DEVELOPING SUITABLE THERMAL MODELS FOR DOMESTIC BUILDINGS WITH SMART HOME EQUIPMENT

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ABSTRACT

Smart Home controls are part of a Smart Home system and allow remote and automated control of heating systems. The key research question is: with the rapid advancement of new wireless and networked control products, which thermal modelling techniques are able to best make use of the real-time performance data arising from in-home sensors and predict the impact of using advanced controls to reduce energy demand and maximise comfort? As part of identifying suitable modelling approaches for Smart Homes, a lumped parameter model which builds on the work done by Bacher and Madsen (2011) using a data-driven "Grey box" model has been developed. The potential for using the measured data and the impacts of advanced controls for this modelling technique are discussed.

INTRODUCTION

In the battle against human-induced Global Warming, the United Nations established the Kyoto Protocol, setting internationally binding Green House Gas (GHG) emission reduction targets. The current UK legislation is set by the Climate Change Act 2008 (Act C.C., 2008) and is consistent with the pledges within the Kyoto Protocol as it requires a 34 per cent cut in the 1990 emissions levels by 2020. In addition the Act sets 'The target for 2050' by when the UK is legally bound to achieve a target of at least 80 per cent reduction on the emissions of 1990, placing the UK at the forefront of the battle against global warming. One of the main areas that the Carbon Plan focuses on, due to the large potential in energy savings that exists, is the UK built environment. Heating and electricity consumption in the housing stock is responsible for almost 25 per cent of the UK's GHG emissions and for 40 per cent of the total energy usage (HM Government, 2011). According to the 'UK Housing Energy Fact File', 61.3 per cent of the energy consumed by the UK households serves solely for space heating (DECC, 2012). Domestic heating controls come into play to help match the household's heat demand (and consequently the fuel used) with the heat actually needed. By allowing the heating system to operate only when and where required and to the minimum acceptable in terms of thermal comfort temperature, good practice of heating controls leads to maximised comfort and minimised energy consumption (Carbon Trust, 2011).

The importance of domestic heating controls is magnified with the rapid advancement of new products (e.g. Smart Home controls as shown in **Figure 1**) that allow for easier and more direct control over heating. Promising new features such as increased speed of response, intelligence, automation, versatility and customisation can help achieve a sustainable balance between energy demand and energy usage.

The aim of this paper is to report on findings from on-going research work to develop suitable performance models and simulation methods for domestic buildings with Smart Home controls. Smart Home controls are part of a Smart Home system and allow remote and automated control of heating systems, lights and appliances. The key research question is: with the rapid advancement of new wireless and networked control products, which thermal modelling techniques are able to best make use of the real-time performance data arising from in-home sensors and predict the impact of using advanced controls to reduce energy demand and maximise comfort? Smart Home systems, including

__Figure 1__ Example of advanced heating controls in a Smart Home. The pictures included have been sourced from RWE SmartHomes http://www.rwe-smarthome.de/web/cms/en/448330/smarthome/

devices such as wireless Thermostatic Radiator Valves, wireless room thermostats, occupancy sensors and window-door opening sensors, can now provide detailed measured data and insights on building performance and occupants' use of heating systems, through frequent readings of air temperature, humidity levels, occupancy and many other performance variables. Smart Home controls can also provide a wide variety of possible control options to households, including personalised schedules and remote access.

There are two distinct parts forming the research methodology. Firstly, a wide academic literature review is conducted on the most appropriate modelling methods for domestic buildings which are equipped with advanced controls and on real-world measured data-driven modelling methods. Secondly, a case study of a UK domestic building equipped with Smart Home technology is presented. In this Smart Home, measured operational data from a range of in-home sensors have been collected. As part of identifying suitable modelling approaches for Smart Homes, a lumped parameter model, which builds on the work done by Bacher and Madsen (2011), using a data-driven "grey box" model is explored. Finally, the potential for using the measured data and for modelling the impacts of advanced controls is discussed.

LITERATURE REVIEW

There are a variety of available methods for modelling the energy use in buildings. The selection of an adequate technique mainly depends on the availability of input data and the required outputs. For example, high-resolution temperature measurements are necessary for evaluating the impact of a building's thermal insulation. On the other hand, generalised assumptions for the thermal conditions in the houses (such as the BREDEM model specified internal temperatures) may suffice for the purposes of a simple energy rating. In this paper, appropriate modelling techniques are identified for making the most out of the real-time performance data arising from in-home sensors in order to predict the impact of using advanced controls to reduce energy demand and maximise comfort in homes.

