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Virtual surface temperature sensor for multi-zone commercial buildings

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Abstract

Multi-zone structure is commonly used in small commercial office buildings, retail stores and supermarket. While there is no adjacent wall between the zones, the impact of a neighbor zone on the current zone can be approximated and analyzed through the application of virtual walls. It is critical to accurately estimate the virtual wall surface temperature in order to evaluate the model uncertainty and apply improved supervisory control on multiple rooftop air-conditioning units (RTUs). We propose an innovative virtual surface temperature sensor based on system-identification to solve this challenge. The validation of the virtual temperature model is processed by the three validation criteria: goodness of fit (G), mean squared error (MSE) and coefficient of determination (R^2) through off-control conditions with data obtained from a building simulation platform. Further, the sensitivity analysis using the on-control three conditions (under-sizing, properly sizing and oversizing condition) is conducted for analyzing and evaluating the performance of this system-identification based virtual sensor.

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Keywords: System identification; Commercial Buildings; RTUs; Virtual sensor; Supervisory control

1. Introduction

Packaged air-conditioning equipment such as rooftop units (RTUs) has been intensively used in commercial buildings. Approximately, they consumed nearly 50% of all cooling conditioned commercial floor space in the United States [1]. Despite their low initial and installation cost, they are expensive to operate. Over 90% of the units are of constant capacity, under-sensed, and have only rudimentary local on-off control. Meanwhile, based on year-long trended data from dozens of stores, it has been found that oversizing is a common problem with RTUs [2]. The over-szied capacity has an average value of 84% for

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cooling and 299% for heating. These issues incur low-energy efficiency, reduce life cycle of equipment, and affect the indoor environment control. To improve the efficiency of RTUs, many solutions were proposed by other researchers, such as a multi-speed fan control, demand-controlled ventilation, multi-stage compressor control, and enthalpy economizer control [3]. However, these techniques all require the installation of additional instruments and therefore encounter significant market resistance; they cannot eliminate other problems such as simultaneous cooling and heating and non-coordinated local control. Advanced supervisory control of multiple RTUs may solve the challenge, but it requires the estimation of the impact from adjacent zones to the current zone. Virtual sensing is considered as a low-cost solution to support this potential technology [4]. The sensor presented in this paper is derived from the heat balance equation and arranged in the linear parametric form. It can be potentially applied to investigate the effect of novel control, estimate model uncertainties in off-control zones, and assess the zone interaction between the current conditioned space and adjacent zones.

2. Background and model development

Fig.1.a illustrates a typical on-off control of a RTU with two-stage heating [2]. The first-stage setpoint of the conditioned space is 68 ºF and the second-stage set point is 66 ºF. Whenever the temperatures of a space vary below the first-stage setpoint, the first-stage heating is turned on to supply heat; it is automatically turned off when the temperatures of the zone are higher than the setpoint plus the dead band, shown as region B in the figure. The second-stage heating is turned on to supply auxiliary heat if indoor temperatures are below 66 ºF. The second-stage remains on until the temperatures in the zone are higher than 66 ºF and out of the operating differential range A. Fig.1.b shows the simulated three-zone one-story commercial building. The height of the building is 3.50 m and all windows are assigned to be of 1.2 m height. The rated cooling capacities are 5kW, 5kW, and 6.5kW, and the rated heating capacities are 4kW, 4kW and 4.5kW for RTU1, RTU2 and RTU3, respectively. The building model is established in Matlab based on HAMBASE [5]. The operating differential temperature is set as 2 ºC for all of them.

The model of this virtual sensor is initially derived from the heat balance equation at a virtual wall surface. Two major assumptions are made, including that 1) air in each zone is well mixed, and 2) heat radiation exchanges between a zone and surfaces are negligible. The linear parametric model in ARX211 form based on heat balance equation consists of: heat flow from the current zone; heat flow from adjacent zones; and heat flow through building components.

