ELSEVIER
CrossMark
Available online at www.sciencedirect.com
ScienceDirect
Energy Procedia 78 (2015) 2844 – 2850
Energy Procedia

6th International Building Physics Conference, IBPC 2015

Measured internal temperatures in UK homes – A time series analysis and modelling approach

Argyris Oraiopoulos[a],*, Tom Kane[a], Steven K Firth[a], Kevin J Lomas[a]

[a]*Building Energy Research Group (BERG), London-Loughborough (LoLo) Centre for Doctoral Training on Energy Demand, School of Civil and Building Engineering, Loughborough University, Loughborough, LE11 3TU, UK*

Abstract

This paper presents an analysis of internal air temperatures measured hourly in the living rooms of 230 domestic buildings in the city of Leicester, UK. Time series analysis is used to identify the mechanisms that shape room temperatures, during the summertime period of July and August, in rooms that are neither mechanically heated nor cooled, and to develop empirical models of room temperatures for use in predicting future temperatures based on past measured values and on future weather conditions. Such models can enable overheating risk alerts for homeowners and public authorities to be more accurately estimated and targeted.

Peer-review under responsibility of the CENTRO CONGRESSI INTERNAZIONALE SRL

Keywords: Houses; Indoor Temperatures; Time Series Analysis; Overheating

1. Introduction

As global temperatures rise and the climate becomes more unstable, heatwaves will be a more common phenomenon [1]. This could result in an increase of energy consumption in UK homes during summer periods due to a higher demand for cooling, but it could also have a substantial impact on heat related morbidity and mortality rates and produce a series of challenges for the emergency services and the national health system [2]. Overheating risk in domestic buildings is often predicted using modelling techniques based on assumptions of heat gains, heat losses and heat storage [3, 4]. Often dynamic thermal simulation software is used in which the modeler is required to decide a number of input assumptions upon which the result is depended. These assumptions often lead to modelling errors and reduce confidence in the results. Recent large-scale data collection studies allow empirical approaches based on measurements alone. Such methods could base the prediction of internal temperatures in dwellings, on previously recorded internal temperatures and external climate data.

Time series analysis has been successfully used in fields such as economics, geophysics, control engineering and meteorology to describe, explain, predict and control processes [5]. Time series data are not simply data collected over time; there has to exist some form of ordering. A definition is given by Bloomfield [6], "*A collection of numerical observations arranged in natural order with each observation associated with a particular instant of time or interval of the time which provides the ordering*

* Corresponding author. Tel.: +44 1509 228540 ; fax: +44 1509 223980.
E-mail address: a.oraiopoulos@lboro.ac.uk

Peer-review under responsibility of the CENTRO CONGRESSI INTERNAZIONALE SRL
doi:10.1016/j.egypro.2015.11.645

would qualify as time series data". The analysis of time series data can be done either in the time domain, where the data are described in terms of the statistical relationships between observations at different times or in the frequency domain, where the fluctuations in one or more series are described in terms of sinusoidal behavior at various frequencies [7].

The aim of the research presented in this paper is to apply the time series analysis method in the field of building physics and more specifically to room temperature data. The study is based on time domain analysis and within that there are three approaches to modelling the behaviour of a series; the smoothing methods, the ordinary least squares models and the stochastic models. Such models have been used to predict thermal loads in homes [8, 9] and thermal conditions in hospital wards [10]. This novel approach is used to explore the mechanisms of the formation of such data series and to develop statistical models that allow the prediction of future temperatures based on past measured values and external climate data.

The application of these statistical models, could lead to the provision of tailored advice to occupants on how and when to act in order to reduce indoor temperatures during hot summer conditions. It could also allow timely information to those caring for the elderly and infirmed in order to prevent adverse health impacts due to increased temperatures in enclosed spaces. By applying an empirical predictive model to national datasets, it can provide significant insights for the developments of future policies in mitigating overheating in homes across the country and allow for a more detailed plan to be issued in the event of a heatwave. Finally, with the aid of the latest developments in generating future external weather data for the 2030s, 2050s and 2080s [11], at-risk households can be supplied with information on how to reduce the risk of overheating in the future.