One of the early attempts to categorise modelling techniques was done by Rabl (1988) in his overview of methods for dynamic analysis of measured data.

Table 1 *Methods for analysis of measured energy use by Rabl (1988)*

Methods for thermal analysis of buildings (Rabl, 1988)			
a) Steady State methods	**Forward**	**Inverse**	**Comments**
Degree day method [ASHRAE 1985]	*		The simplest. Based on fixed reference temperature 18.3 °C. Can go quite wrong for commercial or super-insulated buildings.
Variable base degree day method [ASHRAE 1985]	*		Variable reference temperature. Can be good approximation for annual consumption.
Bin method [ASHRAE 1985]	*		Input: hours in each 2.8 C (5 F) bin of ambient temperature. More flexible than variable base degree day method: can model temperature dependent features, weekends etc.
PRISM [Fels 1986]		*	Needs data for energy use (several periods/year) and for daily average ambient (no T_{int}). Finds reference temperature and heat loss coefficient divided by heater efficiency. Best for weather correction.
ASHRAE TC 4.7	*		Modified bin methods with cooling load factors etc. to account for some transient effects and determine peak loads.
b) Dynamic methods	**Forward**	**Inverse**	**Comments**
Thermal network [Sonderegger 1977]	*	*	In forward direction no limit on complexity of network. For inverse problem network must be simple with equivalent thermal characteristics
Response factor series [Stephenson and Mitalas 1967]	*		Tabulated results for building components [ASHRAE 1985] useful for calculation of peak loads
Fourier analysis [Shurcliff 1984]	*	*	Calculates response to sinusoidal (constant plus diurnal) input. Can be combined with calculation in time domain.
ARMA model [Subbarao 1985]		*	Coefficients lack direct physical interpretation but that can be provided with time constants and admittances.
BEVA [Subbarao 1985]	*	*	Combination ARMA + Fourier methods. Loads calculated in time domain.
Modal analysis [Bacot et al. 1984]	*	*	Diagonalisation of the differential equations for the building. For inverse problem building is approximated by small number modes.
Differential equation [Eq. 2.10 Rabl 1988]		*	Approximates building by linear differential equations Order and coefficients adjusted by data. Can be integrated analytically. Much flexibility for fitting, prediction and control.
Computer simulation [e.g. DOE 2.1, BLAST]	*	*	Very detailed. Potentially the most accurate method. Also models HVAC equipment. Requires much expertise and labor for coding the input.
Hybrid methods	*	*	Computer simulation plus differential equations. To be developed.

***Table 2** Comparison between "white", "black" and "grey box" methods according to Foucquier et al. (2013)*

Comparison between "white", "black" and "grey box" techniques.			
Methods	**Building geometry**	**Training data**	**Physical interpretation**
Physical or ''white box'' method	A detailed description of the building geometry is required	No training data are required	Results can be interpreted in physical terms
Statistical or ''black box'' method	A detailed description of the geometry is not required	A large amount of training data collected over an exhaustive period of time is required	There are several difficulties to interpret results in physical terms
Hybrid or ''grey box'' method	A rough description of the building geometry is enough	A small amount of training data collected over a short period of time is required	Results can be interpreted in physical terms

As shown in **Table 1**, Rabl categorises the available methods into steady state and dynamic methods and comments on the applicability and limitations of each modelling technique. Steady state methods differ from dynamic methods in that constant boundary conditions are assumed over time and usually disregard the heat stored within the building elements, thus offering the advantage of simpler calculating procedures and decreased computing time. In the second column of the table it is stated whether each method would be appropriate for solving forward and/or inverse problems. The difference between forward (or else direct) and inverse (or else parameter estimation) problems has been well explained by Beck and Woodbury (1998). Whilst forward problems deal with known characteristics (in the case of homes, building characteristics, heat transfer functions etc.) and compute the dependent variables (i.e. thermal loads), inverse problems rely on both prior physical knowledge of the model (i.e. building envelope characteristics) and measured data (i.e. measured temperatures, occupancy) to determine some basic parameters or functions that are not known. Since this early work, multiple computer simulation programs are available for performing steady state and dynamic analysis of the building performance. According to Van der Veken et al. (2004) and their comparison of simulation programs, both steady state and dynamic models can be equally useful for building energy assessment. This conclusion was drawn by the fact that the steady state simulation software EPW (the Flemish Energy Performance Regulation calculation method) calculated a net energy demand that deviated by only an insignificant 4 per cent from the equivalent transient calculations of the dynamic models TRNSYS (more information can be found at http://www.trnsys.com) and ESP-r (http://www.esru.strath.ac.uk/Programs/ESP-r.htm).