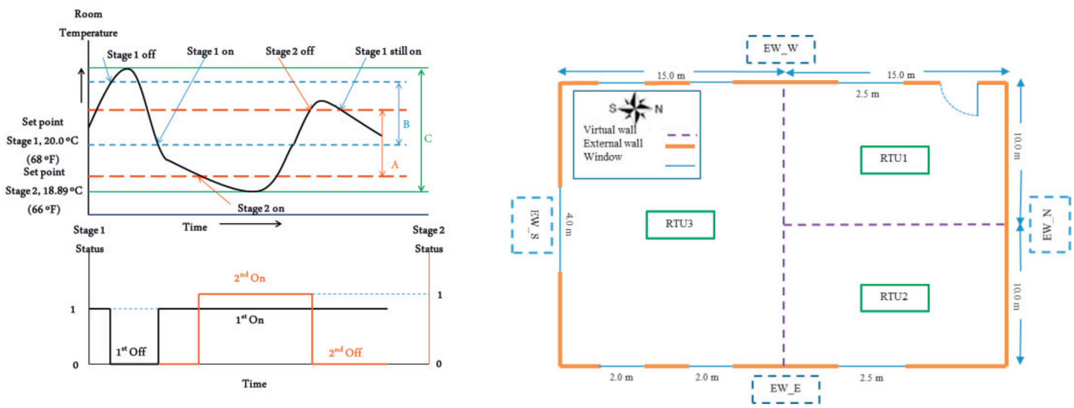

Fig. 1 (a) On-off control of a two-stage heating RTU (b) Layout of the simulated building

3. Model validation

Four categories, consisting of BJ, OE, ARX and ARMAX, are used to compare with the physical model based linear parametric model. These four techniques have been intensively used in building model identification ([6], [7]). The prediction of the physical model based linear parametric equation is validated and compared with the linear parametric model by using an off-control condition of the building example. Three validation criteria: goodness of fit (G), mean squared error (MSE) and coefficient of determination (R^2) are used. Both heating and cooling conditions are compared and only the cooling results are presented here. Results in Table 1 show that ARMAX and ARX have good prediction on the surface temperature. OE and BJ have low performance on the prediction and therefore are discarded.

Table 1 Validation for two days (* means unstable parameter estimation)

Model Prediction	Validation criteria using off-control condition (in July, hottest period)								
	G (%)			R^2 (dimensionless) /100			MSE /100		
Two days	T_{S1}	T_{S2}	T_{S3}	T_{S1}	T_{S2}	T_{S3}	T_{S1}	T_{S2}	T_{S3}
ARMAX 2111	90-91	89-90	85	99	99	97-98	1.4-1.5	2.5-2.6	2.0-2.1
ARMAX 2221	90-92	91-93	86-87	99	99	98	1.0-1.3	1.8-2.0	1.5-1.9
ARX 221	90-94	86-89	85-86	99	99	98	1.4-1.5	2.5	2.0
ARX 211	89-90	83-89	85	99	99	97-98	1.4-1.5	2.6	2.0-2.1
OE 221	*	72-83	*	*	92-97	*	*	6.3-18	*
OE 121	72-88	86-87	62-76	72-99	98	85-94	2.2-11	3.8-4.0	5.7-13
BJ 22211	32-41	40-74	76-84	53-65	63-93	94-97	52-68	15.8-83	2.5-5.3
BJ 11121	82-90	85-90	*	96-99	98-99	*	1.3-4.7	2.3-4.9	*

4. Sensitivity analysis

We carry out the sensitivity analysis by using the three on-control conditions: under-sizing, properly sizing and oversizing conditions to further study the impact of the on-control conditions. The sampling time is set as 1 hour. For under-sizing condition, the off-control zone has slow response. To offset the time-delay, model improvement is need by using long time trended data or increasing the model order until a good performance is reached. The results of the simulated surface temperature and the identified surface temperature from the ARMAX and ARX models are plot in Fig. 2. For one-month data storage, ARMAX2112 and ARX212 can provide good predication. With ARMAX2112, the overall fit goodness is about 86% for T_{s1}, 76-77% for T_{s2}, and 91% for T_{s3}. The good fitness is also demonstrated by the high R^2 value, between 94 to 99%. ARX212, ARX222, and ARMAX2222 all show similar performance as ARMAX2112. ARX792 provides the best prediction, almost overlapping the temperature curve.

