environmental sciences proceedings

MDPI

Proceeding Paper

Artificial Neural Network Models for the Estimation of Air Temperature Cooling and Warming Patterns Inside Urban Clusters: The Case of Courtyards in Athens, Greece †

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† Presented at the 16th International Conference on Meteorology, Climatology and Atmospheric Physics—COMECAP 2023, Athens, Greece, 25–29 September 2023.

Abstract: In the present study, the microclimatic conditions of two courtyards in the city of Athens are evaluated based on filed monitoring data and data predicted by artificial neural network models (ANNs). The study focuses on the development and application of ANNs in order to estimate air temperature and relative humidity values in complex urban forms such as courtyards from a standard meteorological station, using air temperature and relative humidity as the only inputs. The results are then evaluated to identify the prognostic ability of the developed ANNs models, showing a remarkable predictive ability.

Keywords: artificial neural network; urban environment; courtyards microclimate; Athens; Greece

Citation: Thoma, E.; Moustris, K.; Tseliou, A.; Papadopoulos, G.; Tsiros, I. Artificial Neural Network Models for the Estimation of Air Temperature Cooling and Warming Patterns Inside Urban Clusters: The Case of Courtyards in Athens, Greece. *Environ. Sci. Proc.* **2023**, *26*, 97. https://doi.org/10.3390/environsciproc2023026097

Academic Editor: Panagiotis Nastos

Published: 28 August 2023

1. Introduction

The modelling of thermal conditions and human thermal comfort/discomfort in an outdoor urban environment such as a courtyard is a highly topical challenge in modern bioclimatic research. Several scientists all over the world have been involved with the specific topic and their conclusions and research results have found applications in a wide range of fields, including public health, medicine, physiology, sport, biometeorology, engineering, etc. [1,2].

In order for thermal human thermal comfort/discomfort in an outdoor urban environment to be modelled, some meteorological parameters, such as air temperature and humidity, solar irradiation, etc., are required. For this purpose, typical meteorological instruments are used to measure these parameters. It is well known that during measurement taking, there is great possibility for some measurements to be lost or to not be taken at all, for many different reasons. In that case, different statistical or other approaches are applied in order to recover the lost data.

Mohmed et al. [3] applied artificial neural networks (ANNs) to predict environmental conditions, such as temperature, CO_2 concentrations, air relative humidity and light radiation, to enhance crop production systems and improve plant performance and resource use efficiency in a Chinese Solar Greenhouse. Hu et al. [4], in their study, proposed a new technique to retrieve temperature and relative humidity profiles under clear sky conditions in the Arctic region based on artificial neural network (ANN) modelling. Vouterakos et al. [5] developed different ANNs models in order to forecast human thermal comfort/discomfort conditions three days ahead in different locations within the greater Athens area, Greece.

In this work, ANNs models were developed in order to predict air temperature and relative humidity during the warm period of the year (June–September) in two different courtyards located in the urban environment of Athens city, Greece.

2. Materials and Methods

For the scope of the specific work, meteorological data from two courtyards in two different locations in the capital city of Athens were used. More specifically, the present study concerns two courtyards (a small and a large one) inside the urban fabric of Athens, located in the Patissia neighbourhood, between the main streets of Stratigou Kallari and Nirvana. It should be noted that a courtyard in Athens, in most cases, is an irregularly shaped space, with or without vegetation; it is the result of high building density constructions where the old family houses have been replaced by small apartment blocks. An early study of courtyards in Athens showed a remarkable amelioration of thermal comfort during extreme hot weather conditions [6]. In the present study, continuous micrometeorological measurements of air temperature and relative humidity were carried out using Hobo-Pro-type sensors that were housed in makeshift mini multi-plate screens consisting of aluminium foil reflective radiation protective shields. On selected days, an integrated micrometeorological station was placed inside the courtyards, providing solar radiation and wind data.

