Virtual metering of heat supplied by hydronic perimeter heaters in variable air volume zones

Darwish Darwazeh
Department of Civil and Environmental Engineering
Carleton University
Ottawa, Ontario, Canada
Darwish.Darwazeh@carleton.ca

Jean Duquette
Department of Mechanical and Aerospace Engineering
Carleton University
Ottawa, Ontario, Canada
Jean.Duquette@carleton.ca

Burak Gunay
Department of Civil and Environmental Engineering
Carleton University
Ottawa, Ontario, Canada
Burak.Gunay@carleton.ca

ABSTRACT

Equipment-level virtual metering provides a nonintrusive tool to understand energy flows in commercial buildings and monitor building energy performance. Virtual metering accuracy depends on the modelling approach and its ability to capture the underlying physical processes. This paper examines the performance of three virtual metering approaches to estimate the heat supplied by zone-level hydronic perimeter heaters: steady-state inverse greybox modelling, transient inverse greybox modelling, and water-side load disaggregation. Models that represent these three approaches are trained using data from a highly instrumented academic building in Ottawa, Canada. Model parameters are identified using the genetic algorithm and used for creating virtual meters that can estimate the heat added by perimeter heaters into building variable air volume zones. The accuracy of these virtual meters is assessed by comparing them to physical meters installed in these zones. The results indicate that the three modelling approaches can estimate the daily heating energy supplied by perimeter heaters at a normalized RMSE between 13% and 23%.

CCS CONCEPTS

• Computing methodologies~Modelling and simulation~Model development and analysis~Modelling methodologies • Computing methodologies~Machine learning~Cross-validation

KEYWORDS

Virtual metering, radiant heaters, inverse modelling, load disaggregation, building automation system, HVAC equipment

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1. Introduction

Metering of building heating, ventilation, and air conditioning (HVAC) equipment at the zone-level is uncommon due to cost and practical issues, leaving critical quantities unmeasured such as the heat added by perimeter radiant heaters. Virtual meters (VMs) that utilize the data from a building automation system (BAS) are cost-effective alternatives to physical meters to monitor energy performance and capture unmetered heat flows at the zone-level. VMs can be used to support operational decisions and improve energy performance and occupant comfort by enabling early detection, diagnosis, and evaluation of operational faults. However, the accuracy of VMs is highly dependent on the ability of the underlying modelling approach to represent the zone-level heating and cooling processes. The selection of an appropriate data-driven modelling technique involves uncertainty regarding the agreement of the selected model with the physical reality, model complexity, and transferability of the model to other zones.

VMs can be employed to estimate unmetered heat added by zone-level heating devices to understand its impact on the overall energy consumption of a building. Perimeter zones are often equipped with hydronic radiant heaters to satisfy the heating loads. These zones are subjected to internal heat gains from lights, occupants, equipment, solar heat gains through windows, and heat gains by transmission through the envelope. The zone air temperature setpoint is maintained using supply air provided by an air handling unit (AHU) through a variable air volume (VAV) terminal box. Radiant heater VMs can be developed using the following three distinct modelling approaches that represent the heat transfer mechanisms taking place at a perimeter zone:

(1) *A steady-state inverse greybox modelling approach*: this modelling approach is useful for describing linear and stationary relations between model inputs and outputs [1], [2]. Steady-state models are used in the literature to evaluate energy efficiency measures and retrofit performance [3]–[6] and to find the effective thermal resistance of a building wall [7]–[9].
(2) *A transient inverse greybox modelling approach*: this modelling approach describes the dynamic behaviour of the zone at different levels of complexity [10], [11]. Transient models are used in the literature to evaluate building retrofits

[12]–[14], to develop model-based predictive control strategies [15]–[18], to detect HVAC system faults [19]–[21], and to characterize the heating and cooling load patterns [9], [22].

(3) *A load disaggregation modelling approach*: this modelling approach breaks down the total load measured at the source into subsystem loads. Load disaggregation models are used in the literature to disaggregate building total electricity load across zone-level appliances [23]–[25], and to disaggregate building total water consumption across zone-level water devices [26], [27].

