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Data-driven simple thermal models: The importance of the parameter estimates

Vanda Dimitriou*, Steven K. Firth, Tarek M. Hassan, Tom Kane and Michael Coleman

School of Civil and Building Engineering, Loughborough University, Leicestershire LE11 3TU, United Kingdom

Abstract

A simple 1st order data-driven lumped parameter model of a domestic building is developed to explore the effect of using different model parameter values in the model outputs. The adequacy of the Ordinary Least Square estimation technique is explored. Results show that an improved fit to the measured data can be achieved by varying the initial model parameter values of capacitance (up to 78%), resistance (-46%) and effective window area (-59%). This highlights the importance of having a reference set of parameters based on the known physical characteristics of the building. Finally, the model residuals are deemed appropriate to inform the decision making process for further model development.

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Keywords: parameter; estimation; dynamic; thermal; modelling; Lumped Parameter; model calibration; Ordinary Least Squares;

1. Introduction

As advanced equipment is emerging in the domestic sector (e.g. Smart Home equipment), we are faced with a wealth of operational data which is often unused. Appropriate thermal modelling techniques need to be identified

Nomenclature

T_i	is the indoor air temperature (°C)
$T_{i,pred}$	is the indoor air temperature as predicted by the model (°C)
$T_{i,meas}$	is the indoor air temperature as measured by the monitoring equipment (°C)

* Corresponding author. *E-mail address:* v.dimitriou@lboro.ac.uk

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T_a	is the ambient temperature (°C)
C_i	is the heat capacitance (Wh/°C)
R_{ia}	is the thermal resistance of the building envelope (°C/W)
Q_h	is the gas consumption originally measured in m^3 (W)
Q_s	is the global solar irradiance (W/m^2)
A_{eff}	is the effective window area (area for which direct solar gains should be accounted for) (m^2)
α	is the gas coefficient accounting for the boiler efficiency and central heating heat transfer losses (-)

that are able to best make use of the real-time performance data arising from in-home sensors in order to reduce heating energy demand, better inform maintenance and retrofit actions and help towards the reduction of the performance gap [1]. Previously the focus of the research community on the assessment of the thermal performance and dynamics of buildings has drawn on data-driven statistical modelling techniques (e.g. Grey-box modelling techniques) [2-6]. These methods are commonly based on a type of simple dynamic models, the Lumped Parameter model approach, where several layers of the building elements are lumped into one node to simplify the model architecture and calculations. For the Lumped Parameter model development, the building is viewed as a RC- network where resistors are the thermal resistances and capacitors are the heat capacitances of the building elements. They are termed 'lumped' as several layers of the building elements are grouped together into one node. As these models were originally developed in the 1970s, there is a plethora of Lumped Parameter model applications [7-10] of which some include the representation of certain parts of the heating system or of the heating controls (e.g. radiators, Thermostatic Radiator Valves) [2,11].

The implied simplifications in the building representation leads to an important question: how effective can these models be in describing and predicting the building's thermal performance? To begin answering this question the potential and limitations of simple building thermal models in adequately representing the dynamics of the building's thermal performance need to be further explored.

This study focuses on assessing the importance of providing adequate estimates of the model parameters, an area of particular interest [12, 13]. The expected thermal parameters for a typical UK domestic building are calculated and operational data are monitored. A Grey-box modelling technique using Ordinary Least Squares estimation methods is used to form a data-driven 1st order simple state-space model of the building's dynamic thermal performance to assess the adequacy of the previously calculated parameters and the goodness of fit to the monitored data. The performance of the model for different values of parameters is discussed and the implications for future model applications are presented.

2. Case study: A domestic building in Loughborough, UK

A typical UK domestic building was chosen for data collection. In this section a description of the study building is given, followed by a description of the measurement equipment and the data collected.

