Artificial Neural Network based Methodologies for the Spatial and Temporal Estimation of Air Temperature

Application in the Greater Area of Chania, Greece

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Abstract: Artificial Neural Networks (ANN) propose an alternative promising methodological approach to the problem of time series assessment as well as point spatial interpolation of irregularly and gridded data. ANNs can be used as function approximators to estimate both the time and spatial air temperature distributions based on observational data. After reviewing the theoretical background as well as the relative advantages and limitations of ANN methodologies applicable to the field of air temperature time series and spatial modelling, this work focuses on implementation issues and on evaluating the accuracy of the AAN methodologies using a set of metrics in the case of a specific region with complex terrain. A number of alternative feed forward ANN topologies have been applied in order to assess the spatial and time series air temperature prediction capabilities in different horizons. For the temporal forecasting of air temperature ANNs were trained using the Levenberg-Marquardt back propagation algorithm with the optimum architecture being the one that minimizes the Mean Absolute Error on the validation set. For the spatial estimation of air temperature the Radial Basis Function and Multilayer Perceptrons non-linear Feed Forward AANs schemes are compared. The underlying air temperature temporal and spatial variability is found to be modeled efficiently by the ANNs.

1 INTRODUCTION

Air temperature measurements in high resolution time series are available only at limited stations because meteorological data are generally recorded at specific locations and derived from different meteorological stations with non-identical characteristics. Spatial interpolation approaches essentially transfer available information in the form of data from a number of adjacent irregular sites to the estimated sites. Thus, spatial interpolation methods are frequently used to estimate values of air temperature data in locations where they are not measured. Various methods have been developed with the purpose to compare the performance of different traditional spatial interpolation methods for air temperature data (Price et al., 2000); (Chai et al. 2011). Accurate ambient temperature estimates are important not only in spatial but also in temporal scales. Air temperature time series forecasting is one of the most significant aspects in environmental research and in climate impact studies. Time series forecasts are valuable in renewable energy industry, in agriculture for estimating potential hazards, and within an urban context, in air quality studies for assessing the risk of adverse health effects in the general population.

During the last few decades, there has been a substantial increase in the interest on Artificial Neural Networks (ANN). ANNs have been successfully adopted in solving complex problems in many fields. Essentially, ANNs provide a methodological approach in solving various types of nonlinear problems that are difficult to deal with using traditional techniques. Often, a geophysical phenomenon exhibits temporal and spatial variability, and is suffering by issues of nonlinearity, conflicting spatial and temporal scale and uncertainty in parameter estimation (Deligiorgi and Philippopoulos, 2011). ANNs have been proved (Deligiorgi et al., 2012) to be flexible models that

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have the capability to learn the underlying relationships between the inputs and outputs of a process, without needing the explicit knowledge of how these variables are related.

Recently, numerous applications of AANs to estimate air temperature data have been presented, e.g. in areas with sparse network of meteorological stations (Snell et al., 2000); (Chronopoulos et al., 2008) for the prediction of hourly (Tasadduq, Rehman and Bubshait, 2002), daily (Dombayc and Golcu, 2009) and year-round air temperature (Smith et al., 2009) or room temperature (Mustafaraj et al., 2011) as well as for simulating the Heat Island (Mihalakakou et al., 2002).

In this work first we briefly present the theoretical background of ANN methodologies applicable to the field of air temperature time series and spatial modeling. Next, we focus on implementation issues and on evaluating the accuracy of the aforementioned methodologies using a set of metrics in the case of a specific region with complex terrain at Chania, Crete Island, Greece. A number of alternative Feed-forward ANN topologies are applied in order to assess the spatial and time series air temperature prediction capabilities in different time horizons.

2 ANN PREDICTION MODELING

Artificial Neurons are Process Element (PE) that attempt to simulate in a simplistic way the structure and function of the real physical biological neurons. A PE in its basic form can be modelled as non-liner element that first sums its weighted inputs x_1, x_2, x_3, ...x_n (coming either from original data, or from the output of other neurons in a neural network) and then passes the result through an activation function Ψ (or transfer function) according to the formula:

$$y_i = \Psi\left(\sum_{i=1}^{n} x_i w_{ji} + \theta_j\right) \qquad (1)$$

where y_j is the output of the artificial neuron, θ_j is an external threshold (or bias value) and w_{ji} are the weight of the respective input x_i which determines the strength of the connection from the previous PE's to the corresponding input of the current PE. Depending on the application, various non-linear or linear activation functions Ψ have been introduced (Fausett, 1994); (Bishop, 1995) like the: signum function (or hard limiter), sigmoid limiter, quadratic function, saturation limiter, absolute value function, Gaussian and hyperbolic tangent functions. Artificial Neural Networks (ANN) are signal or information processing systems constituted by an assembly of a large number of simple Processing Elements, as they have been described above. The PE of a ANN are interconnected by direct links called connections and cooperate to perform a Parallel Distributed Processing in order to solve a specific computational task, such as pattern classification, function approximation, clustering (or categorization), prediction (or forecasting or estimation), optimization and control. One the main strength of ANNs is their capability to adapt themselves by modifying the interaction between their PE. Another important feature of ANNs is their ability to automatically learn from a given set of representative examples.

The architectures of ANNs can be classified into two main topologies: a) Feed-forward multilayer networks (FFANN) in which feedback connections are not allowed and b) Feedback recurrent networks (FBANN) in which loops exist. FFANNs are characterized mainly as static and memory-less systems that usually produce a response to an input quickly (Jain et al., 1996). Most FFANNs can be trained using a wide variety of efficient conventional numerical methods. FBANNs are dynamic systems. In some of them, each time an input is presented, the ANN must iterate for a potentially long time before it produces a response. Usually, they are more difficult to train FBANNs compared to FFANNs.

FFANNs have been found to be very effective and powerful in prediction, forecasting or estimation problems (Zhang et al., 1998). Multilayer perceptrons (MLPs) and radial basis function (RBF) topologies are the two most commonly-used types of FFANNs. Essentially, their main difference is the way in which the hidden PEs combine values coming from preceding layers: MLPs use inner products, while RBF constitutes a multidimentional function which depends on the distance $r = \|x - c\|$ between the input vector x and the center c (where $\|\cdot\|$ denotes a vector norm) (Powell, 1987). As a consequence, the training approaches between MLPs and RBF based FFANN is not the same, although most training methods for MLPs can also be applied to RBF ANNs. In RBF FFANNs the connections of the hidden layer are not weighted and the hidden nodes are PEs with a RBF, however the output layer performs simple weighted summation of its inputs, like in the case of MLPs. One simple approach to approximate a nonlinear function is to represent it as a linear combination of a number of fixed nonlinear

RBFs $\{z_i(x)\}$, according to (2):

$$\Phi(x) = \sum_{i=1}^{l} z_i(x) w_i \tag{2}$$

Typical choices for RBFs $z_i = F(\|x - c\|)$ are: piecewise linear approximations, Gaussian function, cubic approximation, multiquadratic function and thin plate splines.

A MLP FFANN can have more than one hidden layer. But theoretical research has shown that a single hidden layer is sufficient in that kind of topologies to approximate any complex nonlinear function (Cybenco, 1989); (Hornik et al., 1989).

There are two main learning approaches in ANNs: i) supervised, in which the correct results are known and they are provided to the network during the training process, so that the weights of the PEs are adjusted in order its output to much the target values and ii) unsupervised, in which the ANN performs a kind of data compression, looking for correlation patterns between them and by applying clustering approaches. Moreover, hybrid learning (i.e. a combination of the supervised and supervised methodologies) has been applied in ANNs. Numerous learning algorithms have been introduced for the above learning approaches (Jain et al., 1996).

The introduction of the back propagation learning algorithm (Rumelhart et al., 1986) to obtain the weight of a multilayer MLP could be regarded as one of the most significant breakthroughs for training AANs. The objective of the training is to minimize the training mean square error E_{mse} of the AAN output compared to the required output for all the training patterns:

$$E_{mse} = \sum_{k=1}^{p} E_k = \frac{1}{2N} \sum_{j=Y} \sum_{k=1}^{p} \left(y_i - d_{kj}\right)^2 \tag{3}$$

where: E_k is the partial network error, p is the number of the available patterns and Y the set of the output PEs. The new configuration in time $t > 0$ is calculated as follows:

$$\begin{aligned} w_{ji}(k) = w_{ji}(k-1) - \alpha \frac{\partial E}{\partial w_{ji}} + \\ + \beta [w_{ji}(k-1) - w_{ji}(k-2)] \end{aligned} \tag{4}$$

To speed up the training process, the faster Levenberg-Marquardt Back propagation Algorithm has been introduced (Yu and Wilamowski, 2011). It is fast and has stable convergence and it is suitable for training AAN in small-and medium-sized problems. The new configuration of the weights in the k+1 step is calculated as follows:

$$w(k+1) = w(k) - \left(J^T J + \lambda I\right)^{-1} J^T \varepsilon(k) \tag{5}$$

