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The applicability of Lumped Parameter modelling in houses using in-situ measurements

Vanda Dimitriou*, Steven K. Firth¹, Tarek M. Hassan², Tom Kane³

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

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Abstract

The Lumped Parameter technique is a simplified thermal modelling method, which can be informed by measured operational data whilst allowing for physical interpretation of components and processes. The application of Lumped Parameter methods to the residential sector has been limited, primarily due to the lack of availability of operational data and the complex nature of real-world factors, such as variable occupant behaviours. This work investigates the potential of using the Lumped Parameter technique for modelling the performance of existing houses using high resolution in-situ measurements. Lumped Parameter models are created based on building surveys of eleven existing domestic buildings in the UK. The models are shown to have an average Root Mean Square Error (RMSE) of 1.35°C when compared to measured values of internal air temperature. A parametric analysis of model parameters showed wall thermal resistance, window area, boiler efficiency and infiltration rate as the most significant factors affecting the indoor air temperature calculated values. Model calibration improved the average RMSE to 1.03°C (a 23.7% decrease from initial fit). In conclusion, the Lumped Parameter models were able to realistically represent the majority of the houses, highlighting the technique's potential in informing strategic retrofit decision making across the housing stock.

* Corresponding author. E-mail address: v.dimitriou@lboro.ac.uk, Tel.: +44 1509 223439

¹ E-mail address: s.k.firth@lboro.ac.uk

² E-mail address: t.hassan@lboro.ac.uk

³ E-mail address: t.kane@lboro.ac.uk

Keywords

In-situ data; domestic buildings; lumped parameter models; grey-box modelling; hybrid modelling

1 Introduction

The Lumped Parameter modelling technique, also commonly referred to as Resistance Capacitance (RC) modelling or thermal networks, is the dominant building representation method in simplified dynamic thermal analyses. It has been identified as the most common model for building load prediction, with applications in on-line building optimal control and demand response [1] with some of the earliest studies using this technique appearing in the 1970s [2]. The Lumped Parameter modelling technique is based on the electrical equivalency of Resistances and Capacitances of the thermal networks [3] to represent the building system. It forms the basis of the simplified hourly method used by BS EN ISO 52016-1:2017 [4] for calculating the energy use for space heating and cooling.

The Lumped Parameter technique can be used as a grey-box model, a hybrid model combining the advantages of data-driven and physical modelling. Grey-box models have been found to provide increased accuracy when compared to both black-box (purely data-driven) and white-box (forward) models [5]. Grey-box and, therefore, Lumped Parameter modelling, is informed by operational data from the building, whilst being interpretable from a building physics perspective. As such, the technique is appropriate for use with in-situ measurements, allowing for direct link between the model variables and the building's physical components and between the modelling processes and real heat flows [6].

Lumped Parameter modelling has certain advantages. When compared to more advanced modelling techniques (such as finite difference or response factor used in building simulation software), it requires less detailed model inputs, which is useful for cases where many model inputs are unknown or hard to collect, as is the case in existing buildings (see [7]). When compared to steady state modelling producing monthly results, it provides a simple and comprehensive method for dynamic

thermal modelling and refined building performance output at sub-hourly intervals [8]. The equation-based models can be developed by researchers in their preferred coding language (e.g. using Python or Modelica), which makes them ideal as a prototyping tool and for initial testing of new techniques and building technologies (see [9] and [10]). As the models are much simpler in nature, they run fast, which is useful when a large number of simulation runs are required, as is the case in an optimisation study or a study modelling a large number of buildings at city-scale (see [11]). Finally, the flexibility of the model equations allows to undertake ‘inverse’ modelling enabling the use of different combinations of input datasets. For example, instead of defining temperature setpoints to calculate energy consumption, using energy consumption measurements to calculate internal temperatures (see [12]).

1.1 Previous work using the Lumped Parameter modelling technique for building representation

Lumped Parameter modelling is a well-established methodology for dynamic heat transfer representation of buildings. In the following paragraphs a review of a selection of studies exploring the progression of applications of the Lumped Parameter technique in buildings, since some of the earliest and up to the most recent studies, is provided. More information on the theoretical background of the technique is also available ([13], [14]).

Some of the earliest studies [15] explored low order Lumped Parameter models in various classical problems, providing some of the earliest proofs of the adequacy of the technique in analysing the behaviour of buildings. Further research built on these findings: expanding to higher order models and including additional model inputs (such as solar radiation and occupancy) ([16] [17] [18]); validating the model with multiple tests on a theoretical, analytical and empirical level through comparison of results with analytical calculations and measured operational data [19]; and confirming that by using half-hourly observations of the building’s thermal response, the model parameters could be identified, although some of the parameter values varied significantly from their expected values ([20], [21]).

With the increasing uptake of information technology, research work explored more viable parameter estimation procedures, using linearised models and simplified parameter estimation algorithms, easily applicable to Building Energy Management Systems [22]. More advanced and specialised applications started to appear, such as WinSim [23], a software based on the Lumped Parameter technique, developed to evaluate the effect that the window system has on the building's thermal environment.

Other applications of the Lumped parameter modelling technique at a whole building level include: hybrid applications, exploring different building model representation, combining the Lumped Parameter methodology with detailed physical modelling, such as Conduction Transfer Function [6]; multizonal applications, assessing the adequacy of the technique when applied to multiple zones of a building [24]; and applications in alternative building types, such as thermally activated buildings, with heating systems incorporated into their structure (e.g. underfloor heating) [25]. At the same time, a number of studies focusing on the Lumped Parameter technique narrowed down their scope from a whole building level to specific building components, such as external walls ([26], [27], [28], [29])

One of the main challenges when using the Lumped Parameter technique for building representation, is identifying suitable model architectures that can accurately capture heat dynamics, whilst maintaining relative model simplicity and a low computational cost. The research community has been active in this research area, with studies exploring model complexity to identify important parameters for building system representation ([30], [31], [32]). Despite current advances in computational power and the ability to accommodate increasing model complexities, low order models have proved adequate for building representation, with some of the most recent applications maintaining focus on simpler model architectures ([33], [34]).