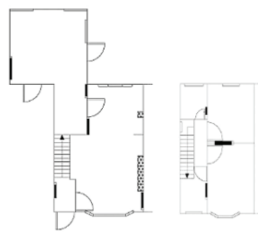


Fig. 1 Ground floor layout (left) and first floor (right) layouts, both with radiator positioning in solid black

2.1. Building description

The house is a two storey traditional semi-detached house built in the 1930s and is situated in Loughborough, UK. In Figure 1 the floorplans of the house are given along with the openings and radiator placement. The ground floor consists of an entrance hallway, a living-dining room and a kitchen. On the first floor there are three bedrooms and a family bathroom. The total floor area amounts to approximately 76m^2. The external walls are 408mm thick, consisting of a masonry inner leaf with a plaster finish, brickwork on the outside and cavity of 40mm without insulation. The floor to ceiling height is 2.6m on both floors. The window and door openings have UPVC frames and are double-glazed. The floors are mainly of suspended timber construction and carpeted only on the first floor. The internal partitions are mainly timber framed. The house is occupied by a family of four.

2.2. Monitoring equipment and data collected

Table 1 summarises the measured data and provides further details on the time intervals and equipment used. Hobo temperature data loggers were placed in each room at a head high level away from obstacles, direct solar radiation, currents and heat sources (when possible) to capture the internal air temperature (T_i). An external company was employed to monitor the whole house gas consumption (Q_h) at a 30 minute interval. Finally, the weather data, comprising of the external air temperature (T_a) and the global solar irradiance (kW/m^2), were retrieved from the Loughborough University on-campus weather station. The monitoring lasted for a four-week time-period during the 2014 heating season; starting the 14th of March and ending the 11th of April 2014.

Table 1 Summary of data collection, specifications and details

Monitoring of:	Positioning:	Equipment used:	Interval (min)
Internal air temperature (^oC)	One in each room including hallways and landing	HOBO U12 / HOBO Pendants	30
Gas consumption (m^3)	Whole house, cumulative measurements (conversion factor used for Loughborough, sourced from http://www.energylinx.co.uk; $1m^3$ equals to 11.363kWh)	Automated meter reader	30
External air temperature (^oC)	On-campus, in close proximity to the building's location	Weather station	30
Global solar irradiance (kW/m^2)	On-campus, in close proximity to the building's location	Weather station	30

3. Methods for evaluation of parameter values

3.1. Calculation of the expected values

Table 2 lists all the R and C values along with the area (m^2) and volume (m^3) of each structural element and the proportion of the total envelope area that each element occupies. For the calculation of the thermal resistance of the building elements the methodology suggested by CIBSE Guide A for the calculation of the U-value of structural elements with one bridged layer was used [14]. The same methodology was used for the calculation of the internal partition walls and the first floor slab. For the rest of the structural elements (i.e. windows, doors, roof, ground floor slab) R-values have been inferred from the U-values (or have been sourced unchanged) from CIBSE Guide A. The heat capacitance of the building elements was also calculated using the CIBSE Guide A (Tables 3.37 to 3.39) which specifies the specific heat and density of each material of the building structure. For the heat capacitance calculation of each building element, the specific heat capacity for each material was multiplied by the density and the volume of the material used. The final capacitance was calculated as the weighted summation of the element layers based on the proportion of volume each layer occupied. The same procedure was followed for the heat capacitance calculation of the internal wall partition, the first and ground floor slabs, the roof, the doors and the windows. The total capacitances of the external building cell, comprising of windows, doors, roof and walls (C_e), the ground floor slab (C_g) and the internal partitions (C_m) have been calculated as the summation of capacitances of all the relevant building elements.

Finally, the total expected capacitance of the building envelope (C_i) is calculated as the summation of C_e and C_m adding the capacitance of the indoor air (calculated as 66.20Wh/^oC), the resistance of the building envelope (R_{ia}) as 0.00898$^oC/W$ and the window area for which direct solar gains should be accounted for (A_{eff}) is calculated as 10.27m^2 (50% of the total window area to account for the internal window shading).

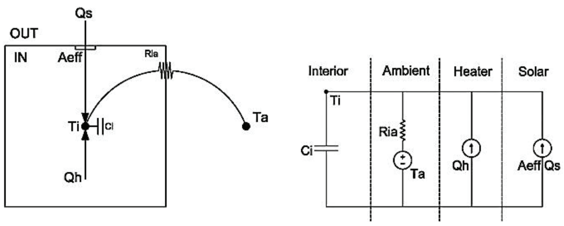
At this stage, some consideration should be given to the degree of confidence one can have in the calculated parameter values. Although accurate in a newer construction or under the experimental conditions at the manufacturing level, the material characteristics taken from the tables of CIBSE Guide A, may vary significantly from the thermal properties of elements of existing houses (especially older houses) mainly due to the material distortion that occurs with time and possible errors in site practice.

