Short-Term Load Forecast in Power Systems: A Comparison of Different Practical Algorithms

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***Abstract*— Electricity demand forecasting has significant impact on planning and operation of a power system. Parameters that affect short and long-term load forecasting are the temperature, calendar day, geographical variations, gross national product, socio-demographic trends, energy efficiency etc. The weather conditions seriously affect load demand on short term. This paper focuses on a comparison of different practical methodologies for short-term load forecast and their application and implementation on real load demand and temperature data for Republic of North Macedonia. The paper provides detailed comparison of several practical algorithms for short-term load forecast: polynomial and sinuses regression, machine learning and artificial neural networks. The power load is considered from the aspect of two variables – temperature and calendar date. A case study is presented and results are discussed and analysed. Finally, conclusion and recommendations are presented.**

***Index Terms*--Load forecast, Machine learning, Artificial Neural Networks, Polynomial regression, Sinuses regression.**

I. Introduction

Power system load curve shows the variation of load with respect to time. Its analysis is very important to determine factors that affect the energy demand in the power system. These factors are the growth and structure of gross national product, socio-demographic trends, temperature of the air, calendar day (working day, weekend and holiday) energy efficiency, climate change, people's customs, habits, mobility, etc. Each of these factors have impact on power system load. Some of them have impact on long term, such as the growth and structure of gross domestic product and, demographic variations. Temperature and calendar day are factors that may have a major influence on power demand and power systems load on short-term. This is a case in Republic of North Macedonia, as a result to the rapid changes in annual season's electricity consumption and load.

Short-term load forecast is a complex problem for which several generations of methods have been applied: analytical methods including regressions methods (linear, quadratic, cubic, sinuses) and time series analysis [1-3], wavelets based methods [4-5], artificial neural networks (ANN) [6-8], deep neural networks [9-10], random decision forests, gradient boosting [11], fuzzy logic [12], combination of methods are also widely used [13-14]. Authors in [15] have elaborated that all methods mentioned above have some of these three limitations: 1) authors are working only with one type of day; 2) Calculations are executed for minor period (e.g. a couple of weeks or months).

This paper provides detailed comparison of several practical algorithms for load forecast on a short-run: polynomial and sinuses regression, machine learning methods including Decision Trees (DT) (bagged trees), Radial Support-Vector Machines (SVM), exponential Gaussian Process Regression (GPR), K-Nearest Neighbors (KNN) method and Artificial Neural Networks (ANN). The proposed methodologies and compared methods try to resolve limitations of the literature existing methodologies mentioned, above. Namely, the compared methodologies (KNN, SVM, GPR and ANN) are applied to all types of days and calculations are performed for wider time horizon. Additional contribution is comparing evaluation of the methodologies implemented for the first time on power system of N. Macedonia. ANN based methodology introduces usage of data for load and air temperatures in the seven past days for load forecast of the day ahead, which results with very accurate load forecast. The results indicate that for short-term load forecasts algorithms based on KNN and ANN give more accurate results than linear and nonlinear regressions and the other tested machine learning methods.

Several measures for comparison are defined and used for evaluation the efficiency of the presented methodologies. The paper also clearly illustrates the advantages and disadvantages of each presented methodology.

II. Short Term Load Forecast Methods

This paper compares several practical methodologies for short-term load forecast: polynomial and sinuses regression, bagged trees, radial support-vector machines, exponential Gaussian process regression, k-nearest neighbor and artificial

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neural networks methods. The considered methodologies are described in the four subsections bellow.

A. Polynomial and sinuses regression

Polynomial regression is deeply investigated in the literature to conduct in-depth research on the relation between electricity demand and temperature. The correlation and determination coefficients (indices) are used as statistical measures to analyze the relation between two variables. The correlation coefficient varies from –1 (negative functional dependence) to +1 (functional dependence). The coefficient of nonlinear correlation estimates nonlinear relation between two variables (has values between 0 and 1). The determination coefficient shows how many percent of one variable are predictable with a second variable using regression analysis (it is in range from 0 to 1) [16].

Another approach is founded on sinuses regression and wavelets. An approximate function consist of a sum of sines of order n:

$$f(x)=\sum_{i=1}^{n} a_i \sin(b_i x + c_i). \quad (1)$$

Given that the power load in a particular date does not only depend on the current ambient temperature, but it is also an inertial system, so some potential peaks in the temperature should be ignored. Therefore, the best fitting function of sinuses is combined with discrete wavelet transform (DWT). The wavelet transform is applied over the best fitting output p, which results in decomposing it in an approximation and J details [17]:

$$p(t)=\sum_{k} a_{Jk}\phi_{Jk}(t)+\sum_{j=1}^{J}\sum_{k} d_{jk}\psi_{jk}(t), \quad (2)$$

where $\Phi_{Jk}(t)$ and $\psi_{Jk}(t)$ are the scaling and wavelet function, respectively, and a_{Jk} and d_{jk} are approximation and detail coefficients at level (J) and level (j), respectively. Power forecast is obtained when inverse DWT is applied over the approximation coefficients.

