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Nonlinear Autoregressive Neural Networks for Air Temperature forecasting

PHILIPPOPOULOS K.[1], TZANIS C.G.[1*], DELIGIORGI D.[2], and ALIMISSIS A.[1]

[1] Climate and Climatic Change Group, Section of Environmental Physics and Meteorology, Department of Physics, National and Kapodistrian University of Athens, Athens, 15784, Greece
[2] Section of Environmental Physics and Meteorology, Department of Physics, National and Kapodistrian University of Athens, Athens, 15784, Greece

*corresponding author:
e-mail: chtzanis@phys.uoa.gr

Abstract In the field of climatic conditions forecasting, the linear classical time series models are inadequate for modelling and predicting accurately the air temperature variability. This work presents the novel application of nonlinear autoregressive neural networks (NAR) in air temperature forecasting. Hourly air temperature data were extracted from the Chania Airport station located at the island of Crete in Greece, for a 10-year period. The NAR is a multi-layer, dynamic, recurrent neural network that employs feedback connections for multi-horizon time series forecasting. Multiple NAR networks were trained with feedback connections for 6, 12 and 24 hours and for forecasting horizons up to 24-time steps. In the context of evaluating the performance of the trained NAR networks the Mean Absolute Error (MAE) was used and specifically the errors are examined in terms of their dependence with the atmospheric circulation. The results indicate that the use of a high degree of feedback decreases the forecasting error and increases the forecasting horizon of reliable air temperature estimation. The forecast error is dependent on the atmospheric circulation and higher MAE values are related with depressions that effect the study area.

Keywords: Air temperature, Machine Learning, Artificial Neural Networks, Dynamic Neural Networks, Forecasting

1. Introduction

Non-linear problems in environmental sciences are increasingly being addressed by using Machine Learning (ML) approaches such as Artificial Neural Networks (ANNs). ANNs can be trained to produce satisfactory results for a large number of applications by simulating the relationship between the input and output variables (Amanollahi et al. 2013; Mirzaei et al., 2019; Alimissis et al., 2018; Philippopoulos and Deligiorgi, 2012, Philippopoulos et al., 2015; Rahimpour et al, 2021; Tzanis et al., 2019; 2021). This relationship in many cases can be non-linear and have a high degree of complexity so that it cannot be adequately modelled by traditional statistical methods. Specifically, ANNs are being used in multiple problems, such as for purposes of function approximation, time series modeling and forecasting, patterns' classification and data clustering (Haykin, 2009).

Most common problems that arise, depending on the application, are initially the selection of the type of ANN to be used and its optimal architecture, as well as practical issues related to the application of the training algorithms. Selecting which type of ANN to use, depends on the generalization capabilities of the network, while its architecture depends on the degree of complexity of the problem under study.

This work aims to assess the predictive ability of nonlinear autoregressive neural networks (NAR) in air temperature forecasting for a region characterized by complex topography (Tzanis et al., 2019). The goal is to present a forecasting statistical framework for short up to mid-term forecasting time scales. Temperature time series were derived from the station at the Chania airport and in detail hourly data were extracted from 2000 to 2009. The data set was divided into three subsets, the training subset consisting the data from 2000 to 2005 and the validation and test subsets that include the data from 2006-2007 and 2008-2009 respectively.

2. Methodology

According to Soman et al., (2010) in meteorological parameters' forecasting a generic classification based on forecasting time scales is presented in Table 1.

Table 1. Forecasting horizon classification

Description	Forecasting timescales
Very-short term	A few seconds to 30 minutes
Short term	30 minutes to 6 hours
Mid term	6 hours to 1 day
Long term	1 day to 1 week or more

In this work the hourly air temperature time series forecasting is based on the use of the dynamic recurrent NAR networks that incorporate time delays and feedback loops. The desired network response is expected to reproduce the time-dependent input-output relationship. More specifically, three different configurations were developed and tested with time delay elements of 6, 12 and 24 degrees. The outputs and inputs of the NAR models are presented in Table 2.