Table 2 List of all building structural elements' geometry, R and C values

TK House	Area (m^2)	Volume (m^3)	Proportion:	R-value ($m^{2o}C/W$)	Capacitance ($kWh/^oC$)	Area adjusted R-value ($^oC/W$)	Capacitance ($Wh/^oC$)
Total external wall	178.95	-	-	-	-	-	-
External cavity wall	121.61	34.42	0.58	0.95	11.79	0.008	11788.53
External windows	20.54	1.03	0.10	0.35	0.14	0.017	135.96
External doors	6.00	0.60	0.03	0.33	0.13	0.055	134.40
Roof	30.80	14.52+7.33	0.15	0.25	1.10	0.008	1099.66
Total internal wall	55.64	-	-	-	-	-	-
Internal partition wall only	43.64	5.24	0.51	2.91	0.42	0.067	422.028
Internal doors	12.00	1.20	0.14	0.33	0.27	0.028	268.80
Slab-first floor	29.30	7.33	0.34	1.02	0.49	0.035	491.67
Slab-ground floor	46.39	13.92	1.00	1.20	6.32	0.026	6318.32
					Building envelope to air:	0.009	7013.46
					Internal partitions:	0.050	424.40
					Building envelope to ground:	0.026	6318.32

3.2. 1st order state-space model, adequacy of calculated parameters and goodness of fit

A simple 1st order model describing the dynamics between the building internal temperature T_i and the ambient temperature T_a was developed. The model will be used as the base-case scenario for future exploration of the potential of the method. Figure 2 shows the relevant lumped parameter model where the heat transfer between the indoor and outdoor temperature nodes is taken into account. The differential equation describing the heat transfer processes occurring at the internal air node is given below:

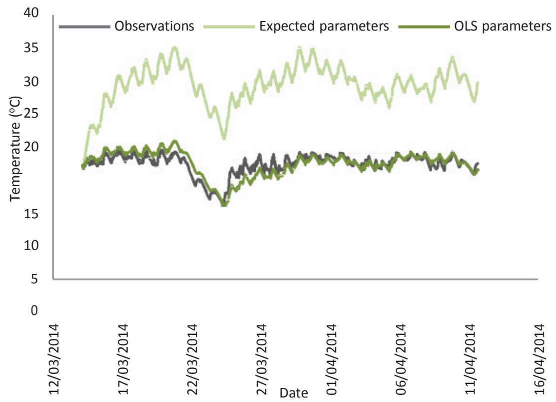


$$dT_{i,pred} = \left[\frac{(T_a - T_i)}{C_i R_{ia}} + \frac{A_{eff} Q_s}{C_i} + \frac{Q_h}{C_i}\right] dt \qquad (1)$$

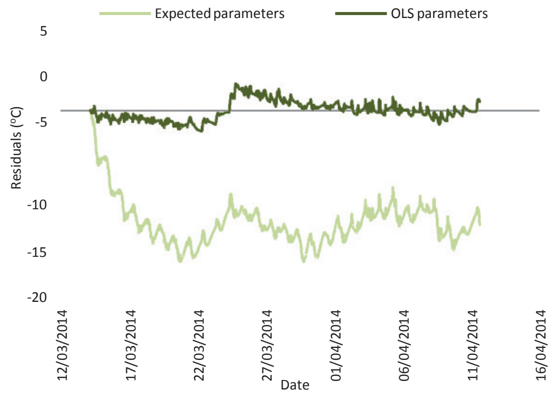
Fig. 2 A 2D representation of the lumped parameter model (left) and the RC-network/electrical analogy (right)

Equation 1 represents a linear deterministic model describing the continuous, dynamic and time invariant heat transfer processes occurring from a building physics perspective. The Ordinary Least Squares (OLS) estimation technique [15] is used to assess the adequacy of the parameter estimates in providing realistic models presenting good fit to the monitored data. First, the initial values of the building thermal parameters as calculated in the previous section are used as the model parameters (R, C and A_{eff} values). An optimization process then calculates new parameters which represent the best fit to the measured data.

