Communicating Thermostats as a Tool for Home Energy Performance Assessment

Michael ZEIFMAN, *Senior Member, IEEE*, Kurt ROTH, and Bryan URBAN
Fraunhofer Center for Sustainable Energy Systems, Boston, USA
mzeifman@cse.fraunhofer.org

Abstract **Communicating thermostats (CTs) can provide a stream of home data, e.g., room temperature and status of heating, ventilation and air conditioning (HVAC) system to participating utility companies. We show how these data can be used to estimate physical home parameters that represent such major categories of home energy performance as wall insulation, air infiltration and HVAC efficiency. The estimation is based on a coarse-grained physics based modeling technology that connects weather data and household thermal comfort preferences with CT data through these parameters. The proposed method is scalable and can be automatically applied to numerous households to identify home improvement opportunities.**

I. Introduction

Communicating thermostats (CTs) are popular consumer electronics devices that control home heating, ventilation and air conditioning (HVAC) system using modern communication means (e.g., smartphones). It is projected that approximately 25 million CTs will be deployed in North America circa 2019 [1]. Although there are various types of CTs with different degrees of sophistication, all of them record such interval data as actual room temperature, thermostat setpoint and HVAC runtime. In many cases, utility companies offer rebates on CTs in exchange for data rights.

Both homeowners and utilities are interested in energy saving. For residential buildings, major saving opportunities are often related to space heating and cooling loads that typically can be reduced by [2]

- Upgrading wall insulation, if the current insulation levels are low
- Sealing of air leaks, if air infiltration is too high
- Upgrading an inefficient HVAC system

A straightforward way to identify these three types of energy saving opportunities in a home is to conduct an onsite home energy assessment by a professional evaluator. However, such assessments are costly, inconvenient to homeowners and difficult to scale. In this paper, we demonstrate how, using CT data, it is possible to estimate home physical parameters that quantitatively characterize these opportunities. The proposed method is based on a coarse-grained physics-based model of a home.

II. Lumped Grey-Box model

In its simplest form, the considered system includes a single lumped wall that models all actual building external walls, a basement and a roof and an additional lumped resistive element modeling air infiltration. The model has two "capacitances" (indoor air and lumped wall) and two "resistances" (lumped wall and convection infiltration), i.e., it is an R2C2 grey box model [3]. Unlike the electrical-analogy based grey box model, however, we use energy balance differential equations to model this system mathematically:

$$C_r \frac{dT_r}{dt} = U_w A_w (T_w - T_r) + L(T_a - T_r) + \eta q^* + q_{\text{int}} \quad (1)$$

$$C_w \frac{dT_w}{dt} = U_w A_w (T_r - T_w) + U_w A_w (T_a - T_w) + q_{ext} \quad (2)$$

where C_r is overall thermal capacitance of the indoor air, U_w and A_w are overall U-value and area of the external surfaces (i.e., building envelope), C_w is overall thermal capacitance of the envelope, q^* is energy consumption rate related to HVAC system (positive for heating, negative for cooling and zero for off-state), η is the thermal efficiency of the HVAC system, q_{int} and q_{ext} are internal and external household heat gains/losses (e.g., solar gains, non-HVAC appliances, window openings), L is the convective heat resistance, and T_r, T_w and T_a are the temperatures of the indoor air, wall and ambient outdoor air.

In this formulation, three parameters U_w, L and η correspond to the three energy saving opportunities. They can be estimated from experimental CT data and compared with known benchmarks. In this way, the home energy saving opportunities can be assessed based on CT data only, with no home visit involved.

III. Parameter Estimation

In the conventional approach, the system of differential equations of type Eqs. (1)-(2) is solved numerically with the equation parameters being simultaneously estimated, which significantly increases the estimation uncertainty. In this work, we use a closed-form solution that improves the parameter estimation since the "theoretical" curve (i.e., the closed-form solution) is fitted to the experimental curve (i.e., CT data, e.g., room temperature) to identify the parameter estimates that yield the best fit.

A closed-form solution to Eq. (1) is given by

$$T_r(t) = A\exp(-s_1 t) + B\exp(-s_2 t) + C \quad (3)$$

where A, B, C, s_1 and s_2 are constants that nonlinearly depend on the parameters of Eqs. (1) and (2). All those parameters, except for q_{int} and q_{ext} can be calculated using publicly-available data. To minimize the generally unknown internal/external heat gains and losses q_{int} and q_{ext}, we restrict data to periods of time when most such effects can be neglected, e.g., to nighttime over heating season.

Figure 1 shows an example of fitting the room temperature solution, Eq. (3) to experimental data obtained for a period from 12 am to 5 am at a home in heating season.

