data, right after the beginning of the COVID-19 pandemic; using more recent data, which could be more representative of "new" normal operation, could be used instead. The uncertainty of each virtual energy meter is critical, and this aspect needs further investigation. These virtual energy meters could be tested in other buildings and configurations to better assess model robustness and generalization. Finally, they could be expanded to heating system applications.

Conclusion

We presented three data-driven virtual energy meters to estimate cooling load at the whole building level. They are based on measurements at: 1) the chilled water plant, 2) the air handling units and 3) the variable air volume boxes and thermostats. Each meter comes with its own merits and drawbacks in terms of calculation complexity (i.e., number of required variables), granularity and uncertainty. These meters could be used for building performance tracking at the building, the AHU and the zone levels, and could be the foundations of new KPI and energy flow mapping tool, targeting appropriate energy usage in relation to actual needs. Cooling load calculations could also be very helpful for load forecasting aiming at optimizing building cooling plant operation or developing load management strategies. Virtual energy meters open up new ways for data utilization in buildings. While dedicated local meters rarely exist, it is possible to leverage existing variables to extract useful information.

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CRediT author statement

Etienne Saloux: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Kun Zhang**: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing – original draft, Writing – review & editing, Visualization.

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