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ORIGINAL PAPER

Development and application of artificial neural network models to estimate values of a complex human thermal comfort index associated with urban heat and cool island patterns using air temperature data from a standard meteorological station

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Abstract

The present study deals with the development and application of artificial neural network models (ANNs) to estimate the values of a complex human thermal comfort-discomfort index associated with urban heat and cool island conditions inside various urban clusters using as only inputs air temperature data from a standard meteorological station. The index used in the study is the Physiologically Equivalent Temperature (PET) index which requires as inputs, among others, air temperature, relative humidity, wind speed, and radiation (short- and long-wave components). For the estimation of PET hourly values, ANN models were developed, appropriately trained, and tested. Model results are compared to values calculated by the PET index based on field monitoring data for various urban clusters (street, square, park, courtyard, and gallery) in the city of Athens (Greece) during an extreme hot weather summer period. For the evaluation of the predictive ability of the developed ANN models, several statistical evaluation indices were applied: the mean bias error, the root mean square error, the index of agreement, the coefficient of determination, the true predictive rate, the false alarm rate, and the Success Index. According to the results, it seems that ANNs present a remarkable ability to estimate hourly PET values within various urban clusters using only hourly values of air temperature. This is very important in cases where the human thermal comfort-discomfort conditions have to be analyzed and the only available parameter is air temperature.

Keywords Urban microclimate · Thermal sensation · Thermal climate indices · Physiologically Equivalent Temperature (PET) index · Neural network architecture · Performance criteria

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Introduction

In recent years, there is an increasing use of artificial neural networks (ANNs) in various aspects of atmospheric environment studies, e.g., to estimate values of dew point (Zounemat-Kermani 2012), reference evapotranspiration (Laaboudi et al. 2012), wind speed (Bilgili et al. 2007), air temperature in remote areas (Chronopoulos et al. 2008), rainfall's spatial interpolation (Sivapragasam et al. 2010), pollen and spore dispersion (Puc 2012; Grinn-Gofroń and Strzelczak 2009), and air pollutant dispersion (Moustris et al. 2010; Tsiros et al. 2009). Despite this increasing use of ANNs and despite also their advantages (i.e., generalization properties, capability of handling high dimensional data and non-linearities), there are, in general, a limited number of ANN applications concerning human thermal comfort-discomfort conditions (Moustris et al. 2009).

In the present study, the focus is on the development and application of ANNs to estimate the values of a complex human thermal comfort-discomfort index inside various urban sites using as only input air temperature from a standard meteorological station. More specifically, it is well documented that to appropriately address the effects of the complex environmental setting in many urban sites (such as streets, urban open areas, urban parks, urban squares, etc) on human thermal stress conditions, state-of-the-art and complex thermal climate indices and models need to be used (Tseliou et al. 2017; Pantavou and Lykoudis 2014; Pantavou et al. 2013; Cohen et al. 2012; Lin et al. 2010; Tseliou et al. 2010; Lin 2009; Lin and Matzarakis 2008; Johansson and Emmanuel 2006; De Dear and Brager 2001). Such a well-known and documented complex biometeorological index (human thermal comfort-discomfor index) is the Physiological Equivalent Temperature (PET) index. PET is based on a climate-chamber analysis of the human energy balance (Höppe 1999; Matzarakis et al. 1999). It has a widely known unit (°C) and it has been shown that it fits quite adequately to a wide range of urban microclimate studies (Shashua-Bar et al. 2012; Cohen et al. 2012; Lin and Matzarakis 2008; Johansson and Emmanuel 2006). In contrast to other indices using only air temperature and relative humidity, PET is a complex index, taking into account some meteorological parameters influencing thermal comfort such as air temperature, relative humidity, wind speed, and mean radiant temperature (MRT) which sums up all short- and long-wave radiation whereas additional parameters such as age, gender, metabolic rate, clothing resistance air pressure, height, and weight are also required.

The main objective of the present work is then the estimation of hourly values of PET index using only air temperature data. For this purpose, ANN models were developed and properly trained in order to predict hourly PET values in different locations within the urban environment using only as input hourly values of air temperature. The study was carried out in Athens (Greece), a city for which the urban heat island along with its implications is well documented (Shashua-Bar et al. 2010; Niachou et al. 2008). First, hourly values of PET index were calculated for different locations within the Athens urban environment. ANN models were then developed and appropriately trained to predict hourly values of PET index using only one meteorological parameter, the air temperature. The estimated PET values by the developed ANN models for different urban environmental configurations were finally evaluated in comparison with the actual-observed PET values to evaluate their performance and predictive ability.

