Neural Network modeling of automatic air temperature time series

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Abstract: *In the paper time series which concerned diurnal values of standard and automatic results of the measurements of air thermal parameters were analyzed. By the means of artificial neural networks an attempt to create the model of mean, maximum and minimum air temperature measured by automatic devices on the basis of standard observations was made. The study was conducted in the period of 2000-2009 on the site of Agro- and Hydrometeorology Wroclaw-Swojec Observatory, Poland. In order to achieve the intended aim single-layer perceptron networks, created in MATLAB (Neural Network Toolbox) and STATISTICA 10, were used. The following aspects were subject to the analysis: the architecture of the developed networks, the number of cycles in the learning process, the changes in Mean Squared Error (MSE), the correlations between the values of the parameters obtained by the means of meteorological instruments and the ones prognosticated by the networks and global sensitivity analysis. The study facilitated the creation of a high quality neuron model, reflecting the correlations between the values of the parameters obtained by the means of standard instruments and the ones prognosticated by electronic sensors.*
Keywords: *standard method, neural networks, air thermal parameters, automatic station.*

Riassunto: *Nel lavoro serie di dati temporali che relativi a valori diurni di dati standard e automatici delle misurazioni dei parametri termici dell'aria sono state analizzate. Per mezzo di reti neurali artificiali è stato fatto un tentativo di creare il modello di temperatura media, massima e minima dell'aria misurata da dispositivi automatici sulla base di osservazioni standard. Lo studio è stato condotto nel periodo 2000-2009 sul sito dell'Osservatorio Agro e Idrometeorologico di Wroclaw-Swojec, Polonia. A tale scopo sono state utilizzate "single-layer perceptron networks", create in MATLAB (Neural Network Toolbox) e STATISTICA 10. I seguenti aspetti sono stati sottoposti all'analisi: l'architettura delle reti sviluppate, il numero di cicli nel processo di apprendimento, le variazioni di errore medio quadrato (MSE), le correlazioni tra i valori dei parametri ottenuti tramite strumenti meteorologici e quelli previsti dalle reti e l'analisi globale di sensibilità. Lo studio ha facilitato la creazione di un modello di neurale di alta qualità, in grado di descrivere le correlazioni tra i valori dei parametri ottenuti mediante strumenti standard e quelli previsti dai sensori elettronici.*
Parole chiave: *metodo standard, reti neurali, parametri termici aria, stazione automatica.*

1. INTRODUCTION

A large amount of data gathered while conducting meteorological measurements with the assistance of automatic stations is difficult to archive and subsequently compile, therefore seeking repeated patterns can facilitate the selection of not only the most frequent but also the most extreme phenomena. A valuable tool used in such type of analysis are artificial neural networks. The results gained due to these means may serve to predict the volume of parameters in the chosen time intervals (Lazzus, 214; Shank *et al.*, 2008; Silverman and Dracup, 2000; Tabari *et al.*, 2015). It will enable the rational modernisation of operational meteorological stations, optimisation of their work, decreasing the cost of their exploitations as well as increasing the lifespan of the tools by minimalizing the burden of data loggers.

Artificial neural networks belong to the so called data mining method i.e. methods which allow big databases to be explored. The natural structure of the human brain was an inspiration for their development. The network consists of connected cells called neurons, which transmit and process signals (Ustaoglu *et al.*, 2008).

The most common are the unidirectional neural structures basing on multi-layer perceptron (MLP), which are capable of reflecting various dependencies with complicated algorithms (Chattopadhyay *et al.* 2011; Mihalakakou *et al.*, 1998; Reusch and Alley, 2002). Their advantage is the fact that they do not require knowledge about the compounds which are present and formed in the analyzed model (Demuth and Beale, 2000).

The aim of the research was to design a neural network which has as input air thermal parameters measured manually, the influence parameters (global radiation, relative air humidity, wind speed and date) and as an output the temperature values obtained by automatic devices. All influence parameters (except date) were measured by electronic sensors. Automatic

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Submitted 25 November 2015, accepted 13 November 2016.

Italian Journal of Agrometeorology - 2/2017
Rivista Italiana di Agrometeorologia - 2/2017

DOI:10.19199/2017.2.2038-5625.005

pyranometer and anemometer were part of Campbell meteorological station as well as sensor which measured both temperature and relative air humidity. All parameters were average daily values calculated from measurements. In researches date means Day of Year (DOY).

Artificial neural networks were used to seek repeated patterns in a time series of analyzed air thermal parameters. With their application the models of analyzed time series were created, which were subsequently compared with the actual course of the air thermal parameters and it was assessed how far they can be explained by a constructed model.