Table 2. NAR inputs and outputs for the estimation of hourly air temperature

Network	Output	Input Data
NAR.T.06h	Current hourly temperature	Network output of the previous 6 time periods
NAR.T.12h	Current hourly Temperature	Network output of the previous 12 time periods
NAR.T.24h	Current hourly Temperature	Network output of the previous 24 time periods

All NAR networks use an iterative procedure and can be used to predict time series for the current time period and for as many future time steps is required. In this application, forecasts were produced for up to 24 in advance in all cases. The NAR models are three-layer networks, where the output layer consists of a linear neuron, where a 6-, 12-, or 24-degree time-delay element is applied. The hidden layer consists of non-linear neurons (hyperbolic tangent) and the input layer, which is fed by the feedback loop of the network. The training of ANNs was performed by using the back-propagation algorithm, where NAR networks are transformed into the equivalent Feed-Forward Neural Networks (FFNNs) so that the Levenberg - Marquardt algorithm can be applied.

Figure 1 shows an example of the architecture of a NAR network with 21 neurons in the hidden layer, a single output and a 12- degree time delay element. The fact that NAR networks use the same training algorithm as FFNNs, leads to the need to apply a methodology for multiple runs in order to avoid trapping the algorithm in local minima. For each prediction model, networks with 1 to 50 neurons in the hidden layer were trained and for any given number of neurons 25 different networks were trained. The selection of the optimal architecture among the 1,250 candidate networks is based on the minimization of the MAE error for the validation subset and for 1 hour forecast horizon.

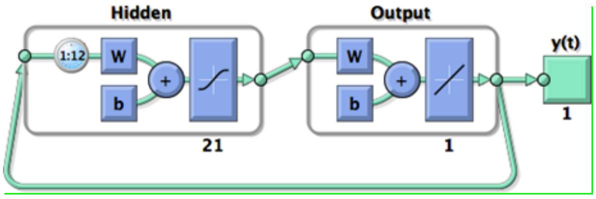

Figure 1. Architecture of a NAR network

The evaluation of the predictive ability of the optimal ANNs for each forecast model is initially performed for the results obtained for a 1-hour forecast horizon. A comparison is performed using the test subset by comparing the mean and the variance of the observed and estimated time series and by calculating the R and R^2 coefficients, the Mean Bias Error (MBE), the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as well as the index of agreement. Finally, for each case the scatter diagrams and the distributions of the model residuals are created. Finally, the distribution of the MAE error for each atmospheric circulation pattern is examined.

3. Results

The optimum ANN architecture of the NAR.T.06h, NAR.T.12h and NAR.T.24h models is presented in Table 3 and is related to the complexity of the hourly temperature estimations.

Table 3. Optimum architecture of the ANNs - Number of neurons in the input, hidden and output layers and degree of feedback)

	NAR.T.6h	NAR.T.12h	NAR.T.24h
Input	0	0	0
Hidden	22	12	24
Output	1	1	1
Degree of feedback	6	12	24

From the comparison of the ANNs predictions for 1 hour forecasting horizon with the observed time series in terms of the mean air temperature and variance (Table 4), it can be concluded that all three models accurately reproduce the basic statistical measures of the observed time series with a low tendency to underestimate in the case of variance. The performance of the networks is presented in Table 5. The NAR.T.24h results are marginally better than those of the NAR.T.06h and NAR.T.12h as they are associated with smaller MBE, MAE and RMSE errors and higher correlation coefficients R and R^2. More specifically, the MAE error is less than 0.5 °C for the NAR.T.12h and NAR.T.24h models.

Table 4. Mean (°C) and variance (°C^2) comparison between the observed and predicted temperature time series for 1 hour forecasting horizon for the test subset

	Mean	Error	Var	Error
Observed	18.69	-	42.08	-
NAR.T.6h	18.68	-0.04	41.60	-1.12
NAR.T.12h	18.68	-0.04	41.59	-1.14
NAR.T.24h	18.69	-0.04	41.59	-1.10

Table 5. Error metrics results for the evaluation of the ANNs prediction ability for the test subset

	R^2	*MBE*	*MAE*	*RMSE*	*d*
NAR.T.6h	0.99	-0.007	0.51	0.75	0.99
NAR.T.12h	0.99	-0.007	0.50	0.72	0.99
NAR.T.24h	0.99	-0.001	0.47	0.66	0.99

The good performance of the models for the next hour temperature forecast, is further confirmed by the very small dispersion around the main diagonal of optimal prediction of the scatter diagrams (Figure 2) and by the high relative frequencies of the residuals' distributions which are close to 0 (Figure 3). The results of the diagrams in combination with the small values of the Mean Bias Error, indicate that the models do not tend to underestimate or overestimate the observed air temperature.