1.2 Originality of this work

The originality of the research reported here is the focus on real-life, existing, occupied houses, when investigating the Lumped Parameter technique's applicability. Lumped Parameter modelling

is a technique that has found multiple applications in previous work and is considered an established methodology for building representation. However, in the past, the applicability of the Lumped Parameter modelling technique could not be extensively explored in the domestic context, due to the lack of sensor data from existing domestic building environments, the high variability in domestic occupancy patterns and the complexity implied when compared to non-residential or controlled environments. Previous work on Lumped Parameter modelling has primarily focused on the non-residential sector, controlled experimental buildings and simulations to evaluate the applicability of the technique. Most of the studies focus on non-residential buildings, such as schools and blocks of offices, and experimental buildings ([6], [16], [19], [20], [22], [35], [27]). With simulation software increasing both in capabilities and popularity, more recent studies have resorted to simulated data for model comparison and validation ([36], [37], [24], [38], [39], [40]). Some work has studied the residential sector, however, either the selected houses have been unoccupied, leading to unrealistic representations of the actual conditions, or the results relevant to domestic buildings have been merged with results from non-residential or controlled environments or, in cases, not discussed at all ([17], [41], [31], [32]). In a recent review of data-driven building energy consumption prediction models [42] it was found that only 19% of the studies focused on houses, with the majority of previous work focusing on non-domestic buildings. The study concluded that focusing on data-driven, and in particular grey-box, methods for the residential buildings is imperative in view of the imminent data availability from in-home sensors and the potential savings that could arise from successfully informing policy strategies. This statement is further supported by the latest published statistics in which the domestic sector is shown as the second most energy intensive sector after transport, accounting for 28% of total energy use in the UK in 2017 [43].

Summarising the findings from the review presented above, 77% of previous studies used non-residential, controlled, experimental buildings and simulations to explore the applicability of the Lumped Parameter technique in buildings. The remaining 23% of studies that considered domestic

properties, presented results that were not directly attributable to real-life homes, highlighting the gap in research offering clear insights into one of the most energy and CO₂ intensive sectors, the domestic sector. The aim of the research reported here was to investigate the potential of the Lumped Parameter modelling technique in representing existing houses. A three-node, 2nd order Lumped Parameter model was selected as a well-researched model for building representation in previous studies of non-domestic and experimental buildings. Individual models were created for a sample of 11 domestic buildings in the UK, studied as part of a wider UK Government funded project into the Smart Home concept [44]. The local weather data, whole-house gas and electricity consumption and internal air temperatures recorded over an 8-week time period were used for model validation and calibration. The focus was on the heating season, as heating accounts for most of the fuel consumed in UK domestic buildings. The applicability of the Lumped Parameter modelling technique during unheated seasons was out of the scope of this paper.

The three stages of this study were:

€ Initial model development and validation (section 6.1): Lumped Parameter Models were constructed using analytical methods, building information gathered from building surveys and occupant questionnaires. The models were run using the local weather data and the recorded gas and electricity consumption as model inputs. The models were then validated through comparison of calculated versus measured internal air temperatures.

€ Parametric analysis (section 6.2): To determine which of the model parameters (e.g. wall thermal resistance, window size, boiler efficiency) had the greatest influence on the model output.

€ Model calibration to the measured data (section 6.3): Based on the results of the validation and the parametric analysis, the most impactful model parameters were altered to determine the best fit of the model outputs to the measured data. The effect on the model parameter values of calibrating the models using in-situ data was assessed.

The methods used and the main findings on the applicability of the Lumped Parameter technique to model the internal temperatures of existing domestic buildings are presented and discussed in the following sections.

2 The selected Lumped Parameter model

Based on model architectures from previous work, a 3-Resistance, 2-Capacitance (3R2C) model was selected to represent the heat transfer flows and temperatures in the buildings (Figure 1). The simple two-time constant model has found multiple applications in explorations of the Lumped Parameter technique for building representation over the years and, although alternative model structures have been explored, the two-time constant model is still identified as one of the most popular for building representation ([15], [16], [19], [20], [22], [23], [37], [31], [40], [34], [33]).

The model has three nodes: i) ‘node i’ which is the indoor air node representing the building indoor air and internal mass (including internal partitions and furniture) as a single node with temperature ‘ T_i ’ and thermal capacity ‘ C_i ’; ii) ‘node e’ which is the building envelope node representing all external walls, roofs and floors with temperature ‘ T_e ’ and thermal capacitance ‘ C_e ’; and iii) ‘node a’ which is the external air node representing the external climate with temperature ‘ T_a ’ (this node represents the boundary conditions and has no capacitance). The three resistances of the model are: i) the thermal resistance ‘ R_{ie} ’ (K/W) between the indoor air node and the building envelope node; ii) the thermal resistance ‘ R_{ea} ’ (K/W) between the building envelope node and the external temperature node; iii) the thermal resistance ‘ R_{ia} ’ (K/W) between the indoor air node and the external air node of the building elements with no inertia (i.e. windows and doors). A single node representation for the building envelope has been selected as the simplest feasible building envelope representation. The two envelope resistances ‘ R_{ie} ’ and ‘ R_{ea} ’ directly relate to the total envelope resistance ‘ R_e ’ and the node positioning which is determined by the value of ‘ ϕ ’.