The research was built upon the assumption that on the basis of entered data the constructed networks would produce the most common patterns and have the ability to train basing on the examples in entered data as well as the ability to generalize phenomena and to find a connection within air temperature values.

The study constitutes the continuation and development of research concerning a comparison of standard and automatic means of measuring basic meteorological parameters, which were carried out by the author (Kajewska and Rojek, 2010; Kajewska-Szkudlarek 2012; Kajewska-Szkudlarek and Rojek, 2015).

The comparison between two methods of meteorological measurements is difficult because of the fact that two sensors are completely different in physical operating principle. Nevertheless improvement of meteorological measurement methods by systematic replacement of manual stations with automatic ones is connected with the concern about retaining homogeneity of long observation databases which are used in climatological researches. In case of smaller meteorological stations it is a common practice to use both measurement methods – the data gathered by the means of automatic measurement is used in analysis, whereas manual instruments are used in case of a failure in automatic system.

2. MATERIALS AND METHODS

2.1. Research Area

The study was conducted in the period of 2000-2009 on the site of Agro- and Hydrometeorology Wroclaw-Swojec Observatory of Wroclaw University of Environmental and Life Sciences.

The Observatory is situated on the outskirts of Wroclaw, about 4 km away from compact urban settings and therefore it remains beyond the influence of the urban agglomeration. Its geographic coordinates are ϕ=51°07'N; λ=17°10'E. The area is surrounded by meadows and farmlands, which represent the majority of agriculture areas of Lower Silesia.

Manual (standard) measurements have been conducted continually in the Observatory since 1961. In 2000 it was equipped with an automatic meteorological station Campbell and since then both standard and automatic measurements have been conducted parallelly.

2.2. Data Collection and Analysis

The analyzed time series were created from the diurnal values of three air thermal parameters: average temperature (*Tm*), maximum temperature (*Tmax*) and minimum temperature (*Tmin*), measured by the means of both methods. The data included the period from January 1st 2000 to December 31st 2009. The number of the entrance files amounted to 3653, which is equal to the number of days in that decade.

Both standard manual thermometers (mercury thermometer and minimum and maximum thermometers) as well as the electronic sensor MP 100A Rotronik were placed in Stevenson screen 2 m below the surface.

The average *Tm* from the standard observations was calculated on the basis of four time measurements: at 1 a.m. (the value read from the diurnal thermo-hygrograms), 7 a.m., 1 p.m. and 7 p.m., whereas *Tmax* and *Tmin* were obtained after reading minimum and maximum thermometers.

The automatic method was used to measure the average diurnal air temperature calculated on the basis of 24 hourly values. Furthermore, the automatic station was programmed to record *Tmax* and *Tmin* along with the time of their occurrence. Measurement accuracy of MP 100A Rotronik sensor at 23°C is ±0.3°C while for standard devices is 0.1°C (mercury thermometer) and 0.2°C (both extreme thermometers).

The influence parameters which included diurnal values of relative air humidity, global radiation and wind speed were measured by automatic sensors.

In order to fulfil the intended aim, single-layer perceptron networks were applied. In practice they are often used for modeling the issues from the area of meteorology and climatology, as it is characteristic of them to build and train easily by the means of simple Error Back Propagation Algorithm (Mihalakakou *et al.*, 2002; Oliveira *et al.*, 2006; Voyant *et al.*, 2014). The networks created for the time series of the analyzed parameters consisted of the entrance-, hidden- and exit layer. The number of neurons in the entrance- and exit layer was determined by the number of variables on the entrance and on the exit layer – it amounted to 7 (temperature measured with standard thermometers and influence parameters) in the first and 3 (temperature obtained from electronic sensors) in the second case. From the range of tested networks two networks were selected which displayed the highest value of the correlation coefficient and the lowest Mean

