Application of Neural Networks for Short Term Load Forecasting in Power System of North Macedonia

Goran Veljanovski, Metodija Atanasovski, Mitko Kostov and Pande Popovski

Abstract – **Air temperature, type of the day and humidity are factors that have significant impact on electricity consumption and power system load on a short term. In the paper, neural networks are successfully applied for load forecasting on a short term in the power system of Republic of North Macedonia. The training of neural network is performed on real input data. The forecast is obtained on the basis on the trained network and learned relationship through training process.**

Keywords – **Neural networks, Load forecast, Power systems.**

I. Introduction

Short term load forecast is very essential for power system operation in secure and reliable manner. The significance of electricity demand forecast relies on several reasons: increased penetration of non–dispatchable, renewable sources, electricity markets structural changes, optimal unit commitment and operation of conventional power plants. Electricity demand forecast depends on several factors: climate parameters (temperature, humidity, wind speed etc.), type of the day (working day, Saturday, Sunday, holiday), demography data, gross domestic product, and economic standard of the people, applied measures for energy efficiency, geography and other factors.

Climate and calendar parameters such as temperature, day type, humidity, and wind speed are one of the factors, which has significant impact on electricity consumption and power system load on a short term. Air temperature impact on system load is especially important from the power system operational management aspects on short run. This fact is evident in the power system of Republic of North Macedonia due to high variations of consumption and load in year seasons.

The number of scientific papers on load forecasting has increased from about 100 before 20 years to more than 1,000 in the last years. Therefore, it is very difficult to make full overview of the existing methodology, and only some papers are mentioned here. There is a number of techniques, which have been used for load forecast, such as: single or multiple linear or nonlinear regressions, stochastic time series, exponential smoothing, state space and Kalman filter, knowledge based approach, neural networks, wavelet transformations, semi parametric additive model, fuzzy logic etc.

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The first generation methods called analytical methods includes time series analysis, regression methods [1-3], similar day method, Wavelet Transform [4-5], etc. Artificial intelligence methods, also known as the second generation of the load forecast methods, mainly comprises artificial neural networks (ANN) [6-8], including deep neural networks [9-10], random forests, gradient boosting [11], fuzzy logic [12]. Compared with the first generation, the second generation has become more important due to reduced errors. Some combination of methods (known as hybrid methods) that belong to the both generations is also possible [13-14]. Authors in [15] have concluded that all the previous methods appear to have at least one of the following two limitations:

- Methods work only with a subset of days (electricity demand forecast is done only for a one day type, e.g., working days);
- Narrow time frame is considered in calculations (e.g., a few months).

This paper investigates the application of neural networks for short term load forecasting in the power system of North Macedonia. In the paper, neural networks are successfully applied for load forecasting on a short term in the power system of Republic of North Macedonia. The training of neural network is performed on real input data. The forecast is obtained on the basis on the trained network and learned relationship through training process. The implementation of the neural networks is performed by using two independent variables: air temperature and type of the day. It means the algorithm calculates suitable power load values around a certain temperature for a specific type of the day. The hourly data (8760 per year) for the temperatures and load are used for the years 2014-2018 as a training dataset, while 2019 (temperatures and load) data are used as a test dataset.

The proposed methodology tries to overcome some of the previous methods limitations mentioned, above. Namely, this methodology works with all types of days and calculations are done for a large time frame. Other contributions of the paper are the use of last seven days for day ahead load forecast and the fact that for the first time neural networks are applied for load forecast in the power system of North Macedonia using real input data.

II. Methods

A. Input Data and Basic Analysis

Historical data on load and temperature was collected for this study. The case study input data includes hourly power

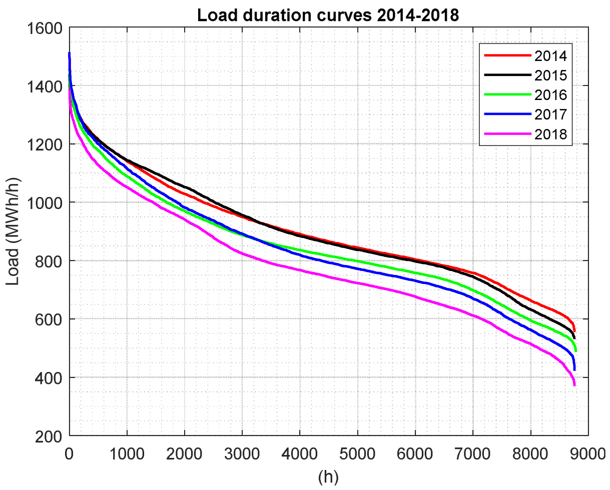

Fig. 1. Load duration curve for years 2014–2018 for power system of Republic of North Macedonia

system load of the Republic of North Macedonia in the years 2014-2019 (8760 per year) [18, 19], as well as corresponding meteorological information on minimum, average and maximum temperatures collected from [20] (Fig. 1).