2. Methodology

2.1. Household Survey

The data used in this study were collected in Leicester during the summer months of 2009 as part of the 4M project [12], which focused on representing carbon emissions from different sources to measure the carbon footprint of the city of Leicester. One of the project themes was *Building Energy*, which investigated the energy demand of the city's domestic buildings. A face-to-face questionnaire was administered to 575 houses that documented the house type, the house age, the type of wall (solid, cavity, filled cavity) and the number of occupants. Table 1 below summarises this information.

Table 1. Statistics of dataset house characteristics.

Categories	*Characteristics*	*Frequency (N)*	*Percentage (%)*	*Categories*	*Characteristics*	*Frequency (N)*	*Percentage (%)*
House Type	Detached	21	9.1	Household Size	1	63	27.4
	Semi-detached[1]	**96**	**41.7**		**2**	**79**	**34.3**
	End-terrace	23	10.0		3	33	14.3
	Mid-terrace	62	27.0		4	35	15.2
	Flat	28	12.2		5	14	6.1
House Age	Pre 1900	19	8.3		6	5	2.2
	1900-1919	27	11.7		7	1	0.4
	1920-1944	**72**	**31.3**	Age of Oldest Occupant	20	15	6.5
	1945-1964	41	17.8	(years)	30	34	14.8
	1965-1980	36	15.7		**40**	**56**	**24.3**
	Post 1980	35	15.2		50	39	17.0
Wall Type	**Solid**	**101**	**43.9**		60	46	20.0
	Cavity	56	24.3		70	40	17.4
	Filled Cavity	73	31.7	Tenure	**Own, outright**	**89**	**38.7**
Loft Insulation	**Above 200**	**122**	**53.0**		Own, mortgage	71	30.9
(mm)	Below 200	43	18.7		Rent	66	28.7
	Not Applicable	49	21.3		Don't know	4	1.7
	Don't know	16	7.0				

[1] Bold text represents the highest percentages in each category

The largest proportion of the houses was semi-detached (41.7%) with mid-terraces covering more than a quarter of the sample (27%), together accounting for almost 70% (68.7%) of the sample. Concerning the age of the houses 20% were built before 1920, 31.3% between 1920 and 1944 and 30.9% after 1965. Almost 44% of the houses have solid walls, while 53% have more than 200mm of loft insulation. More than a third of the sample has two occupants, with the vast majority being above 30 years of age at the time of the survey in 2009.

2.2. Temperature data collection – Internal and External

Hobo pendant type temperature sensors were used to record internal temperatures in the living rooms and main bedrooms over an eight-month period, starting on 1 July 2009. The sensors recorded air temperature at hourly intervals, however as they were not shielded, they will also have recorded a radiant component. From the 951 Hobo sensors that were deployed in 481 houses (94 households did not agree in taking the sensors) only 416 were found to contain valid data from free-running homes (no heating or cooling present) for the same 62 day period in July and August. From the 416 sensors, in 230 homes, 212 are from living rooms and 204 are from bedrooms, hence some of the houses have only got measured temperatures from a single room. This data have already served as a solid basis for research projects focusing on indoor temperatures both in the summer [13] and winter [14]. An example of measured temperature profiles in a living room and a bedroom is given in Figure 1a.