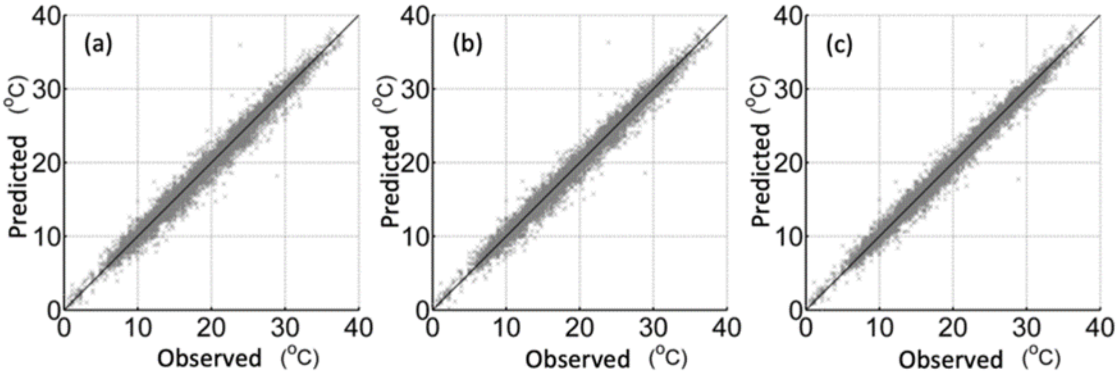

Figure 2. NAR scatter diagrams of the observed (x-axis) versus the predicted (y-axis) time series of air temperature for the test subset for one hour forecast horizon - (a) 6h, (b) 12h and (c) 24h.

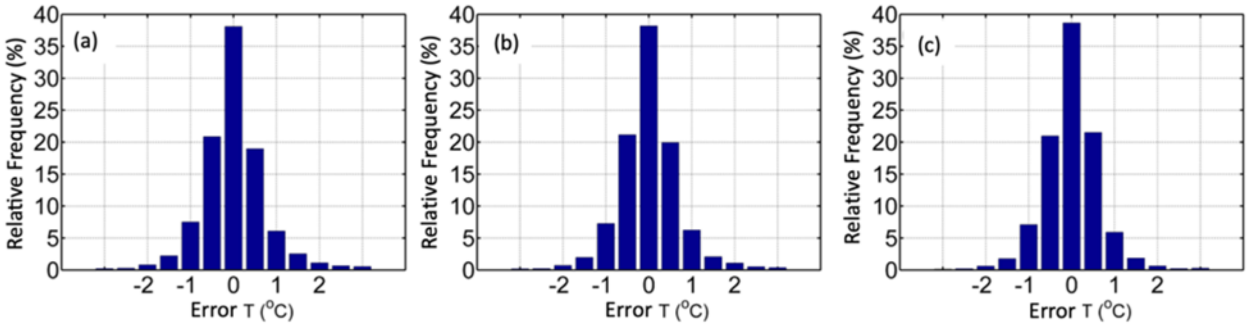

Figure 3. Residuals distributions for the test subset, for one hour forecast horizon - (a) 6h, (b) 12h and (c) 24h

In contrast with the air temperature predictions for the next hour, the models have significant differences in terms of their predictive abilities for longer forecast horizons. In Figure 4 the MAE results are presented for the next 24 timesteps. In more detail, the NAR.T.06h and in a less extent the NAR.T.12h are unstable for forecast horizons greater than 14 hours and the error is greater than 1.5 °C in 4 and 5 hours respectively. In Figure 5 the scatter diagrams for the three models are presented for predictions for 2, 3 and 4 hours in advance. Moreover, the forecasting error is found to depend on atmospheric circulation. In more detail, higher errors are associated with depressions that affect the study area and in contrast the highest model accuracy is related to atmospheric patterns that are observed during the warm period of the year and specifically to smooth pressure fields.