The Jacobian matrix for a single PS can be written as follows:

$$J = \begin{bmatrix} \frac{\partial \varepsilon_1}{\partial w_1} \cdots \frac{\partial \varepsilon_1}{\partial w_n} & \frac{\partial \varepsilon_1}{\partial w_0} \\ \vdots \quad\quad \vdots & \vdots \\ \frac{\partial \varepsilon_p}{\partial w_1} \cdots \frac{\partial \varepsilon_p}{\partial w_n} & \frac{\partial \varepsilon_p}{\partial w_0} \end{bmatrix} = \begin{bmatrix} x_{1_1} \cdots x_{n_1} & 1 \\ \vdots \quad\quad \vdots & \vdots \\ x_{1_p} \cdots x_{n_p} & 1 \end{bmatrix} \tag{6}$$

where: w is the vector of the weights, w_0 is the bias of the PE and ε is the error vector, i.e. the difference between the actual and the required value of the ANN output for the individual pattern. The parameter λ is modified based on the development of the error function E.

3 APPLICATION OF ANN IN AIR TEMPERATURE ESTIMATION

The present work aims to quantify the ability of ANNs to estimate and model the temporal and spatial air temperature variability at a coastal environment. We focus on implementation issues and on evaluating the accuracy of the aforementioned methodologies in the case of a specific region with complex terrain. A number of alternative ANN topologies are applied in order to assess the spatial and time series air temperature prediction capabilities in different time scales.

Moreover, this work presents an attempt to develop an extensive model performance evaluation procedure for the estimation of the air temperature using ANNs. This procedure incorporates a variety of correlation and difference statistical measures. In detail, the correlation coefficient (R), the coefficient of determination (R^2), the mean bias error (MBE), the mean absolute error (MAE), the root mean square error (RMSE) and the index of agreement (d) are calculated for the examined predictive schemes. The formulation and the applicability of such measures are extensively reported in (Fox, 1981); (Willmott, 1982).

3.1 Area of Study

The study area is the Chania plain, located on the northwestern part of the island of Crete in Greece. The greater area is constricted by physical boundaries, which are the White Mountains on the south, the Aegean coastline on the northern and eastern part and the Akrotiri peninsula at the northeast of Chania city (Figure 1). The topography of the region is complex due to the geophysical features of the region. The influence of the island of Crete on the wind field, especially during summer months and days where northerly etesian winds prevail, is proven to cause a leftward deflection and an upstream deceleration of the wind vector (Koletsis, 2009); (Koletsis et al., 2010); (Kotroni, 2001). Moreover, the wind direction of the local field at the broader area of Chania city varies significantly due to the different topographical features (Deligiorgi et al., 2007).

In this study, mean hourly air temperature data are obtained from a network of six meteorological stations, namely Airport, Souda, Platanias, Malaxa, Pedio Volis and TEI (Figure 1). The measurement sites cover the topographical and land-use variability of the region (Table 1). The climatological station at the Airport is representative of the meteorological conditions that prevail at the Akrotiri peninsula and in this application it will be used as the reference station for examining the performance of the temporal and spatial pattern recognition approaches. TEI, Souda and Malaxa stations are situated along the perpendicular to the Aegean coastline north-south axis of the Chania basin,, while the TEI and Platanias stations are representative of the coastal character of the basin. Moreover, TEI station is located at the east and in close proximity to the densely populated urban district of Chania city.

The topography induces significant spatial air temperature variation. In detail, the inland stations at Souda and at the Airport exhibit the highest diurnal temperature ranges (7.75 °C and 6.56 °C respectively), while the spatial minimum is observed at Pedio Volis (2.32 °C), a finding that is attributed to the effect of altitude and the proximity of the site to the Aegean coastline. The highest daily maximum temperature values, averaged over the experimental period, are reported at the Airport (24 °C) and the lowest at Malaxa (19.46 °C).

3.2 Spatial Estimation of Air Temperature

3.2.1 Implementation

For the spatial estimation of air temperature the non-linear Feed Forward Artificial Neural Networks MLPANN and RBFANN are compared. The method aims to estimate air temperature at a target station, using air temperature observations as inputs from adjacent control stations.

The target station is located at Airport, while the concurrent air temperature observations from the remaining sites - control stations (Souda, Malaxa, Platanias, PedioVolis and TEI) are used as inputs in the MLPANN and RBFANN models.

