TOWARDS THE INTEGRATION OF THE URBAN HEAT ISLAND IN BUILDING ENERGY SIMULATIONS

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ABSTRACT

Weather conditions in an urban environment differ from the conditions in a rural environment. This phenomenon is known as the urban heat island (UHI) effect. In this study the urban climate was monitored at five locations in Rotterdam (the Netherlands) for a period of 1.5 years. The urban heat island intensity was subsequently calculated by the difference between these results and measurements of the Royal Dutch meteorological institute (KNMI) at a rural area 5 km from the centre of Rotterdam. A data-driven method based on a neural network was used for the prediction of the UHI intensity. In this method the UHI intensity at a specific time is calculated as a function of eight weather parameters at that specific time as well as the preceding three hours. The results show a mean squared error on the test data of 0.18 °C. The results therefore indicate that the model reproduces the transient behaviour of the UHI intensity in an accurate manner. This approach can therefore be used to convert weather data of a rural area in weather data for an urban area and subsequently be used in building performance simulations.

INTRODUCTION

Howard reported in 1818 that the temperature of the city of London was not to be considered as that of the rural climate (Howard 1833, Mills 2003). The causes of this phenomenon, later called the urban heat island (UHI), were reported by e.g. Oke (1982), Oke (1987), Taha (1997), Santamouris (2001) who indicated that the UHI is a result of: low-albedo, air pollution, reduction of the sky view factor, anthropogenic heat, heat storage, decrease in evaporation and a reduction of wind speed. Nowadays the existence urban heat island is a well-established and well documented phenomenon e.g. Santamouris (2007), Koloktroni et al. (2010), Stewart (2010), Tomlinson et al. (2011), Mavrogianni et al. (2011). Studies on the impact of elevated temperatures reveal that increased temperatures result in increased human mortality (Gosling et al. 2008), the latter being apparent in heat wave events (Pirard et al. 2005, Brücker 2005, Kosatsky 2005). Many of the additional deaths during a heat wave are likely to be caused by an enhanced UHI during the heat wave (Kershaw et al. 2010). The effect of the UHI on building energy consumption has been described in several studies. Based on Gobakis et al. (2011) and Assismakopoulos et al. (2007) it can be concluded that the UHI influences the energy demand significantly. Santamouris et al. (2001) concluded that cooling loads could almost double, which was supported by Hassid et al. (2000) who stated that the cooling energy loads could increase by as much as 100%. IPCC assessment report 4 reports that the UHI can affect comfort, health, labour productivity, leisure activities and climate control within buildings (Wilbanks et al. 2007). Current research addresses the mitigation options in urban design to counteract the effects of the UHI as well as climate change (e.g. Kleerekoper et al. 2012). These studies reveal the effect of e.g. vegetation, water, and materials on the UHI intensity. Building performance simulations typically do not include a model of the UHI, and generally use weather data from meteorological stations in the rural area close to the building of interest. The reason for this might be that there is a need for additional contributions in the area of the UHI in relation to building performance simulation (Barnaby & Crawley 2011). This was also adressed by Hensen (1999) who stated that at that time hardly any research was done in this area. Recent studies have demonstrated several methods to account for the UHI in the weather data. These methods were divided in four categories by Kolokotroni et al. (2007, 2010). They consist of (1) Climatology models (e.g. Taha 1999, Mavrogianni et al. 2011) (2) Empirical models which use heat balance equations and empirically derived coefficients (e.g. Bueno et al. 2012, Runnals & Oke 2000, Erell & Williamson 2006, Levermore & Cheung 2012) (3) Computational Fluid Dynamics models (e.g. Bouyer et al. 2011) and (4) Statistical regression methods (e.g. Wilby 2003, Giridharan et al. 2005, Morris & Simmonds 2001), probability methods and artificial neural networks (e.g. Santamouris et al. 1999, Kolokotroni et al. 2010, Mihalakakou et al. 2002, Kim & Baik 2002, Gobakis et al. 2011). The latter predict the UHI intensity as a function of the main climatic parameters (Santamouris 2007). Models to account for the diurnal variation of the UHI in

Figure 1. Measurement locations in Rotterdam (NL).

climate change projections for building energy simulations have been proposed by Kershaw et al. (2010) and Crawley (2008). These models incorporate the UHI intensity in the weather data as a function of time. Kershaw et al. (2010) provided a sinusoidal function to account for the diurnal variation and Crawley (2008) incorporated the variation by different ratios for five different moments in time. The benefit of these models is that limited or no measurements are required. This study will address an artificial neural network approach as first used to predict the UHI intensity by Santamouris et al. (1999). It was found that these data-driven models can be improved when these are trained by using rural weather parameters of the specific hour as well as the preceding three hours. These trained neural networks can subsequently be used for rural to urban weather data conversion for building performance simulations.

