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Development of a model for urban heat island prediction using neural network techniques

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ABSTRACT

The urban heat island (UHI) phenomenon is mainly caused by the differences in the thermal behaviour between urban and rural settlements that are associated with the thermal properties of urban materials, urban geometry, air pollution, and the anthropogenic heat released by the urban activities. The UHI has a serious impact on the energy consumption of buildings, increases smog production, while contributing to an increasing emission of pollutants from power plants, including sulfur dioxide, carbon monoxide, nitrous oxides and suspended particulates.

This study presents the applicability of artificial neural networks (ANNs) and learning paradigms for UHI intensity prediction in Athens, Greece. The proposed model is tested using Elman, Feed-Forward and Cascade neural network architecture. The data of time, ambient temperature and global solar radiation are used to train and test the different models. The prediction accuracy is analyzed and evaluated.

1. Introduction

The urban heat island (UHI) phenomenon serves as a trap for atmospheric pollutants, deteriorates the quality of life and has a socio-economic impact in the urbanised areas (Santamouris, Paraponiaris, & Mihalakakou, 2007; Santamouris, Pavlou, Synnefa, Niachou, & Kolokotsa, 2007). Important research has been accomplished over the last hundred years to quantify its impact on the urban climate (Akbari, Konopacki, & Pomerantz, 1999; Mihalakakou, Flokas, Santamouris, & Helmis, 2000; Santamouris, 2001). Various heat island studies have been performed in Europe during the last 15 years (Santamouris, 2007). Urban heat island and increased urban temperatures (Livada, Santamouris, & Assimakopoulos, 2007; Livada, Santamouris, Niachou, Papanikolaou, & Mihalakakou, 2002; Mihalakakou, Santamouris, & Papanikolaou, 2004), exacerbate the cooling load of buildings, increase the peak electricity demand for cooling and decrease the efficiency of air conditioners (Cartalis, Synodinou, Proedrou, Tsangrassoulis, & Santamouris, 2001; Hassid et al., 2000; Kolokotroni, Giannitsaris, & Watkins, 2006; Santamouris et al., 2001). Moreover the urban agglomeration has a negative impact on the cooling effectiveness of natural and night ventilation (Geros, Santamouris, Karatasou, Tsangrassoulis, & Papanikolaou, 2005) and contributes to the increase of outdoor pollutants' concentration (Crutzen, 2004; Taha, 1994).

Consequently, the prediction of the urban heat island behaviour has gained a significant attention. Although a number of modelling approaches for urban heat island do exist (Mirzaei & Haghighat, 2010), the complexity of the phenomenon, the bulk of urban details required to attain an accurate urban model and the increased cost and computational time of the analytical modelling approaches has led to the exploration of other prediction methods.

Artificial neural networks (ANNs) have been used in a number of prediction studies that involve atmospheric time series data. Yi and Prybutok (1996) predicted daily maximum ozone levels in Texas metropolitan areas with a standard three-layer ANN model with nine inputs and four hidden nodes and found it to be superior to statistical methods. A three-layer ANN model with 17 inputs was developed by Jiang et al. (2004) to predict the air pollution levels of cities in China. Inputs to the models were not site-specific, allowing the model to be applied to a number of locations across China. Air temperature, wind speed, and relative humidity in Saskatchewan, Canada were predicted for 24 h in advance by ANN models developed and applied by Maqsood, Khan, and Abraham (2004). They found that combining the outputs of a standard Feed-Forward ANN, a recurrent ANN, a radial basis function network, and a Hopfield network into a simple "winner-take-all" ensemble led to more accurate predictions of wind speed, relative humidity, and air temperature than any of the individual component networks. Ruano, Crispim, Conceicão, and Lúcio (2006) used a multi-objective genetic

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algorithm to develop a radial basis function ANN model for the prediction of air temperature in a secondary school building in Portugal. Air-conditioning control scheme simulations indicated that temperatures could be more consistently managed and that air conditioner run times could be reduced using an ANN model. Tasadduq, Rehman, and Bubshait (2002) used a back propagation ANN with batch learning scheme for 24-h prediction in ambient temperature on a coastal location in Saudi Arabia. They found that temperature can be predicted even with only one input with good accuracy.

Additionally, a number of urban heat island prediction studies are based in the ANN technology (Santamouris, Mihalakakou, & Papanikolaou, 1999). A neural network architecture was developed to predict the urban heat island intensity in Athens, Greece, during both day and night (Mihalakakou et al., 2004) using data for a two-year time period. Another study uses input data from meteorological stations as well as historic measured air temperatures within the city to predict the urban heat island intensity in London based on neural network architecture (Kolokotroni, Davies, Croxford, Bhuiyan, & Mavrogianni, 2010).

It should be underlined here that most urban heat island NN prediction studies require a large set of data to train the neural networks and predict the phenomenon in an accurate and acceptable manner. The present paper presents an effort to predict the urban heat island intensity in Athens based on limited available data series using various neural networks architectures. The overall effort is structured in three more sections. Section 2 provides the description of the region and the experimental sites. Section 3 analyses the selection and configuration of ANN while Section 4 includes the experimental results and discussion. Finally, Section 5 summarises the conclusions.