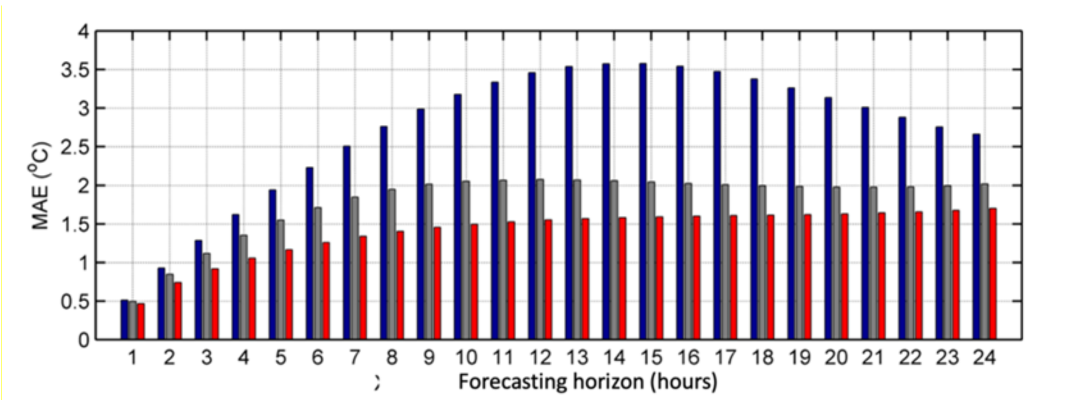

Figure 4. MAE of air temperature for forecasting horizon up to 24 hours for the NAR.T.06h (blue), NAR.T.12h (grey) and NAR.T.24h (red) for the test subset.

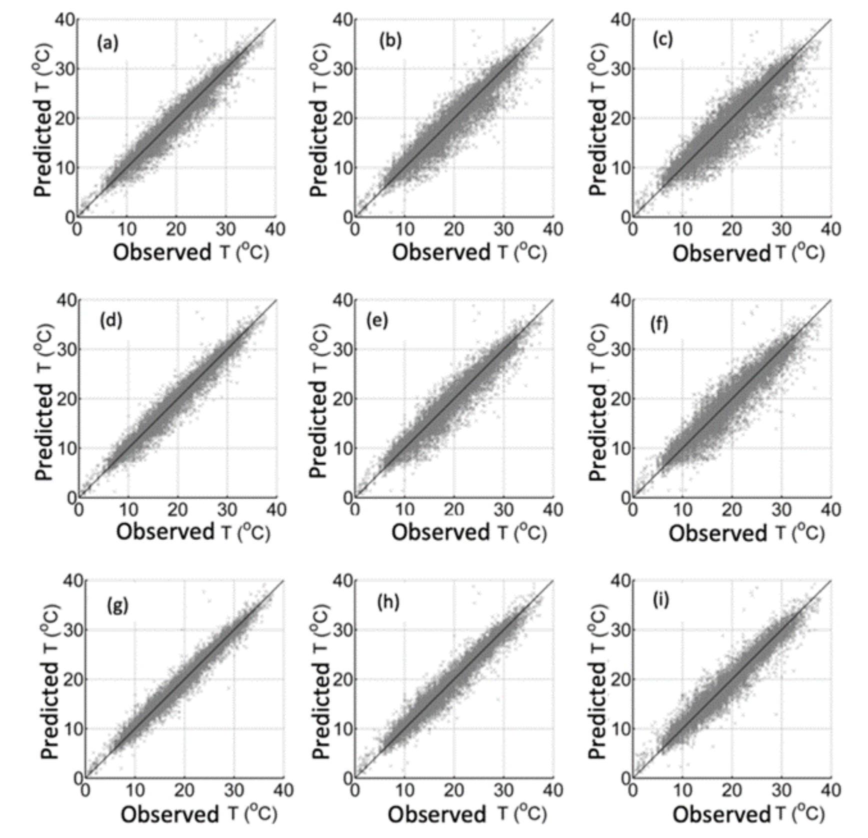

Figure 5. Scatter plots for the observed vs. predicted air temperature for 2, 3 and 4 hours in advance for the NAR.T.06h (a-c), NAR.T.12h (d-f) and NAR.T.24h (g-i) models.

4. Conclusions

The use of dynamic recurrent artificial neural networks (nonlinear autoregressive neural networks - NAR) in air temperature forecasting is found to produce robust short- and medium-term forecasts. It has been shown that using a high degree of feedback leads to a decrease of the forecasting error and increases the forecasting horizon of the models. In addition, the forecasting error is found to depend on the atmospheric circulation and is higher when depressions affect the area of study. The limitation of the use of NAR models is related to the requirement of a representative data for training the models, in order to achieve a satisfactory generalization ability.

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