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A validated methodology for the prediction of heating and cooling energy demand for buildings within the Urban Heat Island: Case-study of London

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Abstract

This paper describes a method for predicting air temperatures within the Urban Heat Island at discreet locations based on input data from one meteorological station for the time the prediction is required and historic measured air temperatures within the city. It uses London as a case-study to describe the method and its applications. The prediction model is based on Artificial Neural Network (ANN) modelling and it is termed the London Site Specific Air Temperature (LSSAT) predictor. The temporal and spatial validity of the model was tested using data measured 8 years later from the original dataset; it was found that site specific hourly air temperature prediction provides acceptable accuracy and improves considerably for average monthly values. It thus is a very reliable tool for use as part of the process of predicting heating and cooling loads for urban buildings. This is illustrated by the computation of Heating Degree Days (HDD) and Cooling Degree Hours (CDH) for a West–East Transect within London. The described method could be used for any city for which historic hourly air temperatures are available for a number of locations; for example air pollution measuring sites, common in many cities, typically measure air temperature on an hourly basis.

Keywords: Urban Heat Island; Prediction; Heating; Cooling; Buildings; ANN

1. Introduction

Urban warming, commonly referred to as the ‘Urban Heat Island’ phenomenon (UHI), is a well established effect. The formation of distinct urban climates is mainly attributed to the urban–rural variation of a number of factors commonly linked with urbanisation; these include the thermal properties of surfaces, the urban morphology, and air pollution levels; (Oke, 1987, 1995). As a result of this variation, larger amounts of solar short wave radiation are captured, absorbed and stored in urban surfaces than in rural surfaces during the day. In addition, urban canyons are also characterised by smaller sky view factors and, thus, lower rates of long wave radiation loss during the night. The evaporative cooling potential of highly impermeable built-up areas is also limited. Anthropogenic heat emissions are also greater in cities. The formation of different types of heat islands and the differences between surface and air distribution has previously been described (Oke, 1995).

The magnitude of the UHI has been studied mostly in terms of the temperature differences between rural and urban locations. The spatial and temporal distribution of the Urban Heat Island intensity varies significantly between cities. In most cases, intensities typically peak

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several hours after sunset rendering the heat island essentially a night time phenomenon. There are many studies on the quantification of UHI in large cities and reviews on research in Europe and other areas have been published (for example Santamouris, 2007; Roth, 2007; Memon et al., 2009).

This paper focuses on a temperate climatic region using London as a case-study, where temperature differences between core urban and surrounding rural locations of several °C are commonly observed. An extensive series of measurements were undertaken by Watkins et al. (2002), illustrating in detail the spatial and temporal patterns of London's heat island. However, the relationship of the local temperature distribution with land use and building form is much less well understood (Kolokotroni and Giridharan, 2008; Giridharan and Kolokotroni, 2009).

The rise in external ambient temperatures in urban environments, compared to rural environments, is associated with a series of interconnected impacts:

- *Comfort*: In buildings without air conditioning, comfort levels during the summer will tend to decrease. During the winter comfort will tend to increase.
- *Energy*: It is possible that in order to meet raised comfort requirements, the use of air conditioning systems will increase, followed by a rise in summer time energy use. However, heating loads during winter will tend to reduce.
- *Health*: There is a well established relationship between higher outdoor temperatures and the risk of heat-related mortality. However, the death toll due to cold during winter will tend to decrease with higher winter temperatures.

The above listed effects are being studied in the UK by a consortium of meteorologists, building scientists, urban modellers, planners, urban and building designers and epidemiologists to research how cities can adapt to a changing climate (LUCID, 2009). The work involves the development of urban climate models and energy models at a variety of scales-city, neighborhood, street and building. The suite of models are interrelated and have been described in Mavrogianni et al. (submitted for publication). This paper focuses on one of the models; the London Site Specific Air Temperature (LSSAT). It describes the development of the model, present results of its validation by comparison with measurements and discuss its results and its application in the form of prediction of Heating and Cooling Degree Days.

For the prediction of urban air temperatures there exist a range of models varying in complexity and these were briefly reviewed in Kolokotroni et al. (2007). These can be classified into the following four categories:

1. Climatology models, for example (Taha, 1999). A new model is recently being developed for London (Mavrogianni et al., submitted for publication).
2. Empirical models using heat balance equations and empirically derived coefficients, for example the Cluster Thermal Time Constant model (CTTC) (Swaid and Hoffman, 1990) and further developed as the CAT model by Erell and Williamson (2006).
3. Computational Fluid Dynamics models, for example (Tabahashi et al., 2004).
4. Statistical regression methods, probability methods and artificial neural networks, for example (Mihalakakou et al., 2002).

The model described in this paper is based on Artificial Neural Network (ANN) modelling and falls under category 4 of the above list. A description of the model was published in 2009 (Kolokotroni et al., 2009) and a summary is included in Section 2 of this paper for completeness. Section 3 presents new data in the form of measurements carried out in 2008; these data were used to validate the model. Section 4 presents the computation of Heating Degree Days and Cooling Degree Hours for January and August for 20 locations on an East–West Transect of London for 2 years; 2000 which is the year of the original dataset and 2008 which is the year of the validation data.

2. The LSSAT model: existing study

This section explains how LSSAT was developed; this was described first in Kolokotroni et al. (2009) but a summary is included here for completeness. As reported before (Watkins, 2002), an extensive measuring campaign took place in 1999–2000, during which hourly air temperatures were measured in 77 locations with the Greater London Area (GLA) for approximately 16 months (to include two summers). These are the fundamental data to be used here for the development of the LSSAT model. The predictions of these models for a given Fixed Temperature Station (FTS) together with the description of the FTS in terms of its urban on site characteristics as reported in Kolokotroni and Giridharan (2008) can be used to extrapolate for other locations and times.

The LSSAT model is an Artificial Neural Network (ANN) model and was developed using MATLAB 6.5 (2004). In general, the neural network architecture procedures on which the model is based could be divided into the following steps:

1. Design the neural network: select the type of the network and input parameters and determine the structure and number of layers and neurons.
2. Train the network: conduct the learning or training process.
3. Test and diagnostic check: carry out the simulation result analysis.
4. Optimization of the neural network by trial and error: compare the different types of network models and choose the best one as the final solution.