The above-measured meteorological parameters from the two courtyards, such as air temperature (°C) and relative humidity (%), were combined with the corresponding air temperature and relative humidity values for the same time period (July and August 2019), measured by the standard meteorological station belonging to the National Observatory of Athens (NOA). Then, the whole dataset was used for the appropriate ANNs training. More concretely, four different ANNs models were trained and developed (Figure 1). The first (ANN#1) was developed in order to predict air temperature in the small courtyard, for the period June–September, on an hourly basis. The second model (ANN#2) was developed in order to predict relative humidity in the small courtyard for the period June–September on an hourly basis. The third model (ANN#3) was developed in order to predict air temperature in the large courtyard, for the period June–September on an hourly basis, and finally the fourth and last model (ANN#4) was developed in order to predict relative humidity in the large courtyard for the period June–September on an hourly basis. At this point, it has to be mentioned that the output of each model was used as the input for the next model (Figure 1).

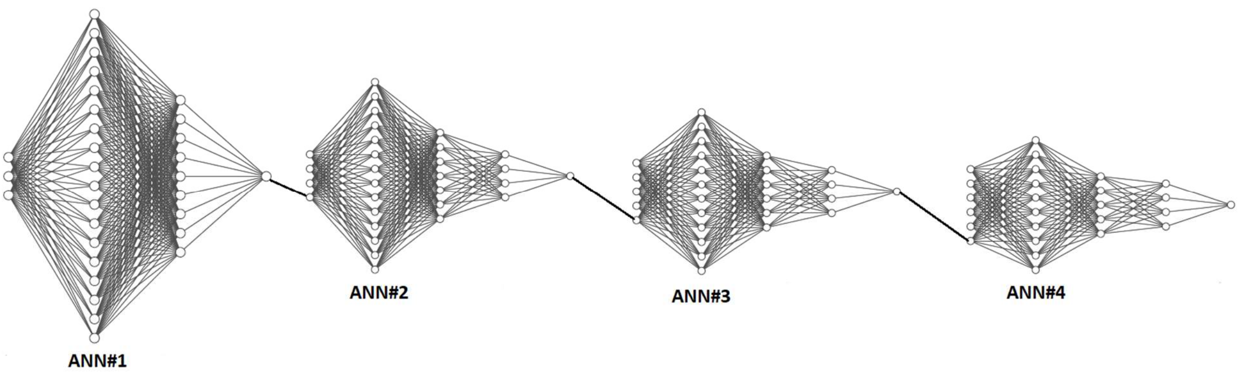


Figure 1. Topology of the four developed ANNs models.

For the development of the four ANNs predicted models, MatLab software (version: R2022b) was used. The architectural structure of each model was derived using the trial-and-error method. Table 1 presents the architectural structure of the four developed ANNs models.

Table 1. Architectural structure of the four developed ANNs models.

	Number of Inputs	Number of Hidden Layers	Artificial Neurons	Activation Function	Learning Algorithm
ANN#1	3	2	(18,9)	Hyperbolic tangent	Levenberg–Marquardt
ANN#2	4	3	(14,7,4)	Sigmoid	Levenberg–Marquardt
ANN#3	5	3	(12,6,4)	Sigmoid	Levenberg–Marquardt
ANN#4	6	3	(10,5,4)	Sigmoid	Levenberg–Marquardt

Table 2 shows the input and output data of each one of the four developed ANNs models.

Table 2. Input and output for each one of the four developed ANNs models.

	Temp (NOA) (°C)	RH (NOA) (%)	Temp (SC) [1] (°C)	RH (SC) (%)	Temp (LC) [2] (°C)	RH (LC) (%)
ANN#1	Input	Input	Output	---	---	---
ANN#2	Input	Input	Input	---	---	---
ANN#3	Input	Input	Input	Input	Output	---
ANN#4	Input	Input	Input	Input	Input	Output

[1] Small Courtyard. [2] Large Courtyard.

For the appropriate training of each one of the four developed models, the whole dataset was divided int three subsets. The first subset (training subset-TrS) was 70% of the whole dataset. The second (cross validation subset-CV) was 15% of the whole dataset, and the third was the testing subset (TeS), covering the remaining 15% of the total data. The TeS was totally unknown to the developed ANNs model and was used in order that the forecasting ability of the developed model could be evaluated. In any case, the division of the whole data into the three subsets was carried out in a random way using MatLab software.