While these three modelling approaches are used in the literature for building energy management and building operation, to our knowledge, no comparisons have been made of these modelling approaches for virtual metering of heat added by perimeter radiant heaters. To this end, this paper examines the performance of the three modelling approaches by developing VMs that can estimate the heat supplied by zone-level perimeter heaters. Measurements collected from seven zones in a highly instrumented academic building in Ottawa, Canada, are used to train the models. The accuracy of the VMs is assessed by comparing them to physical meters installed in these zones. The performance of the modelling approaches is evaluated, and their strengths and weaknesses are described through illustrative examples.

2. Analysis Approach

The analysis approach utilized in this study consists of two stages, as illustrated in Fig. 1. In stage 1, zone model structures are formulated via the application of the three modelling approaches presented in Sec. 1. The models are trained using data collected from seven zones in a highly instrumented academic building in Ottawa, Canada. Model parameters are identified using the genetic algorithm (GA). In stage 2, the values identified for model parameters are used to develop VMs to estimate the heat added by perimeter radiant heaters. The root-mean-square error normalized by the range of daily measured heat at each zone (NRMSE) is used to assess the accuracy of the VMs and evaluate the performance of each modelling approach.

2.1 Data collection and processing

Data from seven perimeter zones in an academic building in Ottawa, Canada, are collected at 15-minute intervals from November 2019 to January 2020. As shown in Fig. 2, the seven zones are served by two VAV terminal boxes VB_1 and VB_2 that use supply air from an AHU. The supply air is reheated in the VBs before it is discharged into the seven zones via discharge air diffusers. These zones are equipped with hydronic radiant heaters that use hot water from a steam/hot water heat exchanger. The radiant heaters use modulating valves to control the hot water flow rate into the zones. Measurements of zone air temperature, $T_{z,1}$(°C) to $T_{z,7}$(°C), modulating valve state, X_1(%) to X_7(%), and the occupancy indicators, B_1 to B_7, are collected for each zone, whereas, measurements of discharge air temperature, $T_{da,1}$(°C) and $T_{da,2}$(°C), and discharge airflow rate, $\dot{V}_{da,1}(m^3/s)$ and

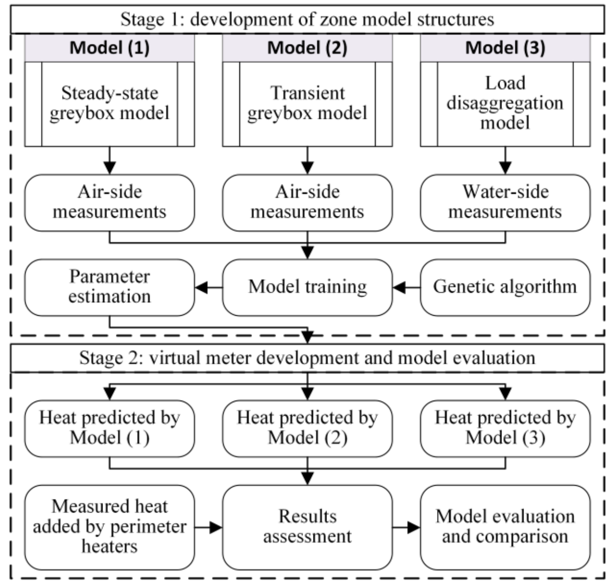

Figure 1: Process used for evaluating the performance of three distinct zone modelling approaches

$\dot{V}_{da,2}(m^3/s)$, are collected from the two VAV terminal boxes. Additionally, the total hot water load measurement, $q_w(kW)$, is collected at the heat exchanger hot water outlet. The zone air temperature and the discharge air temperature are modelled as single temperature nodes by averaging the measurements at every time step. Finally, the discharge airflow rate from the VAV