Squared Error (MSE). This choice was the result of the search for the best match of the model to the actual data. The first model was the neural network with 6 neurons in the hidden layer and hyperbolic tangent as the network activation function in this layer, whereas in the exit layer the linear function was applied. The second model was consisted of 4 hidden neurons, logistic activation function was used in this layer and also linear function in the exit.
The data set was divided into three subsets: learning (network training) encompassing 70% of all the values, test (the control over the learning process) – 15%, and validation (the final verification and selection of the best network) – 15%. The division was carried out at random without disrupting the continuity of the series. It is performed in order to eliminate the phenomenon of the network overlearning, which is also referred to as overfitting. It consists in the fact that in the learning process the network is very good at mapping the correlations which occur in the input data, which makes it lose its abilities to generalize and then the created model has much poorer quality for the independent data. The separation of the test trial allows for the assessment what progress is made by the network in modeling and it also allows for the implementation of early stopping technique. The error for the learning data systematically decreases, whereas for the test data, which did not take part in the learning process, it starts to rise and it is the best time to finish the network learning (Demuth and Beale, 2000).
The second set of the independent data – validation set – serves the purpose of verifying the network accuracy. If the error in this trial is comparable with the error in the test trial, it is considered that the model maps the reality well and will work for other data. Because of the fact that there were negligible differences between the three subsets all the presented diagrams are concerned with the learning, testing and validation processes together.
In the study the following aspects were analyzed: the architecture of the developed networks, the number of cycles in the learning process, the changes in the mean squared error and the correlations between the values of the parameters obtained from the measurements taken by the means of meteorological gauges as well as the parameters prognosticated by the networks for three subsets.
The first step was to subject the data set to standardization transformation (Eq. 1).
Standardization was carried out by the means of the formula:

$$Z = (x - \mu) / \sigma, \qquad (1)$$

where Z stands for the result of the Z test, x – the observed value of the variable, μ – average, and σ – standard deviation.
As the result of the transformation, within the data set the average equal zero and variance equal 1 were obtained. It was considered to be beneficial for the training process and the functioning of the perceptron networks (Demuth and Beale, 2000).
The second step was to analyze differences between two methods of temperature measurements. Differences were calculated in such a way that automatic values were subtracted from the standard data.
The third step was to carry out seasonal decomposition of mean, maximum and minimum temperature time series both for standard and automatic values. In order to isolate individual constituents of examining concatenations a seasonal decomposition was a car ride out over a period of one year using an additive model. A seasonal ingredient, a trend, long term fluctuations as well as a random component of time series were isolated from the data.
The last stage of the study was to create the neural model of automatic *Tm*, *Tmax* and *Tmin* time series on the basis of standard values and influence parameters. All analysis were performed in MATLAB (*Neural Network Toolbox*) and STATISTICA 10.

3. RESULTS AND DISCUSSION

The Fig. 1 presents the course of differences between mean, maximum and minimum air temperature measured with standard and automatic devices. The average difference between the values from the manual and automatic measurements amounted to 0.8°C (*Tm*), 0.9°C (*Tmax*) and 1.1°C (*Tmin*). In the case of *Tm* the

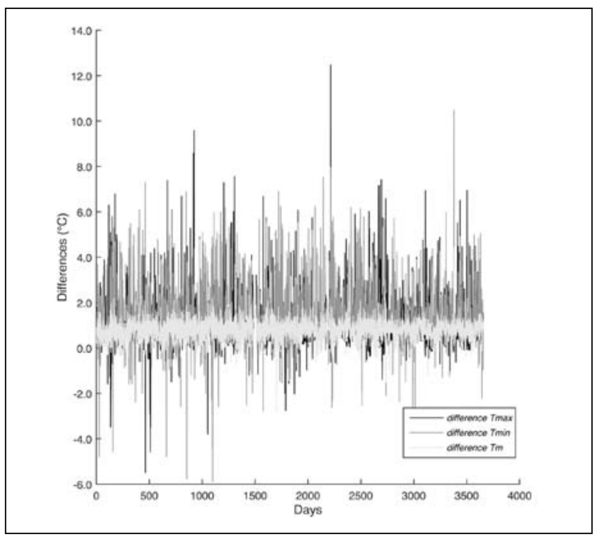

Fig. 1 - Course of differences between air temperatures (°C) measured with standard and automatic method.
Fig. 1 - Andamento della differenza fra temperature dell'aria misurata con metodo standard e automatico.

most significant differences occurred in 2009 (+4.4°C) and 2004 (-2.8°C). The range of difference variability for both extreme temperatures was definitely broader. They were contained in the range from -5.5°C in 2001 to 12.5°C in 2006 (*Tmax*) as well as from -5.9°C in 2003 to 10.5°C in the last year of the study - 2009 (*Tmin*) (Fig. 1). However, it should be noted that such a large difference values occurred incidentally.

The results of seasonal decomposition of analyzed parameters indicate a one year seasonality of temperature's time series (according to the nature of the phenomenon) (Fig. 2 a, b) and the presence of random component in temperature measurements both standard and automatic (Fig. 5 a, b). On the Fig. 3 time series without annual seasonality and on the Fig. 4 the trend of the course of temperature were shown. Due to the limited volume of the article seasonal decomposition results were presented on figures only for maximum temperature.