The study period is from 19 July 2004 to 31 August 2006 and due to missing observations the input datasets consist of 12416 simultaneous samples of hourly observations for each station. The 60% of the available data (7450 cases from 19 July 2004 at 23:00:00 to 1 Oct. 2005 at 09:00:00) was used for building and training the models (training set), the subsequent 20% as the validation set (2483 cases from 1 Oct. 2005 at 10:00:00 to 26 March 2006 at 11:00:00) and the remaining 20% (2483 cases from 26 March 2006 at 12:00:00 to 31 Aug. 2006 at 22:00:00) as the test set which is used to examine the performance of both the RBFANN and the MLPANN models. In MLPANNs the validation

Table 1: Geographical characteristics of the meteorological stations.

Station Name	Latitude (°N)	Longitude (°W)	Elevation (m)	Characterization
Airport	24° 07′ 00′′	35° 33′ 00′′	140	Rural
TEI	35° 31′ 09′′	24° 02′ 33′′	38	Suburban – Coastal
Souda	35° 30′ 30′′	23° 54′ 40′′	118	Suburban
Platanias	35° 29′ 46′′	24° 03′ 00′′	23	Rural – Coastal
Malaxa	35° 27′ 57′′	24° 02′ 33′′	556	Rural
Pedio Volis	35° 34′ 11′′	24° 10′ 20′′	422	Rural

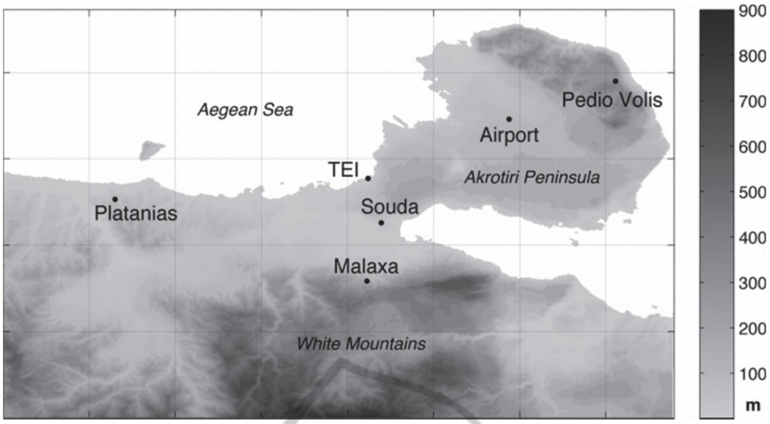

Figure 1: Area of study and location of meteorological stations.

set is used for early stopping and to determine the optimum number of hidden layer neurons and in the RBFANNs to determine the optimum value of the spread parameter of the radial basis function. Large spread values result into a smooth function approximation that might not model the temperature variability adequately, while small spread values can lead to networks that might not generalize well. In our case the validation set is used for selecting the optimum value of the spread parameter, using the trial and calculating the error procedure by minimizing the MAE.

The optimum architecture for the MLPANN model is 5-17-1 (5 inputs, 17 hidden layers and 1 output neuron). The RBFANN used had five inputs and a radial basis hidden layer with 7450 artificial neurons using Gaussian activation functions radbas(n) = $\exp(-n^2)$. The output layer had one PE with linear activation function.

3.2.2 Results

The model evaluation statics for the Airport station for both MLPANN and RBFANN approaches are presented in Table 2. A general remark is that both models give accurate air temperature estimates with MAE values less than 0.9 °C and with very high d values and minimal biases. Furthermore the explained variance is 95.9% for the RBFANN model and 96.3% for the MLPANN scheme. The metrics indicate that MLPANN slightly outperforms the trained RBFANN network.

The comparison of the observed and the predicted air temperature values for both models are presented in Figure 2 scatter plots and the respective residuals' distributions are given in Figure 3. Limited data dispersion is observed for both models and in both cases the residuals are symmetrically distributed around 0 °C.

Table 2: ANN based model performance.

	MLPANN	RBFAAN
R	0.981	0.979
R^2	0.963	0.959
MBE (°C)	-0.008	0.034
MAE (°C)	0.819	0.871
RMSE (°C)	1.067	1.120
d	0.990	0.989

Moreover, a time series comparison between the observed and the predicted air temperature form the MLPANN and RBFANN models are presented in Figure 4 for the period 10-23/8/2006. The predicted air temperature time series follows closely the observed values with no signs of systematic errors.