Data and methodology

Field monitoring data

The monitored sites are located inside the Athens' urban fabric and include a street's sidewalk, an urban square, an urban park, a vegetated courtyard inside a typical urban complex, and a gallery attached to the courtyard (Fig. 1). Athens, a city characterized by a Mediterranean, mild humid climate, has dry—warm hot—summers that can be particularly hot whereas heat waves are common during the months of July and August (Nastos and Matzarakis 2013; Theoharatos et al. 2010; Giles et al. 1990; Prezerakos 1989).

These sites (Fig. 1) represent a wide range of configurations and settings in the urban environment, especially in terms of shading: the values of the sky view factor (SVF), estimated by the use of fish-eye photographs, were found to be 0.20, 0.37, 0.07, 0.05, and 0.04 for the street's sidewalk site, the urban square, the urban park, the vegetated courtyard, and the gallery attached to the courtyard, respectively. Note that the urban park is not shown in Fig. 1 since it is located about 2 km northeast of the urban cluster. A detailed microclimatic analysis of the courtyard and the attached gallery was presented in Tsiros and Hoffman (2014). In all cases, continuous measurements of both air temperature and relative humidity were carried out using "Hobo Pro"-type sensors that are combined sensors of air temperature/relative humidity and data loggers. In addition, inside the courtyard, an integrated mini meteorological station was placed to provide data for other meteorological parameters for selected representative time periods to derive wind speed data and also first-order estimates for the mean radiation temperature (T_{mrt}) and to compare them to model-obtained values for this parameter. For a detailed description of the instrumentation used, the reader should refer to the work of Tsiros and Hoffman (2014).

The human thermal comfort-discomfort index PET

For the thermal comfort and thermal stress estimation within the various urban configurations, the Physiological Equivalent Temperature index was used (Höppe 1999; Matzarakis et al. 1999). All calculations for the PET index and the mean radiant temperature, required for PET estimation, are performed using the Ray-Man model. The Ray-Man model has been developed at the Meteorological Institute, University of Freiburg, Germany (Matzarakis et al. 2007, 2010). The model calculates the radiation flux within environmental configurations on the basis of parameters including day of year, time of the day, albedo and solid–angle proportions of the surrounding environmental surfaces, cloud cover, and the Linke turbidity factor of the atmosphere. To accurately describe a site's

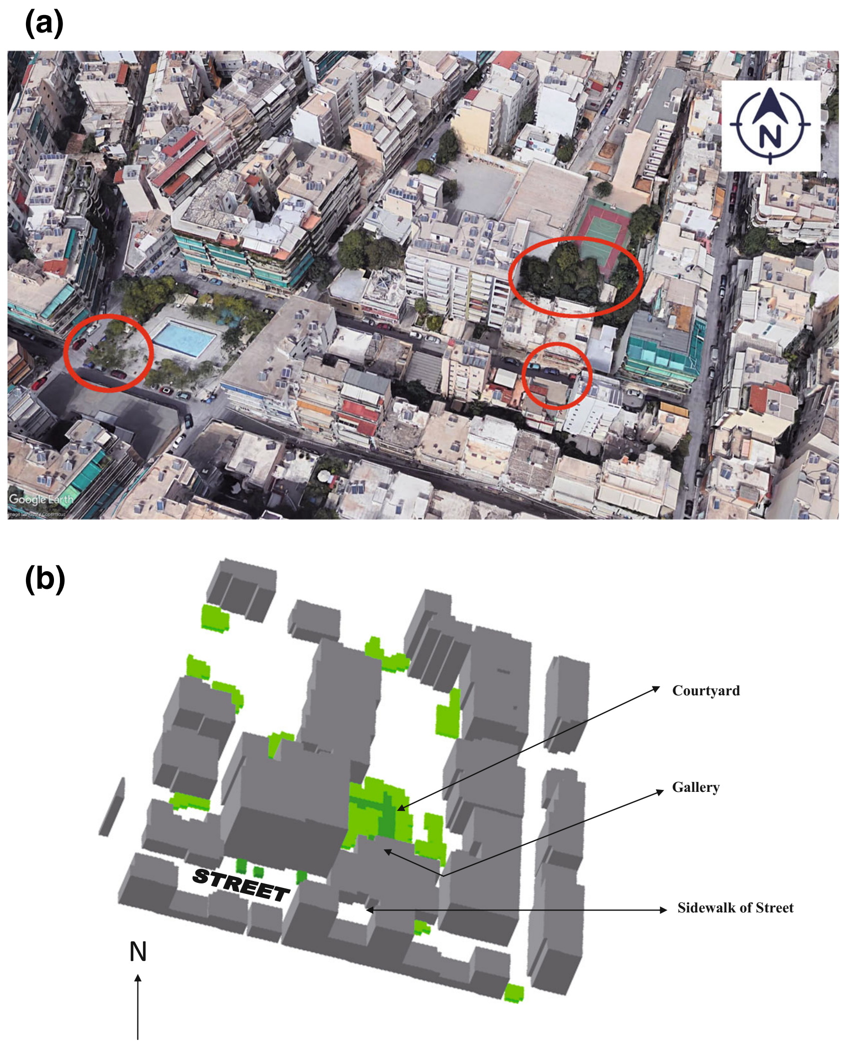

Fig. 1 The study area for the evaluation of the ANN models. **a** The urban cluster with the different urban environment configurations shown in circles: the courtyard along the attached gallery, the street, and the square. **b** Detailed picture of the location of the courtyard, the gallery, and the street's sidewalk