The variability of the periodic components was similar for both methods of temperature measurements. In the case of *Tmax* it ranged from -15.0°C in the winter to 14.0°C in the summer season (Fig. 2 a, b), which means that in winter *Tmax* values were lower by maximum 15.0°C and in the summer were higher by 14.0°C than values which result from the trend. For *Tmin* periodic component amounted to from -12.0°C to 10.0°C while for *Tm* it ranged from -13.0°C to 12.0°C.

The next stage of the seasonal decomposition was to subtract seasonal fluctuations (Fig. 3 a, b). *Tmax* time series without periodic component fluctuates from -2.5°C to 29.0°C for standard and from -4.0°C to 28.0°C for automatic devices. The variability for *Tmin* ranged from -13.0°C (standard) and -14.0°C (automatic) to accordingly 19.0°C and 17.5°C whereas for *Tm* it fluctuates from -8.0°C (standard measurements) -9.0°C (electronic sensor) to 22.0°C (both).

The next step was to separate trend from the time series (Fig. 4 a, b). For all analyzed parameters the temperature tendencies in the ten year period were steady and the values result from the trend ranged from 1.0°C (*Tmax* standard) and 3.0°C (Tmax automatic) to 25.0°C (both methods). For Tmin it amounted to from-10.0°C to 16.0°C (standard) and from -13.0°C to 15.0°C (automatic) while for Tm from -4,5°C to 19.0°C (standard) and from -5,5°C to 18.0°C (automatic).

The last element of time series isolate by the means of seasonal decomposition was the random component (Fig. 5 a, b). It makes it difficult to identify the structure of the phenomenon. These errors are produced by occasional causes that continuously vary and cannot be determined in detail. In the case of Tmax measured with liquid thermometer it fluctuated from -8.5°C to 6.0°C and from -7.5°C to 6.5°C for electronic sensor.

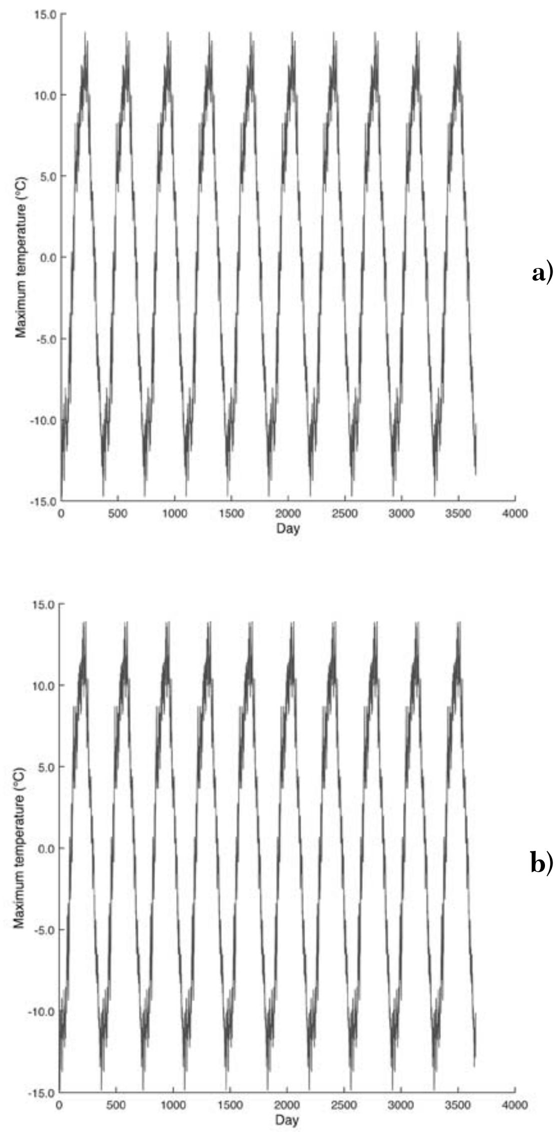

Fig. 2a,b - Periodic component of time series of maximum temperature measured with standard (a) and automatic (b) station.

Fig. 2a,b - Componente periodica della serie temporale della temperatura massima misurata con stazione standard (a) e automatica (b).

For *Tmin* it ranged from -9.0°C to 7.0°C (standard instruments) and from -8.0°C to 8.0°C (automatic) whereas for *Tm* it varied from -8.0°C to 7.0°C in both cases.

On the basis of standard data and influence parameters the neural models of *Tmax*, *Tmin* and *Tm* were created. From multiple networks two models were chosen to analysis: MLP 7-4-3 and MLP 7-6-3.