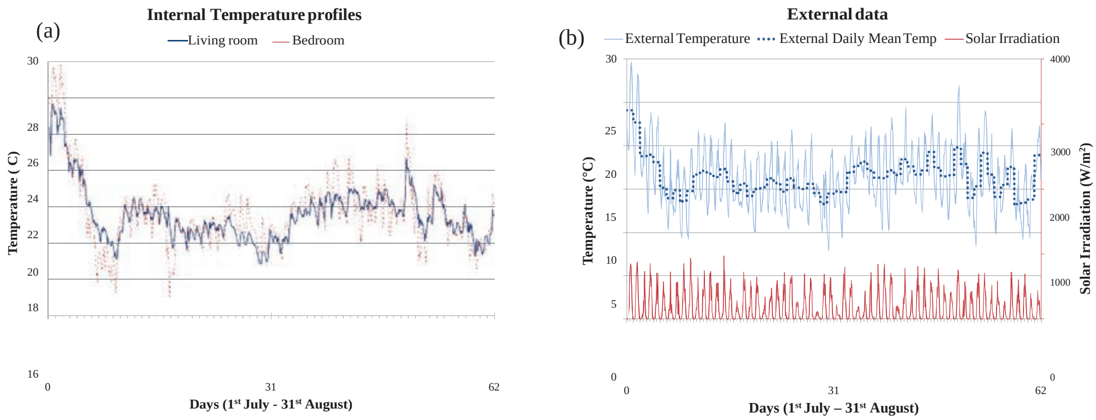

Figure 1. (a) temperature profiles of living room and main bedroom as measured during the monitoring period; (b) external weather data as recorded by the weather station at De Montfort University.

The external weather data were obtained from De Montfort University, in the middle of Leicester, for the purposes of the 4M project. Figure 1b illustrates the external temperature together with the external mean temperature and the solar irradiation data as recorded during the period between the 1st July and 31st August 2009. It can be observed that the monitoring period started with some very high temperatures. During the first day the external temperature reached a peak of 29.7°C, while the lowest temperature, 7.9°C, was in the middle of the monitoring period. For most of the time the daily mean temperature was below 20°C and above 13.5°C. During the first and the last weeks there were sudden falls in the daily mean temperature of around 4°C (3rd July, 21st & 28st August) and also a substantial increase of more than 5°C at the last day .

2.3. Time series analysis

The first step in time series analysis is to describe the data by plotting and obtaining simple descriptive measures of the main properties of the series, checking for trends and seasonal variations as well as for outliers and turning points. Secondly, one aims to explain the variations of the series (if more than one variable have been measured, make use of the variation in one in order to explain the variation in another). Thirdly, one tries to predict future values of the series and lastly controlling the future values by adjusting the input process variables accordingly to ones needs. The steps in this analysis are based on the univariate time series modelling construction theory derived from the work of Box and Jenkins [15], outlined in Figure 2.

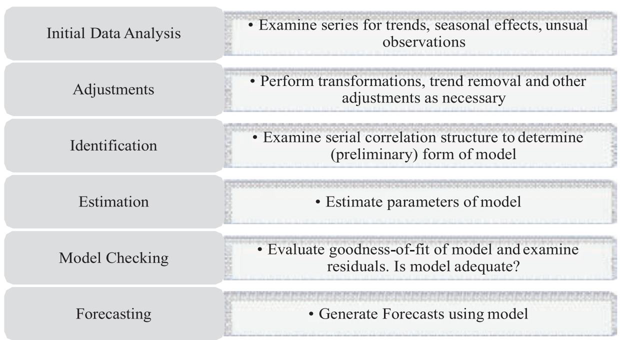

Figure 2. Time series analysis objectives [After 15].

The principle of stochastic time series modelling is that it explicitly deals with stationary data. A series is considered to be stationary if it exhibits no trend (no systematic change in the mean) and no other seasonal or cyclical variations (periodic variations). Hence it is important to examine the series for any of these components (trend, seasonal variation, cyclical variation) and attempt to remove them, a procedure also known as the decomposition of the series. It is therefore essential to define these components in the context of this study's dataset before proceeding to the decomposition. According Kendal and Ord [16] trend is "*a smooth broad movement of a non-oscillatory kind extending over a considerable period of time*". For the purposes of this work the definition of trend will be based on this definition and the relative meaning of the phrase "*a considerable period of time*" will be defined as the length of the dataset, i.e. 62 days. Hence, the long term trend will be considered as the day-to-day variation and it will be referred to as daily variation (*D*) from here and on. Chatfield [5] recommends that a seasonal variation is annual in period and since the extent of the data set is less than annual, it will not be considered as existing in the series. The definition of cyclical variation will be based on suggestions by Kendal and Ord [16] and Chatfield [5] that the diurnal fluctuations of internal temperatures do exhibit a cyclical pattern and therefore this variation within a day will be referred to as diurnal variation (*U*) from here on.

