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Estimating time constants for over 10,000 residential buildings in North America: towards a statistical characterization of thermal dynamics

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ABSTRACT
Understanding the dynamic response of a building is essential in the design of sustainable energy-efficient buildings. Using data from over 10,000 smart thermostats, this study identifies patterns in the dynamic thermal response of residential buildings in Canada and the United States (US). The data set consists of one year of measurements recorded at 5-minute intervals for the indoor and outdoor air temperature as well as HVAC equipment run times.

This study focuses on identifying effective values of time constants for the houses by applying the following procedure. First, periods complying with the following basic criteria are identified: a) the house is under free-floating conditions (i.e. when the HVAC system is switched off) for more than three hours and b) the outdoor temperature remains approximately constant (the outdoor temperature change is smaller than or equal to 2°C). Second, for each identified period, time constant values are determined by tracking the temperature responses of the house. These values are determined assuming the characteristic exponential decay of a first-order resistance-capacitance (RC) thermal model. Finally, a statistical analysis is applied to identify a typical range of effective time constant values according to month.

Consequently, calculations show significant differences between estimated values for the summer and winter months, which may be attributed to occupant behaviour. In winter, the majority of time constants range from 15 to 55 hours. In summer, most of time constants vary between less than 1 hour and 18 hours due to occupants opening windows. In addition, the dependence of the time constant on the age of the home is investigated.

KEYWORDS
Time constant estimation; pattern recognition; dynamic thermal response; residential building; statistical analysis.

INTRODUCTION
In support of sustainable development and energy efficiency, effective energy management in buildings is increasingly recognized as a priority. In Canada and the US, the building sector accounts for approximately 28% and 40% of the national energy consumption, respectively. The residential sector is a major contributor to the energy use of both the Canadian and American building sectors, making up 62% and 53% of their total energy consumption, respectively. Moreover, in both countries, more than 40% of the total energy demand in a residential building is used to heat and cool the occupied spaces (Office of Energy Efficiency, 2016; U.S. Energy Information Administration, 2009, 2018).

With the increased adoption of the Internet-of-Things (IoT) such as smart thermostats, numerous homeowners are outfitting their residences with home automation and data acquisition systems. A recent study predicted that, by 2025, IoT applications would offer a potential economic impact of $200-300 billion a year in relation to the residential sector (Manyika et al., 2015). In the building and urban environment, big data sources are becoming increasingly more prominent and the release of certain anonymized data sets for data science could progressively become the norm. As a result, the building industry will face a critical dilemma: how will performance data from potentially thousands—or even millions—of buildings be reasonably integrated into design and energy management? This unprecedented level of access to raw data will promote the potential of machine learning, visual analytics, and data-driven statistical modelling techniques in estimating the building's dynamic thermal response (Miller, Nagy, & Schlueter, 2017). Grey-box model approaches use operational data from numerous real buildings to calibrate a simplified physical model, in the effort of providing good approximation of a building's thermal response (Vivian, Zarrella, Emmi, & De Carli, 2017).

In this study, the operational data of real homes are analyzed to recognize patterns in their dynamic thermal response. This paper focuses on proposing a method of estimating the typical thermal time constant values for residential buildings located in Canada and the US. The estimation is based on temperature measurements and equipment runtimes acquired from smart thermostats. When limited information is available, the knowledge provided in this paper can: i) assist in the generation of simple grey-box models that could guide the preliminary design of new residential buildings (Vivian et al., 2017), and ii) assist in the development and adoption of effective load management strategies for existing buildings.

METHODOLOGY

Data Collection

Ecobee, a Canadian home automation company, has established the Donate Your Data (DYD) program for its smart thermostat users to donate measured time series data to science. The meta-data from this program are user-reported, anonymized and include details such as the geographic location, age of home, total floor area, style of home, and number of occupants. Recorded at 5-minute intervals, the Ecobee thermostats collect measurements for temperature, humidity, occupancy detection, and HVAC equipment runtimes. For the building time constant estimation, over 10,000 residential buildings were monitored between March 2016 and February 2017. The Ecobee smart thermostats control the HVAC system based on the indoor control temperature, which is an average temperature of the building based on readings from the thermostat and any additional remote sensors present.

Building Time Constant Estimation

Diurnal and seasonal variations in outdoor temperature, solar energy and occupant behaviour account for the main thermal losses and gains between the building and its surroundings. The time constant is a measure that characterizes a building's ability to retain heat. With no influence from a heating or cooling system, theoretically, the thermal time constant provides an indication of how fast the building will take to achieve a new thermal equilibrium in response to changes in its internal and external thermal conditions. As demonstrated in Figure 1, the time constant can be found by applying a step input to the building and then recording the time the building takes to realize 63.2% of the final value in the step change (Equation 1).

The first step in estimating the time constant of a building is the identification of suitable time periods for analysis. In this study, these analysis periods are selected according to following

basic criteria: a) the house is under free-floating conditions (i.e. when the HVAC system is switched off) for more than three hours, and b) the outdoor temperature remains approximately constant (the outdoor temperature change is smaller than or equal to 2°C).
The measured time series data for HVAC equipment runtimes and the outdoor temperature are used to determine if the criteria are met during each analysis period.