More recent work by Foucquier et al. (2013) reviews the state of the art in modelling techniques for building energy performance prediction. As shown in **Table 2** the modelling methods are distinctly divided into three categories; the "white box" method, the "black box" method and a combination of the two, the "grey box" method. "White box" or physical methods employ heat transfer equations to predict the energy performance of a building. The solution of the equations heavily depends on the fine description of the building model and thus "white box" models are best suited for newly designed buildings where most of the thermal properties are known. In contrast to physical models "black box" methods use mainly statistical methods and machine learning techniques to describe the behaviour of the building as a system. Since "black box" methods disregard the physical features of the building (its geometry and thermal characteristics) the interpretation of the results in physical terms is not always feasible and generalised conclusions valid for buildings other than the specified case study cannot be drawn. Lastly, a hybrid of the two above methods, the "grey box" method, can bridge the gap between limited physical knowledge of the building and limited measured data. "Grey box" methods use basic prior knowledge of the building characteristics combined with a reasonable amount of measured data to estimate the missing physical parameters and best describe the building thermal performance.

In most previous applications of modelling the energy use and thermal performance of dwellings the "white box" method has been used. This has been necessary as measuring and collecting in-situ performance data has been both expensive and time consuming, due to the sensors required and the efforts of data collection. One such example comes from Firth et al. (2010) where a Community Domestic Energy Model (CDEM) has been developed in order to predict the CO_2 emissions of the existing English housing stock.

However, recent technological advances and policy measures in Smart Meters and Smart Home equipment mean that a "grey box" approach to modelling dwelling energy use and thermal performance may become a viable option on a large scale. Homes equipped with Smart technology will record numerous performance data, and so the modelling approach falls into the category of an inverse problem and its solution requires a "grey box" modelling technique. The following section focuses on the literature related to this topic and is dedicated to case studies using "grey" methods.

"Grey box" model application review

The "grey box" method is a popular technique that has found application in many different types of building energy studies, an extensive review of which has been conducted by Foucquier et al. (2013). However, some of the applications mentioned in this paper instead of using monitored data from existing buildings use the output of building simulation software as the input dataset for the statistical analysis. As the data come from a simulated environment, the complexity and uncertainty of the model can increase. This paper will only focus on case studies where actual measured data from the buildings have been collected.

In their paper on identifying suitable models for the heat dynamics of buildings Bacher and Madsen (2011) use RC-network models of increasing complexity to represent the different parts of the building and likelihood ratio tests to determine the performance of each model. Through this method of evaluation an appropriate model including only the most important parameters is fitted to the heat dynamics of the building.

When parameter estimation is needed genetic algorithms are usually employed as the statistical tool of the “grey box” method. One such example comes from Wang and Xu (2005) in their report on parameter estimation of internal thermal mass of building dynamic models. Using the lumped parameter method and operational data from the case study they focused on developing a genetic algorithm capable of estimating the internal thermal parameters of the building network.

Another paper comes from Andersen et al. (2000) where a lumped parameter model is formulated as a system of stochastic differential equations and statistical methods are implemented for parameter estimation. The interesting addition of this work is the introduction of submodels for the radiator power and the solar radiation and the conclusion that radiator power should be modelled separately due to the different excitation of the input variables.

As observed in the literature review, lumped parameter models are the dominant physical modelling method selected in the field of building energy modelling with “grey box” techniques. Despite their limited accuracy, the reduced complexity and short computational time, they often outperform the complex building simulation approaches that require excessive amounts of effort and time, especially when multiple iterations are necessitated. Work on improving the lumped parameter models to account for more complex buildings is ongoing. One such example is the work on multi-layered constructions by Gonzalez et al. (2013) where the Dominant Layer Model is presented. Here a set of simple rules can be followed to ensure that all layers are taken into account and that the simplified lumped parameter method can result in more accurate calculations.