Having defined the possible components of the time series, the decomposition to a stationary series can be achieved by following two different approaches, the selection of which depends on the assumptions made regarding the relationship between these four components. If the components are related in an additive way, then it is the additive model that should be considered. If they are related in a multiplicative way, then it is the multiplicative model that should be applied. Both models are defined below (with the observed value at time t denoted as Y_t):

$$\text{Additive model:} \qquad Y_t = T_t + S_t + C_t + R_t$$

$$\text{Multiplicative model:} \quad Y_t = T_t \times S_t \times C_t \times R_t$$

Where, Y_t is the internal temperature at time t, T_t is trend at time t (in this case the daily variation (D_t)), S_t is the seasonal variation at time t (this will be considered as non-existent), C_t is the cyclical variation at time t (in this case the diurnal variation (U_t)), R_t is residual at time t. In order to calculate the individual components of a series, a number of transformations need to be applied on the observed data, such as moving averages, exponential smoothing and differencing. However, before applying the transformations throughout the data set it is essential to test the approach on a single house.

2.4. Initial study of one house

It is sensible to choose a house with structural and household characteristics that occur frequently within the sample and where the measured temperature profiles in the living room and main bedroom do not present any irregularities in relation to the external temperature. From Table 1, it can be observed that the most common structure related characteristics across the whole sample is the semi-detached house with solid walls, built between 1920 and 1944 while the most common household related characteristic is having two occupants in the house. There are 14 houses with these characteristics in the sample and they form a group that will be referred to as the 'most common'. Having narrowed the options for the selection of the house from 230 to 14, the next step was to select a house from the most common group and inspect and compare the mean values of different internal temperature metrics between selected house, the most common group (14), the semi-detached houses (96) and the whole sample (230). These are then calculated and presented in Table 2 below.

Table 2. Temperature comparisons between the Case Study house, subgroups and across the whole sample.

Temperature metrics (°C)	Living room				Bedroom			
	Sample (230)	*Semis (96)*	*Most Common Group (14)*	***Case Study***	*Sample (230)*	*Semis (96)*	*Most Common Group (14)*	***Case Study***
Mean	22.23	22.17	21.81	**21.63**	22.40	22.38	22.07	**21.73**
Max	26.70	26.66	26.45	**26.85**	27.68	27.84	27.26	**28.54**
Min	20.14	20.10	19.65	**19.25**	19.91	19.85	19.55	**18.93**
St D	1.34	1.33	1.36	**1.50**	1.58	1.61	1.55	**1.85**

The figures in Table 2 indicate that the thermal conditions inside the selected house were within acceptable limits and therefore can be considered as typical compared to the rest of the groups. Furthermore, a visual inspection of the temperature profiles for the living room and main bedroom of the selected house was carried out in order to check for any anomalies. The graphs in figure 1 indicate that the house selected did not present any unusual observations in terms of peak or low temperatures during the monitoring period. Both living room and bedroom plots are following the external temperature, however the internal temperature of the living room is a lot smoother compared to the one measured in the bedroom. Possibly this is due to the orientation of the house resulting in higher temperature spikes in the bedroom area than in the living room.

3. Results

This section presents the results of the decomposition of the living room temperature data measured in the case study house. Figure 3a shows the observed (measured) data (Y_t). This is a non-stationary series that needs to be transformed in order to apply the stochastic modelling time series method. The transformations help identify the components of the series which are then removed to convert the series to stationary and allow for the best model fit. Having applied a number of different transformations, presented here are the transformations which exhibit the best results. Since the trend has been defined as the daily variation (the long term changes in temperature on a day to day basis) it will be calculated as the 24 hour moving average of the daily mean. Figure 3b presents the temperature profile of the daily variation (D_t) of the series. The calculation of this transformation should also be centred as a day consists of an even number of days (24). Consequently, the daily variation is given by the following equations.

$$D_t^r = \frac{(Y_{t-11} + Y_{t-10} + \cdots + Y_{t-1} + Y_t + Y_{t+1} + \cdots + Y_{t+12})}{24}, \qquad D_t = \frac{(D_t^r + D_{t+1}^r)}{2}$$