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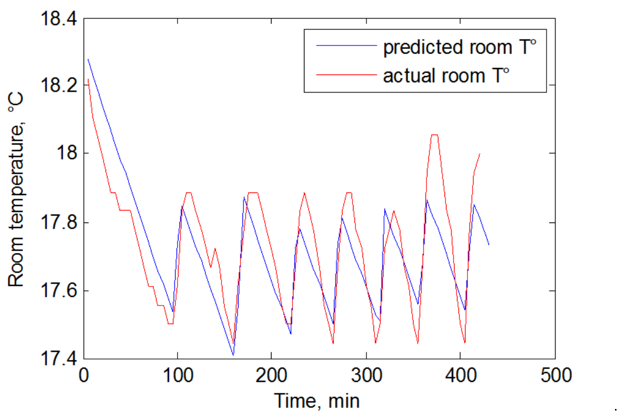


Fig. 1. Preliminary results from fitting a closed-form solution, Eq. (3) to CT data from a home. Room and ambient temperatures and wind speed are recorded every 5 min, and HVAC runtime is recorded every second by the CT. Nighttime data for March 3, 2016 are shown. The source energy rate ηq* was approximated as a constant during "on" time and 0 during "off" time. The infiltration over this low-wind night is neglected: $L = 0$. The best-fit results are: $\hat{U}_w = 1/17$ Btu/ h·ft^2·°F, $\widehat{hq}^*$=1.45 kW. Parameter q* can be estimated from utility bills [4].

Since the parameter L characterizing air infiltration can be strongly coupled to parameter U_w (i.e., the U-value), its estimation by curve fitting (i.e., optimization) can become unreliable. One way to overcome this problem is to use a sample of estimates of U-values obtained for different nights, and correlate these estimates with the data on wind speed/direction for the same nights. Using well-known models for infiltration dependence on wind and the obtained correlation, the air infiltration can be characterized [5].

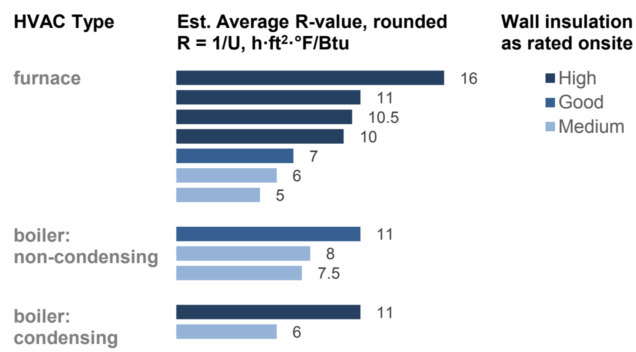
IV. Case Study

Sixteen homes in Massachusetts, USA, participated in a pilot study organized by Eversource Energy in March-April 2016. The homes were equipped with CTs and the CT data for each home were recorded remotely. The main goal of this study was to test the feasibility of the proposed approach by comparing the quantitative estimates of the overall wall insulation with categorical estimates of building insulation levels obtained in onsite evaluations.

The estimations were obtained separately for each night and every home. The curve fitting was performed in MATLAB, with average computational time per home per night of about 0.2 s on a 3.0 GHz computer. In this way, about 60 values of U-value estimates for each home were obtained. After outliers were removed, the remaining values were correlated with average nightly values of wind speed. These values were cleaned from outliers and correlated with average nightly values of wind speed. We found this correlation to be statistically significant only in one home. The cleaned U-values were then averaged and compared with the categorical "ground truth." For four homes, these estimates were unreliable as no heating cycles were observed during the pilot, most likely because of very high insulation levels.

The developed model, Eqs. (1)-(3) has a simple source term for heat input and, accordingly, is most applicable to single-zone homes equipped with gas furnaces. About half of the homes in the pilot were equipped with gas furnaces, while other homes were equipped with boilers. Table I shows the results.

TABLE I
Home Insulation Estimation



It is seen in the Table that, generally, higher estimated R-values correspond to higher grades in online evaluations, especially for the homes with gas furnaces. We believe this correspondence is indicative of the feasibility of the proposed approach. For the homes with boilers, the correspondence is less clear. We attribute this to such factors as (1) a single lumped wall/ direct heat source model can be too coarse for homes with boilers and/or multiple CTs, and (2) relatively few nights with multiple HVAC cycles (see Fig. 1) for majority of homes.

V. Conclusion

We have developed a computational procedure to remotely evaluate home energy performance and performed a preliminary evaluation. The initial results suggest that the approach is both feasible and scalable, but further work is needed to improve and validate the methodology.

VI. Acknowledgment

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