CASE STUDY: SMART HOME IN LOUGHBOROUGH

An initial exploration of the selected modelling method was realised for a typical UK domestic building. The building was occupied by a family of five and thus the applicability of the modelling methods to real-life households was investigated. In contrast to experimental buildings and laboratory environments where most of the parameters can be controlled and adapted, this study explores the uncertainties involved in real domestic buildings where occupant behaviours and heating practices play a significant role in the total energy performance. In this section a description of the study building is given, followed by a description of the measurement equipment and the data collected.

House description

The house is a two-storey traditional detached house built in 1930 and is situated in Loughborough, UK. In **Figure 2** the floorplans of the house are given along with the openings and radiator placement. The groundfloor consists of an entrance hallway, a living room, a small conservatory and a kitchen and the first floor has two bedrooms and a family bathroom.

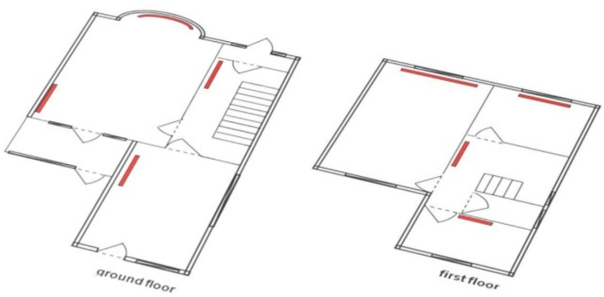

Figure 2 *Floorplans of groundfloor (left) and first floor (right) with radiator positioning (in red)*

The total floor area amounts to approximately $105m^2$. The external walls are 275mm thick, consisting of a masonry inner leaf with a plaster finish, brickwork on the outside and cavity with insulation that has been introduced after the original construction and its properties and treatment remain unknown. The floor to ceiling height of the groundfloor is 2.65m and 2.55m on the first floor. The majority of window, door openings are made of UPVC and are double-glazed. The floors are mainly of suspended timber construction. The internal partitions are mainly solid or timber framed.

Measurement equipment and data collected

The property was chosen to offer easy access and a friendly environment as extensive research was necessitated. The case study lasted for a period of

***Table 3** Summary of data collection, specifications and details*

	Monitoring of:	Positioning:	Equipment used:	Interval (min)	Number of sensors on each element:
Data from standalone monitoring equipment	Internal air temperature (°C)	Living room/placed on shelf	HOBO U12	30	1
		2 Bedrooms/placed on shelf	HOBO U12	30	1
		Kitchen/placed on shelf	HOBO U12	30	1
		Hallway/placed on shelf	HOBO Pendant	30	1
		Conservatory/placed on shelf	HOBO Pendant	30	1
		Bathroom/placed on shelf	HOBO U12	30	1
	Surface temperature (°C)	One on each radiator/6 radiators	ibutton	30	1
		Multiple on 2 radiators	ibuttons	30	5
		Entrance hall/external wall	ibutton	30	1
		Kitchen/external wall	ibutton	30	1
		Living room/internal wall	ibutton	30	1
Data from Smart Home equipment	Thermostatic Radiator Valves measurements (°C)	On the supply pipe of each radiator	Smart Home sensor Danfoss (http://heating.danfoss.com/)	1	1
	Internal air temperature (°C)	Living room and hallway	Smart Home sensor Danfoss (http://heating.danfoss.com/)	1	1
	Gas consumption (m^3)	Whole house	Automated meter reader	30	1

one month. **Table 3** summarises the measured data and provides further details on the time intervals and equipment used. **Figure 3** demonstrates the HOBO data loggers[1] (HOBO pendants and U12s) and 1-wire i-button[2] temperature sensors that were used for data collection.

***Figure 3** HOBO pendants for room air temperature, HOBO U12 for room air temperature, illuminance and humidity levels and 1-wire ibuttons for surface temperature monitoring.*

The monitoring included multiple components of the heating system and of the building envelope. Heat-emitter temperatures were collected from multiple points of two of the radiators to provide an accurate approximation of the surface temperature. The surface temperature of all the remaining heat emitters was collected from a single point of their surface. Monitoring equipment was also attached to both internal and external walls. The monitoring equipment was mounted on the wall-side surface of the radiators and duct tape was used for the attachment to the surface. Hobo data loggers were placed at a head high level away from obstacles, direct solar radiation, currents and heat sources when possible. Lastly, an external company was employed to monitor the whole house gas consumption at a 30 minute interval.