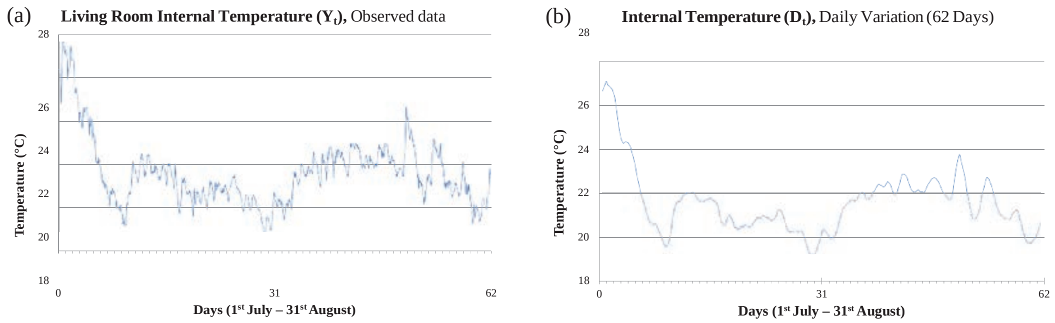

Figure 3. (a) temperature profiles of observed data; (b) temperature profiles of daily variation.

Figure 4a (upper plot) presents the temperature profile of the diurnal variation (U_t). This variation can be identified by applying a process that averages all the values at 1am throughout the 62 days, all the values at 2am, all the values at 3am, till the last hour of the day throughout the dataset. That creates a 24 hour data set of averages from all the hourly values of the data that is represented by the example in the equation below (U_{1am}). The deduction of the diurnal variation (U_t) and the daily variation (D_t) from the observed data results in the stationary data series presented in figure 4a (lower plot).

$$U_{1am} = \frac{(Y_{1am} - D_{1am})_{day\ 1} + \cdots + (Y_{1am} - D_{1am})_{day\ 62}}{62}$$

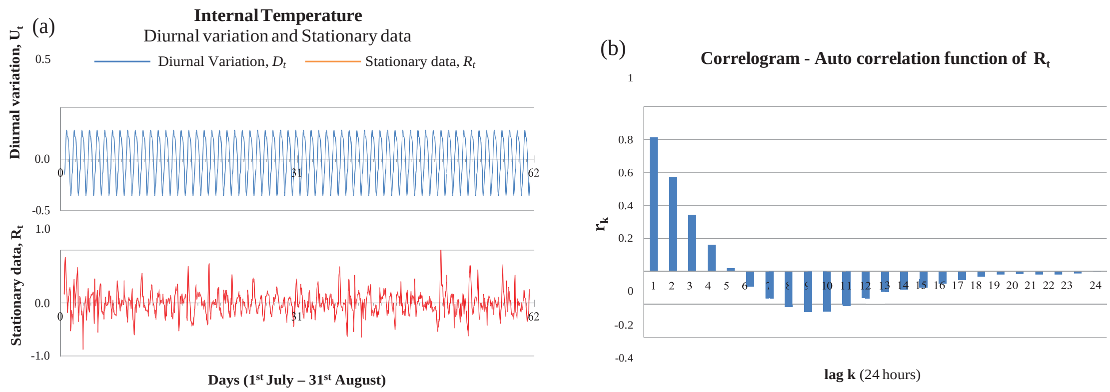

Figure 4. (a) diurnal variation & stationary data; (b) correlogram of residual stationary data (R_t).

To check whether the decomposition of the data has been successful the mean and the variance of the residual series (R_t)

should be zero, which indeed is the case in the residual stationary data series above. However it is the correlogram that will allow identifying the form of the best model fit. Figure 4b presents the plot of the correlation coefficient between a measurement and one *k* hours (lags) apart (otherwise known as correlogram or the autocorrelation function (ACF)) of the residual series R_t. By examining the structure of the ACF one can determine the form of the model to provide the best fit. According to Kendal [16], an ACF that decays exponentially suggests that an auto regressive moving average (ARIMA) model should be selected. The spikes of the partial ACF would determine the order *p* of the model. Further work will explore these issues for the whole sample of homes and across different model structures.