Figure 3 (a) presents plots of two calculations of the predicted internal temperature $T_{i,pred}$, using the initial parameter values from Table 2 and the optimized parameters using OLS parameters, against time. The difference in using the two different sets of parameters is apparent. The initial values as calculated at the previous section provide a poor fit to the observed data. The OLS set of parameters present a significantly improved model fit. However, even with the improved parameters the model deviates significantly from the reality. This was expected due to the very basic model that is being explored and is likely to improve as the model complexity is increased to incorporate



(a)



(b)

Fig. 3 (a) Plots of $T_{i,meas}$ and $T_{i,pred}$ for both the expected set of parameters and the OLS parameters; (b) Comparison of the residuals from the two models where $T_{i,pred}$ was calculated using the expected and OLS parameters.

more terms. Figure 3(b) shows the residuals of the two models for a better visual interpretation of the model results. In future work, combined with daily averages of the different variables, this type of graph can be used to inform the model development as new terms are introduced to the model structure.

Table 3 summarises the findings. The optimised parameters changed significantly from the expected values. The capacitance C_i in particular presented the most significant change with an increase of 78% in its original value, with an optimized value of 13390.61 (Wh/°C). The difference in the expected and optimized capacitances is almost equal to the capacitance of the building envelope adjacent to the ground, which was excluded from the calculations of the expected C_i that consisted only of the capacitances of the envelope to air, internal medium and air capacitance. This could be an indication that all capacitances of the building structure should be accounted for at this basic lumped parameter model and/or that the capacitances of the medium, air or envelope to air were underestimated at the initial parameter calculation step. In contrast to the increase in the capacitance optimised values, the resistance and the effective window area values considerably decreased, by -46% and -59% respectively. A poorer resistance was expected due to the assumption made at the calculation step of the R-values that the thermal characteristics of all elements are the same in an old building as those given by manufacturers' literature. The decrease in the effective window area was also anticipated, as a result of the effect of any existing shading effects which obstruct the direct solar gains to the building indoor air node. Additionally, statistical metrics are used to assess the model performance and adequacy. The Residual Sum of Squares (SSE) is used to assess the goodness of fit (the lower the value, the better the model describes the data) and the Root Mean Square Error (RMSE) is the metric used to translate the SSE value into °C of offset from the data, assuming that the exact same pattern exists in the predicted data. It is apparent that the two different sets of parameters can result in two very different model outputs, with a variation in the model fit of over 10°C and a very significant difference in the SSE of less than -99%. Finally, the F-statistic is used to compare the significance of the two models (the higher the value, the more significant the model).

Table 3 Expected parameter values and parameters values providing a better fit

		Parameter value	Difference from expected (%)	Deterministic model		
				Residual sum of squares, SSE	Root mean square error, RMSE (°C)	F-statistic
Expected	Capacitance-C_i (Wh/°C)	7504.06	-	201543.29	12.16	356.48
	R-value-R_{ia} (°C/W)	0.00898	-			
	Effective area-A_{eff} (m^2)	10.27	-			
Improved fit - OLS	Capacitance-C_i (Wh/°C)	13390.61	+78	1404.98	1.02	1684.62
	R-value-R_{ia} (°C/W)	0.00484	-46			
	Effective area-A_{eff} (m^2)	4.26	-59			

4. Conclusions

A methodology is proposed to guide the parameter estimation for a simple thermal model for buildings from a 'building physics' perspective, to ensure that the model will eventually be less dependent on (although driven by) the monitored data, enabling more adequate predictions and pursuing a minimized performance gap. A critical examination of different set of parameter estimates using a simple lumped parameter model and the Ordinary Least Squares estimation technique showed that an improved fit to the measured data can be achieved due to the significant variation in the initial parameter values (up to 78%). This highlights the importance of having a reference set of parameters based on the known physical characteristics of the building. The Ordinary Least Square methodology proved adequate for the exploration of the model development. Finally, plots and metrics of the model residuals can help calibrate the model to achieve a better fit to the monitored data where significant deviations can be seen. Possible applications of the calibrated model include the assessment of the building's thermal performance to inform retrofit decision making and the prediction of energy consumption under variable conditions.

This work is of significant interest to the building physics community for identifying models for domestic buildings with in-home sensors based on real-time data and to the UK government for promoting smart metering as an energy efficiency strategy and for bridging the performance gap. Further work will expand the findings of this paper in a study of 12 UK homes by using the guidance provided to develop models of increased complexity to meet the challenge of using real-time data streams of building performance in modelling existing buildings.

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