"Grey box" model application

This section describes the initial exploration of a "grey box" model suitable for the building under study. The methodology described by Bacher and Madsen (2011) is followed for identifying a suitable model for the heat dynamics of this particular building. The statistical tool R, CTSM-R by R Core team (2013) was used. The detailed measurements as described in the previous section combined with some basic knowledge of the building's geometry and thermal properties were used to form a learning model with a physical approach. **Table 4** lists the available input data that were collected throughout November 2013. The data are 30min-interval averaged values of readings coming from the whole building.

***Table 4** Available input datasets*

Ti (°C)	the indoor temperature as measured by the Hobo sensors
Tt (°C)	internal air temperature readings from the Smart Home TRVs
Th (°C)	the surface temperature of the heat emitters (radiators)
Tm (°C)	the average from the internal and external surface temperature readings of an internal wall
Te (°C)	the average from the internal and external surface temperature readings of two external walls
Ta (°C)	the ambient temperature as measured by an on-campus weather station in very close proximity to the building's location
Ph (kWh)	the gas consumption originally measured in m^3 (conversion factor used for Loughborough, sourced from http://www.energylinx.co.uk; $1m^3$ equals to 11.363kWh)
Ps (kW/m^2)	the global solar irradiance from the weather station

[1] More information and the product specifications can be found at http://www.onsetcomp.com/

[2] More information and the product specifications can be found at http://www.maximintegrated.com/

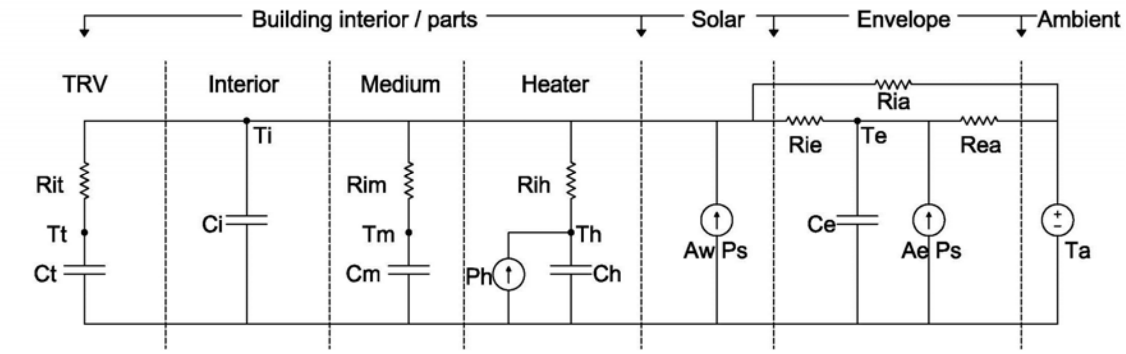

***Figure 4** Lumped parameter full model*

As an addition to the model proposed by Bacher, the model used for this study is extended to account for the Smart Home Thermostatic Radiator Valves mounted on each radiator of the building. The full lumped parameter model is demonstrated in **Figure 4**. It includes seven parts, each representing one of the building's elements that take part in the heat flow process and one of the state variables. The part at the left end of the model represents the TRV temperature (Tt), thermal resistance (Rit) and heat capacitance (Ct).

The stochastic differential equations describing the heat flow within the building as determined by the lumped parameter model, as well as the observation equation that links the measurement to the measurement error are listed below:

$$dT_i = \begin{bmatrix} \frac{(T_t - T_i)}{C_i R_{it}} + \frac{(T_m - T_i)}{C_i R_{im}} + \frac{(T_h - T_i)}{C_i R_{ih}} \\ + \frac{(T_e - T_i)}{C_i R_{ie}} + \frac{(T_a - T_i)}{C_i R_{ia}} + \frac{A_W P_S}{C_i} \end{bmatrix} dt + \sigma_i d\omega_i \qquad (1)$$

$$dT_t = \frac{(T_i - T_t)}{C_t R_{it}} dt + \sigma_t d\omega_t \qquad (2)$$

$$dT_m = \frac{(T_i - T_m)}{C_m R_{im}} dt + \sigma_m d\omega_m \qquad (3)$$

$$dT_h = \left[\frac{(T_i - T_h)}{C_h R_{ih}} + \frac{P_h}{C_h}\right] dt + \sigma_h d\omega_h \qquad (4)$$

$$dT_e = \left[\frac{(T_i - T_e)}{C_e R_{ie}} + \frac{(T_a - T_e)}{C_e R_{ea}} + \frac{A_e P_S}{C_e}\right] dt + \sigma_e d\omega_e \qquad (5)$$

Observation equation

$$Y_k = T_{s,k} + e_k \qquad (6)$$

The first term of the differential equations (1 to 5) multiplied with dt is the deterministic part and the second term is the stochastic part with a system noise process $d\omega$. In each equation C stands for the heat capacity (in $\frac{kWh}{^oC}$) and R for the thermal resistance (in $\frac{m^2\ ^oC}{W}$).