environmental configuration for accounting the shading effects on solar radiation and on long-wave radiation flux calculations, the Ray-Man model has options to insert obstacles, topography, and sky view factors (the ratio of free sky space to the entire fish-eye view) appropriately obtained by fish-eye photographs of the sky taken from the measurement locations. Recent testing studies showed that the model is able to calculate reasonably values of radiation fluxes within typical urban complexes (Matzarakis et al. 2010). To calculate the PET index values at the various sites, air temperature, relative humidity, and wind speed data recorded at the sites along with the values of SVFs are inserted into the Ray-Man model.

The developed ANN models

In the present work, multi-layer perceptron (MLP) ANN models were developed using the back-propagation training algorithm to predict PET hourly values. The MLP-based ANN models consist of an input layer where all the input data (input nodes) for the appropriate training are presented to the model. After the input layer, one or more hidden layers with a number of hidden artificial neurons follow. All artificial neurons are fully interconnected with the artificial neurons of the previous layer and so on. Finally, the output layer is the "terminal layer" of the MPL model where the artificial neurons called also as targets are presented. In each loop called epoch, the model calculates the error between the predicted value by the model and the corresponding target value and this error is back-propagated from layer to layer. By this way, the performance of the model is optimized by adjusting the weights of input nodes (Werbos 1988).

For the prediction of PET hourly values, two different ANN models were developed and appropriately trained. The first one was trained to predict PET hourly values during the warm period of the year (May–September), and the second one was trained in order to predict PET hourly values during the cold period of the year (October–April).

Data from two standard meteorological stations were used. These meteorological data have been recorded by the Hydrological Observatory of Athens (HOA) operated by the National Technical University of Athens (NTUA) covering the 7-year period 2005–2011 (http://hoa.ntua.gr). The first meteorological station is named Ilioupoli (Fig. 2) and is located within the municipality of Ilioupoli installations in the foot of Ymittos Mountain (206 m above sea level). The second meteorological station is named Penteli (Fig. 2) and is located inside the Petraki Monastery on Penteli Mountain (729 m above sea level).

The aforementioned meteorological data concern hourly values of air temperature (°C), air relative humidity (%), wind speed (m/s), and global solar irradiation (W/m^2) on a horizontal surface covering the period 15/06/2005–31/12/2011 (108,696 available hours). It should be noted that air temperature ranged between − 7.3 and 41.6 °C, a temperature range capable of covering most areas of Greece and especially regions within the greater Athens area.

The PET index values were calculated for both locations (Penteli and Ilioupoli) on an hourly basis using the Ray-Man model. In biometeorological studies, the height of 1.1 m above ground is considered as the mean gravity center of the human body (Matzarakis et al. 1999). The required hourly values of wind speed at 1.1 m above the ground for use in the Ray-Man model and the available wind speed values (108,696 hourly values) recorded by anemometers mounted in both cases on the top of a meteorological mast had to be adjusted using the well-known parameterization of the logarithmic wind profile (Arya 2001) as it is described in Eq. (1):

$$u(z) = u_{\mathrm{ref}} \cdot \frac{\ln\left(\frac{z}{z_0}\right)}{\ln\left(\frac{z_{\mathrm{ref}}}{z_0}\right)} \tag{1}$$

where, $u(z)$ is the wind speed at height (z) above the ground level, (z_o) is the aerodynamic roughness length of the surface, and u_{ref} is the measured wind speed by the anemometer at the (z_{ref}) height above the ground level. In our case, $z = 1.1$ m and $z_{ref} = 10.0$ m. The aerodynamic roughness length of the surface for the given monitoring sites was taken $z_o = 0.4$ m for Penteli and $z_o = 0.8$ m for Ilioupoli taking into account the topography of each site.

Using the hourly values of the air temperature, air relative humidity, wind speed at 1.1 m above the ground level, and the corresponding hourly values of global solar irradiation, the hourly values of PET were calculated applying the Ray-Man model.