For the evaluation of the predicted ability of the developed ANNs models, appropriate statistical evaluation indices were used, such as the mean bias error (MBE), the mean absolute percentage error (MAPE), the index of agreement (IA) and the correlation coefficient (R) [7].

3. Results and Discussion

Table 3 depicts the values of the statistical evaluation indices for each one of the four developed ANNs-predicted models.

Table 3. Statistical evaluation indices.

		MBE	MAPE (%)	IA	R
ANN#1	TrS	+0.2 °C	1.7	0.997	0.974
	TeS	+0.5 °C	2.3	0.968	0.955
ANN#2	TrS	+0.7%	5.2	0.988	0.911
	TeS	+2.9%	9.3	0.888	0.863
ANN#3	TrS	+0.1 °C	0.6	0.997	0.989
	TeS	+0.1 °C	0.6	0.997	0.989
ANN#4	TrS	+0.0%	1.1	0.999	0.997
	TeS	−0.1%	2.2	0.989	0.976

According to Table 3, it seems that the four developed ANNs models presented a remarkable predictive ability. Concerning ANN#1 and ANN#3, which predict the air temperature in the small and the large courtyard, respectively, the MBE is small (+0.1 °C ≤ MBE ≤ +0.5 °C), indicating a very good prognosis. The meaning of the symbol (+) is that both models overestimate the air temperature. The MAPE ranging between 0.6% and 2.3% for the testing dataset of ANN#1 indicated a very small error for air temperature forecast. At the same level, the values of IA showed a very good agreement between the predicted and observed values of air temperature for both the small and the large courtyard. Finally, comparing the values of the statistical evaluation indices for both the training dataset (TrS) and the testing dataset (TeS), it is obvious that there was homogeneity between the training and the testing stage of the developed ANNs models. This means that the developed models are able to serve as global predictive tools.

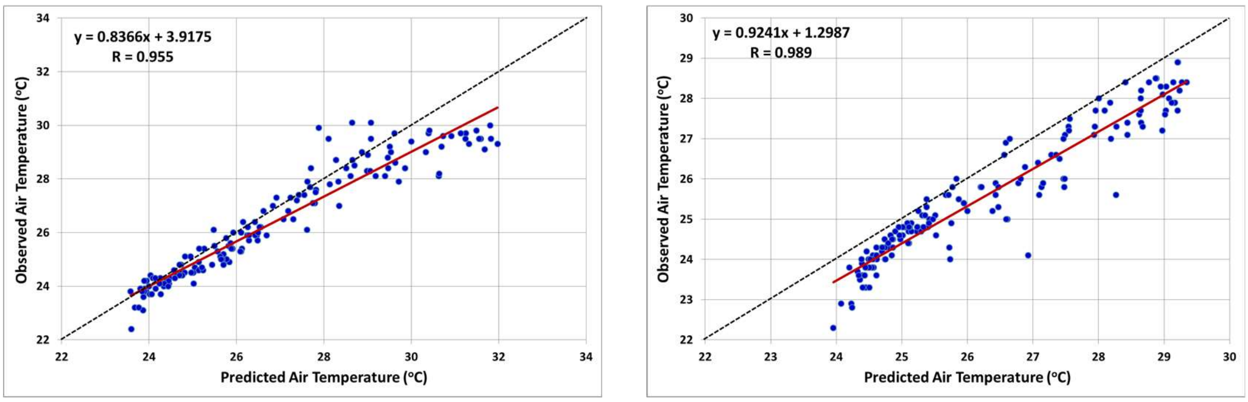
At the same level is the forecasting ability of models ANN#2 and ANN#4, which predict the air relative humidity (RH) in the small and the large courtyard, respectively. The MBE was between −0.1% and +2.9%. Furthermore, the MAPE took values from 1.1% up to 9.3%, showing a very good prognosis for RH. The IA was very close to unit (0.888 ≤ MBE ≤ 0.999), indicating that the predicted values of RH were very close to the observed values.