The measure for the quality of the models were the values of Pearson correlation coefficients between

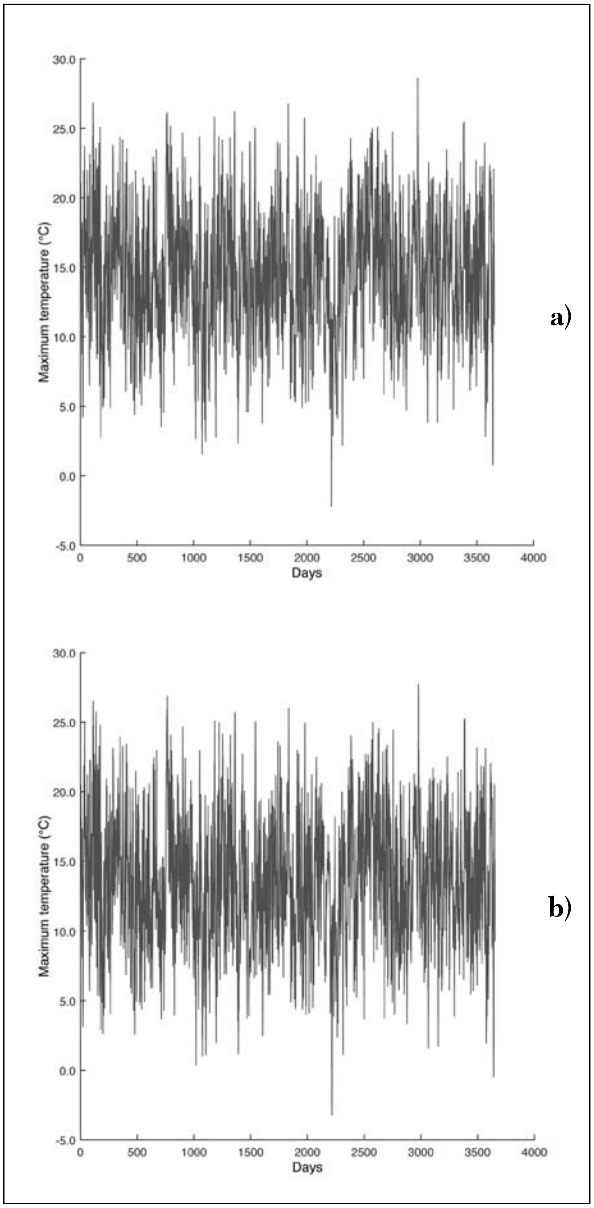

Fig. 3a,b - Time series of maximum temperature measured with standard (a) and automatic (b) station without periodical fluctuation.
Fig. 3a,b - Serie temporale della temperatura massima senza fluttuazione periodica, misurata con stazione standard (a) e automatica (b).

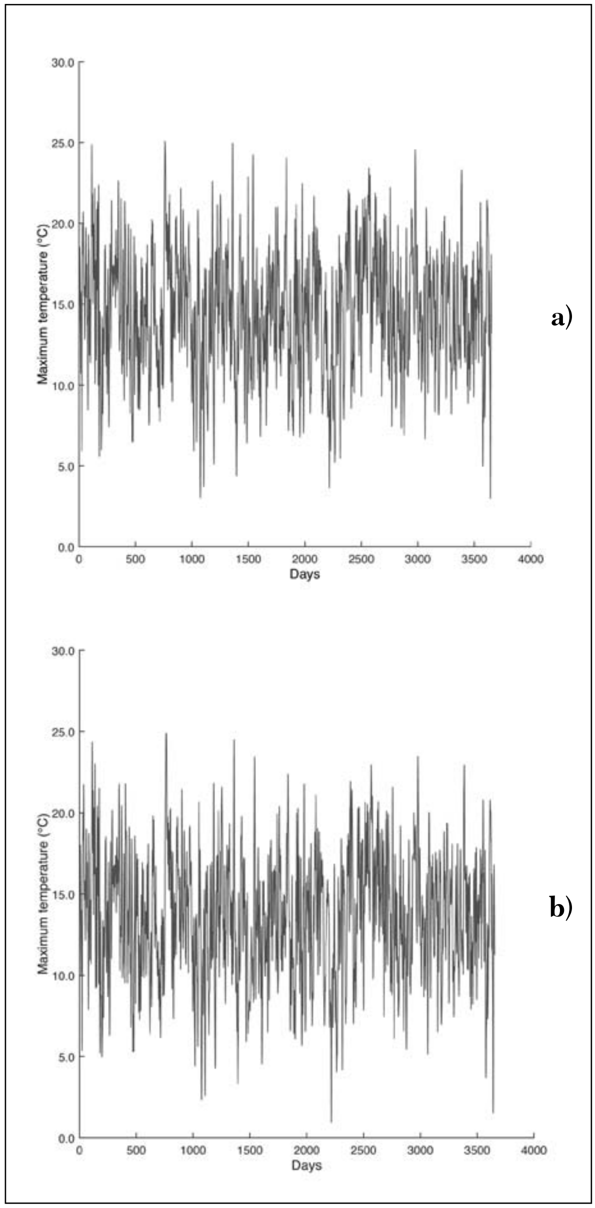

Fig. 4a,b - Trend of time series of maximum temperature measured with standard (a) and automatic (b) station.
Fig. 4a,b - Andamento della serie temporale della temperatura massima misurata con stazione standard (a) e automatica (b).

