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A single-variate building energy signature approach for periods with substantial solar gain

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ABSTRACT

The use of regression analysis for the identification of building performance parameters based on measurements is often difficult due to collinearity between the outdoor temperature and the global solar radiation (S). This study proposes a method to overcome this issue. The proposed method is based on using the seasonal symmetry of S to pair data from time-periods equidistant from the winter solstice. In addition, a method to utilize synthetic data to fine-tune the paired-data approach is presented. To evaluate the paired-data approach, two years data from a multifamily building in Umeå was used to estimate the heat loss factor (air-to-air transmission including air leakage). The results were compared with results obtained when S was very low ($S \approx 0$). It was found that, the fine-tuned paired-data approach resulted in a modest deviation in the heat loss factor with an average absolute deviation of 4.0%. The small deviation indicates that the paired-data approach can extend the use of single-variate regression models for accurate identification of heat loss factors to situations where the solar gain is substantial. The paired-data approach was also used to calibrate a commercial energy building simulation tool.

1. Introduction

A buildings energy signature (ES) is described by Hammersten [1] as a set of parameters that describe its energy performance. In ES models, the energybalance of a building is described as a constant-parameter linear system, and the parameters are estimated with regression analysis of performance data. Typical ES approaches consist of linear, change-point linear, and multiple-linear regression models, and these are described, for example in the ASHRAE Inverse Modeling Toolkit (IMT) [2]. ES models have been widely used for evaluation of retrofit savings and they are an important part of verification protocols such as those found in AHSRAE Guideline 14 [3]. To support calculation of ES models in such protocols, the IMT was developed. Recently, Paulus, Claridge and Culp [4] developed an algorithm to automate the process of selecting an appropriate ES model in the IMT.

The use of the ES approach for parameter identification is however less frequently used, due to the often strong collinearity between independent parameters such as the outdoor temperature (T_o) and the global horizontal solar radiation (S). This makes it difficult to identify the associated parameters with a reasonable degree of accuracy, which is a problem because highly accurate regression coefficients in ES models are needed in a number of applications. For instance in calibrating forward-driven models [5,6], benchmarking building energy performance [7], and enabling feedback of built performance versus calculated performance. Previous studies of modeling solar gain in regression analysis where accurate parameter identification has been the main focus, includes among others Flouquet [8]. Flouquet, showed that taking the solar gain into account through a solar aperture parameter in the energy balance led to a reduced bias of the model parameters for daily, weekly and monthly synthetic data.

Danov et al., [9] corrected the bias introduced in the overall heat-loss factor due to solar-gain through differences with a reference ES model fitted to data from a period of relatively low S. This approach is fairly straightforward but the accuracy is dependent on the reference model that is used and how free it is from solar influence. Consequently, this method can be assumed to perform especially well in geographic locations where sufficiently long periods of low S exist. The ideal period for the identification of transmission losses with the ES approach would thus be a period for which the solar heat gain is negligible. For geographic locations fairly close to the poles, this is achieved during the darkest winter months. Similar conditions were also achieved in a study performed in Belgium [10]

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Nomenclature

A	Total envelope area above ground m^2
A_e	Equivalent solar collecting area m^2
C_p	Specific heat capacity of air kJ/kg °C
G	Heat loss to ground kW
G_{ida}	Synthetic data obtained from the IDA-ICE simulation kW
P_{airh}	Supplied heating power to the air heaters in the ventilation system kW
P_{elec}	Supplied electrical power kW
P_p	Heat gained from occupants kW
P_{rad}	Supplied heating power to the radiator system kW
P_{sol}	Heat gain from the sun kW
$P_{sol,ida}$	Synthetic data obtained from IDA-ICE simulation kW
P_{tr}	Balances heat losses due to transmission and air leakage together with contributions from P_{sol} kW
Q_L	Uncontrolled airflow due to air leakage m^3/s
Q_s	Controlled ventilation supply airflow m^3/s
S	Global horizontal solar radiation kW/m^2
T	Indoor temperature °C
T_o	Outdoor temperature °C
T_s	Temperature of Q_s °C
U_t	Overall U-value above ground kW/m^2 °C
α	Part of electricity that contributes to space heating (gain factor)
η	Utilization factor of incident solar radiation on windows
ρ	Density of air kg/m^3

where the analyzed building was shielded from solar gain during the measured period by an opaque canvas.

The main focus of the present study was to investigate suitable regression methods that can be used when data is collected for periods with substantial solar gain. This study used daily average data from a multifamily building located in Umeå, Sweden where S is very small close to the winter solstice. This means that data are available for a period where the solar gain is almost zero and thus can be used as a reference.