METHODOLOGY

For this study a prognostic data-driven model was developed for the UHI of Rotterdam. The study started with the measurements of the UHI intensity of five locations in Rotterdam which were analysed by a Fourier analysis to obtain the diurnal variation of the UHI intensity. In a next step the potential of the UHI prediction for Rotterdam based on an artificial neural network was analysed. This analysis started by using the input parameters en network architecture as reported by Koloktroni et al. (2010), later possible improvements to the network for the UHI prediction of Rotterdam were analysed. In the remainder of this section, first the measurements in Rotterdam are described, followed by a description of the method used to determine the diurnal variation of the UHI. The section ends with the description of the artificial neural network as used in this research.

Experimental set-up

At five locations in Rotterdam the weather was measured (as shown in figure 1) from 01-04-2011 to 31-10-2012 (579 days) by Standard Campbell weather stations with an added 4-component radiation sensor (Hukseflux NR01) and Black Globe temperature sensor (Sensor Data). The measured components that are used in this study are the dry bulb temperatures in the urban areas, which are compared to the dry bulb temperature in the rural area (at Rotterdam Airport). The five locations where the measurements took place in the city of Rotterdam were; (1) City centre, located in the centre of Rotterdam which consist of high-rise and low-rise buildings, with a relatively low amount of inhabitants, high on traffic as its location is next to the central train station. (2) Ommoord, located in a residential area with low-rise buildings in which the dwellings are built in parallel rows. (3) Rijnhaven, located near a canal and harbour, the area consist mainly of high-rise buildings. (4) Spaanse polder, located in a business area which mainly consists of low-rise industrial halls and offices. (5) Vlaardingen, located in a residential area near a public green space. For the rural area, the measurements of the Royal Dutch Meteorological Institute (KNMI) of Rotterdam were used. This station is located at Rotterdam airport roughly 5 km from the centre of Rotterdam and mainly consists of grass land. The time interval at which the data is considered is by one hour time steps, resulting in a total of 13,896 readings for each station.

Determination of diurnal variation

Both the models of Kershaw et al. (2010) and Crawley (2008) incorporate the UHI intensity in rural weather data as a function of time. The diurnal variation of the UHI intensity in Rotterdam was therefore analysed as a function of time, which enables to the time of maximum and minimum UHI intensity as well as the typical variation over a day. This diurnal variation of the UHI was determined by a Fast Fourier transformation applied to the average UHI intensity of Rotterdam. As a result the sinusoidal functions with the best fit for the diurnal variation are identified. The transformation was performed for periods of one month, this monthly period is equal to the period used to indicate the diurnal variation in e.g. Allegrini et al. (2012). The fourier transform was performed by using the Fast Fourier transform algorithm (Cooley and Turkey 1965) in MATLAB R2012a (version 7.14.0.739). In the evaluation of the transformation three harmonics as well as a constant were taken into account, namely with a frequency of one day, half a day and one third of a day. This leads to the following expression for the transformations for each month.

$$UHII(t) = a_0 + \sum_{k=1}^{3} A_k \cdot \cos(k\omega_0 t + \varphi_k) \qquad (1)$$

Where UHII is the urban heat island intensity at a specific time, a_0 is the constant value for each month, A_k the amplitude of a specific harmonic of a specific month, ω_0 the angular velocity and φ_k the phase change for a specific harmonic.