The temperature estimation errors are further examined by calculating the MAE hourly values (Figure 5). The analysis for both ANN models reveals two maxima, which are observed during the early morning warming period and during the late afternoon temperature decrease. The increase in the model errors can be attributed to the different heating and cooling rates between stations, a mechanism that is highly site specific and is greatly influenced by the local topography. For the remaining hours, both models are very accurate with errors less than 0.7 °C, a fact, which indicates the ability of the models to estimate in high accuracy the maximum, minimum and diurnal temperature range for the examined site.

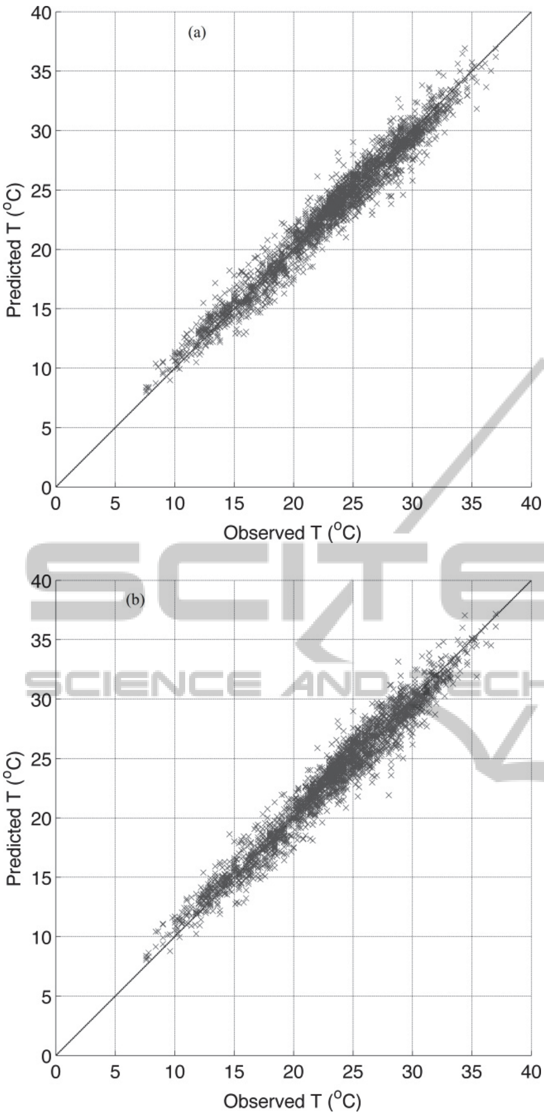

Figure 2: Comparison of the observed and predicted air temperature values for the (a) MLPANN and (b) RBFANN schemes.

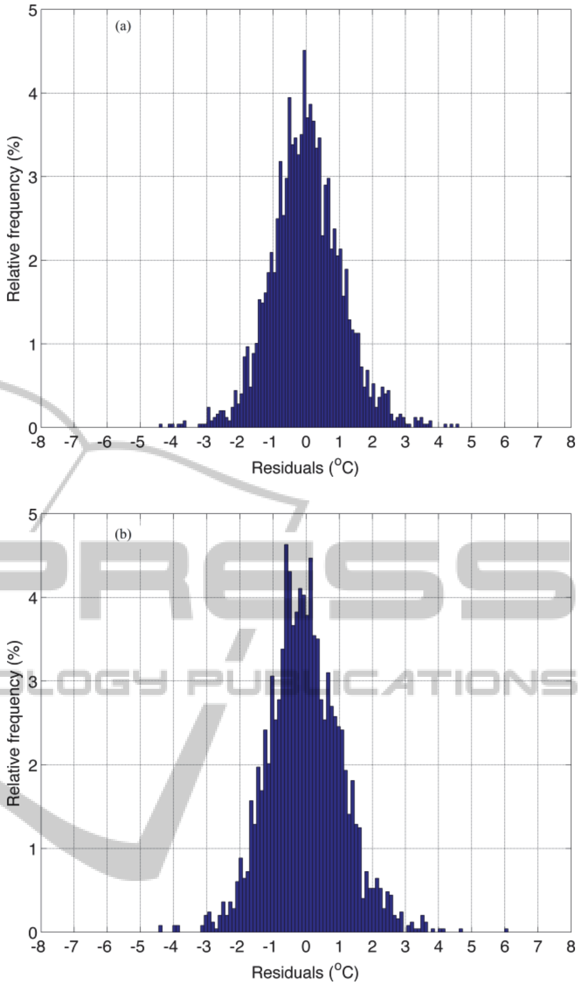

Figure 3: The residuals' distribution for the (a) MLPANN and the (b) RBFANN models.