2. Measured data and case study building

The analyzed building is a low-rise, two floor, multifamily building, built during the years 1970 and 1971 in Umeå, Sweden. The HVAC system consists of hydronic radiators and a constant air volume ventilation system. The heated area is 925 m^2, and the window to envelope area is about 7.4%. The building is described further in [5]. The measured data for the study included: T_i, T_o, relative humidity, wind speed and direction, supplied energy for space heating, S, air-supply velocity and T_S from the air-handling unit. Data on the supplied energy were retrieved from the local energy company (electricity) and the property owner (district heating). Air temperatures and humidity were measured with manufacturer-calibrated loggers with a specified average temperature and relative humidity error of ±0.3 °C and ±5%, respectively. S, wind speed, and wind direction were collected – for weather file compilation purposes – from a weather station located less than 5 km from the site, that is managed by the Swedish Meteorological and Hydrological Institute (SMHI) [11]. The air rate from the air handling unit was spot measured during the heating season with a thermal velocity probe with a specified error of $\pm 0.03\ \mathrm{ms}^{-1}$. The associated flow rate, Q_s was subsequently calculated based on measurement of the cross section area of the duct. The parameters (T_i–T_o) and S are presented in Fig. 1 with boxplots [12]. In Fig. 1 the thick black horizontal lines indicate the medians, the bottoms and tops of the boxes show the first and third quartiles, and the small circles indicate outliers, which have been defined as any points outside the whiskers. The whiskers are shown as vertical lines that go from the ends of the boxes and to the most extreme data points within 1.5 times the length of the boxes.

It can be seen in Fig. 1 that S was lowest and almost zero during the winter months (November through January) and that there were fairly large differences in (T_i–T_o) between the two analyzed years.

3. Formulation of models

Steady-state models can be chosen depending on the required level of model prediction, data quality etc. The simplest version of the ES approach, described by Fels [13] is when a constant T_i is assumed and the supplied energy from the grid is plotted against T_o. If more detailed data exists, T_i and ventilation data can also be included in the power balance and the thermal performance parameters can be determined by a least square fit to the following power balance [14].

$$P_{tr} = P_{rad} + P_p + \alpha P_{elec} - Q_s(T_i - T_s)\rho C_p = (AU_t + Q_L\rho C_p)(T_i - T_o) + G - P_{sol}. \quad (1)$$

where, $Q_s(T_i - T_s)\rho C_p$ accounts for the heat transfer associated with the difference between T_s and T_i. The heat losses from the domestic hot water circulation system are included in P_{rad}. The additional heating from domestic hot water usage is assumed to roughly balance the heat losses due to the domestic cold water usage and is thus omitted.

Further assumptions were made for the heat gained from the occupants, (P_p) and the electrical gain factor (α). P_p was calculated based on knowledge of the number of tenants in the building (collected from public records) and assuming a daily occupancy schedule of 14 h and 80 W of emitted heat per person in accordance with [15]. For the studied building, α is smaller than 1 due to the use of electricity outside the building such as entrance lighting. In addition, not all domestic electricity is utilized for heating. Examples of this are cooking on electric stoves with spot ventilation that surpasses the heat recovery system or dishwashers or washing machines from which electrically heated water leaves the building. Based on Swedish conditions, the national guideline [15] recommends an α of 0.7, and this value was used in this work. Lastly, the dynamic effects in the data were minimized by averaging the data over four days before the least square fits were conducted. Based on the assumption that ($G - P_{sol}$) in Eq. (1) is constant during the analyzed period, ($AU_t + Q_L\rho C_p$) and ($G - P_{sol}$) can thus be obtained from a linear regression where ($AU_t + Q_L\rho C_p$) is the air-to-air transmission, including air leakage, (heat loss factor).

3.1. Bias introduced by variation in P_{sol} and G

The fundamental assumptions in Eq. (1) are that Q_L, P_p, and ($G - P_{sol}$) are constant during the analyzed period and thus independent of $T_i - T_o$. For fairly air-tight buildings, $Q_L\rho C_p$ is very small compared to AU_t which means that the term ($AU_t + Q_L\rho C_p$) can be treated as a constant. The variation in P_p is independent of the size of the building because P_p is a stochastic variable. If data are collected during a fairly short period, the variation in G will also be fairly small due to the large thermal inertia of the ground. Thus, the variation in P_{sol} introduces the largest bias in the parameter estimates from Eq. (1). This is illustrated in Fig. 2, where the left side of Eq. (1) (P_{tr}) is plotted versus ($T_i - T_o$) for April and October data from the year 2013/14. Each data point in Fig. 2 represents averaged values over four days.

It can be seen in Fig. 2 that a model fit to the April data yields a larger slope ($AU_t + Q_L\rho C_p$) compared to the October data. The main