Furthermore, two different ANN models were developed, as described above, one for the warm and one for the cold period of the year. Each one of the developed ANN models consists of one input layer, one hidden layer, and one output

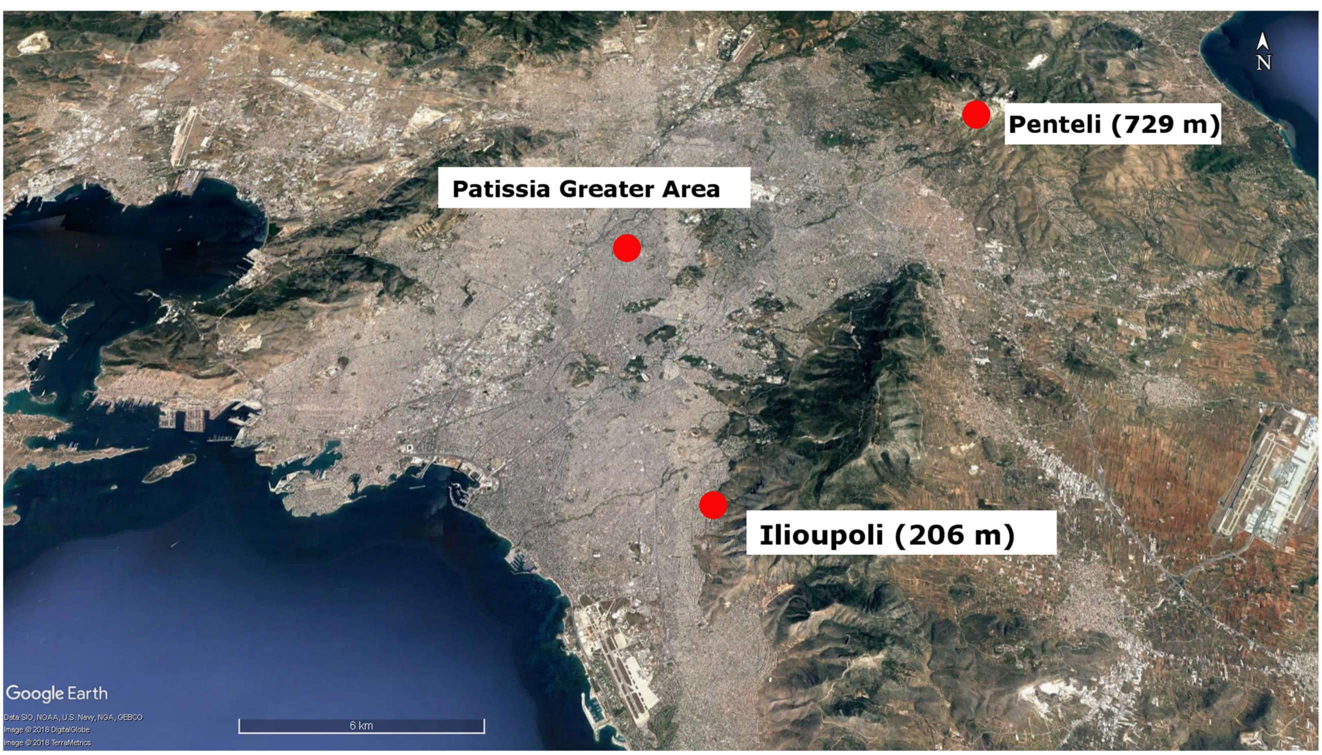

Fig. 2 The wider area of Athens city. The location of Ilioupoli and Penteli standard meteorological stations along with the location of field monitoring sites in the Patissia Greater Area (close to downtown area of Athens) is shown

Table 1 Statistical evaluation indices for the general evaluation of the accuracy of the developed ANN models (10% testing data set for Penteli and Ilioupoli meteorological stations)

	Number of predicted hours (10% of the whole data set)	MBE (°C)	RMSE (°C)	IA	R^2
ANN model for the warm period of the year	4579	0.6	2.2	0.988	0.957
ANN model for the cold period of the year	6289	0.9	3.0	0.966	0.888

layer. The optimum number of hidden artificial neurons in the hidden layer was found after a trial and error method. For the appropriate training of the developed ANN models, the number of month (1–12), the number of day (1–31), the hour of the day (1–24), and the hourly air temperature (°C) were used as input-training data. The target-predicted value of the trained ANN model was in both cases the corresponding hourly PET value which was previously calculated by the Ray-Man model. By this way, the two developed ANN models were able to predict the hourly values of PET using only the number of the month, the number of day, the hour of the day, and the hourly air temperature. During the training phase, 80.0% of the total data set was used as the training data set, 10.0% was used as the testing data set, and 10.0% was used as the cross validation data set (Nastos et al. 2011).

Evaluation statistical indices-ANN models performance evaluation

To test the performance of the developed ANN models, the corresponding PET hourly values were calculated for the selected locations inside the urban environment with different configurations as previously mentioned and shown in Figs. 1 and 2.