Figure 2 depicts a daily diagram of power system of Republic of N. Macedonia for the day Jan 08, 2014. Three typical points (minimum daily load P_{min}=836MW, average daily load P_{avg}=1100MW, maximum daily load P_{max}=1293MW) are marked on the diagram and they are used in the analysis from each daily diagram. An average daily load is an average of all 24-hourly loads on a daily diagram. The average daily loads in correlation with average daily temperatures are used in this paper for analysis and forecast. In [21, 22] was shown that there is a strong negative correlation between the power load and the air temperature. The determination coefficients for polynomial regression and sinuses regression of the maximum, average and minimum daily load due to the average daily temperature are very high, which means that the regression analysis shows high prediction degree of the daily typical loads from the air temperature [21-23].

B. Neural Network Structure and Design

In order to achieve the objective of forecasting electrical load, first, multilayer artificial neural networks (ANN) are constructed. The theory of ANN is well known in the literature [1, 6, 7, 8 and 24]. Multilayer feed forward ANN are used in this research for prediction. The basic element of a feed forward neural network is the neuron, which is a logical-mathematical model that seeks to simulate the behavior and functions of a biological neuron [1].

The number of input neurons is usually set equal to the number of input variables. Input variables for this research are the following: Day of the week; Temperatures (average temperature) of the seven previous days; Average loads of the seven previous days. For the days of the week, numbers from 1 to 7 are used and for holidays according to calendar number 8 is used.

This results in 15 neural network input values. The output of the neural network represents the forecasted load data for

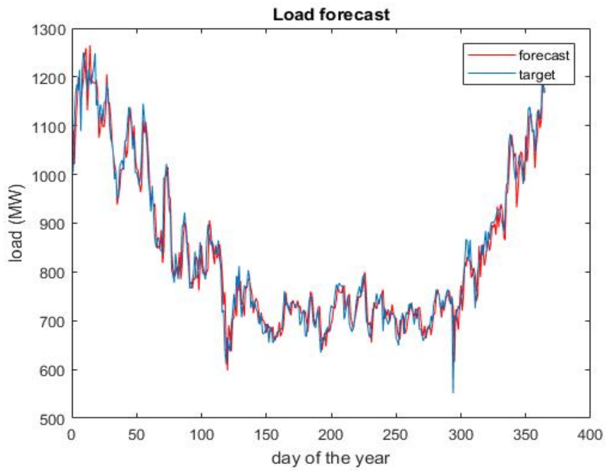

Fig. 2 Load forecast for the year 2019

the forecasting day. The model is consisted of one hidden layer with 10 hidden neurons per layer.

C. Neural Network Training

After the network has been designed, the next step is to train the network. Training an ANN is an iterative process. For training the proposed neural network, Levenberg Marquardt technique is used.

For training the network, the proposed algorithm uses 70% of the average day loads data and temperatures, while 15% are used for the network validation and 15% for testing the network. The division of data in the proposed algorithm is done randomly.

III. Results and Discussion

After proper training of the network, its generalization performance needs to be validated. New data that is not used during training will be fed into the network to see if it can predict these "unseen" data well.

The results obtained from testing the trained ANN on new data for 365 days of the year 2019 are presented in Fig. 2. The graph depicts a plot of 'actual' and 'forecast' load in MW values for the day of the year. In addition, for evaluation of the numerical predictions success, several alternative quantities have been calculated and shown in Table I. The quantities used to evaluate the model performance are the following:

Mean-squared error (MSE):

$$MSE = \frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{n}. \tag{1}$$

Mean-absolute error (MAE):

$$MAE = \frac{|p_1 - a_1| + \cdots + |p_n - a_n|}{n}. \tag{2}$$

Root mean-squared error (RMSE):

TABLE I
MEASURES FOR MODEL EVALUATION

MAE(%)	MAE (MW)	MSE (MW^2)	RMSE (MW)
3.04	30.4	1397	37.38

$$RMSE = \sqrt{\frac{(p_1 - a_1)^2 + \cdots + (p_n - a_n)^2}{n}} \quad (3)$$

In Eqs. (1)-(3), n represents the total number of instances, $p_1,.., p_n$ are the predicted response values, $a_1,.., a_n$ are the actual response values.

It is evident that there is a high level of accuracy of ANN to forecast electricity demand.

IV. CONCLUSION

The presented results confirm the applicability and efficiency of ANN in short-term electricity demand forecasting. Average daily loads and temperatures are used as historical data. The forecasted average load for the day ahead with high level of accuracy, gives the possibility to the system operator to estimate the necessary amount of energy day ahead. The methodology presented in the paper uses the last seven days for day ahead load forecast and for the first time ANN are applied for load forecast in the power system of North Macedonia using real input data. For future work, experiments should be extended on real input data for power systems in the region of South East Europe.

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