After the application of linear regression analysis between the observed and the predicted values for the four different ANNs models, Figures 2 and 3 were developed. Figure 2 presents the scatterplots between the observed and predicted values of air temperature according to the TeS, for both the ANN#1 and ANN#3 models.

Figure 3 depicts the scatterplots between the observed and predicted values of air relative humidity according to the TeS, for both ANN#2 and ANN#4 models.

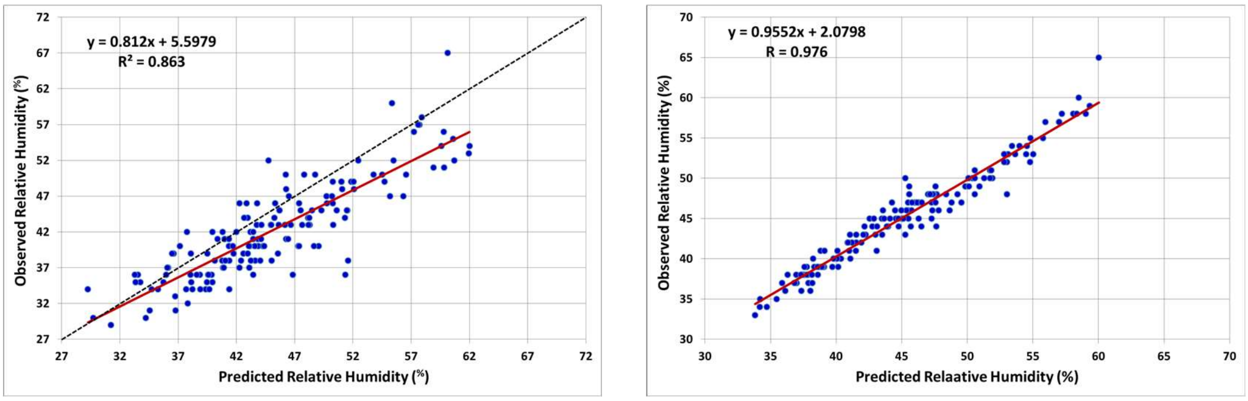
According to Figure 2 and the values of the regression coefficient (R) (see Table 3), it is obvious that there was a very good agreement between the observed air temperature values and the corresponding predicted values for both the small (ANN#1) and the large (ANN#3) courtyard, respectively.

From Figure 3 and the values of the regression coefficient (R) (see Table 3), it is obvious that there was a very good agreement between the observed RH values and the corresponding predicted values for both the small (ANN#2) and the large (ANN#4) courtyard, respectively.



(**a**) (**b**)

Figure 2. Scatterplots between the observed and predicted air temperature values for both ANN#1 (**a**) and ANN#3 (**b**) developed predictive models, according to the testing dataset (TeS) values.



(**a**) (**b**)

Figure 3. Scatterplots between the observed and predicted air relative humidity (RH) values for both ANN#2 (**a**) and ANN#4 (**b**) developed predictive models, according to the testing dataset (TeS) values.

4. Conclusions

Concluding, it can be said that the developed predicted ANNs models present a remarkable predictive ability for predicting the air temperature as well as the air relative humidity for both a small and a large courtyard, respectively, within the urban environment of a Mediterranean city like the Greek capital city, Athens. Applying the developed ANNs models, we were able to predict air temperature and relative humidity in urban courtyards using only the corresponding hourly values of air temperature and relative humidity from a standard meteorological station.

Author Contributions: Conceptualization, E.T. and K.M.; methodology, E.T., K.M., A.T. and G.P.; ANNs development, K.M.; validation, E.T., K.M., A.T., G.P. and I.T.; investigation, E.T., A.T., G.P. and I.T.; data curation, E.T., A.T., G.P. and I.T.; writing—original draft preparation, E.T. and K.M.; writing—review and editing, E.T., K.M., A.T., G.P. and I.T.; supervision, K.M. and I.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available to anyone upon request to the Correspondence Author.

Acknowledgments: The last author wishes to dedicate this work to the memory of his late mentor, colleague and friend Milo Hoffman. In addition, the participation and presentation of this work in COMECAP 2023 was funded by the University of West Attica.

Conflicts of Interest: The authors declare no conflict of interest.

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