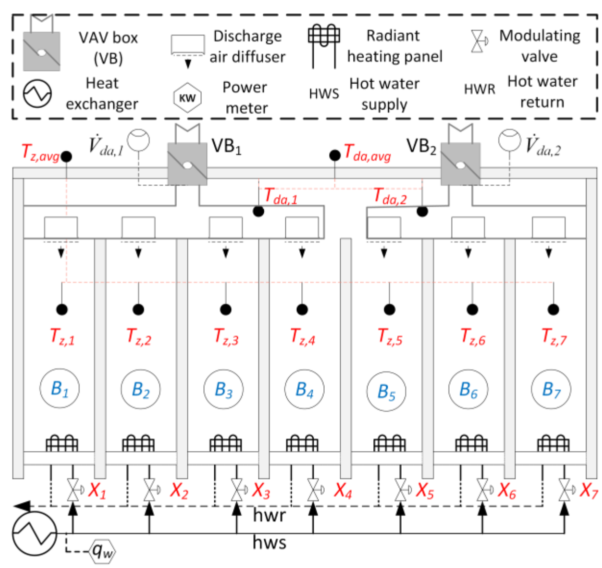

Figure 2: Data collected from seven perimeter zones in the academic building. $T_{z,i}$(°C), X_i(%), and B_i represent zone air temperature, modulating valve state, and occupancy indicator in zone i, respectively. $T_{da,j}$(°C) and $V_{da,j}(m^3/s)$ represent discharge air temperature and discharge airflow rate from VB_j, respectively. $q_w(kW)$ represents the total hot water load.

terminal box, and the occupancy indicator signals, B_1 to B_7, are summed up for the seven zones.

2.2 Development of zone model structures

The transient inverse greybox model structure is formulated by approximating the transient heat flow by an equivalent thermal network model comprising one resistance and one capacitance (*i.e.,* 1R1C network). The thermal capacitance represents the lumped thermal capacitance of a zone, and the thermal resistance represents the effective thermal resistance between indoors and outdoors, including heat transfer through walls and windows and via air infiltration. A linear relationship is assumed between the hot water modulating valve position (X_{rad} (%)) and the heat added by the radiant heater. Similarly, a linear relationship is assumed between a binary occupancy indicator (B_z) and internal heat gains from lights, occupants, and equipment. The effect of solar heat gains is minimized by only considering data points occurring after 4 pm and before 9 am. Under these assumptions, the transient inverse greybox model for the seven zones under study is expressed as:

$$c_a \cdot \rho_a \cdot \left(\sum_{z=1}^{7} \dot{V}_{da,z}^{k-1}\right) \cdot \left(T_{z,avg}^{k-1} - T_{da,avg}^{k-1}\right) = \left(\frac{\left(T_{oa}^{k-1} - T_{z,avg}^{k-1}\right)}{x_1}\right) + \left(x_2 \cdot \sum_{z=1}^{7} B_z^{k-1}\right) + \left(\sum_{z=1}^{7} d_z \cdot X_z^{k-1}\right) - \left(x_3 \cdot \frac{T_{z,avg}^{k} - T_{z,avg}^{k-1}}{\Delta t}\right) + e \quad (1)$$

where $\dot{V}_{da,z}$ (m^3/s) is the discharge airflow rate from the discharge air diffuser at Zone (z); and T_{da} (℃), T_z (℃), and T_{oa} (℃) are the discharge air temperature, the zone air temperature, and outdoor air temperature, respectively. The superscript k is the index number of each measurement, and Δt (sec) represents the timestep interval. The factors c_a and ρ_a are the specific heat of air (1006 J/kg·°C) and the air density (1.2 kg/m3), respectively. Model parameters x_1 to x_3 estimate the effect of the zone thermal resistance, occupant-related internal heat gains, and the transient response of zone thermal capacitance, respectively, on the energy balance of the zone. The error term e captures unmodelled heat flows within the zone. Parameters d_1 to d_7 estimate the individual radiant heater capacities for Zones (1) to (7).

The steady-state modelling approach assumes no thermal storage in the zone, and hence no change in the zone air temperature occurs over time [28]. The steady-state model is formulated by setting the transient term in Equation (1) to zero (*i.e.,* $T_{z,avg}^{k} - T_{z,avg}^{k-1} = 0$).