the series prognosticated by the means of the neural networks and the actual ones (Tab. 1).
The obtained correlation coefficients were very high – 0.995 and 0.996 in training, test and validation trials. Such high values indicate that the networks are of good quality and they maps the course of time series very well. The results were obtained after 108 (MLP 7-4-3) and 221 (MLP 7-6-3) learning cycles. In the course of the network learning process MSE values were gradually decreasing and the largest falling gradient for MSE occurred in the first five cycles. Moreover, the validation errors do not significantly deviate from the errors occurring in the test samples and learning samples (about 0.7 – 0.9), which indicates good generalisation of the data structure by the networks.
In Figg. 6 and 7 a, b results obtained in learning, test and validation are drawn together because the fact that there were not visibly differences between the three phases.
In the scatter plots there is a graphic presentation of the

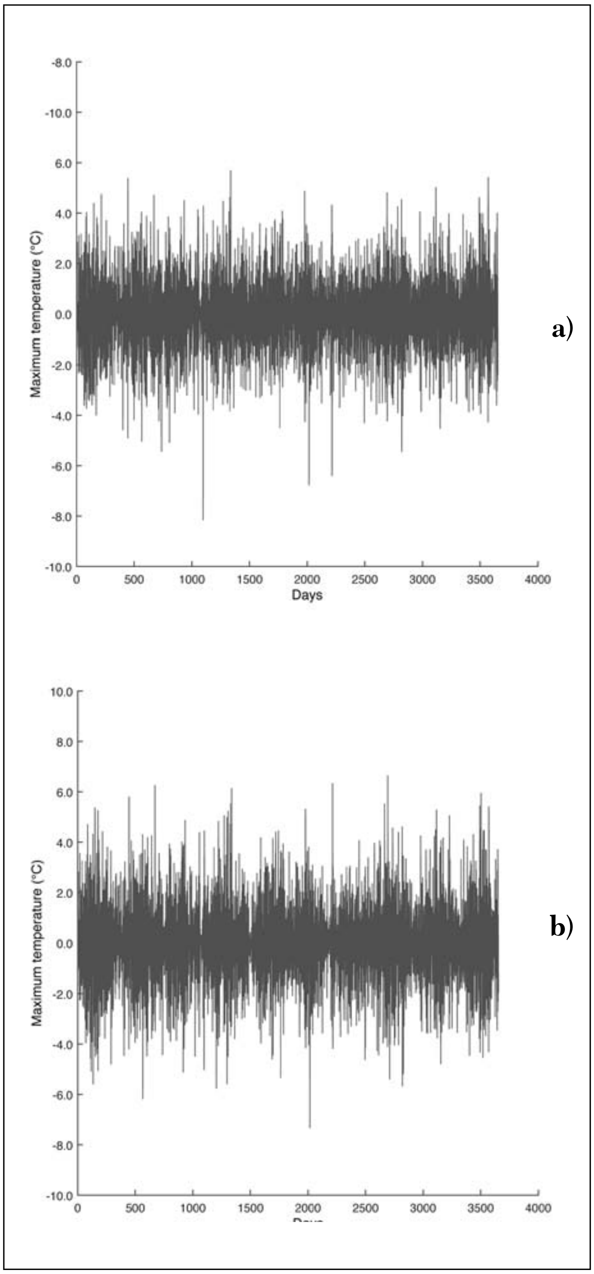

Fig. 5a,b - Random component of time series of maximum temperature measured with standard (a) and automatic (b) station.
Fig. 5a,b - Componente casuale della serie temporale della temperatura massima misurata con stazione standard (a) e automatica (b).

