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Development and implementation of control-oriented models for terminal heating and cooling units

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ABSTRACT

Two control-oriented models that can predict the temperature of a perimeter office space were developed by using the data gathered from light intensity, motion and temperature sensors, and terminal heating and cooling units. One model had five unknown parameters while the second had ten unknown parameters and an immeasurable state. The models' parameters were estimated in recursion by employing the Extended Kalman Filter. The appropriateness of the models to the dataset was analyzed through a residual analysis, and the predictive accuracy of the models was contrasted. Both models could make offline predictions over a two day horizon at less than 0.75 °C mean absolute error. It was concluded that the one-state model was able to mimic the temperature response of small perimeter office spaces parsimoniously. The one-state model was implemented inside four building controllers serving eight private office spaces. In tandem with Gunay et al. [1]'s occupancy-learning algorithm, the one-state model was employed to determine optimal start and stop times for the temperature setback periods. Results of this implementation indicated that the duration of the weekday temperature setback periods could be increased more than 50% for both heating and cooling—in contrast to the default control scheme. EnergyPlus simulation results suggest that this accounts for about 30% reduction in heating and 13% reduction in cooling loads without affecting the indoor air temperature during occupied periods.

1. Introduction

Integration of real-time sensory measurements into physical models describing the heat transfer characteristics of a thermal zone has found many applications in commercial buildings such as: (a) the optimal start/stop scheduling of heating and cooling units [2–5], (b) the model-based predictive control (MPC) algorithms [6–9], and (c) the detection of envelope degradation and operational faults (e.g., poorly-installed or water-saturated insulation) [10–13]. However, selection of a physical model with a parsimonious set of predictors, and subsequent identification of its parameters are not trivial tasks [14].

Because a building's physical characteristics and occupants' behaviour change during the life of a building (e.g., changes in furnishings, envelope degradation or retrofit), even models derived from detailed physical descriptions and tuned from vast amount of historical data can become unrepresentative in time [15,16]. Measurements from a small number of sensors and meters cannot be used to innovate our understanding of a large thermal network with many parameters and unmeasured states (e.g., wall temperatures) [17]. For example, when Maasoumy, et al. [18] employed the Unscented Kalman Filter (UKF) algorithm to estimate ten different parameters and five states (by taking measurements for one of these states), they observed that the parameters of heat transfer can diverge to physically unreasonable values. When Kummert et al. [19] employed a model with over fifty parameters, this issue was tackled by keeping the majority of these parameters constant during operation and letting only very few of them change in time. But, acquiring accurate prior estimates for the parameters that are held constant requires historical operations data and can be labour-intensive to gather. Moreover, it requires the creation of a detailed physical model that accurately represents the building's as-built geometry, thermophysical properties of its materials, air leakage and distribution characteristics, and internal heat gains and operational schedules. Furthermore, given the distributed nature of the computational power to the local controllers in individual thermal zones, it is challenging and impractical to implement detailed

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Nomenclature

T_1	Temperature at model node 1 (°C)
T_2	Temperature at model node 2 (°C)
T_m	Measured temperature (°C)
T_{out}	Outdoor air temperature (°C)
T_{da}	VAV terminal unit's supply air temperature (°C)
C_1	Thermal capacitance at model node 1 (J °C^{-1})
C_2	Thermal capacitance at model node 2 (J °C^{-1})
R_1	Thermal resistance at model node 1 (°C W^{-1})
R_2	Thermal resistance at model node 2 (°C W^{-1})
Q_{rads}	Heat gains due to radiant panel heaters (W)
Q_{int}	Casual heat gains (W)
Q_{sol}	Solar heat gains (W)
Q_{vav}	Heat gains from the VAV terminal unit (W)
q_{vav}	Volumetric airflow rate (L/s)
E_{lux}	Photodiode sensor illuminance reading (lux)
Occ	Occupancy (1 present, 0 absent) (0 or 1)
$Rads$	Radiant panel heater valve position (1 open, 0 closed) [0,1]
μ_{arr}	Mean of the first arrival times (h:m)
σ_{arr}	Standard deviation of the first arrival times (h)
μ_{dpt}	Mean of the last departure times (h:m)
r_{abs}	Ratio of absent weekdays
T_{sp}	Setpoint temperature (°C)
T_{sb}	Setback temperature (°C)
$q_{vav,sp}$	VAV terminal unit's supply airflow rate setpoint (L/s)
$T_{da,sp}$	VAV terminal unit's supply air temperature setpoint (°C)
D_{sb}	Mean weekday temperature setback periods (h)
t	Time or current time (s)
k	Timestep index
x	Model parameters and states
u	Sensory model inputs
w	Wiener process
v	Measurement noise
Q	Covariance of the process noise
R	Covariance of the measurement noise
P	Covariance of the model
F	Jacobian of the model
H	Jacobian of the measurement model
K	Kalman gain
I	Identity matrix

physical models within existing building automation systems (BAS) [20].