4. Conclusion

This paper presents the time series analysis of the internal air temperatures in the living room of a case study house, measured between 1st July and 31st August 2009 in Leicester, UK. The observed data underwent two sequential sets of transformations in order to remove the daily and diurnal variations respectively. The first transformation was the deduction of a straight forward twenty four hour moving average of the daily mean temperature while the second one was a more explicit transformation involving calculating the mean of the hourly values throughout the data set. Having identified and removed the daily and diurnal variations from the series, the serial correlation structure is sufficient to allow the identification of the best model fit. There are 3 main conclusions drawn from this study:

- The analysis was based on a house with structural and household characteristics that occur frequently within the sample.
- Early results show that time series analysis can be used to explain measured room internal temperature data.
- An autoregressive integrated moving average (ARIMA) model can be used to model the internal temperatures in houses.
- Such a model could predict future internal temperatures based on past values and provide essential information regarding overheating alerts during hot summer conditions.

5. Acknowledgements

This research was made possible by the support from the Engineering and Physical Sciences Research Council (EPSRC) for the London-Loughborough Centre for Doctoral Research in Energy Demand (grant EP/H009612/1). The 4M consortium was funded by the Engineering and Physical Sciences Research Council (EPSRC) under their Sustainable Urban Environment programme (grant EP/F007604/1).

6. References

[1] Health Protection Agency (HPA). Health Effects of Climate Change in the UK 2012: current evidence, recommendations and research gaps. London, UK; 2012.

[2] Grogan H, Hopkins PM. Heat stroke: implications for critical care and anaesthesia. *British Journal of Anaesthesia*, 2002;88: 700–07.

[3] Hacker JN, Belcher SE, Connell R.K. Beating the Heat: keeping UK buildings cool in a warming climate. UKCIP Briefing Report. UKCIP. Oxford, UK; 2005.

[4] Porritt SM, Cropper P, Shao LC, Goodier CI. Ranking of interventions to reduce dwelling overheating during heat waves. *Energy and Buildings*, 2012;55:16-27.

[5] Chatfield C. *The analysis of time series: an introduction*.5th ed. London: Chapman & Hall; 1996.

[6] Bloomfield P. *Fourier analysis of time series: an introduction*. New York: John Wiley; 1976.

[7] Reddy TA. *Applied data analysis and modeling for energy engineers and scientists*. New York: Springer; 2011.

[8] Pfafferott J, Herkel S, Wapler J. Thermal building behaviour in summer: long term data evaluation using simplified models. *Energy and Buildings* 2005;37:844-52.

[9] Ogunsola OT, Song L, Wang G. Development and validation of a time series model for real time thermal load estimation. *Energy and Buildings* 2014;76:440-49.

[10] Iddon CR, Mills TC, Giridharan R, Lomas KJ. The influence of hospital ward design on resilience to heat waves: an exploration using distributed lag models. *Energy and Buildings* 2015;86:573-88.

[11] Eames M, Kershaw T, Coley D. On the creation of future probabilistic design weather years from UKCP09. *Building Services Engineering Research and Technology* 2011; 32:127-42.

[12] Lomas KJ, Bell MC, Firth SK, Gaston KJ, Goodman P, Leake JR, Namdeo A, Rylatt M, Allinson D, Davies ZG, Edmondson JL, Galatioto F, Brake JA, Guo L, Fill G, Irvine KN, Taylor SC, Tiwary A. The carbon footprint of UK cities: 4M: measurement, modelling, mapping and management, ISOCARP Review 06, International Society of City and Regional Planners; 2010. p.168–91.

[13] Lomas KJ, Kane T. Summertime temperatures and thermal comfort in UK homes. *Building Research & Information* 2013; 41:259-80.

[14] Kane T, Firth SK, Lomas KJ. How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling. *Energy and Buildings* 2015; 86:817-832.

[15] Box GEP, Jenkins GM. *Time series analysis: forecasting and control*. San Francisco: Holden-Day; 1970.

[16] Kendal M, Ord, KJ. *Time series*. 3rd ed. London: Edward Arnold; 1990.