For these locations, the hourly PET values were calculated with the Ray-Man model based on measured microclimatic data. Then, for the same locations, the developed ANN models were applied in order to estimate the corresponding PET hourly values. This allowed the predicted hourly PET values by the developed ANN models to be compared with the corresponding hourly PET values derived by the application of Ray-Man model to site-specific microclimatic data at the various locations. For this purpose, data are used from microclimatic measurements carried out in several urban sites in the city of Athens during the summer period of the year 2007. This year was selected for the purpose of the present study since it was exceptionally hot for south-eastern Europe and Greece: a number of heat waves hit the area at the end of June, in July, and in August, and Greece experienced an all-time record-breaking hot summer (daily maximum air temperature on June 26th 2007 of 44.8 °C recorded at the

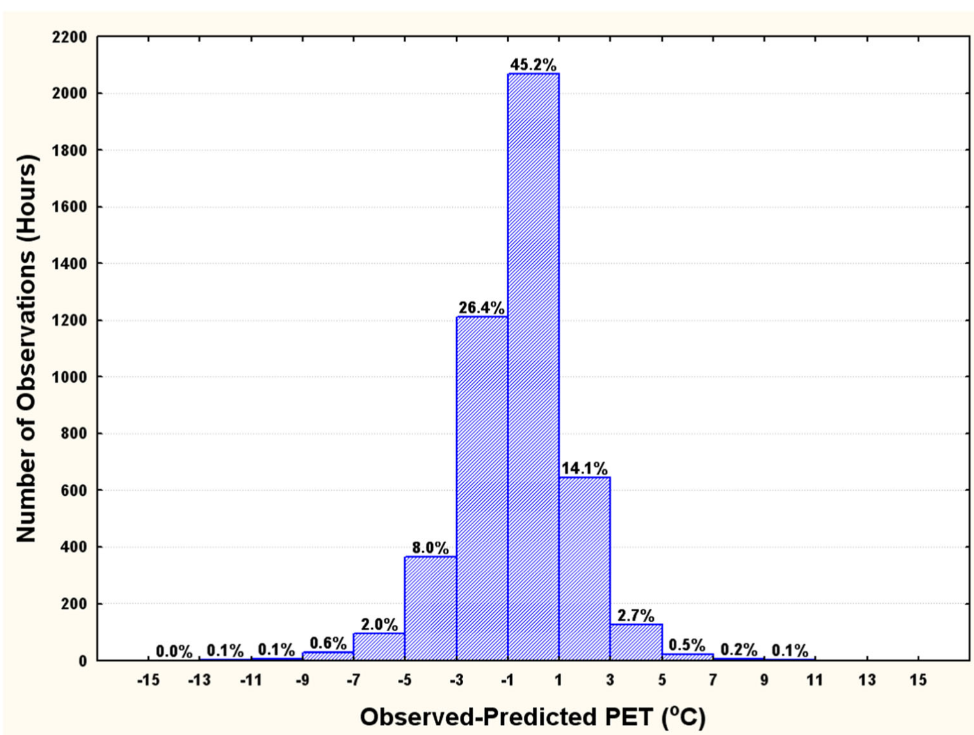

Fig. 3 Frequency distribution of differences between predicted and observed PET index values (10% testing data set for Penteli and Ilioupoli—warm period of the year)