3.3 Temporal Estimation of Air Temperature

3.3.1 Implementation

For the temporal forecasting of air temperature ANNs are used as function approximators aiming to estimate the air temperature in a location using the current and previous air temperature observations from the same site.

In this application the Feed-Forward Artificial Neural Network architecture with one hidden layer is selected for predicting the air temperature time series.

Separate ANNs are trained and tested for predicting the one hour (ANN-T1), two hours (ANN-T2) and three hours (ANN-T3) ahead air temperature at Airport station, based on the current and the five previous air temperature observations from the same site Therefore, the input in each ANN is the air temperature at t, t-1, t-2, t-3, t-4 and t-5 and the output is the air temperature at: t+1 for the ANN-T1, t+2 for the ANN-T2 and t+3 for the ANN-T3.

The study period is from 19 July 2004 to 31 August 2006. In all cases, the first 60% of the dataset is used for training the ANNs, the subsequent 20% for validation and the remaining 20% for testing, as was described for the case of spatial estimation of air temperature.

The optimum architecture (number of PEs in the hidden layer) is related to the complexity of the input and output mapping, along with the amount of

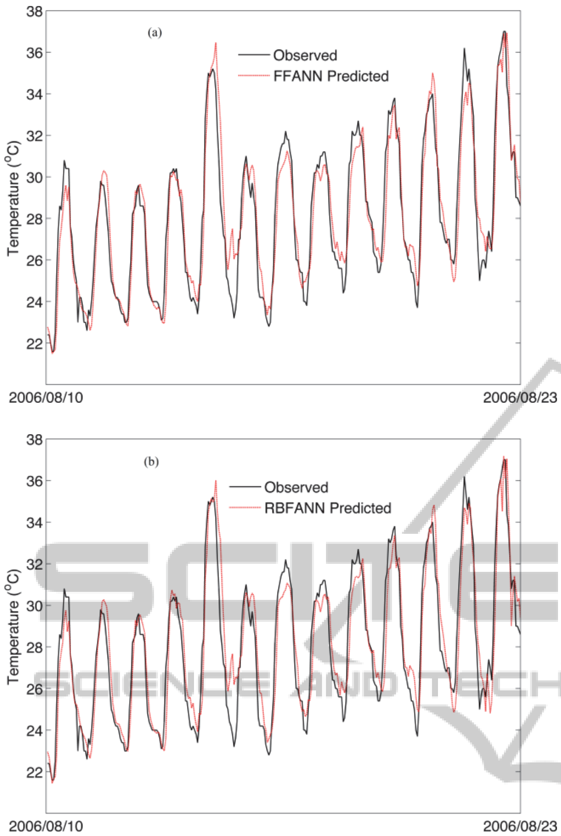

Figure 4: Comparison of the observed and predicted time series for the (a) MLPANN and (b) RFBANN models.

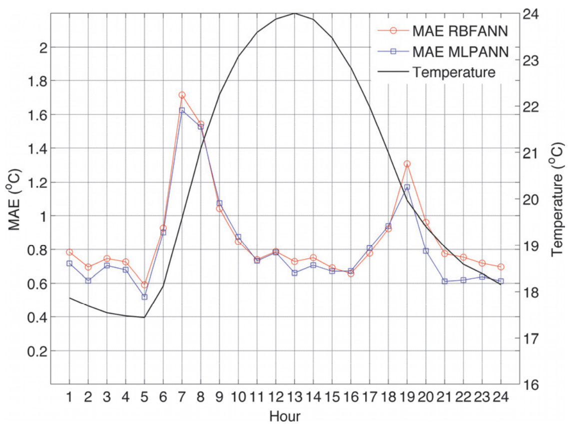

Figure 5: Hourly MAE values and comparison with the hourly temperature evolution and the Airport station.

noise and the size of the training data. A small number of PEs result to a non-optimum estimation of the input-output relationship, while too many PEs result to overfitting and failure to generalize (Gardner and Dorling, 1998). In this study the selection of the number of PEs in the hidden layer is based on a trial and error procedure and the performance is measured using the validation set. In each case, ANNs with a varying number from 5 to 25 PEs in the hidden layer were trained using the Levenberg-Marquardt backpropagation algorithm with the optimum architecture being the one that minimizes the Mean Absolute Error (MAE) on the validation set. A drawback of the backpropagation algorithm is its sensitivity to initial weights. During training, the algorithm can become trapped in local minima of the error function, preventing it from finding the optimum solution (Heaton, 2005). In this study and for eliminating this weakness, each network is trained multiple times (50 repetitions) with different initial weights. A hyperbolic tangent sigmoid transfer function tansig(n) = 2/(1+exp(-2n))-1 was used as the activation function Ψ for the PEs of the hidden layer. In the output layers, PEs with a linear transfer function were used.

