"Environmental Engineering" 10th International Conference
Vilnius Gediminas Technical University
Lithuania, 27–28 April 2017
http://enviro.vgtu.lt

eISSN 2029-7092 / eISBN 978-609-476-044-0

Article ID: enviro.2017.079
DOI: https://doi.org/10.3846/enviro.2017.079

Local Prediction of Precipitation Based on Neural Network

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Abstract. The paper is focused on analysis of local neural network model of precipitation. We use basic multilayer perceptron neural network with the time-window on input data to predict the precipitation. We predict the precipitation in the next day from the local meteorological data from past days. Data from the past 60 years were used to train the predictor. Obtained prediction model is specific for given area of Košice City in Slovakia, as the prediction is based on the statistics of the weather in given area. This precipitation predictor is multiple-input-single-output architecture with a single value per day resolution on output. Obtained results show that good local temperature prediction accuracy is possible with chosen setup, but it is worse for the precipitation prediction. Also the training requirements of precipitation predictor seem to be significantly higher then for the temperature predictor. Obtained prediction results can be used for applications based on local meteorological station data, although they are not as accurate as the state of art agency predictions based on satellite data. In the paper we will analyze design of the precipitation predictor based on existing design of the temperature predictor and provide the reader with recommended setup of such predictor for application with his/her local precipitation data.

Keywords: precipitation, prediction, neural network analysis, Slovakia.

Conference topic: Water engineering.

Introduction

Slovakia belongs to the northern moderate climatic zone. The weather in Slovakia changes a lot by the influence of dry continental air from the west and the humid ocean air from the north. The topography of Slovakia is very diverse and the altitude is an important factor affecting the temperature and precipitation. The weather is usually warmer in the lowlands than in mountain. The Eastern Slovakia lowland, where Košice – the second largest city in Slovakia is situated, is the warmest and the driest region of eastern Slovakia with an annual average temperature around 8°C and precipitation around 600 mm. The coldest places are mountainous area – the High Tatras in the north with the average temperature of –3°C and with precipitation over 2000 mm (SHMI 2015).

Multilayer perceptron with single hidden layer should be sufficient for realization of such nonlinear weather predictor. We expect it based on our past experience with local temperature prediction (Vaščák *et al.* 2015). However, the physical processes of precipitation do differ from these of temperature, so individual parameters of predictors might differ too. Our temperature predictor (Vaščák *et al.* 2015) was designed to produce daily temperature profile with 15 minutes resolution for the next day based on measured data from last three days. Predictor was based on multilayer perceptron with 1008 inputs, 48 hidden neurons and 96 outputs. Training was performed on 10 years of historical data. Achieved accuracy was 88% on 1 year testing data from the Kosice city. Obtained predictor was applied in the local district heating plant.

Multiple meteorological parameters prediction based on neural networks was studied in the work of Raza and Jothiprakash (2014). They used multiple-input-multiple-output architecture of predictor and predicted seven meteorological parameters for the next day based on these same seven parameters measured this day. They used from 14 to 26 hidden neurons with several neural network architectures and trained them using 10 years of historical data. Parameters were: min/max temperature, humidity, wind speed, sunshine length, dew point and evaporation. From the sensitivity analysis of input variables they concluded that relative humidity is the most influential input of their predictor with the temperature as the second. They also found the recurrent neural network to have best results; however this can be caused by the fact that they used only a single day data as the input of predictor.

Methodology

Our proposed precipitation predictor is based on results of Vaščák *et al.* (2015) and Raza, Jothiprakash (2014). It is multiple-input-single-output architecture with single value per day resolution. Input parameters are: day in the year, min/max/avg temperature, humidity, average wind speed, wind direction three times during day, pressure and precipitation. They are 11 parameters in total. For the seven days long input the topology will be 77 inputs, 1 output, 5 to 10 hidden neurons (Fig. 1).