Neural network approach

This study aims at a prognostic data driven model, meaning that the focus is not on the UHI intensity determining factors but solely on predictive capability of the model by using multiple parameters. Data driven models to predict the UHI intensity have been used in earlier studies e.g. Santamouris et al. (1999), Mihalakakou et al. (2002), Kim & Baik (2002), Wilby (2003), Kolokotroni et al. (2010), Gobakis et al. (2011) which use either multiple linear regression, or neural network techniques to predict the UHI intensity on a daily or hourly bases. In this study a feedforward neural network is used, meaning that the output of a neuron cannot influence its input. The initial input parameters were based on Kolokotroni et al. (2010), who reported that the neural network was trained with the hourly values of: air temperature, relative humidity, cloud cover, air speed of the rural area and the corresponding UHI intensity. These inputs were different from the input data driven model described in Kim & Baik (2002), who used: air speed, cloud cover, relative humidity and the maximum UHI intensity of the previous day. Three additional parameters were added in order to identify if the model performance could be improved. The three additional parameters were: (1) solar elevation, (2) hour of the day and (3) the wind direction. A further inprovement of the model was achieved by training the network with these weather parameters of the specific hour as well as the preceding three hours. Using inputs of a previous day or hour is not uncommon for the determination of weather parameters, see e.g. in Skartveit et al. (1998), Ridley et al. (2010) where weather parameters of the previous hour are used in the determination of the direct and diffuse component of global insolation. For the neural network both the hour of the day and the wind direction were introduced by a sines and cosin component of either the wind direction in degrees from north or the time as an angle on a 24 hour clock. This was done to account for the otherwise introduced discontinuity between hour 24 and 1. The data of 579 days were randomly divided in training data (70%), validation data (15%) and test data (15%), which is a generally used division of the available data. The training data were used for training the network, the performance was assessed by the mean squared error on the validation data during the training. The neural network performance for the validation data was tested for eight different training functions in MATLAB R2012a (version 7.14.0.739), namely: (1) One step secant backpropagation, (2) Conjugate gradient backpropagation with Fletcher-Reeves updates, (3) RPROP backpropagation, (4) Conjugate gradient backpropagation with Polak-Ribiere updates, (5) Scaled conjugate gradient backpropagation, (6) Conjugate gradient backpropagation with Powell-Beale restarts, (7) BFGS quasi-Newton backpropagation and (8) Levenberg-Marquardt backpropagation. The neurons in the hiddenlayer were log-sigmoid neurons, the output layer consisted of a purelin neuron. For each of these training functions the number of neurons in the hiddenlayer was increased from 6 to 22 neurons by adding two neurons at a time. The network training was repeated 20 times for each of the steps in order to ensure a global minimum. Subsequently the network architecture with the lowest mean squared error on the validation data was chosen from the complete network training set as the network to use in the further evaluation. The performance goal during the training was a mean squared error of zero. The training of the network was terminated when the performance gradient was lower than 10^{-10} or there were six validation failures, meaning that the network performance did not improve for six epochs.

EXPERIMENTAL RESULTS

At five locations in Rotterdam the UHI intensity was measured directly. This section will first adresses these intensities, subsequently the diurnal variation of the UHI intensity is determined.

Urban heat island intensity in Rotterdam

The analysis of the hourly data from 01-04-2011 to 31-10-2012 showed an average urban heat island intensity over this period between 0.53 and 1.16 °C for the five locations. The maximum UHI intensity varied between 5.3 and 8.8 °C for the five locations, the maximum was found in the Center. The frequency distribution of the UHI for the five locations over the complete period are shown in Figure 2, the indicated distribution is the generalized extreme value distribution. A negative UHI intensity is not uncommon and is reported in several studies e.g. Oke (1982), Oke (1987), Carnahan & Larson (1990), Klysik & Fortuniak (1999), Runnalls & Oke (2000), Kalnay & Cai (2003), Giridharan et al. (2005), Kim & Baik (2005), Crawley (2008), Rizwan et al. (2008), Steeneveld et al. (2011), Mavrogianni et al. (2011). Oke (1987) reported that the occurrence of a negative urban heat island intensity might be restricted to city centres with deep and narrow urban canyons (higher aspect ratios). This is supported by the measurements, the strongest negative intensity was namely found in Rijnhaven, which had the highest aspect ratio of the five locations (aspect ratio Rijnhaven: 1.11).