way in which the network reflects the actual value of the variable (Fig. 6 a, b). The observation is facilitated by the y=x line, which perfectly visualizes the matching of the data to the model. The points are located along the straight in case of MLP 7-4-3 (Fig. 6 a) and MLP 7-6-3 (Fig. 6 b) alike, however, they are not exactly on it. The reason for it is the noise which occurs in the data which the network recognized correctly and it did not adjust to it.
In the Fig. 7 (a, b) there is presentation of the residues, which are the differences between analyzed time series and their prediction. For three analyzed parameters histograms indicate that the residues are distributed more or less normally around zero, which is consistent with the general assumption of the normal noise contained in the data. For *Tm* in approximately 1550 (MLP 7-4-3) and 1650 (MLP 7-6-3), for *Tmax* 950 (MLP 7-4-3) and 1050 (MLP 7-6-3), for *Tmin* 900 (MLP 7-4-3) and 1050 (MLP 7-6-3) for over 3650 cases the modeled values differ from the actual ones by no more than -0.2 – 0.2°C.
At the end of the study, a general analysis of the model sensitivity to entry data was carried out (Tab. 2). It can be used to assess post factum how justified the choice of certain variables was and to determine how the quality of the model changes once each of the variables is excluded. The result of the analysis is interpreted in the following way: when the value of the changeable is higher than 1, removing this variable from learning data set can result in the deterioration of the model quality and the other way round: the value of the changeable lower than 1 suggests that there is no impact on the model. The sensitivity study shows that out of 7 entry modes Tm (standard) has the biggest impact on a model, followed by Tmax and Tmin. The remaining parameters and data influence the model to a much lesser degree. It should be noted that six times higher value was observed for Tm indicator in case of MLP 7-6-3 in comparison to MLP 7-4-3, whereas for other parameters the values obtained for both networks were comparable.

4. CONCLUSIONS

1. Simple single-layer perceptron networks are a useful tool for modeling the time series of mean, maximum and minimum temperature measured by the means of electronic sensors.

Number	Architecture	Number of epochs	Learning		Test		Validation		Activation function	
			r	MSE	r	MSE	r	MSE	Hidden layer	Output layer
1	MLP 7-4-3	108	0.995	0.928	0.995	0.833	0.996	0.864	Logistic	Linear
2	MLP 7-6-3	221	0.995	0.824	0.996	0.724	0.996	0.756	Tanh	Linear

Tab. 1 - Summary of neural network learning.
Tab. 1 - Sintesi della fase di apprendimento della rete neurale.

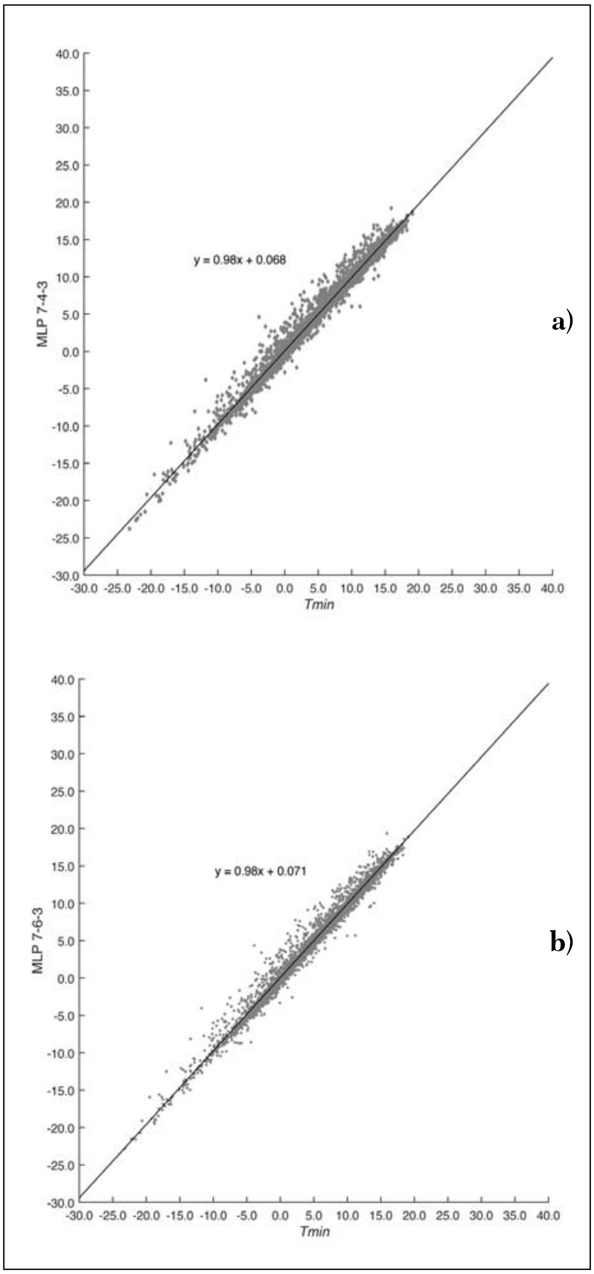

Fig. 6a,b - Scatter plot for time series of minimum temperature measured with automatic station - actual and predicted by MLP 7-4-3 (a) and MLP 7-6-3 (b).
Fig. 6a,b - Scatter plot della serie temporale della temperatura minima misurata con stazione automatica - attuale e prevista da MLP 7-4-3 (a) e MLP 7-6-3 (b).