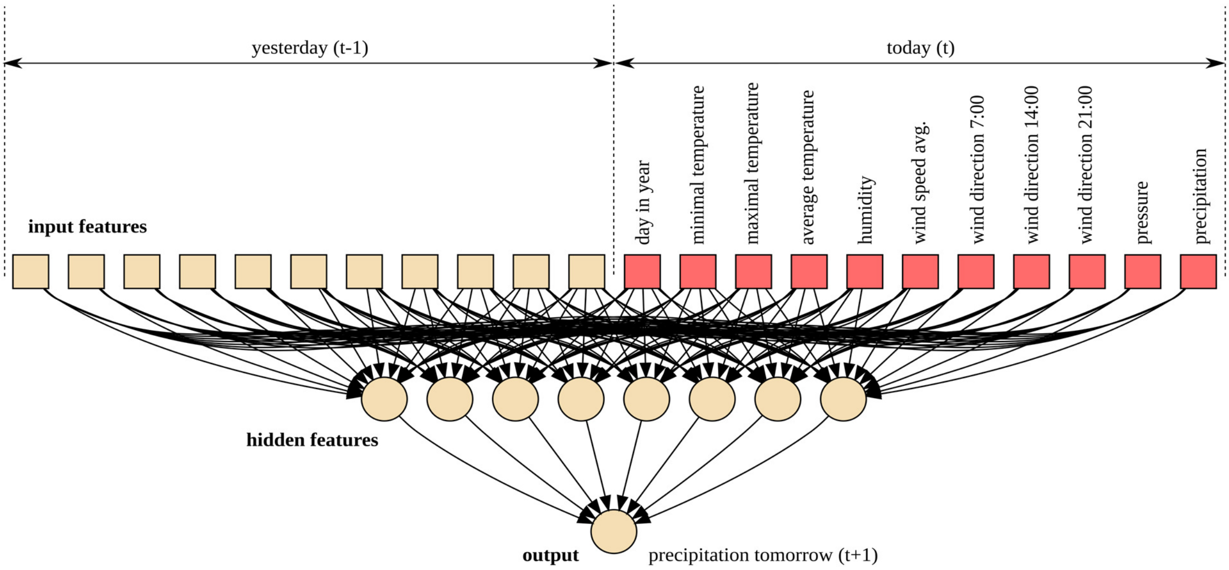

Fig. 1. Neural network predictor topology 22-8-1 with two days long input (t and t-1) and the following day precipitation output (t+1), with 8 hidden neurons and 11 inputs per day. In actual experiments we used 7 days input window (t,…, t-6)

This type of weather predictor can be characterized by:

- data are treated as time series,
- meteorological data from a single geographic location are used, e.g. single meteorological station,
- multiple meteorological variables are used on input: temperature, humidity, pressure, etc.,
- inputs are organized in sliding time window over several days, depending on the time resolution (e.g. 15min) the total number of inputs can easily reach 1000 or more for few days input,
- simple multilayer feed-forward neural network is used as a nonlinear prediction tool, one or two layers of hidden features is used,
- historical data from given location are used for the training of neural network, e.g. 10 or 50 years of data.

Similarly to our realized temperature predictor, we expected precipitation prediction results to achieve similar accuracy and the training time. Although, the setup is different. Instead of the 15min resolution and 10 years of historical data in (Vaščák *et al.* 2015), we use here a lower resolution data (one sample per day), but longer training set of 50 years. Also, we will try to predict only a single value of tomorrow precipitation, instead of the 15min daily temperature profile in our past work.

We use feed-forward neural network with the backpropagation algorithm (Werbos 1994) and also a modified backpropagation algorithm – backpropagation with stochastic weight update (Koščák *et al.* 2010, 2015). As a data set for the experiments we use daily data from 1951 till 2014 measured in the Košice city. Data have been divided into two sets: the training data from between 1951 till 2013 and the testing data from the year 2014. All 11 relevant variables of meteorological data are used as the input of predictor. Used length of sliding time window of neural network input is 7 or 5 days from past and the output is a 1 day ahead prediction. Topology of neural network is 77 input neurons and 1 output neuron for the precipitation predictor and 2 output neurons for combined precipitation and temperature predictor. The number of hidden neurons depends on the particular experiment. Output of the precipitation predictor is directly the precipitation in millimeters, for the temperature prediction it is the actual average temperature in degrees Celsius.

Results

We realized experiments with several setups of neural networks. Data were properly preprocessed, with approximation of missing values or elimination of given day. They were normalized to the (0,1) interval for the neural network usage and organized into series of time windows. We will illustrate the results on few chosen setups.

The *77-8-2 combined precipitation and temperature predictor* obtained very quickly good temperature prediction performance (see Fig. 2). The topology of neural network is 77 input neurons, 8 hidden neurons, 2 output neurons, learning rate γ = 0.004 and number of training cycles is 13200 iterations (15 minutes learning time).