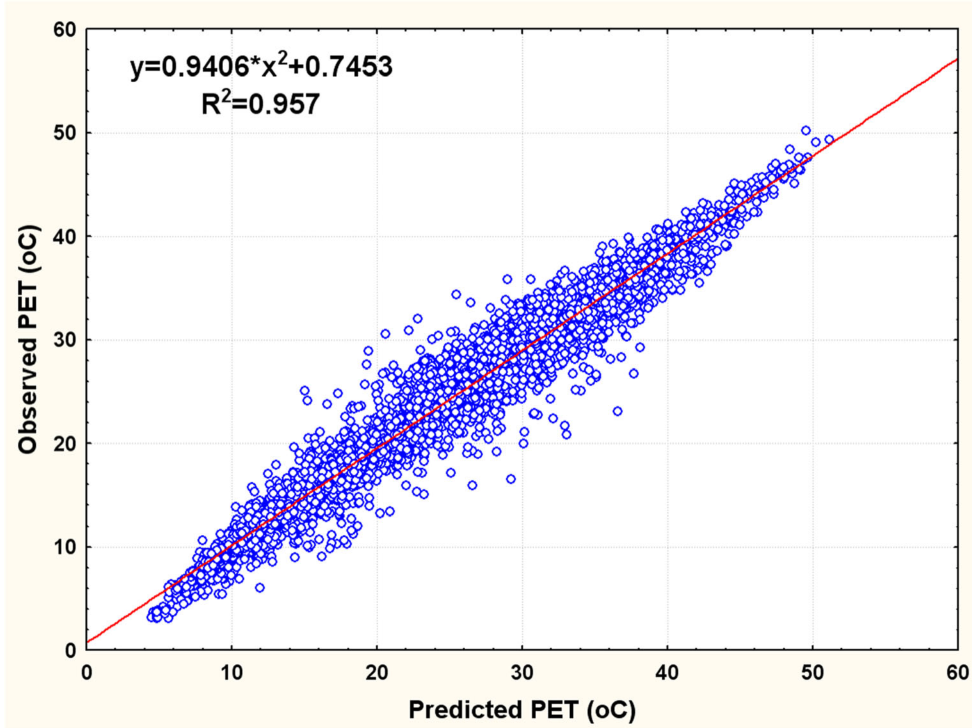

Fig. 4 Scatter plot for predicted vs observed PET index values (10% testing data set for Penteli and Ilioupoli—warm period of the year)

National Observatory of Athens station) with nocturnal air temperatures also to remain at high levels (Founda and Giannakopoulos 2009). In the present study, the data used were based on the continuous measurements carried out from July 27 to August 28.

For the evaluation of the predictive ability of the developed ANN models, some well-established statistical evaluation indices were used. More specifically, the mean bias error (MBE), the root mean square error (RMSE), the index of agreement, and the coefficient of determination (R^2) were applied in order for the predictive accuracy to be investigated (Moustris et al. 2010; Nastos et al. 2011).

In addition, since the main interest in the present study is to predict thermal sensation classes according to PET values, some special performance indices were used to evaluate model's predictive ability of PET human thermal comfort-discomfort classes, i.e., to investigate if the model accurately predicts PET values within the correct human thermal sensation classes. These specific performance indices are the true predictive rate (TPR), the false alarm rate (FAR), and the Success Index (SI) (Moustris et al. 2010). The TPR indicates the ratio of the predicted PET values by the models that belong to specific sensation classes and were predicted correct. The FAR indicates the ratio of the fault predictions, i.e., the models predict PET values that do not belong in the same sensation classes as the actual-observed PET values. Finally, the SI indicates the ratio of the general success of the ANN models to predict if the PET values belong in a specific sensation class or not.

Table 2 Values of performance indices values (10% testing data set for Penteli and Ilioupoli meteorological stations—warm period of the year)

PET class	Thermal sensation	*X* (hours)	*Y* (hours)	*Z* (hours)	*W* (hours)	TPR (%)	FAR (%)	SI (%)
PET ≤ 4	Very cold	0	15	0	4564	0.0	–	99.7
4 < PET ≤ 8	Cold	123	66	23	4367	65.1	15.8	98.1
8 < PET ≤ 13	Cool	634	125	162	3658	83.5	20.4	93.7
13 < PET ≤ 18	Slightly cool	914	233	206	3226	79.7	18.4	90.4
18 < PET ≤ 23	Neutral	455	214	224	3686	68.0	33.0	90.4
23 < PET ≤ 29	Slightly warm	382	228	209	3760	62.6	35.4	90.5
29 < PET ≤ 35	Warm	434	249	172	3724	63.5	28.4	90.8
35 < PET ≤ 41	Hot	286	117	168	4008	71.0	37.0	93.8
PET > 41	Very hot	105	2	85	4387	98.1	44.7	98.1

Table 3 Statistical performance indices of the ANN models for PET index classes at the E-W street's sidewalk. Warm period of the year 2007

PET class	Thermal sensation	X (hours)	Y (hours)	Z (hours)	W (hours)	TPR (%)	FAR (%)	SI (%)
PET ≤ 4	Very cold	–	–	–	–	–	–	–
4 < PET ≤ 8	Cold	–	–	–	–	–	–	–
8 < PET ≤ 13	Cool	–	–	–	–	–	–	–
13 < PET ≤ 18	Slightly cool	–	–	–	–	–	–	–
18 < PET ≤ 23	Neutral	8	13	50	170	38.1	86.2	74.2
23 < PET ≤ 29	Slightly warm	37	56	5	143	39.8	11.9	75.0
29 < PET ≤ 35	Warm	18	20	6	197	47.4	25.0	89.6
35 < PET ≤ 41	Hot	11	29	12	189	27.5	52.2	83.3
PET > 41	Very hot	48	0	32	161	100.0	40.0	87.1