In addition to the three resistances and two capacitances, there are three model parameters: ‘ a ’, the boiler efficiency; ‘ A_w ’ (m²), the window area corrected for frame type, transmittance and orientation, incorporating an adjusting factor for the solar gains to an appropriate angle of incidence;

and 'N' (ac/h), the number of air changes per hour due to infiltration, which is embedded in 'Q_i', the heat loss due to infiltration term.

The model has five input variables to account for weather conditions and heat gains to the indoor air node: i) 'T_a' (°C), the measured external air temperature; ii) 'Q_h' (W), the measured gas consumption at the meter level assuming that all gas consumption contributes to space heating gains, including gas consumption used for purposes other than space heating, such as Domestic Hot Water and cooking; iii) 'Q_e' (W), the measured electricity consumption at the meter level; iv) 'Q_s' (W/m²), the measured average solar irradiance on the horizontal plane; and v) 'Q_i' (W), the heat loss due to infiltration. The building envelope temperature, 'T_i' (°C), is used as the calibration variable, the variable whose measurements need to match with the model predictions.

There are two model output variables: the difference between two time steps (dt) in the indoor air temperature, 'dT_{i,pred}' (°C), which is used for model calibration through comparison with the indoor air 'T_i' measurements; and the difference between two time steps (dt) in the envelope temperature, 'dT_{e,pred}' (°C).

The ordinary differential equations describing the heat transfer processes occurring at the indoor air node and at the building envelope node at a whole house level are given below.

Figure 1 T_iT_eT_a lumped parameter model with Q_h, Q_s, Q_e and Q_i at the T_i node. A two-dimensional representation of the lumped parameter model (left) and the electrical analogy (right)

$$dT_{i,pred} = \left[\frac{(T_e - T_i)}{C_i R_{ie}} + \frac{(T_a - T_i)}{C_i R_{ia}} + \frac{aQ_h}{C_i} + \frac{Q_e}{C_i} + \frac{A_w Q_s}{C_i} + \frac{Q_i}{C_i} \right] dt \quad (1)$$

$$dT_{e,pred} = \left[\frac{(T_i - T_e)}{C_e R_{ie}} + \frac{(T_a - T_e)}{C_e R_{ea}} \right] dt \quad (2)$$

3 In-situ data

The building survey data and high-resolution operational data were collected through a Research Council's UK collaborative project [45] [44]. Monitored data from eleven homes collected over an 8-week time-period during the heating season of 2014 were used for this work.

3.1 Building survey data

Table 1 shows a summary of the building characteristics for the building sample used. The sample of the eleven houses, was dominated by detached dwellings with high floor areas, (128m² on average), which is significantly higher than the national average floor area of 94m² [46]. As the house sample is dominated by older detached dwellings, high overall thermal capacitances and high envelope heat losses were expected. All homes were heated with gas-fired boilers, supplying hot water to wall-mounted room radiators. For the boiler efficiencies the Building Research Establishment's Product Characteristics Database was used. The efficiencies ranged from an estimated 0.910 in the most efficient boiler of House 4 to 0.650 in the least efficient boiler of House 8, with average boiler efficiency across the eleven houses of 0.836. The secondary heating systems have been also reported where applicable.

House number	House type	Construction type	Construction age	Floor area (m ²)	Heating type	Secondary heating	Boiler efficiency ^a
4	Detached	Solid wall with cavity wall extension	1850-1899 (ext. 1996-2002)	231.1	Gas-fired water central heating system with radiators	Open-fire wood-stove	0.910
7	Detached	Cavity wall	1965-1974	93.8		-	0.895
8	Detached	Cavity wall	1965-1974	104.2		Gas fired in two rooms	0.650
9	Detached	Solid wall with cavity wall extension	1919-1944 (ext. post 2002)	134.7		Electric fire	0.890
10	Detached	Solid wall with cavity wall extension	1919-1944 (ext. unknown)	108.3		Gas fired	0.886
11	Detached	Cavity wall	1945-1964	112.9		Gas fired	0.888
13	Detached	Cavity wall	Post 2002	197.6		Gas fired	0.795
15	Semi-Detached	Cavity wall	1965-1974	78.1		Open-fire wood-stove	0.890
17	Detached	Cavity wall	1965-1974	108.9		Gas fired	0.800
18	Detached	Cavity wall (extension too)	1965-1974 (ext. 1981-1990)	138.6		Gas fired	0.800
19	Semi-Detached	Cavity wall	1945-1964	104.1		Open-fire wood-stove	0.800

^a The boiler efficiency for each dwelling was identified using the boiler product code collected during the building survey stage and through the Building Research Establishment's (BRE) Product Characteristics Database

Table 1 Characteristics of the eleven study houses

3.2 Sensor measurements

Table 2 summarises the measured operational data and provides details on the time intervals and equipment used. A combination of Hobo pendant UA-001-64 and Hobo U12-012 sensors manufactured by Onset were used to capture the indoor air temperature. The sensors were placed in each room between waist and head height, away from obstacles, direct solar radiation, currents and heat sources, when possible, and logged air temperatures at 15min or 30min intervals. The sensors had a measurement resolution of 0.03°C, were accurate to $\pm 0.35^\circ\text{C}$ and a measurement range or between 0 to 50°C. Calibration prior to the installation and post study checks of a sub-sample of the sensors found the sensors to be accurate within $\pm 0.4^\circ\text{C}$. Gas consumption was also recorded. For more details on the gas monitoring process see [44].