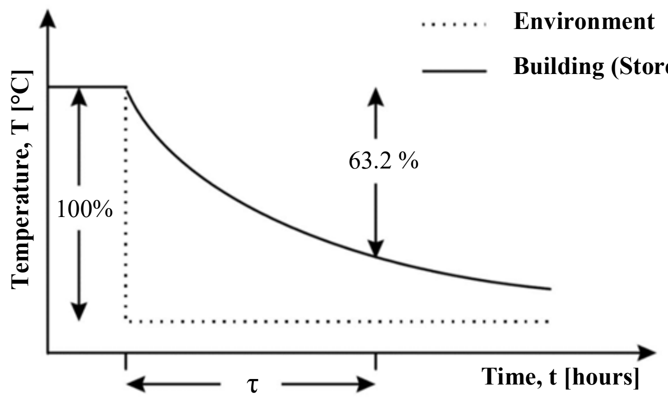

Figure 1: The time constant, τ, is the time needed for the building to realize 63% of the final value of an applied step change.

The second step is the determination of a time constant for each identified analysis period by treating the thermal space of every home as a first-order resistance-capacitance (RC) model (Vivian et al., 2017). While this is a relatively simple model, it provides a useful characterization of the dynamic behaviour of the house. Assuming the characteristic exponential decay of a first order system:

$$T(t) = T_f + (T_i - T_f)e^{-t/\tau_{bldg}} \tag{1}$$

where t represents time elapsed in hours, T_i represents the initial indoor temperature, T_f represents the long-term final temperature of the indoor space in free-floating conditions, and τ_{bldg} represents the estimated time constant value.

Considering plausible physical constraints and using the least squares method, the following parameters of a regression function are calculated according to Equation 1 and the recorded indoor temperature measurements $T(t)$: a) the long-term final indoor temperature b) the change in indoor temperature $(T_i\text{-}T_f)$, and c) the time constant value to be estimated. The time constant values were estimated with the use of the programming language Python. Next, these estimated values are then filtered, retaining only those whose corresponding R-squared values are 0.7 or higher. The R-squared value of 0.7 was visually determined to be the minimum acceptable value representing an accurate fit of the regression line to the observed data.

Identification of Typical Building Time Constant Values

In the previous step, multiple time constants are found for each building and organized according to month for analysis purposes. For each residence, a monthly average of the estimated time constant values can be obtained by weighing these estimated values by their corresponding R-squared values from the previous step. Statistical learning methods, particularly visual analytics, are then used to identify typical time constant values among the weighted averages. Histograms, kernel density estimations (KDE) (a method to estimate frequency distributions), and other statistical analysis tools are used to identify patterns in the distribution of time constant averages. Furthermore, possible correlations between the time constant averages and the age of the home have been investigated.

RESULTS

Figure 2 and 3 show typical results obtained for the time constants for the months of August and February, respectively. The time constants are plotted versus the age of the home.

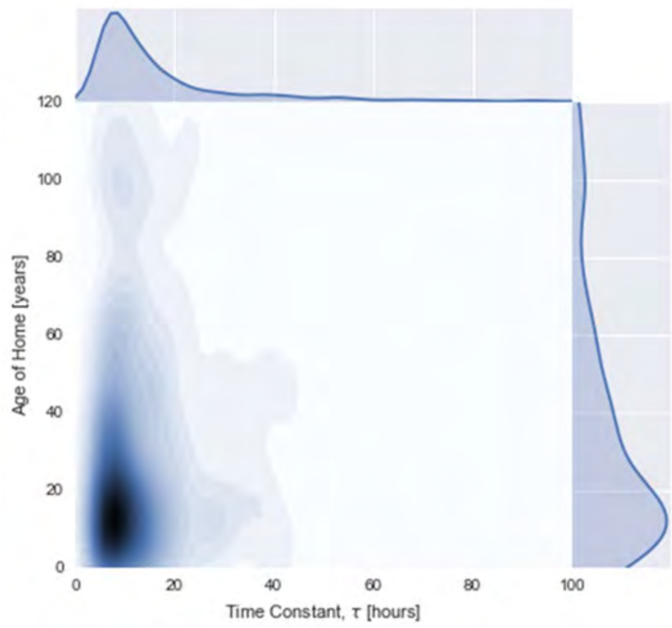

Figure 2: For August 2016, KDEs representing the building age distribution (right), time constant distribution (top), and their relationship to each other (center).