The optimum topologies of the selected ANNs that minimized the MAE on the validation set are presented in Table 3. In all cases, the architecture includes six PEs in the input layer and one PE in the output layer. The results indicate that the number of the neurons in the hidden layer is increased as the lag for forecasting the air temperature is increased.

Table 3: Optimum ANN architecture – number of PEs at the input, hidden and output layer.

FFANN-T1	FFANN-T2	FFANN-T3
6 – 12 – 1	6 – 13 – 1	6 – 21 – 1

3.3.2 Results

The model evaluation statistics for the Airport station are presented in Table 4 and the observed and AAN based predicted air temperature values are compared in the scatter plots of Figure 6. A general remark is that the ANNs performance is decreased with increasing the forecasting lag. In all cases the MAE is less than 1.4 °C and the explained variance decreases from 97.7% for the ANN-T1 to 88.7% for the ANN-T3 model.

The ANN-T1 model exhibits very good performance, as it is observed from the limited dispersion along the optimum agreement line of the one-hour air temperature (Figure 6a). The data dispersion for the ANN-T2 (Figure 6b) and for the ANN-T3 (Figure 6c) scatter plots is increased and a small tendency of over-estimation of the low air temperature values along with an under-estimation of the high air temperature values is observed. This finding is furthermore established from the increased MBE for the ANN-T3 model (°C).

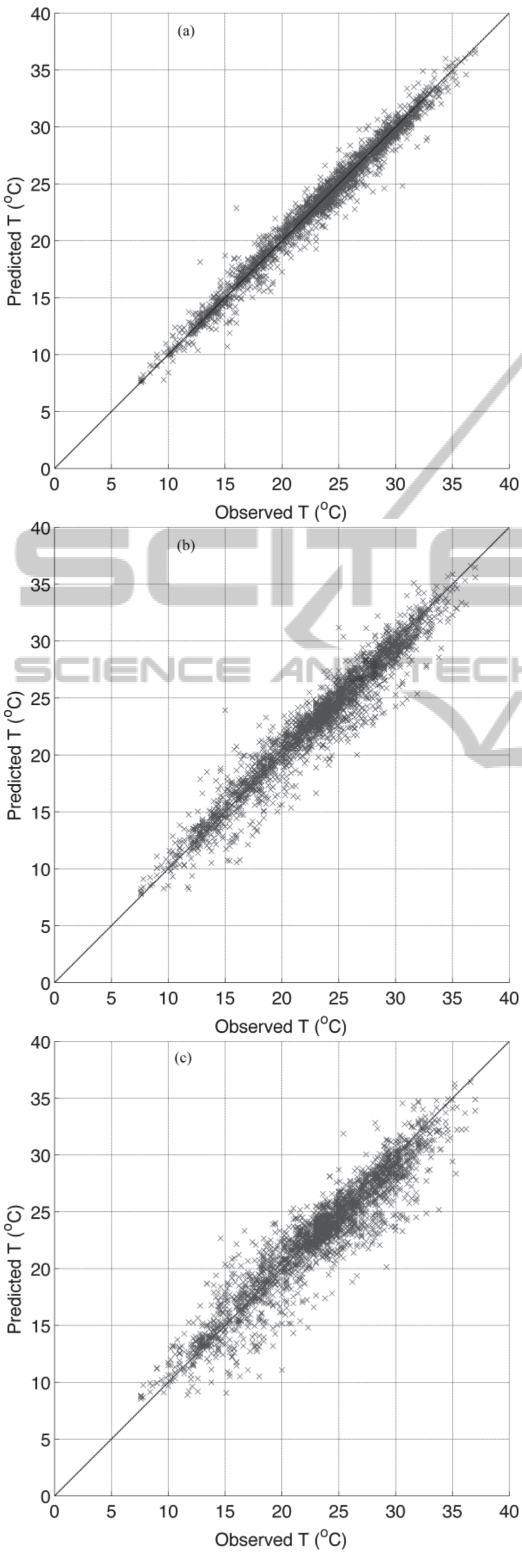

Figure 6: Comparison of the observed and ANN based predicted air temperature values for the (a) one-hour, (b) two-hour (b) and (c) three-hour ahead estimation.