Electricity consumption was recorded at the meter level in each of the participating houses. For this, Current Cost transmitters and EnviR monitor were used to transmit 6-second measurements of whole house electricity consumption. More information regarding the electricity consumption monitoring at the meter, and at the appliance level, can be found in [47].

For the external air temperature and solar irradiance, weather station measurements were used. The weather station was located within 3km of the homes under study.

Monitoring of:	Equipment used:	Interval	Positioning:
Indoor air temperature (°C)	HOB0 U12 / HOB0 Pendants	30min / 15min	One in each room including hallways, landings, conservatories and utility rooms
Whole-house gas consumption (m³)	Automated meter reader	30min	Whole-house cumulative measurements at meter level
Whole-house electricity consumption (W)	CurrentCost transmitter and EnviR monitor	6sec	Whole-house cumulative measurements at meter level
Weather data including external air temperature (°C) and solar radiation (kW/m²)	-	15min	Campus weather station, within 3km of the dwellings

Table 2 Summary of data collection, specifications and details

4 Calculation of model parameters

An analytical approach has been used, to determine the plausible parameter values based on building physics methods. Table 3 summarises the initial estimates for the model parameters as calculated using information collected through the building survey and the methodologies described below.

Parameter	C _i	C _e	R _e	θ	R _{ie}	R _{ea}	R _{ia}	N	A _w
House	4	14598	24160	0.01013	0.0076	0.00253	0.009	0.962	11.324
	7	6391	4442	0.0232	0.0174	0.0058	0.01907	1.337	6.049
	8	8322	4639	0.0221	0.01657	0.00552	0.01259	1.34	5.084
	9	12048	5311	0.00284	0.00213	0.00071	0.01463	1.211	10.127
	10	8760	5039	0.00443	0.00332	0.00111	0.00637	1.478	13.623
	11	8373	5206	0.01815	0.01361	0.00454	0.01791	1.478	5.657
	13	13867	7966	0.01652	0.01239	0.00413	0.0094	0.959	7.177
	15	5567	3781	0.03449	0.02587	0.00862	0.02032	1.372	5.309
	17	7465	5197	0.00469	0.00351	0.00117	0.02432	1.415	5.157
	18	10385	5642	0.01728	0.01296	0.00432	0.02006	1.524	5.635
	19	7659	4739	0.02043	0.01532	0.00511	0.01419	1.524	9.116

Table 3 Summary of calculated parameter values

A simplified method proposed in BS EN ISO 6946:2017 [48] was used for determining the U-values and, therefore, the resistance ‘R_e’ and ‘R_{ia}’ of the building elements. The Combined Method was used for the calculation of the U-values and CIBSE Guide A [49] was used for the calculation of R.

A method was identified for the calculation of the positioning of the envelope node within the building envelope structure when a single node representation of the building envelope is used. This was needed to calculate the values of resistance between the envelope node and the indoor and external air nodes, ‘R_{ie}’ and ‘R_{ea}’, from the initially calculated ‘R_e’ value. It is expressed by the following equations [16]:

$$R_k^* = \sum_{i=1}^{k-1} (R_i + \frac{R_k}{2}) \quad (3)$$

$$\theta = 1 - \left(\frac{\sum_{k=1}^n C_k R_k^*}{C_e R_e} \right) \quad (4)$$

$$R_{ie} = \theta R_e \quad (5)$$

$$R_{ea} = (1 - \theta) R_e \quad (6)$$

where ‘R_k’ is the resistance between the middle of layer k of the construction and the external air (m²K/W), ‘R_k’ is the resistance of the layer k of the construction (m²K/W), ‘R_i’ is the resistance between layer k of the construction and the external air (m²K/W), R_e is the total resistance of the

building envelope ($\text{m}^2\text{K/W}$), ' C_e ' is the total capacitance of the envelope (Wh/K), ' C_k ' is the capacitance of the layer k (Wh/K), ' R_{ea} ' is the resistance between the envelope node and the indoor air node ($\text{m}^2\text{K/W}$) and ' R_{ie} ' is the resistance between the envelope node and the external air node ($\text{m}^2\text{K/W}$). Due to the uncertainty regarding the different layers of the building envelope components, the same node positioning was assumed for the different houses. Accordingly, a ' $\square$ ' value of 0.75 as calculated for a standard wall construction was used in this study as the initial value for all houses (Table 3).

The heat capacitance was calculated as the summation of the capacitances of each assumed layer based on the proportion of element volume they occupy. The thermal properties for each of the layers were sourced from the respective tables of CIBSE Guide A [49].

The method provided in the UK Standard Assessment Procedure 2012 for calculating the solar gains for openings was used. The average solar irradiance at a horizontal plane (W/m^2) was adjusted by a factor of 0.9 representing the ratio of typical transmittance to that at a normal incidence and a factor of 0.76 for the total solar transmittance of the glazing at normal incidence $g_{\perp}$ (unitless). The opening area ' A ' (m^2) for the building as measured was also adjusted using a frame factor FF of 0.7 (unitless) and a solar access factor ' Z ' of 0.77 (unitless). The factor ' R_{h-inc} ' (unitless) was also calculated for each window and used to convert from horizontal to vertical solar flux for the 8-week period under consideration and this was also incorporated in the calculation of the effective window area for solar gains, ' A_w '. The resulting equation for ' A_w ' is given below [50]:

$$A_w = 0.9 \cdot A \cdot R_{h-inc} \cdot g_{\perp} \cdot FF \cdot Z \quad (7)$$

For the calculation of the infiltration rates the Standard Assessment Procedure 2012 [50] methodology was used allowing for shelter and wind corrections.