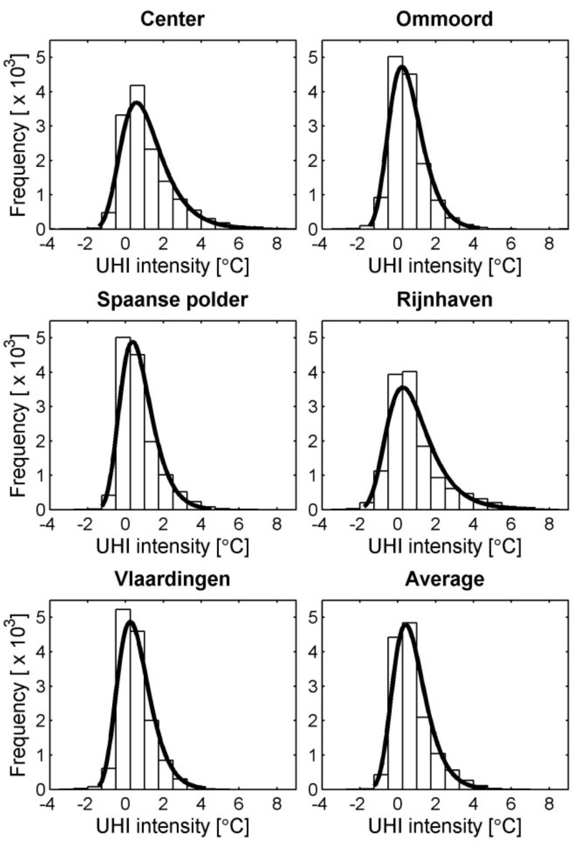

Figure 2. Measured UHI intensities from 01-04-2011 to 31-10-2012 for five locations as well as the average UHI intensity. The shown distribution is a fitted generalised extreme value distribution.

Diurnal variation of the urban heat island

The diurnal variation of the UHI intensity in Rotterdam was determined by a Fourier transformation of the average UHI intensity at the five locations in Rotterdam. Figure 3 shows the average diurnal variations for each month in one year from November 2011 to October 2012. It is shown that the variation during a day changes over the year. The maximum urban heat island intensity was found during the night and the minimum roughly at 10:00h. Moreover, it is visible from the average UHI intensity that the effect decreases rapidly during the morning and increases gradually during the day reaching its maximum during the night. The UHI intensity is relatively constant during the night (20:00h to 5:00h), which was also reported by e.g. Tumanov et al. (1999).

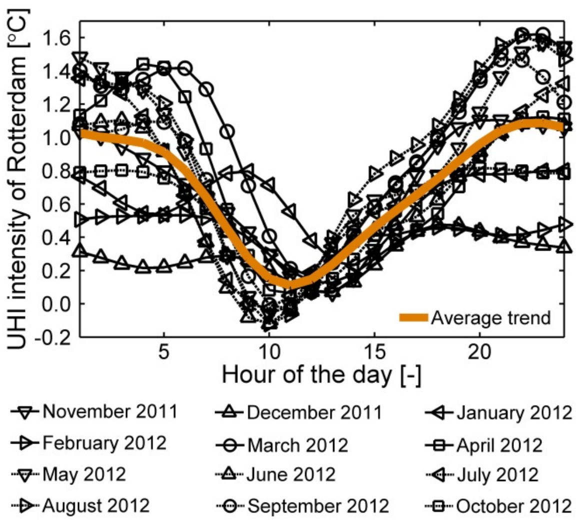

Figure 3. Diurnal variation of the UHI intensity in Rotterdam. The time is displayed in UTC+1 throughout the complete year.

MODELLED RESULTS

A neural network was trained in order to derive a data-driven model of the average UHI intensity in Rotterdam. This model included the same weather parameters as described by Kolokotroni et al. 2010 to determine the UHI intensity, meaning that wind speed, temperature, relative humidity, global horizontal irradiance and cloud cover were taken into account. In addition to these parameters the hour of the day, wind direction and solar elevation were added. The hour of the day was added based on its usage in existing time-based models (Kershaw et al. 2010, Crawley 2008). The hour of the day was also used as a UHI predictor in a neural network as reported by Gobakis et al. (2011). The hour of the day might be used by the network for accounting for the changing anthropogenic heat production over a day. The solar elevation was added to account for the effect of seasonal variation, which can potentially be learned by the trend in variation of the solar elevation over a year. Note that Gobakis et al. (2011) used the date to account for the seasonal variation. Network A in Figure 4 shows the mean squared error (MSE) of the neural network that was trained with five weather parameters to determine the UHI intensity.