Specifically, denoting the number of cases where the PET values were observed and predicted in the same human thermal sensation class as X, the number of cases that were observed in a specific human thermal sensation class but not predicted in the same thermal class as Y, the number of cases that were predicted in a specific human thermal sensation class but not observed in the same thermal class as Z, and the number of the rest cases as W, for each PET human thermal sensation class, the following indices are calculated (Schlink et al. 2003; Papanastasiou et al. 2007):

$$\mathrm{TPR} = \frac{X}{X+Y} \tag{2}$$

$$\mathrm{FAR} = \frac{Z}{Z+X} \tag{3}$$

$$\mathrm{SI} = \frac{X+W}{X+Y+Z+W} \tag{4}$$

Results and discussion

As mentioned above, for the appropriate training of the developed ANN models, the areas of Penteli and Ilioupoli (Fig. 2) were selected. After the training phase using 90.0% of the available data for both locations, the testing set (10.0% of the available data) was applied to the developed ANN models. According to the results of the testing phase, the developed ANN models present a remarkable predictive ability. The values for MBE, RMSE, IA, and R^2 were found to be 0.6 °C, 2.2 °C, 0.988, and 0.957, respectively, for the warm period of the year and 0.9 °C, 3.0 °C, 0.966, and 0.888, respectively, for the cold period of the year (Table 1).

Figure 3 shows the frequency distribution of the differences between the predicted and observed PET values according to the 10.0% testing data set for Penteli and Ilioupoli during the warm period of the year whereas in Fig. 4, the associated scatter plot is depicted.

According to Fig. 3, it seems that 85.7% of the predicted hourly PET values differ with the observed values by ± 3.0 °C. Moreover, in Fig. 4, it is shown a strong linear correlation between predicted and observed values with a coefficient of determination $R^2 = 0.957$. This means that the developed ANN model is able to explain 95.7% of the data variance.

Table 2 presents the values of TPR, FAR, and SI for the associated testing data set (Penteli and Ilioupoli) concerning the warm period of the year.

Table 4 Statistical performance indices of the ANN models for PET index classes at the urban square with limited vegetation. Warm period of the year 2007

PET class	Thermal sensation	X (hours)	Y (hours)	Z (hours)	W (hours)	TPR (%)	FAR (%)	SI (%)
PET ≤ 4	Very cold	–	–	–	–	–	–	–
4 < PET ≤ 8	Cold	–	–	–	–	–	–	–
8 < PET ≤ 13	Cool	–	–	–	–	–	–	–
13 < PET ≤ 18	Slightly cool	4	0	12	224	100.0	75.0	95.0
18 < PET ≤ 23	Neutral	46	16	21	157	74.2	31.3	84.6
23 < PET ≤ 29	Slightly warm	25	31	5	179	44.6	16.7	85.0
29 < PET ≤ 35	Warm	16	7	10	207	69.6	38.5	92.9
35 < PET ≤ 41	Hot	13	8	8	211	61.9	38.1	93.3
PET > 41	Very hot	72	2	8	158	97.3	10.0	95.8

Table 5 Statistical performance indices of the ANN models for PET index classes at the urban park. Warm period of the year 2007

PET class	Thermal sensation	X (hours)	Y (hours)	Z (hours)	W (hours)	TPR (%)	FAR (%)	SI (%)
PET ≤ 4	Very cold	–	–	–	–	–	–	–
4 < PET ≤ 8	Cold	–	–	–	–	–	–	–
8 < PET ≤ 13	Cool	–	–	–	–	–	–	–
13 < PET ≤ 18	Slightly cool	2	0	22	216	100.0	91.7	90.8
18 < PET ≤ 23	Neutral	22	22	41	155	50.0	65.1	73.8
23 < PET ≤ 29	Slightly warm	29	47	4	160	38.2	12.1	78.8
29 < PET ≤ 35	Warm	21	22	6	191	48.8	22.2	88.3
35 < PET ≤ 41	Hot	15	24	18	183	38.5	54.5	82.5
PET > 41	Very hot	36	0	24	180	100.0	40.0	90.0

According to Table 2, for all sensation classes, SI valued range from 90.4% up to 98.1%. This means that the developed model is able to predict PET values within the correct sensation class in a remarkable accuracy. Also, even during the warm period of the year (April–October), hours with cold and very cold human thermal sensation do appear due to the fact that the Penteli meteorological station is located at the North side of Athens city in a quite high height above sea level (729 m a.s.l).

Similar results are also obtained for the developed ANN models concerning the cold period of the year but are not presented here because the present work focuses on the predictive ability of the developed ANN models during the warm period of the year for different environment configurations.

After the abovementioned evaluation of the developed ANN models, using the 10.0% testing data set for Penteli and Ilioupolis, the values of PET index for a number of different locations with different urban environment configuration were predicted applying the developed ANN models for the warm period of the year 2007.

In Table 3, the results for the case of a street are shown.

The specific street has an approximate East-West (E-W) orientation and the obtained results refer to the sidewalk. Table 3 shows that the values of SI range between 74.2% (comfortable) up to 89.6% (warm). This means that the developed and trained ANN models with data from Penteli and Ilioupoli are able to predict very well the sensation class according to PET index using only air temperature in a quite different environment configuration.