According to Table 4.21 from CIBSE Guide A [49] infiltration rates ' N ' for two storey dwellings can range from 0.15ac/h in very airtight constructions and up to 1.00ac/h in very leaky houses. Since there were no specific infiltration data collected during the building survey stage the initial values for ' N ' were assumed to lie within the acceptable range mentioned above, with values varying

273 depending on the dwelling's age band. To calculate the heat losses due to infiltration the equation
 274 below has been used [51]:

$$Q_i = c_p \cdot \rho \cdot \frac{N}{3600} \cdot V \cdot \Delta T_t \quad (8)$$

275 where 'Q_i' is the heat loss due to infiltration (W), 'c_p' is the air specific heat capacity (1000J/kg/K),
 276 'ρ' is the air density (1.2kg/m³), 'N' is the number of air changes per hour due to infiltration (ac/h),
 277 'V' is the volume of the air inside the building (m³) and 'ΔT_t' is the difference between external
 278 and indoor air temperatures (K).

279 **5 Model calibration methods, uncertainty and validation**

280 **5.1 Goodness of fit**

281 To assess how closely to the measured data the model predicts, the goodness of fit of the model
 282 was evaluated across the 8-week time-
 283 period; and (iii)
 284 RMSE, the root mean square error between the predicted by the model values of indoor temperature,
 285 'T_{i,pred}' (°C) and the measurements for indoor air temperature, 'T_{i,meas}' (°C).

286 **5.2 Parametric analysis**

287 Differential parametric analysis on a One-parameter-At-a-Time (OAT) [52] basis was used to
 288 identify the parameters that are most influential on the model's thermal behaviour, by assessing the
 289 impact that changes in each model parameter can have on the model outputs, i.e. the indoor air
 290 temperature 'T_{i,pred}' and the building envelope temperature 'T_e'. Local sensitivity analysis was
 291 chosen as it is a simple approach, with easily interpretable results and low computational costs [53].
 292 This type of analysis is justified as it is able to identify clusters of parameters with significant impact
 293 on the model outputs, where the absolute ranking of parameters in terms of significance is not of
 294 the outmost importance [52], which was the requirement for this work.

295 The exploration began with the expected model parameter values as calculated using analytical
 296 methods. Each parameter value was then modified. In the case of the capacitances, 'C_i' and 'C_e',

the resistances, ‘ R_e ’ and ‘ R_{ia} ’, the infiltration rate and the opening area for solar gains, ‘ A_w ’, the value was varied within a range of -75% and +75% of its original value. In the case of the boiler efficiency ‘ η ’ and the envelope node positioning ‘ ϕ ’, a different approach was selected, as subjecting the parameters to the same relative variation of -75% and +75% would have led to unrealistic, not physically interpretable values for the parameters. For example, varying the boiler efficiency base value of 0.65 by +75% would have resulted in a value of 1.14 (>1), a non-plausible value for heating systems installed in domestic buildings such as the houses explored. Exploring the same deviation across all variables would have resulted in a more uniform parametric analysis, however, maintaining results that are physically interpretable was a priority for this work. To ensure that a range of realistic values was examined, a set of values was selected instead (0.65 to 0.95 for ‘ η ’ and 0.30 to 0.90 for ‘ ϕ ’). Where appropriate these values were informed by data collected through the building surveys (Table 1). Finally, the percentile change in the model’s output ‘ $T_{i,pred}$ ’ mean, standard deviation and RMSE values when compared to using the base value for each parameter and the alternative values explored were calculated.

5.3 Ordinary Least Squares calibration

The Ordinary Least Squares (OLS) method was used to calibrate the models. According to the method of least squares model of best-fit is considered the one that minimises the sum of the squares of the residuals (i.e. Sum of Squared Error, SSE) [54]:

$$\sum_{i=1}^n e_i^2 \quad (9)$$

where e_i is the difference between the dependent variable’s calculated value using the model and the measured operational data at each time step i . For this to be achieved the necessary condition for each of the parameters is [54]:

$$\frac{\partial \sum_{i=1}^n e_i^2}{\partial \text{par}} = 0 \quad (10)$$

The Generalised Reduced Gradient algorithm in MS Excel was selected to minimise the Error Sum of Squares (SSE) at a 0.0001 precision.

Constraints were established for each model parameter, to ensure that calibration to the measured data was achieved, whilst maintaining parameter values that were physically plausible and interpretable. As shown in Table 4, in selecting the model constraints to be used in conjunction with the OLS parameter estimation technique, the empirical values of model parameter uncertainty from [55] were used. In addition, findings from the parametric analysis were used, to establish whether varying a specific parameter was expected to significantly impact the model output and to inform the decision of allowing the respective parameter to vary during the OLS estimation or not.

Parameter	Empirical values of parameter uncertainty	Impact on main model output ¹	Parameter allowed to vary
C_i	12.25%	High on variance	Yes
C_e	12.25%	Very low	No
R_e	30-40%	High on mean	Yes
R_{ia}	30-40%	High on mean	Yes
ac/h	33.33%	High on mean	Yes
A_w	N/A	High on mean	Yes
a	N/A	Medium on mean	Yes
θ	N/A	Very low	No

¹Impact on main model output has been assessed through the parametric analysis of section 6.2

Table 4 Parameter constraints used during constrained optimisation

5.4 Model validation

In this work, the selected model was validated through application to the dwelling sample (11 houses) and comparison with measured data. In addition, the model was validated through comparison of its performance (in terms of resulting RMSE values) against results reported from similar, fairly recent explorations of the technique for an experimental, test building [34]. Results of significance of model parameter values on model output have also been validated, through comparison with studies performing similar sensitivity analyses on Lumped Parameter models [53] and other building energy modelling techniques [52].