2. Experimental site description

The Greater Athens Area (GAA) is situated on a small peninsula located on the southeastern edge of the Greek mainland (Fig. 1). It is divided by high mountains in three main parts, which are connected by small openings. The central part is the Athens basin which covers an area of 450 km^2, with a population density of 8000 inhabitants per square kilometer, with the main axis orientated from SSW to NNE. Athens basin is surrounded by high mountains in the north (Parnitha, 1426 m), in the west (Egaleo, 458 m) and in the east (Hymettus, 1026 m and Penteli, 1107 m), while it is open to the sea from the south (Saronikos Gulf). The other parts of the Athens area are the Thriassion plain west of the Athens basin and the Mesogia plain in the east. There are only small openings through which the Athens basin communicates with these plains as well as the rest of Greek mainland. These openings play an important role in air mass exchange between the Athens basin and the Thriassion and Mesogia plains.

The city of Athens is characterised by a strong heat island effect, mainly caused by the accelerated industrialisation and urbanisation during recent years. From previous measurements' analysis is found that maximum heat island intensity in the Athens centre is almost 16 °C while the mean value for the major central area of Athens reaches 12 °C. Also, absolute maximum temperatures in the central area is close to 15 °C higher than in the suburban areas, while absolute minimum temperatures are up to 3 °C higher in the centre (Santamouris, 2001).

In a study performed by Livada et al. (2002) reporting the results of the heat island study in Athens, it is found that near the sea, the air temperatures are higher in the cold period due to the influence of the sea which supports the maintenance of high air temperatures. It is also reported that high air temperatures during the hot period of the year or low air temperatures in the cold period is mostly related to the synoptic weather conditions and it cannot reasonably considered as an index for the heat island effect development.

The increase of the cooling load in Athens and the ecological footprint of urban heat island is studied by Santamouris, Paraponiaris, et al. (2007) and Santamouris, Pavlou, et al. (2007). Given the actual penetration of air conditioning in the country, the ecological footprint due to the heat island ranges 1.5–2 times the city's surface area. Moreover the maximum potential ecological footprint provided that all buildings are air conditioned is almost

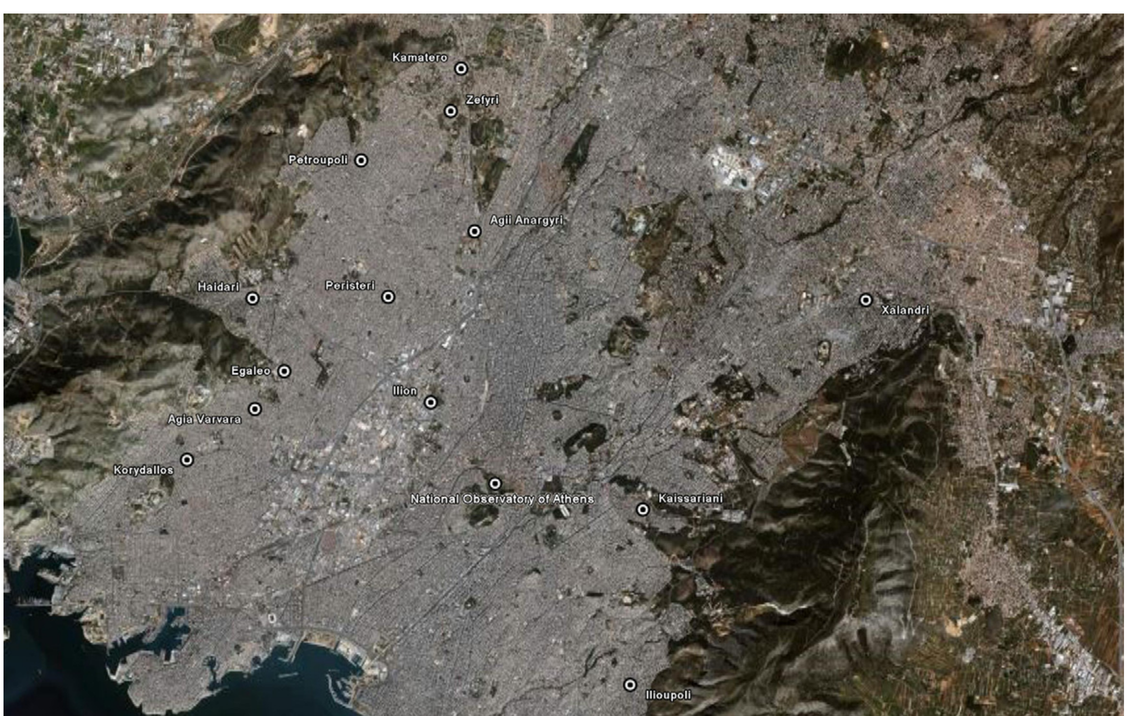

Fig. 1. The location of the 14 meteo station in the GAA.