In Table 4, the results in the case of an urban square are shown. The square has a small vegetative coverage and presents increased PET values leading thus to increased number of hours with heat stress conditions.

In the case of the urban square with limited vegetation, the developed ANN model for the warm period of the year shows a remarkable ability to predict PET values within the correct human thermal comfort-discomfort sensation class. The values of SI range between 84.6% (comfortable) up to 95.8% (very hot).

On the contrary, the urban park (Table 5) presents smaller PET values, compared to the square, leading thus to, in general, decreased number of hours of heat stress conditions.

The values of SI are ranging between 73.8% (comfortable) up to 90.8% (slightly cool) indicating a very good performance of the developed ANN model in case of the urban park.

Table 6 Statistical performance indices of the ANN models for PET index classes at the vegetated courtyard inside an urban cluster. Warm period of the year 2007

PET class	Thermal sensation	X (hours)	Y (hours)	Z (hours)	W (hours)	TPR (%)	FAR (%)	SI (%)
PET ≤ 4	Very cold	–	–	–	–	–	–	–
4 < PET ≤ 8	Cold	–	–	–	–	–	–	–
8 < PET ≤ 13	Cool	–	–	–	–	–	–	–
13 < PET ≤ 18	Slightly cool	–	–	–	–	–	–	–
18 < PET ≤ 23	Neutral	144	0	53	43	100.0	26.9	77.9
23 < PET ≤ 29	Slightly warm	165	54	18	3	75.3	9.8	70.0
29 < PET ≤ 35	Warm	155	30	3	52	83.8	1.9	86.3
35 < PET ≤ 41	Hot	159	19	12	50	89.3	7.0	87.1
PET > 41	Very hot	155	0	17	68	100.0	9.9	92.9

Table 7 Statistical performance indices of the ANN models for PET index classes at the gallery attached to the vegetated courtyard inside an urban cluster. Warm period of the year 2007

PET class	Thermal sensation	*X* (hours)	*Y* (hours)	*Z* (hours)	*W* (hours)	TPR (%)	FAR (%)	SI (%)
PET ≤ 4	Very cold	–	–	–	–	–	–	–
4 < PET ≤ 8	Cold	–	–	–	–	–	–	–
8 < PET ≤ 13	Cool	–	–	–	–	–	–	–
13 < PET ≤ 18	Slightly cool	–	–	–	–	–	–	–
18 < PET ≤ 23	Neutral	2	0	61	178	100.0	96.8	75.0
23 < PET ≤ 29	Slightly warm	31	76	17	117	29.0	35.4	61.7
29 < PET ≤ 35	Warm	20	29	10	182	40.8	33.3	84.2
35 < PET ≤ 41	Hot	22	19	11	189	53.7	33.3	87.9
PET > 41	Very hot	38	4	18	181	90.5	32.1	91.3

Similar results are obtained also for the case of a courtyard with irrigated vegetation (Table 6), presenting, in general, limited number of hours with high stress conditions.

According to Table 6, the values of SI are ranging between 77.9% (comfortable) up to 92.9% (very hot) indicating a very good predicted ability for the vegetated courtyard inside an urban cluster. This is also the case of the gallery attached to the courtyard (Table 7).

The values of SI are ranging between 61.7% (slightly warm) up to 91.3% (very hot). This means that even in the case of the gallery attached to the vegetated courtyard inside an urban cluster, the developed ANN models present a fairly good predictive ability.

In all cases, based on the values of the statistical errors, the ANN models were found capable of estimating PET classes.

Conclusions

In this work, ANN models were developed and applied in order to predict human thermal comfort-discomfort sensation using only air temperature. The developed ANN models appear to be capable to deal with thermal comfort estimations in cases where the application of complex and input-demanding thermal indices is not always straightforward (e.g., some input parameters may be difficult to assign values, not all required input data are readily available, etc). In addition, assuming ANN models are adequately trained, the simple method used in the present study may be used to estimate values of complex thermal comfort indices such as PET at any site using as only inputs air temperature data recorded at a reference meteorological station.

According to the results, it seems that the developed ANN models are able to predict PET values in a very good accordance with the actual-observed values in different urban environment configurations. The most important is that the models present a remarkable accuracy to estimate the human thermal comfort-discomfort sensation compared to the corresponding PET classes.

Limitations, however, should also be mentioned: the training of ANNs requires, in general, a large number of meteorological data time series; this could be an important limitation in some cases. In addition, in the context of modeling alternative scenarios to deal with design options inside the urban fabric to ameliorate thermal conditions, these models cannot be used since they are, in general, not easily interpretable models. Future efforts should focus on efficient techniques to manipulate the results of ANN models to be used for interpretation of modeled scenarios in urban heat island problems, keeping in mind the warming trends during summertime.

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