The load disaggregation model structure is formulated by breaking down the total energy used by radiant heaters into individual zone energy use based on the modulating valve state.
As shown in Fig. 3, the total hot water load (q_w (kW)) measured at a steam/hot water heat exchanger is disaggregated across the

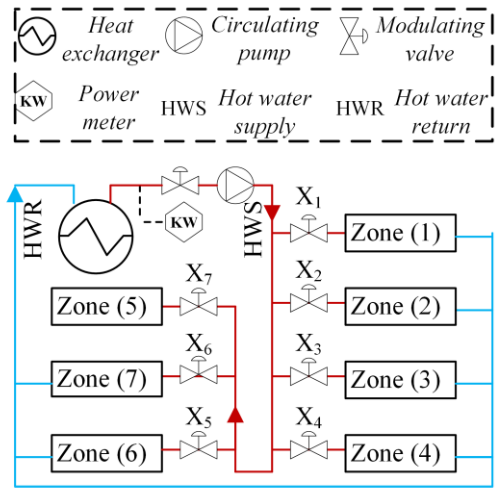

Figure 3: A schematic showing the disaggregation of total hot water load measured at the outlet of a steam/hot water heat exchanger across zone-level radiant heaters using the modulating valve state signal X_1 to X_7.

seven zones served by that heat exchanger based on the modulating valve signal (X_z (%)), as expressed in Equation (2).

$$q_w = \left(\sum_{z=1}^{7} d_z \cdot X_z\right) + e \quad (2)$$

Model parameters d_1 to d_7 correspond to the radiant heater capacity at Zones (1) to (7), respectively. The error term e accounts for measurement errors and any potential system leakage.

2.3 Development of virtual meters and model assessment

The measurements collected from the seven perimeter zones are used to train the three models formulated in Sec. 2.2. An optimization problem is formulated to minimize the root-mean-square error (RMSE) between the estimated and measured discharge air load for the transient and steady-state inverse greybox models, and between estimated and measured total hot water load for the load disaggregation model. The GA is employed to solve the optimization problem and search for optimal model parameters. The estimated values of model parameters corresponding to each modelling approach are used to develop VMs to estimate the heat added by the radiant panels at each of the seven zones. In addition to the measurements shown in Fig. 2, physical meters are installed to measure the heat added by the radiant heaters. The measured heat is used to verify the accuracy of the VMs and evaluate the performance of the three modelling approaches.

3. Results and discussion

Table 1 summarizes the VM results corresponding to each modelling approach. The NRMSE indicates better performance for the load disaggregation and the transient modelling approaches as compared to the steady-state modelling approach. The high NRMSE for the steady-state modelling approach can be related to modelling assumptions and model inputs. For example, Fig. 4

Table 1: VM results assessment for the three modelling approaches

	Zone 1	2	3	4	5	6	7	Overall
Measured heat (kWh)	335	231	275	406	335	194	358	2133
Transient inverse greybox modelling approach								
Data required	$[T_{oa}(°C)]$, $[T_z(°C)]$, $[T_{sa}(°C)]$, $[\dot{V}_z\ (m^3/s)]$, (B_z), $[X_z\ (\%)]$							
Predicted heat (kWh)	346	216	337	460	358	177	359	2253
NRMSE	19%	18%	23%	21%	15%	17%	13%	14%
Steady-state inverse greybox modelling approach								
Data required	$[T_{oa}(°C)]$, $[T_z(°C)]$, $[T_{sa}(°C)]$, $[\dot{V}_z\ (m^3/s)]$, (B_z), $[X_z\ (\%)]$							
Predicted heat (kWh)	141	52	259	119	89	161	104	925
NRMSE	31%	26%	20%	37%	29%	18%	30%	23%
Load disaggregation modelling approach								
Data required	$[q_w\ (kW)]$, $[X_z\ (\%)]$							
Predicted heat (kWh)	332	222	283	394	325	183	356	2095
NRMSE	19%	18%	20%	18%	15%	17%	13%	13%

compares the VMs predicted heat supplied by radiant heaters at Zones (1) to (7) to measurements collected from physical meters installed at these zones. The total heat predicted by applying the steady-state modelling approach for the seven zones is around 43% of the total measured heat. This considerably low value is believed to be related to the steady-state model structure, which assumes that the zone air temperature remains constant over time. By looking at