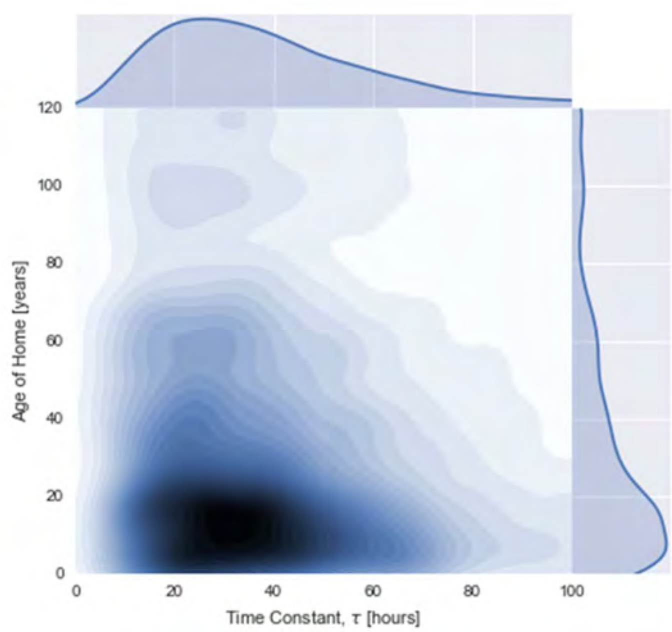

Figure 3: For February 2017, KDEs representing the building age distribution (right), time constant distribution (top), and their relationship to each other (center).

The patterns observed in August and February are very similar to time constant distributions seen throughout the rest of the warmer months and colder months, respectively. For the warmer months, specifically June through September, most of time constants fall within a range of less than 1 hour to 18 hours as seen in Figure 2. The colder months, meaning October through May, have most of their time constants varying between approximately 15 to 55 hours as demonstrated in Figure 3. As seen in both Figure 2 and Figure 3, the greater part of the buildings observed are between 0 and 35 years old.

DISCUSSION

Comparing Figure 2 and Figure 3, the warmer and colder months show significant differences between their resulting time constant averages; for the same group of homes, the warmer months have time constants that are much lower in value. The occurrence of different time constants for one building at different times of the year is an interesting phenomenon. In principle, the time constant should only depend on the materials and physical configuration of the house, which should not be expected to change. This decrease in value for the time constant averages may be linked to occupant behaviour. During the warmer months, it is reasonable to expect occupants to have their windows open and leave them open for longer periods of time due to more favorable weather conditions; open windows decrease a building's ability to resist changes in external thermal conditions thus reducing the effective resistance. Moreover, there is also a trend observed shared by both the warmer and colder months: the variance of time constants narrows with an increase in the age of home. The broad range of values for younger buildings and the narrow range of low values for older buildings suggest the introduction of a larger variety of construction methods and materials—some more energy efficient than others—over the last 120 years.

Understanding a building's natural dynamic thermal response is crucial to the design of heating, ventilation, and air conditioning (HVAC) systems, the maintenance of a comfortable environment for occupants, and the management of their electrical load profile (Palensky & Dietrich, 2011). In future studies, the proposed method will be extended to a larger data set of approximately 27,000 smart thermostats in North America to examine the relationship of the time constant to other variables. The variables to be considered include type of home (e.g. semi-detached, row house, condominium), geographical location and floor area. Considering that the age of home is user-reported, it would be interesting to see if the relationship observed between the time constant and the age of home persists in a larger sample of homes. Other considerations taken into account to select the periods of interest will include the effects of weather conditions, solar gains and occupancy which are currently not being tracked.

As we seek increasingly low-energy solutions for buildings, HVAC systems are being designed as more responsive to changes in a building's internal (e.g. occupants, appliances) and external thermal conditions (e.g. temperature, humidity, solar gain). The most commonly used software tools for building performance simulation (e.g. EnergyPlus or TRNSYS) require extensive computational power and a large number of assumptions about the building's geometry, its characteristic physical properties, its environment and its occupancy (Zawada, 2017). In addition, many of these inputs end up being assumptions based on the experience and intuition of professional experts. As a result, simple, reliable building models (e.g. grey-box models) have been receiving more attention of late, because there is often a need to model building performance when the required inputs are limited (e.g. only age, location and building type) and the energy modelers are less experienced. When limited building information is available, the knowledge acquired from this study will be used to facilitate preliminary estimations of dynamic parameters (such as RC values) in the rapid generation of control-oriented models.

CONCLUSIONS

This study presents a statistical methodology for the identification of typical time constant values of residential buildings for the heating, cooling and intermediate shoulder seasons (i.e. when houses are typically in passive mode with open windows). Preliminary results for different times of the year have been presented. Based on a simple physical model and measurement data from smart thermostats in North America, the proposed method for making preliminary estimations of the time constant offers benefits for researchers, home automation companies, utilities and homeowners who seek to reduce energy costs while maintaining occupant comfort The advantages include facilitating the creation of simpler models for testing and control scenarios, providing a better understanding of consumer behaviour and needs, and promoting energy conservation and efficiency. A major result of the present study is the observation that time constants vary seasonally: from less than 1 hour to 18 hours during summer, to 15 to 55 hours during winter. This result is most likely due to open windows that directly couple the interior of a house to the exterior environment through a high effective thermal conductance. Future studies will focus on extending the proposed method to a larger data set and examining the relationship of the time constant values to other variables including type of home, geographical location and floor area.

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