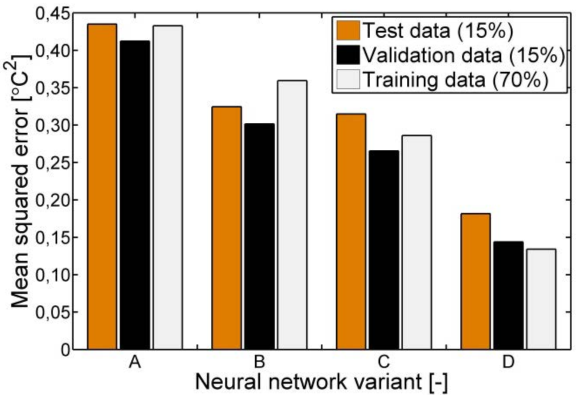

Figure 4: Mean squared error on test data, validation data and training data of four different neural networks. Network A is trained with five UHI determining weather parameters, 17 neurons in the hiddenlayer, the training function was scaled conjugate gradient backpropagation. Network B is trained with eight parameters, 17 neurons in the hiddenlayer and scaled conjugate gradient backpropagation as training function. Network C is trained with eight parameters, 20 neurons in the hiddenlayer and Levenberg-Marquardt backpropagation. Network D is trained with eight parameters for the hour in question as well as the preceding three hours, 20 neurons in the hiddenlayer and Levenberg-Marquardt backpropagation as training function.

The improvement of the network performance by adding the parameters as described above is visible by comparing network A with network B. The addition of the parameters resulted in a change in the MSE on the validation data and test data of -26% and -25% respectively. A re-analysis of eight different training functions as well as nine different network architectures resulted in a network with a lower MSE (network C in Figure 4). This network consisted of 20 neurons in the hiddenlayer with Levenberg-Marquardt backpropagation as training function. The MSE with network C changed with -36% and -28% for the validation data and test data respectively when compared to network A. Kim and Baik (2002) used the maximum UHI intensity of the previous day as one of the predictors in a data driven models based on a multiple linear regression analysis. In this study the eight weather parameters of the preceding three hours are used in an addition to the weather parameters as described above, which to the best of our knowledge has not been done before to predict the UHI intensity. For the network training a reanalysis of the network architecture and training function was performed, the network with the lowest MSE on the validation data is shown a variant D in Figure 4. This network consisted of 20 neurons in the hiddenlayer with Levenberg-Marquardt back-propagation as training function. The MSE with network D changed with -65% and -58% for the validation data and test data respectively when compared to network A. The addition of the UHI intensity predictors of the previous hours therefore improved the neural network performance. A comparison was made between the measured temperature in the urban area and the urban modelled temperature as well as the measured rural temperature. Based on this comparison the advantage of using a model of the UHI can be shown. Figure 5a shows the rural, urban and urban modelled temperature of five continues days with a typical UHI are shown. The results show that the model reproduces the trend and intensity of the UHI in an accurate manner. Figure 5b shows the predicted UHI intensity for five days, in which there was a non-typical diurnal variation of the UHI. The results indicate that the neural network is accurate for this period as well.

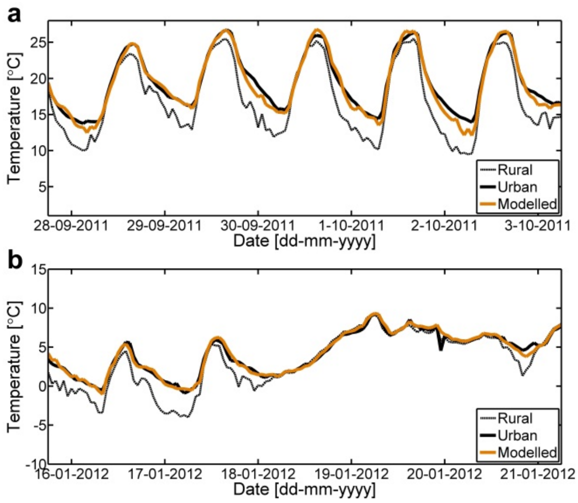

Figure 5: Measured en modelled urban temperature. (a) Shows the perdiction of the UHI for five days with a typical diurnal variation. (b) Shows the predicton during a period with a minimal UHI intensity.

