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Thermal sensation prediction by soft computing methodology

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ABSTRACT

Thermal comfort in open urban areas is very factor based on environmental point of view. Therefore it is need to fulfill demands for suitable thermal comfort during urban planning and design. Thermal comfort can be modeled based on climatic parameters and other factors. The factors are variables and they are changed throughout the year and days. Therefore there is need to establish an algorithm for thermal comfort prediction according to the input variables. The prediction results could be used for planning of time of usage of urban areas. Since it is very nonlinear task, in this investigation was applied soft computing methodology in order to predict the thermal comfort. The main goal was to apply extreme leaning machine (ELM) for forecasting of physiological equivalent temperature (PET) values. Temperature, pressure, wind speed and irradiance were used as inputs. The prediction results are compared with some benchmark models. Based on the results ELM can be used effectively in forecasting of PET.

1. Introduction

There is rising interest for margin of urban planning, environmental health and the quality of life (Ghasemi et al., 2015). Public open spaces are recognized as the opportunity for achieving healthy environment for inhabitants in cities. Pleasant thermal comfort allows adequate conditions for longer duration of stay of users at the urban open space, which can contribute to health, relaxation, socialization and entertainment of children and adults. Staying outdoors can save energy for heating or cooling devices for work.

The importance of the thermal comfort of urban spaces is reflected in the sociological sense. The frequency of usage of urban open spaces is strongly affected by the relation between microclimatic conditions of urban spaces and human comfort. Therefore this relation must be taken into consideration during urban design and planning (Cohen et al., 2012). In order to describe and assess human thermal comfort the concept of thermal index was developed at the beginning of the 20th century by Gagge, Hill and Barnard (Taleghani et al., 2013). The possibility to assess the human thermal condition by one single number which integrates all relevant parameters was first recognized by Fanger in 1972 (Charalampopoulos et al., 2013). Since then more than 40 indices were developed and among most used ones are Predicted Mean Vote (PMV), Physiologically Equivalent Temperature (PET), Standard Effective Temperature (SET) and Perceived Temperature (PT) (Daneshvar et al., 2013). PET was introduced by Hoppe and Mayer and represents equivalent to the air temperature at which the heat balance of the human body is maintained with core and skin temperatures equal to those under the conditions being assessed. Numerous research in outdoor thermal comfort assessment which included PET were conducted for different climatic regions and areas like Italy (Salata et al., 2016), Iran (Daneshvar et al., 2013), Greece (Charalampopoulos et al., 2013), Spain (Algeciras and Matzarakis, 2015) and other.

Although the most of previous studies were focused on finding suitable way of selecting and further incorporating the number of influencing factors into the thermal comfort index models (Matzarakis et al., 1999) there is evident lack of investigations where prediction of thermal index was analyzed. We assert that predicted outdoor thermal comfort index should be regarded as additional useful parameter, besides predicted outdoor temperature, for planning inhabitants' activities in outdoor spaces. Therefore, the aim of present study was to develop and assess performances of predictive models of outdoor thermal comfort index. Starting from assumption that observed data were created as a result of nonlinear stochastic underlying process, focus was just on soft computing methods. Three methods were used for creating predictive models:

1) Extreme learning machine (ELM) (Huang et al., 2006; Huang et al., 2006),
2) Artificial neural network (ANN) (Liang et al., 2006) and
3) Genetic programming (GP) (Koza, 1992).

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Table 1
Summary statistics of input data.

Inputs	Parameters description	Maximum	Minimum
Input 1	Air temperature (T_a) (°C)	36.3	9.3
Input 2	Vapor pressure (VP) (hPa)	25.6	10.1
Input 3	Wind speed (W_s) (m/s)	7.5	0.0
Input 4	Global radiation (R_s) (W/m^2)	1142.7	0.0

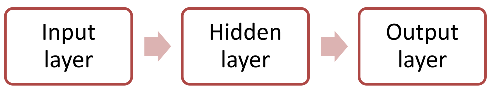

Fig. 1. The topological structure of the ELM.

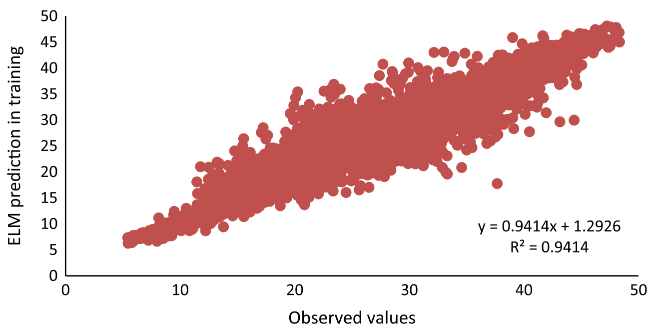

Fig. 2. Actual and forecasted values of PET by using ELM.

The predictive models were based on experimentally acquired data in Nis, Serbia.

2. Methodology

2.1. Physiologically equivalent temperature

In this study physiological equivalent temperature (PET) was used as thermal comfort indicator which is a thermal index recommended by the German Association of Engineers and officially used by the German Meteorological Servicen. PET index was derived from the human energy balance expressed in °C and it is suitable for urban and regional planners because of the simplicity of interpretation. Additional advantage of PET is that it could be used not only for summer conditions, but through the whole year. The PET index calculation was performed using the RayMan model developed by Matzarakis et al. (2007).

The data were collected at Observatory Nis in Serbia. Observatory is located inside the study area. Meteorological data was collected from automatic weather station. Input parameters for PET estimation were air temperature, vapor pressure, wind speed and global radiation. Data was taken during the July and August of 2015. Descriptive statistics for relevant variables is provided in Table 1.

2.2. Extreme Learning Machine

Extreme Learning Machine (ELM) was developed by Huang et al. (2006a, 2006b) as a learning algorithm for single hidden layer feed forward networks (SLFNs). This approach has several advantages as compared with conventional learning algorithms. These advantages could be:

1) Easy application,
2) Fast training and
3) Good generalization.

Table 2
ELM, ANN and GP models for PET prediction.

ELM			ANN			GP		
RMSE	R^2	r	RMSE	R^2	r	RMSE	R^2	r
2.3976	0.9466	0.9754	2.4077	0.9465	0.9707	2.6188	0.9387	0.9647

Topological structure of the ELM network is presented in Fig. 1. There are three layers in the network. Input layer acquires input samples and sends it to the hidden layer. The Hidden layer is standard single hidden layer with hidden nodes and activation function. There were weight vectors between hidden layer and output layer.

Predictive performance of the proposed model was assessed using following criterions: the root means square error (RMSE), coefficient of determination (R^2) and Pearson coefficient (r).

3. Results

Fig. 2 shows the ELM prediction of the PET values. The prediction accuracy is very high according the coefficient of determination. In other words ELM methodology has very good regression capability for the observed data. The most of the observed points are aligned along the line.

The ELM prediction accuracy was compared with artificial neural network (ANN) (Liang et al., 2006) and genetic programming (GP) (Koza, 1992) and results. Table 2 presents the prediction accuracy of the three models. Based on the results it can be concluded that the obtained PET values are characterized by favorable thermal comfort in 2016.

4. Conclusion

In the study PET prediction was described by the ELM method that showcases its benefits to predict PET. Forecasting of the PET values is complex task due to the many indicators and factors. ELM model was developed to estimate the PET based on four input parameters. Accuracy level of predicted values was assessed in comparison to ANN and GP results. The simulation results shown that ELM model was able to predict PET favorably so that it provides the most accurate predictions. It can be concluded that the prediction of PET is of great importance with a view to deciding on staying at this urban open space in a favorable period.

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