6 Results

6.1 Results using parameter estimates based on building physics

The model was found to both over and under predict across the sample of houses (Figure 2). The worst fit was seen in Houses 7 and 19 with constant overpredictions and only a few instances when the model was able to calculate temperatures that related more clearly to the measured air

temperatures. The mean predicted temperature varied between 16.34°C in House 17 and 21.96°C in House 18. The difference in mean air temperature between the measured and predicted ranged from 0.08°C in House 18 and 1.43°C in House 19. The highest standard deviation of 2.511°C was seen in House 18, which presented the highest variability of values across the model output ' $T_{i,pred}$ '. The lowest standard deviation of 1.291°C was presented in House 19. In terms of best model fit, the lowest RMSE value of 0.92 was presented in House 13 and the highest, indicating the worst model fit, was 1.98 in House 10. On average for the 11 houses the difference between measured and calculated mean air temperature was 0.87°C, for the standard deviation was 0.49°C and the average RMSE was 1.35°C.

Although there was no clear indication why the model predictions deviated more significantly, the model seemed to be susceptible to errors when a bigger change occurred in the model inputs. This was observed more clearly in Houses 9, 15, 17 and 18, where the model started to under-predict significantly towards the end of the 8-week time-period, when the external air temperature dropped significantly.

Houses 4, 15 and 19 had secondary heating that used fuel other than gas or electricity from the mains. The model presented a good fit despite the existence of secondary heating in House 4, which could be an indication of secondary heating not being used regularly during the 8-week period under study. In Houses 15 and 19 a less good fit to the measured data was seen, indicating that secondary heating might have been used more frequently, to either partially replace the use of central heating or cover additional heating needs in order to achieve thermal comfort for the occupants. Significant use of secondary heating was indeed observed in House 15, whereas in House 19 this could not be confirmed due to lack of data on secondary heating practices.

Figure 2 $T_{i,\text{meas}}$ (°C) and $T_{i,\text{pred}}$ (°C) for all houses for the whole 8-week time period using equivalent metrics for the measured data

6.2 Parametric analysis

As shown in Table 5, consistently across the 11 houses, changes in the capacitance parameters ' C_i ' and ' C_e ' did not present any significant impact on the mean temperature of indoor air, with a 0.34%-0.17% and 0.28%-0.28% change in the mean temperature when compared to the 0% base value respectively. The resistances ' R_e ' and ' R_{ia} ' presented a more significant impact on the mean indoor air temperature with the lower resistances (-75% from the base value) resulting in -24.34% and -26.08% change in the mean temperature respectively and the higher resistances (+75% from the base value) resulting in an increase of 6.45% and 7.35% in the mean temperature respectively. These findings are in agreement with previous work that identified the impact of U-values, which are very closely related to the resistance values, as more significant than those of thermal mass (capacitance) [52]. Variations in the window area for solar gains presented changes in the mean air temperature ranging between -8.24% and up to 8.24%. This was expected, as in a previous study focusing on assessing significance of parameters on Lumped Parameter models, window dimensions proved to belong amongst the most important parameters affecting model calculated internal air temperatures [53]. The infiltration rate had a significant effect in the mean air temperature that ranged between +31.80% for lower infiltration rates and down to -15.54% for higher infiltration rates. Infiltration has also been proven to be a significant factor in a previous study that identified infiltration as one of the most important parameters influencing building energy modelling output (energy demand) [52]. An increase in the boiler efficiency ' η ' and the envelope node positioning ' ϕ ' resulted in increase in the mean air temperature of 15.50% and a less significant 2.70% respectively. The highest impact on the mean air temperature resulted from changes in the infiltration rate, the boiler efficiency, the thermal resistances and the window area for solar gains. In terms of impact on the standard deviation, the internal medium capacitance ' C_i ' proved to be important with a very significant change of -30.23% for a +75% change in the parameter's base value. This was expected as the capacitance of the building elements, the building's thermal mass, is responsible for controlling the fluctuations in temperature. Other

400 significant parameters proved to be the window area for solar gains with an increase of 19.77% for
401 a +75% change in the parameter's base value and the boiler efficiency with an increase of 12.10%
402 for a 0.95 efficiency value.

403 In terms of impact on the resulting RMSE value, influencing factors were the infiltration rate, the
404 two resistances, ' R_{ia} ' and ' R_e ', and the window area for solar gains.