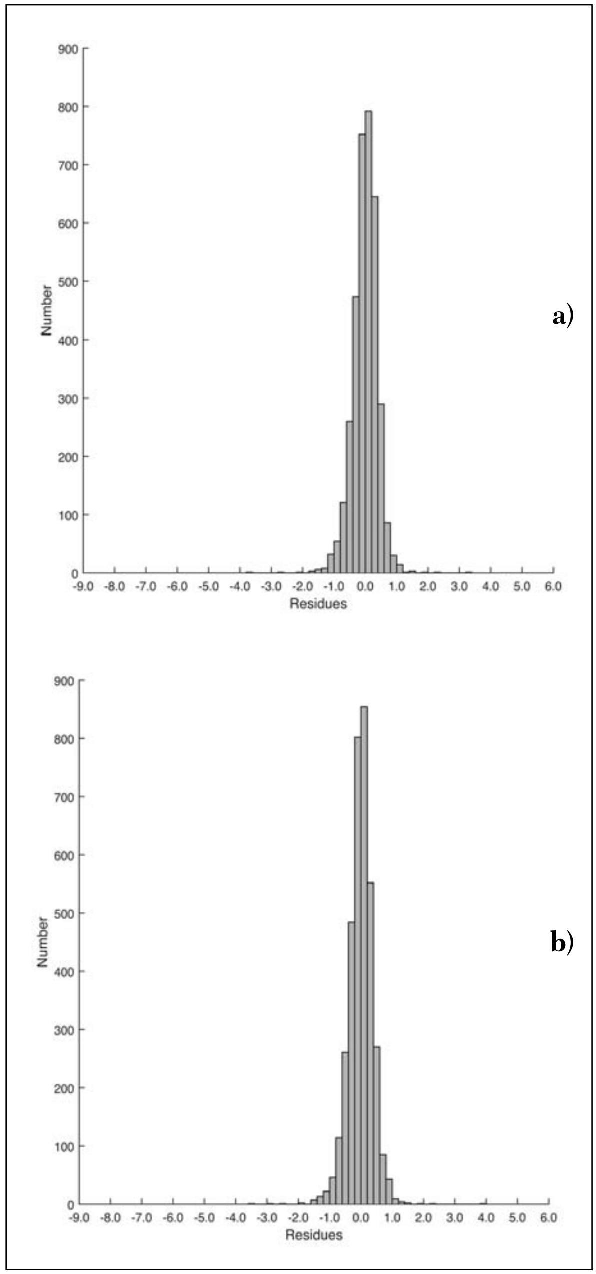

Fig. 7a,b - Histogram of residues for time series of mean temperature measured with automatic station - actual and predicted by MLP 7-4-3 (a) and MLP 7-6-3 (b).
Fig. 7a,b - Istogramma dei residui della serie temporale della temperatura media misurata con stazione automatica - attuale e prevista da MLP 7-4-3 (a) e MLP 7-6-3 (b).

2. The number of neurons in the entrance layer and exit layer equalled the number of variables at the entrance and the exit, that is 7 and 3, whereas the number of neurons in the hidden layer amounted to 4 (MLP 7-4-3) or 6 (MLP 7-6-3).
3. Correlation coefficients determining the compatibility of the prognosticated time series with the actual values amounted approximately to 0.995 and 0.996 in training, test and validation trials.
4. Values of Mean Squared errors were similar (0.7 - 0.9) in three subsets which indicates good generalisation of the data structure by the networks and avoidance of the problem of data overfitting.
5. The global sensitivity analysis shows the most

Number	Architecture	Tm standard	Tmax standard	Tmin standard	Global radiation	Relative air humidity	Wind speed	Date
1	MLP 7-4-3	50.642	24.989	14.659	1.045	1.030	1.029	1.001
2	MLP 7-6-3	321.939	22.442	23.051	1.045	1.057	1.022	1.001
Mean		186.290	23.715	18.855	1.045	1.043	1.025	1.001

Tab. 2 - Global sensitivity analysis.
Tab. 2 - Analisi di sensibilità globale.

significant role of mean temperature and then maximum and minimum temperature measured with standard method in the created model.

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