In order to indicate the model accuracy over the whole period the regression coefficient was determined for both the case in which the modelled urban temperature and the rural temperature are used to represent the urban temperature, note that the latter is the commonly used method in building energy simulations. The adjusted coefficient of determination (R^2) for the neural network and the rural data are 0.996 and 0.980 respectively, therefore a stronger relation was found for the modelled urban temperature. The regression line on the data of the neural network is shifted 0.04 °C from the exact solution, and therefore shows a close fit to the measured data. Figure 6 shows the regression analysis. It can be seen that that there is a close agreement between the estimated urban temperature and the measured urban temperature.

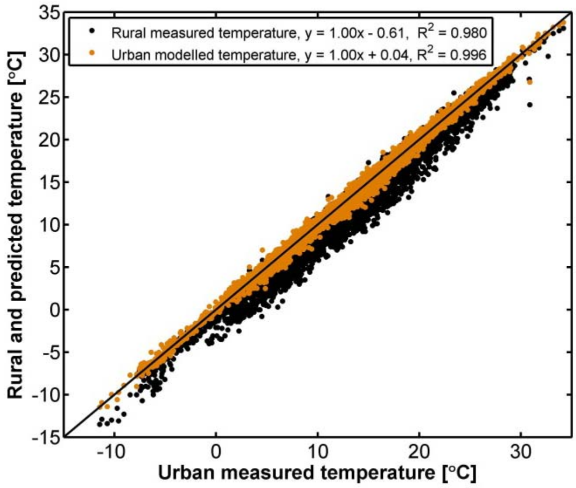

Figure 6. Comparison between the rural temperature, urban temperature and the modelled urban temperature.

DISCUSSION

This paper has provided a systematic analysis on how to convert rural temperatures to urban temperatures by the use of a neural network. While the study has provided several new insights, it is also important to mention the limitations of this study:

- The applicability of the developed neural network is limited to prediction the average UHI of Rotterdam.
- The study is based on the average UHI of Rotterdam, which was based on the measurements results of five locations, namely: City center, Ommoord, Rijnhaven, Spaanse polder and Vlaardingen.
- The measurements which were used for the neural network training were based on the period from 01-04-2011 to 31-10-2012. Long term changes in the UHI intensity by e.g. alterations in city size or alterations of population density can therefore not be taken into account by the use of the neural network.

In spite of these shortcomings, the present study has provided new and valuable insights. It has been shown that the artificial neural network approach as first described by Santamouris et al. (1999) and later by Mihalakakou et al. (2002), Kim & Baik (2002), Kolokotroni et al. (2010), Gobakis et al. (2011) does provide reliable results for the prediction of the UHI intensity of Rotterdam as well. Moreover, it has been shown that the addition of UHI determining parameters of the hours before the hour in question significantly improved the neural network performance (decrease in mean squared error of 65% on validation data). This also indicates that the UHI intensity at a certain time is a result of the weather determining parameters at that time, as well as the previous hours.

CONCLUSION

A data-driven method based on a neural network was used for the prediction of the average UHI intensity of Rotterdam. The results showed a mean squared error on the test data of 0.18 $°C^2$ indicating that this neural network approach does reproduce the UHI intensity of Rotterdam in an accurate manner. For the UHI of Rotterdam it was found that this existing method for UHI intensity prediction can be further improved by training the network with eight rural weather parameters of the specific hour as well as the preceding hours. This indicates that the UHI intensity at a certain time is a result of the weather determining parameters at that time, as well as the previous hours. This approach of weather data conversion can be used to convert weather data of a rural area in weather data for an urban area which can subsequently be used in building performance simulations. It should be noticed that one of the limitations of this approach is validity of a neural network, the application is namely limited to the location for which the neural network was trained.

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