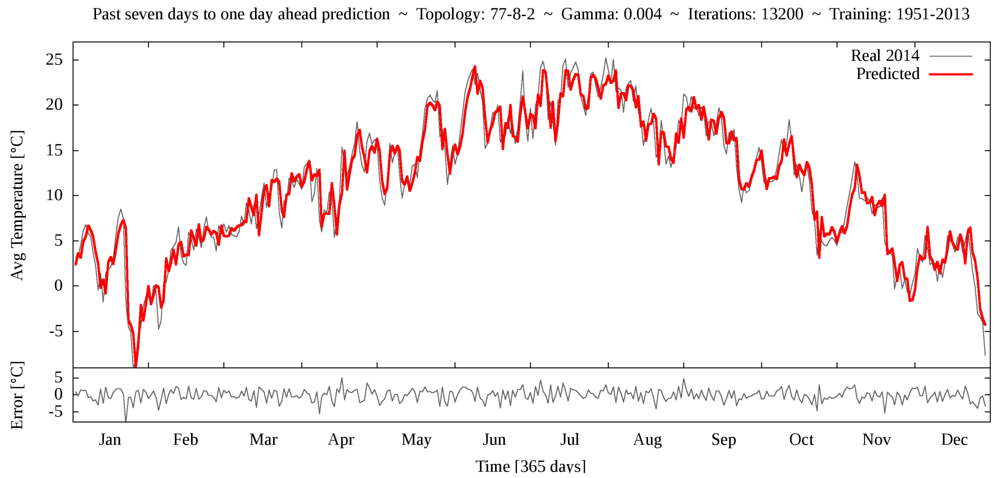

Fig. 2. Average temperature prediction after 13200 learning cycles with the stochastic weight update backpropagation learning

The prediction is quite accurate, although some shift of the red line to the right is visible. It means that the predictor still gives too much focus to the past day temperature. The performance of this combined predictor on the precipitation prediction was not good, 13200 training cycles was not enough. With this example we want to show that temperature prediction with given setup works well.

The *77-8-1 precipitation predictor with 170000 training cycles* obtained best precipitation prediction performance in this round of experiments (see Fig. 3). The topology of neural network is 77 input neurons, 8 hidden neurons, 1 output neuron, learning rate $\gamma = 0.04$ and number of training cycles is 170000 iterations (1.5 hour learning time).

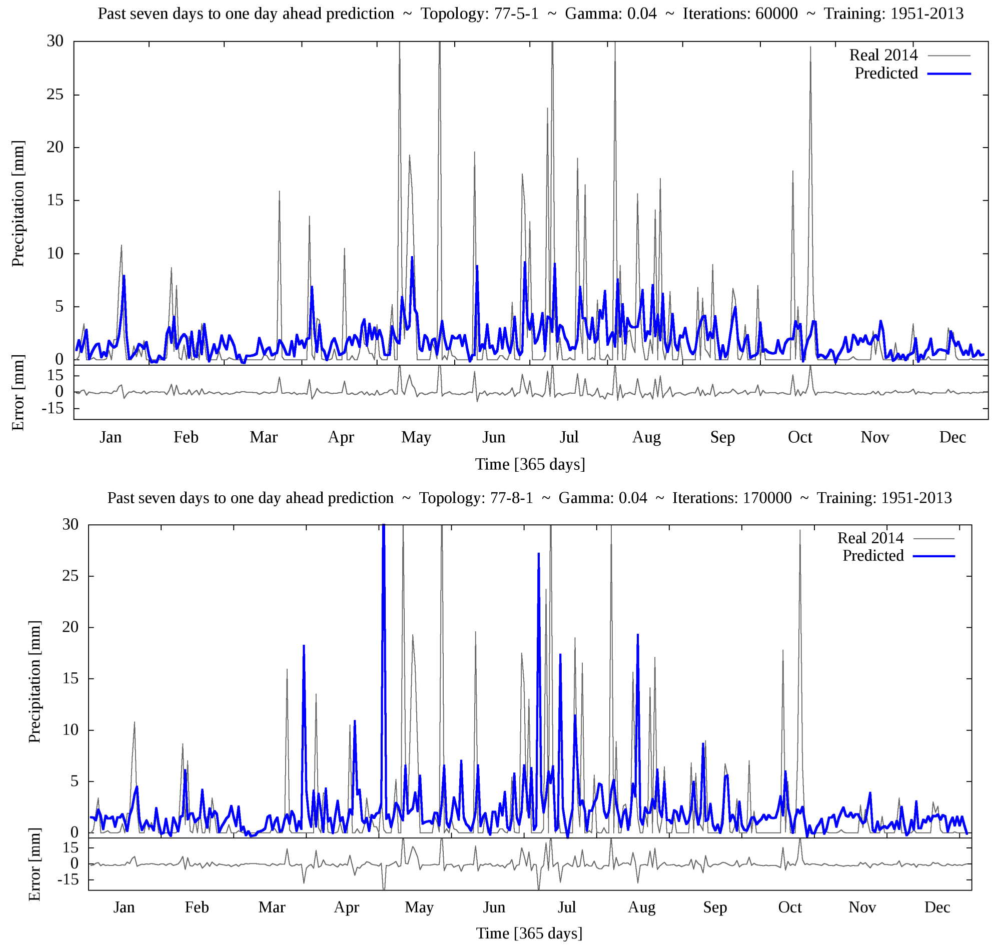

Fig. 3. Precipitation prediction with 60000 and 170000 learning cycles with regular backpropagation learning. The first prediction tends to not miss any rain, errors are mostly positive. It also predicts small rain too often. The second prediction with 170000 cycles is better in the prediction of the intensity of rain, however it often fails with the prediction of the exact time of rain. It is the best result we obtained with the precipitation prediction with discussed predictor architecture