In recognition of the challenges associated with detailed physical models, researchers have been developing either purely empirical (e.g., neural networks) models [21–23] or grey-box models that are loosely attached to the physical problem (e.g., low-order state-space models) [6,20,24–27]. Due to their simplicity, these models can adapt to changing conditions autonomously with the use of empirical data gathered through a small number of sensors/meters [28,29].

1.1. Research objectives and outline

This paper presents two control-oriented models which can predict the temperature response of a perimeter office space using a small number of low-cost building sensors that are typically built-in for standard building operations. The models recursively learn their parameters by employing the Extended Kalman Filter (EKF). The models were developed using the sensory data gathered from three private office spaces. Upon the model development, one of the models was selected and implemented inside local building controllers serving eight ceiling-mounted radiant panel heaters and two variable air volume (VAV) terminal unit. The model was utilized to compute the length of the setback-to-setpoint transition period. Implementation challenges and results were analyzed. Energy savings potential was investigated through the simulations of the monitored offices' EnergyPlus model.

2. Methodology

2.1. Measured data

Experiments were conducted in three west-facing private offices of identical construction and geometry in an academic building in Ottawa, Canada. The following data were collected throughout the experiments: occupancy (Occ), indoor and outdoor air temperature (T_{m}, T_{out}), indoor light intensity (E_{lux}), ceiling-mounted radiant panel heater state ($rads$), and the variable air volume (VAV) terminal unit's discharge air temperature (T_{da})and airflow rate (q_{vav}). The sensor locations and office layout are shown in Fig. 1.

One of these offices (room 1) was monitored over a 98 day period. During this monitoring period, the outdoor temperatures have changed from −10 to 30 °C. During the seasonal switch over to cooling (until May 6), the indoor temperatures exceeded 30 °C. Two of the offices (rooms 2 and 3) were monitored over a 40 day period during the cooling season. Thus, the radiant panel data were not gathered in rooms 2 and 3. Ventilation and cooling for the rooms 1 and 2 were provided by the same VAV unit. Thus, they share the same discharge air temperature and airflow rate data records. The photodiode-based indoor light intensity sensors (spectral response range 350–1100 nm and 60° field of view) were placed on the ceilings at identical locations in each office. They were able to measure the light intensities between 0 and 1076 lx. On a few sunny afternoons, the sensor reached to its upper limit (1076 lx)—meaning that the indoor light intensity was likely slightly more than the 1076 lx. The indoor, outdoor and the VAV unit's discharge air temperature were measured by employing 10 kΩ thermistor sensors. The VAV unit's discharge airflow rate was computed by multiplying the square root of the discharge air pressure sensor by a constant. The value of the constant was selected from ASHRAE [30] based on the size of the VAV unit's inlet diameter (356 mm). The occupancy data were generated from the movements detected by the passive-infrared (PIR) motion sensors—5 m range and 100° horizontal and 80° vertical coverage (symmetrical about the sensor normal). In a time frame of fifteen minutes, if a movement was detected, the room was assumed occupied. This time delay value was selected in line with prior research [31–33] and after analyzing the empirical likelihood distribution of observing a movement as a function of the time-elapsed since the last movement detection [34]. Fig. 2 presents the sensory data extracted from the archiver of the BAS in 15 min timesteps—this was the default sampling rate in the controls network. Because a control-oriented model needs to make predictions in presence of uncertainties typical to a commercial BAS instrumentation, the instrumentation was not upgraded or calibrated specifically for this study—i.e., the instrumentation was assumed as-is. Simply put, if the errors due to the instrumentation and the models were excessive, the model would fail to represent the temperature response in the prediction time horizon anyways.

2.2. Control-oriented models

In the monitored perimeter office spaces, the heat transfer is governed by environment, occupant and HVAC-driven loads. The