DISCUSSION AND RESULT ANALYSIS

It is important that the model's performance is evaluated and validated and that the adequacy of the "grey box" method on this or any other similar case is justified.

When evaluating the performance of the model both statistical and physical tests need to be performed to make sure that the model conforms to the statistical assumptions and that the results are realistic.

Figure 5 presents the auto-correlation function (ACF) and the cumulated periodogram (CP) of the residuals. Although the CP presents a good fit and the residuals could be interpreted as white noise, the ACF shows that the model could be following a periodic signal. The heat dynamics are not represented very accurately and this is an indication that the model could be improved.

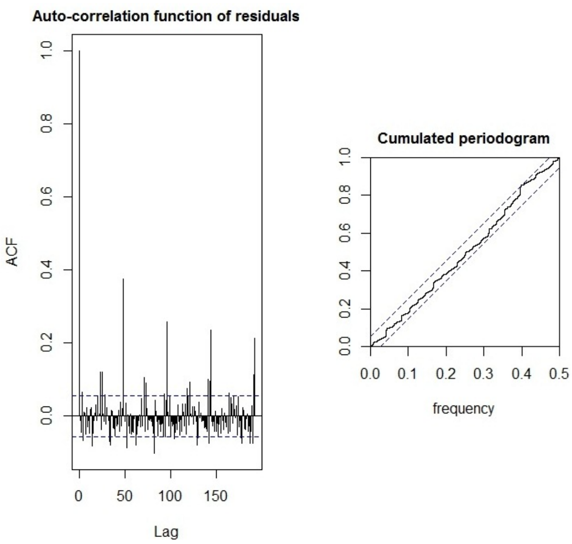

***Figure 5** Auto-correlation function (ACF) left, cumulated periodogram (CP) right*

By plotting the residuals against the gas consumption data in **Figure 6** a correlation can be seen between the peaks of the two diagrams. This was expected as the whole house gas consumption was assumed to serve solely for space heating. The need for disaggregating the gas used for space heating from the gas used for domestic hot water and cooking is highlighted. It should also be noted that the heat emitter surface temperature follows a very similar pattern to the gas consumption and an interaction between the residuals and T_h should also be considered.