The prediction is not as good as the temperature prediction (Figure 2), although the number of training cycles is much higher (170 000 vs. 13 200). Obtained predictor manages to match the distribution of rain thorough the year, and also in many cases the intensity of rain. It is not good in the prediction of exact timing of rain and it still predicts small rain for the days when no rain happened.

On the Figure 4 we show the example of error course of the neural network predictor training. The first picture is from the best precipitation predictor (Figure 3). It is measured using the testing set – the 2014 year data, while the training is done using 1951–2013 training data. The still decreasing testing set error curve means that there is further potential to improve the prediction accuracy by the longer training. Experiments with the stochastic weight update for the precipitation showed similar results to the regular backpropagation training.

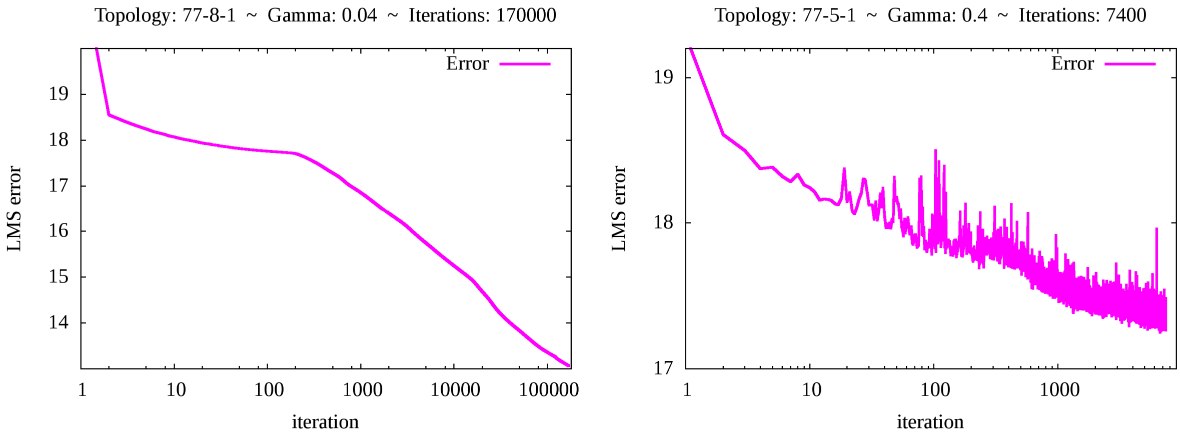

Fig. 4. Error of neural network on learning of 170.000 iterations predictor from Figure 3 with regular backpropagation training and of the another predictor which uses stochastic weight update training. The stochastic weight update training error course is less smooth, it is a feature of this type of learning. The errors are measured using the testing set – the 2014 year data, while the training is done using 1951–2013 training data. The still decreasing testing set error curve means that there is further potential to improve the prediction accuracy by the longer training

We tried to predict specific amount of precipitation in millimeters for every day. Another type of precipitation prediction can be to predict just whether for a given specific day it will or it will not rain, or to predict the chance of rain for some range of days. This prediction can then be combined with the standalone prediction of the intensity of rain for the predicted day.

Conclusions

Variable nature of the weather in Central Europe, determines conditions for rather regular occurrence of atmospheric precipitation. In Slovakia, precipitation is a limiting factor e.g. for the possibility of cultivation of certain agricultural crops, or for spreading of certain tree species. Precipitation has a significant impact on the overall availability of water resources in some regions of Slovakia. Despite the variable nature of the weather and relatively small extent of the country, there are several regions with various annual precipitation regimes in complex natural conditions of Slovakia (Zeleňáková *et al*. 2014). Similarly, the spatial distribution of precipitation caused by windward, respectively leeward effects, in individual cases is quite complicated (Zeleňáková *et al*. 2013). However, in the long term, the dependence of total rainfall on the altitude and also clear decline in total precipitation from the north to the south can be identified in the precipitation field of Slovakia (SHMI 2015). Our predictor based on neural network and local weather data shown some potential. Although not as good as the local temperature prediction, or agency predictions based on satellite data, we expect our prediction results to be usable for applications based on local meteorological station data. Also, we see potential for further improvement by using more complex structure of predictor.

Funding

This work was supported by the VEGA [1/0609/14].

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