Table 4: ANN based model performance.

	FFANN-T1	FFANN-T2	FFANN-T3
R	0.988	0.967	0.942
R^2	0.977	0.935	0.887
MBE (°C)	-0.068	-0.225	-0.405
MAE (°C)	0.589	0.996	1.361
RMSE (°C)	0.844	1.427	1.904
d	0.994	0.983	0.968

Regarding the residuals distributions (Figure 7), the errors for the ANN-T1 and for the ANN-T2 are approximately centered at 0 °C, while for the ANN-T3 model the maxima of the distribution is shifted to negative residual values, a fact which is attributed to the tendency of the ANN-T3 model to underestimate the air temperature values.

4 CONCLUSIONS

The ability of neural networks to spatial estimate and predict short term air temperature values is studied extensively and is well established. We reviewed the theoretical background and the relative advantages and limitations of ANN methodologies applicable to the field of air temperature time series and spatial modeling. Then, we have applied ANNs methodologies in the case of a specific region with complex terrain at Chania coastal region, Crete island, Greece. Details of the implementation issues are given along with the set of metrics for evaluating the accuracy of the methodology. A number of alternatives feed-forward ANN topologies have been applied in order to assess the spatial and time series air temperature prediction capabilities. For the one hour, two hours and three hours ahead air temperature temporal forecasting at a specific site ANNs were trained based on the current and the five previous air temperature observations from the same site using the Levenberg-Marquardt back-propagation algorithm with the optimum architecture being the one that minimizes the Mean Absolute Error on the validation set. For the spatial estimation of air temperature at a target site the non-linear Radial Basis Function and Multilayer Perceptrons non-linear Feed Forward AANs schemes were compared. The underlying air temperature temporal and spatial variability is found to be modeled efficiently by the ANNs.

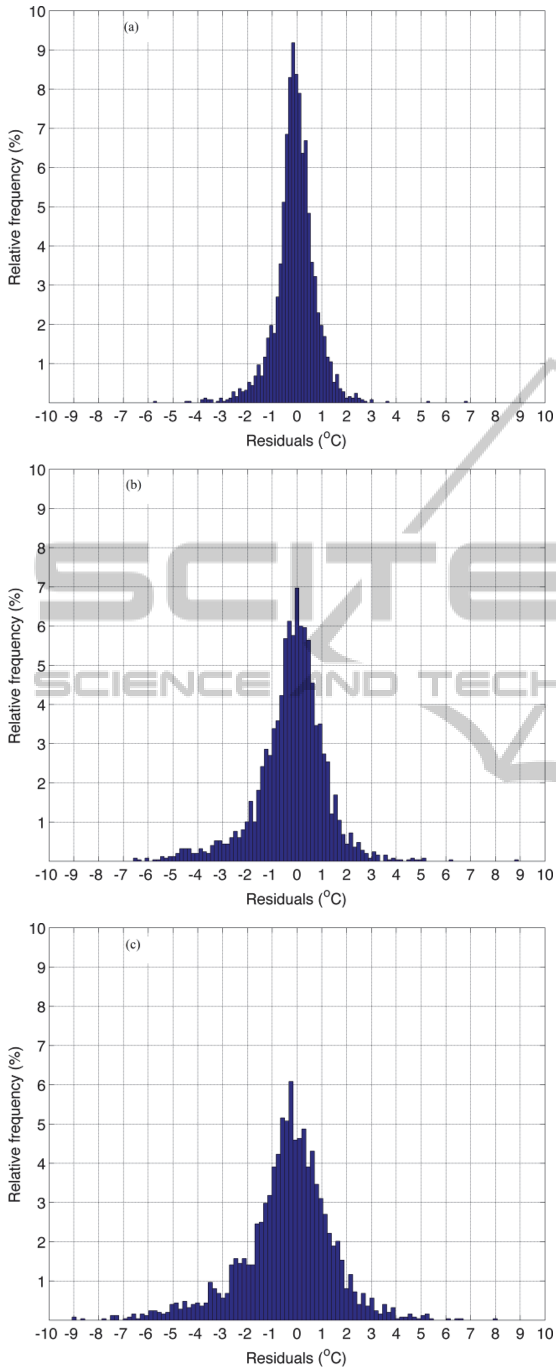

Figure 7: Comparison of the residuals distributions for the (a) FFANN-T1, (b) FFANN-T2 and (c) FFANN-T3 models.

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