405

Percentile change in model output's, $T_{i, pred}$, mean μ^1 when compared to using the base value for the parameter	Percentile change in parameter:	-75%	-50%	-25%	(Base value) 0%	25%	50%	75%
	C_i	0.34%	0.17%	0.06%	0.00%	-0.06%	-0.11%	-0.17%
	R_{ia}	-26.08%	-12.23%	-4.71%	0.00%	3.20%	5.55%	7.35%
	C_e	0.28%	0.17%	0.11%	0.00%	-0.11%	-0.17%	-0.28%
	R_e	-24.34%	-11.10%	-4.21%	0.00%	2.86%	4.88%	6.45%
	A_w	-8.24%	-5.50%	-2.75%	0.00%	2.75%	5.50%	8.24%
	ac/h	31.80%	18.06%	7.85%	0.00%	-6.23%	-11.33%	-15.54%
	Values explored for parameter:	Base value 65%	70%	75%	80%	85%	90%	95%
	a	0.00%	2.54%	5.15%	7.75%	10.36%	12.90%	15.50%
	Values explored for parameter:	Base value 0.3	0.4	0.5	0.6	0.7	0.8	0.9
	θ	0.00%	0.75%	1.32%	1.84%	2.24%	2.53%	2.70%
Percentile change in model output's, $T_{i, pred}$, standard deviation σ^2 when compared to using the base value for the parameter	Percentile change in parameter:	-75%	-50%	-25%	(Base value) 0%	25%	50%	75%
	C_i	190.70%	67.44%	22.67%	0.00%	-13.95%	-23.26%	-30.23%
	R_{ia}	17.44%	4.07%	0.58%	0.00%	0.00%	0.58%	1.74%
	C_e	4.07%	2.33%	1.16%	0.00%	-1.16%	-1.74%	-2.91%
	R_e	12.79%	1.74%	0.00%	0.00%	0.58%	1.16%	1.74%
	A_w	-2.33%	-4.07%	-2.91%	0.00%	4.65%	11.63%	19.77%
	ac/h	32.56%	10.47%	1.74%	0.00%	1.16%	3.49%	6.40%
	Values explored for parameter:	Base value 65%	70%	75%	80%	85%	90%	95%
	a	0.00%	0.64%	1.27%	3.18%	5.73%	8.92%	12.10%
	Values explored for parameter:	Base value 0.3	0.4	0.5	0.6	0.7	0.8	0.9
	θ	0.00%	-2.78%	-4.44%	-5.00%	-5.00%	-3.89%	-2.22%
Percentile change in model fit in terms of RMSE ³ when compared to using the base value for the parameter	Percentile change in parameter:	-75%	-50%	-25%	(Base value) 0%	25%	50%	75%
	C_i	141.93%	40.88%	10.79%	0.00%	-4.12%	-5.63%	-6.02%
	R_{ia}	218.49%	58.91%	0.11%	0.00%	15.98%	33.50%	48.95%
	C_e	2.57%	1.60%	0.75%	0.00%	-0.68%	-1.30%	-1.87%
	R_e	235.23%	75.79%	14.79%	0.00%	6.21%	27.63%	50.34%
	A_w	22.06%	3.85%	-3.16%	0.00%	10.95%	28.01%	49.73%
	ac/h	389.07%	188.59%	64.14%	0.00%	9.20%	58.08%	107.35%
	Values explored for parameter:	Base value 65%	70%	75%	80%	85%	90%	95%
	a	0.00%	-5.10%	-8.30%	-9.02%	-6.85%	-2.29%	4.04%
	Values explored for parameter:	Base value 0.3	0.4	0.5	0.6	0.7	0.8	0.9
	θ	0.00%	0.29%	1.21%	2.44%	3.80%	5.21%	6.68%

¹The mean value calculated using the time-series of the predicted indoor air temperature, T_i , after the percentile change (of the first row) or the change of value (indicated in the second and third rows)

²The standard deviation values calculated using the time-series of T_i as explained in footnote 1

³The RMSE values calculated using the time-series of T_i as explained in footnote 1

6.3 Results following model calibration

The final model provided results that sit in between the initial model calculations and the measured data, providing a clear improvement in the initial model fit, whilst maintaining realistic values for the model parameters.

As seen in Figure 3, in most cases, the calibrated model provided results that were closer to the measured values, in terms of both mean and standard deviation. The RMSE values for the calibrated model were also consistently lower than the RMSE values of the initial parameter model. By varying the model parameters within acceptable limits and using the OLS technique, the gap between the model output and the measurements has been substantially reduced. Similarly to the initial model, the final model consistently presents higher variation than the measured values. The same cannot be said for the mean air temperature for which no particular trend can be identified.

Looking at the final model on average for the 11 houses, a very clear improvement from the initial model was seen, with the calibration lowering the average mean temperature by 0.22°C and resulting in a very small error of 0.02°C ($+0.29\%$) from the average mean measured temperature.

The best fit of the final model in terms of mean air temperature was seen in House 17, with an error of $+0.04^{\circ}\text{C}$ from measured mean and the worst fit in House 9, with an error of $+0.16^{\circ}\text{C}$ from measured mean. These results highlight the potential of the model to be used in indoor air assessment applications for which the mean air temperature is an appropriate metric. Although the final model offers a significantly improved representation of the variation in indoor air temperatures than the initial model, a significant difference of 35.52% (0.4°C) was observed between the final model and the measured data for the standard deviation, indicating that the model was less able to predict the half-hourly temperature values exactly. This could be attributed to the simplified nature of the model, with a single node representing the internal environment and a single node representing the building envelope, and the deterministic approach followed. The average RMSE across the eleven houses of the final model was 1.03°C , showing that the model was able to estimate indoor air temperatures within almost 1°C of accuracy on average. In all houses, the reported RMSE

values sit within the range of values reported in applications of the technique in experimental buildings (0.33°C-1. 90°C) [34], validating the model and indicating that the technique presents similar performance in real houses and test buildings.

Figure 3 Comparison of the initial and final model fit in terms of model output mean, standard deviation and RMSE values and in terms of percentile deviation from the measured data

Figure 4 presents the calculated parameter values of the final model, plotted against the initial parameter values. Parameters ‘ C_e ’ and ‘ $\square$ ’ have not been included in the constrained OLS parameter estimation, instead the expected values for the two parameters were used. From the plots it was concluded that the internal medium capacitance ‘ C_i ’ was usually underestimated, reaching the upper limit of allowed variance in most houses. This could be due to the effect of furniture and other thermally massive objects that were inside the houses but were not taken into account when

calculating the expected values for the capacitance ' C_i '. No other parameter was consistently under or over estimated. Most parameters varied around the expected value, as a better fit for the models

Figure 4 Initial and final model parameters across all houses

was pursued. The resistance ' R_{ia} ' was the parameter that remained closer to the expected parameter values across the 11 houses. The boiler efficiency ' η ' reached the upper and lower limits of acceptable values, deviating significantly and consistently from the expected values, indicating that an optimum value might exist outside the range of acceptable values.