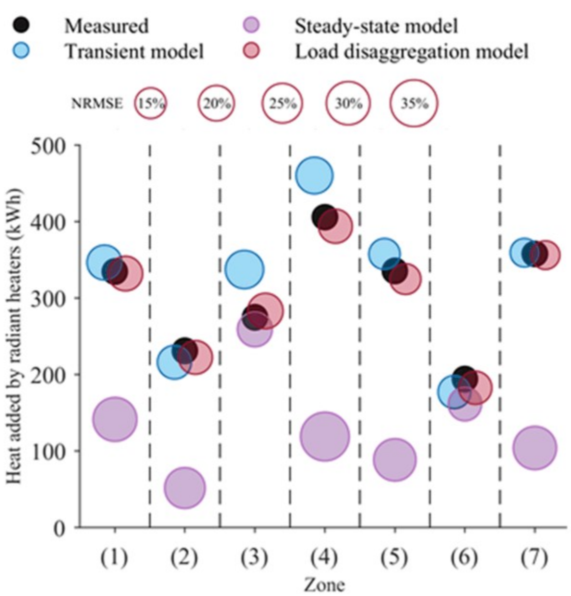

Figure 4: Predicted heat supplied by radiant heaters at Zone (1) to (7) compared to measured heat for the three modelling approaches. The NRMSE, given by the size of the bubbles, indicates better performance for the load disaggregation and transient models compared to the steady-state model.

the zone air temperature behaviour for Zone (2) for a typical day in December, it is noticed that the zone air temperature starts to decay as soon as the VAV system shuts down at 20:00 hrs. causing the zone air temperature to decline from 22.18 ℃ to 19.24 ℃. The zone air temperature starts rising again upon the start-up of the VAV system at 9:00 hrs. Data points corresponding to these periods do not meet the steady-state assumption in the underlying steady-state model structure. When these data points are used as inputs to the steady-state model, the corresponding VM accuracy declines as indicated by the NRMSE values in Table 1.

The load disaggregation and transient modelling approaches are better able to predict the heat supplied by radiant heaters at similar accuracy. However, as shown in Table 1, these two modelling approaches require different model inputs, such as the measurements of total hot water load only needed for the load disaggregation model. Hence, the availability of model input data from different buildings may be used to guide the selection between these two modelling approaches. VMs created by applying these two modelling approaches can be implemented in the BAS to provide insights to building operators and facility managers into the unmetered heat added by radiant heaters. The estimated heat can be used to detect operational inefficiencies and establish a performance benchmark for zone-level radiant heaters.

While an initial evaluation of the three modelling approaches is presented in this paper, the following related research topics have yet to be explored: a) impact of temporal averaging of measurements on the performance of the steady-state modelling approach, b) performance of the three modelling approaches as the number of zones increases, and c) develop visualization tools to present the VMs results to different building stakeholders.

4. Conclusion

The performance of three distinct modelling approaches used to create VMs to estimate the heat supplied by zone-level perimeter radiant heaters has been presented. VMs were created by using model parameters that were identified using the genetic algorithm. The accuracy of the VMs was assessed by comparing the heat estimated by the VMs to measurements obtained from physical meters installed at seven zones in an academic building in Ottawa, Canada. The accuracy assessment indicated that the three modelling approaches could estimate the daily heating energy supplied by perimeter heaters at a normalized RMSE between 13% and 23%. The load disaggregation modelling approach and the transient modelling approach showed better performance in creating radiant heater VMs as compared to the steady-state modelling approach due to modelling assumptions. The performance of the three modelling approaches was compared through illustrative examples. The results of this study demonstrate how the underlying zone modelling approach impacts the accuracy of zone-level VMs. The radiant heater VMs developed in this study provide an alternative to physical meters that can be used to improve overall building operation.

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