With the current design practice, under-sizing almost never happens. Proper-sizing RTUs have high run time factor (RTF) and low normalized on-off cycles (N). The simulated data for 12 hours and 2 days are first applied for the system identification. The results show that ARX221 is the best consistent model for predicting the temperature. However, all models perform lower than undersized on-control conditions with goodness of fit drops to less than 50%. The poor performance is due to the data chaos from the short duration and the narrow temperature range (less than 1 ºC in the proper-sizing condition). One month simulation data is then applied. Performance of ARX211 and ARMAX2111 is improved with goodness of fit rising up to 86% for Ts_1, 72% for Ts_2, and 90% for Ts_3. With two-day data storage, ARX791 provides good prediction with MSE falls between 0.3 and 2.1% (plot in Fig. 2.)

Majority of RTUs are oversized due to the design practice [8] and should be our main concern in the future study. Similar to the sensitivity analysis with properly sizing on-control, ARX211 is the best consistent model for predicting short durations with 12 hours data storage. With oversized RTUs, compressors and/or solenoid valves of gas furnaces cycle more frequently than the proper-sizing conditions to maintain indoor temperatures. This leads to higher room temperature chaos within the dead band temperature of an on-off controller. To improve model prediction performance, longer data should be used, two days or one month in this simulation. With two days data, ARX791 shows the best prediction compared to other models, e.g. ARX211 and ARMAX2111 (in Fig. 2)

5. Conclusion

This study develops an innovative virtual surface temperature sensor based on system-identification method. The proposed model is trained and validated through the simulated data from the building simulation platform. Results show that the virtual surface temperature based on parametric model (ARX) is suitable for predicting surface temperature at virtual walls. With sensitivity analysis using the three on-control conditions, the performance of ARMAX and ARX models is lower than the off-control condition. ARX211 performs well for the one month period of properly-sizing and over-sizing control. When under-sizing exists, ARX212 and ARX792 have better prediction performance.

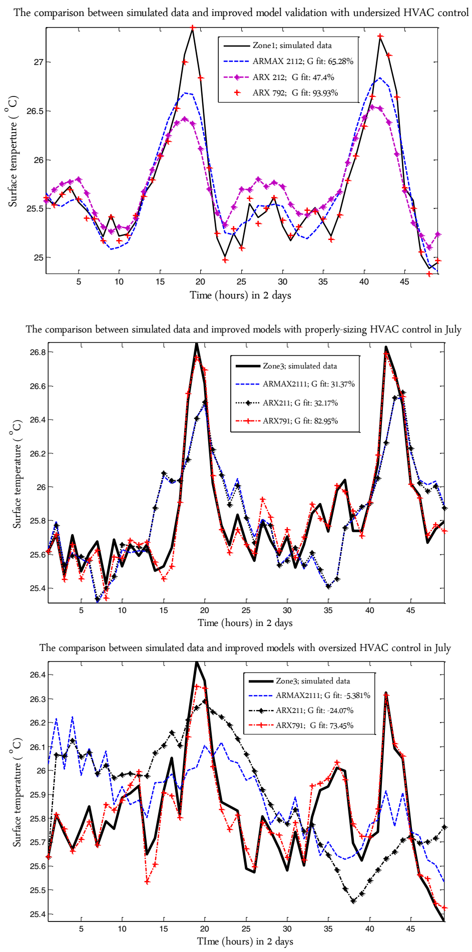

Fig.2. Comparision between simulated data and three validated models for undersize in Zone 1(top), proper size in Zone 3 (mid), and oversize in Zone 3 (bottom)

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Biography

Dr. Yuebin Yu is an assistant professor. He received his Ph.D. degree in Building Performance and Diagnostics from Carnegie Mellon University, Pittsburgh, PA, USA. He focuses his resarch and professional activities in smart building technology, active utilization of passive energy, and model-based built environment evaluation.