7 Discussion

The selected model was based on model structures that have proven successful in previous studies. Although based on previous work, the model proposed here had a new structure, with a different set of parameters and inputs. Each of the model parameters related to a physical property of the existing building. This model was evaluated and validated through comparison with measured data. The combination of data-driven modelling with realistic parameter values is the core principle of grey-box modelling, where physical interpretation of results is a requirement. One of the priorities of this study was to maintain plausible and physically interpretable values for the model parameters, thus ensuring that all modelling work could be related to the actual building envelope performance. Throughout this work the model parameters were assessed against the expected (based on building surveys and guides) values of thermal properties of the building envelope and proved reliable. Local sensitivity of the selected model was performed on a-One-parameter-At-a-Time (OAT) basis, to evaluate the effect of varying a single model parameter, while all other parameters maintained their reference value. Local sensitivity analysis presents a simple, easily interpretable, time-efficient and low-cost method. This method is able to provide insights as to which cluster of parameters significantly affects the model outputs, which was the requirement for the work presented here. However, there are certain limitations, with correlations between model parameters not taken into consideration and uniform probability being assumed for all model parameters. Despite these limitations, local sensitivity analysis methods maintain popularity in building energy modelling [56] and are the first, essential step towards the identification of important parameters. Coupling of parameters through global sensitivity analysis could provide further insights on model sensitivities and could form part of future work.

8 Conclusion and significance

The suitability of the Lumped Parameter modelling technique to represent real-life occupied houses and the potential of using simplified grey-box methods to estimate internal temperatures have been discussed. The main conclusions from this work are:

€ The calculated parameter values using analytical methods and building survey data managed to follow the reference data series quite closely in most cases, with an RMSE of 1.35°C on average across the 11 houses. This was achieved despite the use of total gas consumption measurements at the meter level, which did not disaggregate between space heating, domestic hot water and other uses. In addition, the existence of secondary heating in the houses seemed to affect the model fit in some cases but not consistently across the house sample, which could be an indication of intermittent use of secondary heating in the homes of the study. Even in those cases where use of secondary heating was suspected, the highest RMSE value presented was 1.7°C, which is considered low especially given the deterministic, purely analytical approach followed for calculating the model parameters and the lack of data training in the initial model. Future monitoring studies could more carefully monitor secondary heating and further work could focus on the exploration of the modelling methods used in a non-heating season to enhance the understanding of the potential of simplified models in houses throughout the year.

€ The mean value of indoor air temperature was mostly affected by the external envelope resistance ' R_e ' (-24.34% to 6.45% change in model output), the non-inertia elements (e.g. windows and doors) resistance ' R_{ia} ' (-26.08% to 7.35% change in model output), the window area for solar gains ' A_w ' (up to 19.77% change in model output), boiler efficiency ' η ' (up to 15.50% change in model output) and the infiltration rate ' ac/h ' (+31.80% for lower infiltration rates and down to -15.54% for higher infiltration rates). The swing in the indoor air temperatures was mostly affected by the indoor air and internal elements heat capacitance ' C_i ' (down to -30.23% change in model output), highlighting the need for better

guidance when defining and calculating this parameter. The least significant parameters in terms of goodness of model fit to the measured data proved to be the building envelope heat capacitance ' C_e ' and the envelope node positioning ' φ '.

€ Improved fit to the reference data and realistic parameter values were achieved by applying constraints to the possible parameter values, using constrained OLS, and varying all parameters apart from the building envelope capacitance and building envelope node positioning parameters, ' C_e ' and ' φ '. On average across the eleven houses the final model presented an RMSE of 1.03°C, which compares well to RMSE values ranging between 0.33°C and 1.90°C, reported in similar applications of the technique in experimental buildings [34]. The model's potential in indoor air assessment applications for which the mean air temperature is an appropriate metric was shown. Most parameter values deviated slightly from the expected values, with the exception of the internal medium capacitance ' C_i ', the window area ' A_w ' and the boiler efficiency ' η ' that reached the outer limits of possible values in order to achieve a better fit, indicating that a global optimum value might exist outside the range of acceptable values.

From the findings of this study, the Lumped Parameter modelling technique's potential as a non-invasive method for assessing building performance is highlighted. The use of modelling methods informed by in-situ data helps provide a realistic representation of houses in real-world settings. This knowledge contributes significantly in the assessment of individual buildings, as it helps close the gap between modelled and reported performance. Using models that are representative of real houses, in-depth exploration for each building could help inform better control and operation practices and influence behavioural changes to reduce energy consumption. The use of models closely resembling real operational conditions can form the basis of more accurate forecasting models of internal conditions, energy consumption and resulting CO₂ emissions, with potential applications in model predictive control, fault detection, energy performance and thermal comfort prediction.

The use of Lumped Parameter models to describe real-life domestic building systems may reduce the need for extensive building surveys, resulting in a cost-effective and time-efficient approach to modelling existing buildings. Readily available information, such as the information included in the Energy Performance Certificates (EPCs), could also be used as a starting base to inform the inputs needed to develop the models. Furthermore, it is expected that increasing amounts of operational data will be collected from the homes through network connected sensors (such as smart home equipment and smart meters). These data-streams could also inform the model development, allowing for a non-intrusive approach to building energy modelling, by keeping the disruption of the occupants to a minimum. The resulting simplified and streamlined approach provides the opportunity to expand modelling from an individual building level to a wider neighbourhood or urban level. Such tools could be used by research bodies and policy makers to explore retrofitting and renewable energy integration scenarios, to identify best solutions for CO₂ emissions reduction and fuel poverty alleviation, by assessing possible impact across the nation's housing stock and informing decision making at a strategic level.

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