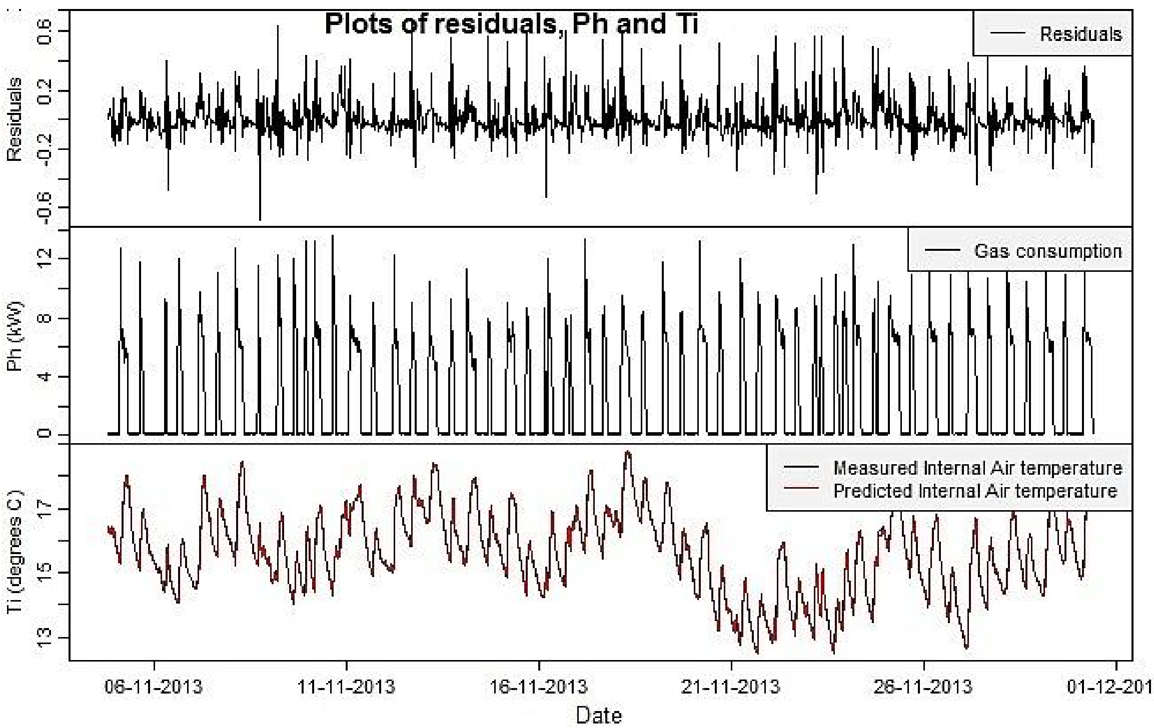

Figure 6 *Plots of residuals against gas consumption data (P_h). Measured (in black) and predicted (in red) internal air temperatures are presented in the last diagram.*

From a physical point of view some of the estimated parameters of the building can be checked against empirical values. The thermal resistance of the building envelope is estimated at 0.87 $\frac{m^2K}{W}$ which is a very reasonable value for an insulated cavity wall, considering that a 1930's cavity wall[3] with two brick leaves has a U-value of 1.8 $\frac{W}{m^2K}$ which equals to an R-value 0.56 $\frac{m^2K}{W}$. The effective window area of the building (i.e.the window area through which solar radiation enters the building) was estimated at 4m^2 which seems quite low compared to a total area of 25m^2 of openings that can be identified through the building plans. This low value could be due to the orientation of the house and obstructs from neighbouring buildings and/or plantation. The effective area of the envelope (i.e. the area affected by the global solar radiation) was calculated at 276 m^2, which exceeds the calculated total external area of the house (approximately 220m^2). Finally, the heat capacity of the external wall was calculated at 0.56 $\frac{kWh}{^oC}$. The estimated values show that although the model describes the study building quite accurately, further improvements could be made so that the parameters are closer to the real values.

There is scope here for identifying the potential of this model. By extending the lumped parameter model to include even more variables that have not been taken into account such as ventilation and the implied heat losses, more realistic results could be achieved. On the other hand, taking a closer look at a single room of the house could offer a higher resolution insight and more direct and precise findings regarding the heat flows that could more easily be tested against physical knowledge.

CONCLUSION

This paper presents an initial exploration of the applicability of a "grey box" model in a real-life domestic Smart Home. The demonstrated model is not a finalised model. However, the results provide insights into identifying the correct path for further research on appropriate modelling techniques for measured data arising from Smart Home equipment.

Through literature review amongst the various modelling techniques that are available for the energy performance of buildings, "grey box" techniques have been identified as the most appropriate method for using high-resolution data.

The application of a "grey box" model to the case study has shown that a typical domestic UK building equipped with Smart Home equipment (or any other equipment that can offer similar datasets of monitored temperatures) can be modelled effectively by using this method. This statistically and physically validated model can offer insight into the heat flows within the building and the heating system.

Finally, combined with real-time Smart Home data the model could potentially offer valuable insights on the heating practices and possible retrofit options to lower energy demand.

[3] 1930's cavity wall U-value has been sourced from http://www.uwe.port.ac.uk/hi4web/insulation%20calcs/section1.htm.

NOMENCLATURE

T_k, the temperature measured in °C, k refers to the part of the building where $k= i$ (internal air), t (TRV), h (heat emitter), m (internal walls), e (building envelope), a (ambient air);

C_k, the heat capacity of the part k of the building in $\frac{kWh}{^oC}$;

R_{ik}, thermal resistance between the internal air and the part k of the building in $\frac{m^2\,^oC}{W}$;

R_{ea}, thermal resistance between the ambient air and the building envelope in $\frac{m^2\,^oC}{W}$;

A_w, effective window area for solar gains to the internal air in m^2;

A_s, effective building envelope area for solar gains to the envelope in m^2

σ_κ^2, variance of the Wiener process, again k stands for the part of the building

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