B. DT, SVM and GPR methods

Several machine-learning methods for power load forecasting were investigated. One of the presented algorithms is the DT diagram. DT diagram graphically presents the decision-making process, showing the key factors important for the decision, the conditions that must be met, and all possible solutions. DT is sensitive to the data it is trained on - different training data may lead to different decisions and completely different forecasts. In DTs, overfitting the training data is not a problem. One important factor is the number of included instances (trees), which is calculated by constantly increasing the number of trees until the accuracy stops improving.

The second machine learning method presented is Support-Vector Machines (SVM), which maps the input training data (support vectors) to a higher dimensional features space, and construct a decision surface with special properties in this space to ensure the high generalization ability of the network [18]. It minimizes the following problem:

$$\min_{f}\|f\|_K^2 + C\sum_{i=1}^{l}|y_i - f(x_i)|_{\varepsilon}, \quad (3)$$

where C is a "regularization parameter" that regulates an adjustment between empirical error and complexity of the used hypothesis space, x and y are variables of training data containing l instances, f is a function that characterizes a hyperplane, K is the kernel that expresses the reproducing kernel Hilbert space (RKHS) and the RKHS norm of the function f.

The third investigated machine learning method for short-term load forecast is Gaussian Process Regression (GPR). The Gaussian distribution is commonly used for modelling noise, and therefore, it can be used for modelling a finite set of variables with real values. GPs are methods of extending the multivariate Gaussian models to infinite-sized sets of variables with real values. With this extension, GPRs are expressed as distributions, but over random functions [19].

C. K-nearest neighbour method

Another approach to forecast power system load is KNN machine learning method [20]. The load in this approach as in the other methods is depending on average temperature and date - the algorithm examines k power loads around a certain date and temperature.

Another aspect is normalization of the variables measured on different scales – the impact of variables with different scales can result to a bias. The variable date (range, 1 to 365) will affect the forecast more than the variable air temperature (range, –15 to +30C), i.e. the influence of the variable date on the calculated distance will be higher than the temperature. Converting the data to an equivalent measure can eliminate this issue. Therefore, a normalization is used for the variables in [0–1] range.

The performance is measured by 10-fold and Leave-one-out cross-validations applied over and compared for training and testing datasets in order to avoid overfitting. Fig. 1 illustrates the phases of this approach.

D. Artificial neural networks

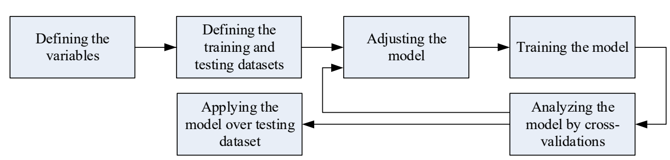

Figure 1. Phases of the KNN approach

ANN networks for power load forecasting were also considered [21]. The approach utilizes multilayer feed forward ANN, where the neuron is the elementary part of a feed forward neural network.

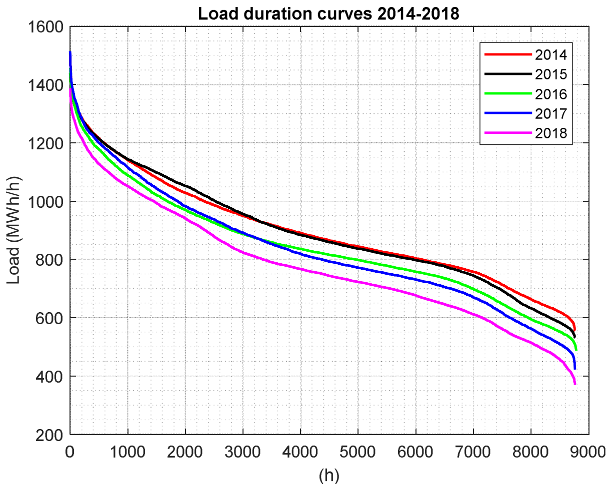

Figure 2. Load duration curves for power system of Republic of North Macedonia

The number of input neurons matches the number of input variables: day of the week; average temperatures and loads in the previous seven days. This model operates with 15 ANN input values. There is one hidden layer with 10 hidden neurons per layer. The proposed ANN uses Levenberg Marquardt method, randomly partitioning data: 70% training data, 15% validation data and 15% testing data.

III. Case Study

A. Dataset overview and basic analysis

Load data is 8760 values per year for average power loads in Macedonian power system for a period of five years, 2014-2019 [22, 23] and the corresponding meteorological data for temperatures Tmin, Tavg and Tmax (minimum, average and maximum) [24] (Fig. 2). In the analysis, training dataset consists of data for 2014-2018 years and testing dataset consists of data for the year 2019. The power load is a dependent variable, while the average temperature and date are independent variables. The forecast is for minimum, average and maximum load for each day since the dataset consists of average temperatures for the days, not hourly values. For the temperatures, historical records from internet are used [24].

Three typical points for each day are used in a daily diagram of Macedonian power system: minimal, average and maximal load (Pmin, Pavg, Pmax). An average load is average of all 24-hour loads.

The measures used to estimate the models efficiency are the following: Mean-squared error (MSE), Mean-absolute error (MAE), Root mean squared error (RMSE) and correlation coefficient (R).

$$MSE = \frac{\sum_{i=1}^{n} (y_{i*} - a_i)^2}{n}, \quad MAE = \frac{\sum_{i=1}^{n} |y_{i*} - a_i|}{n} \qquad (4)$$

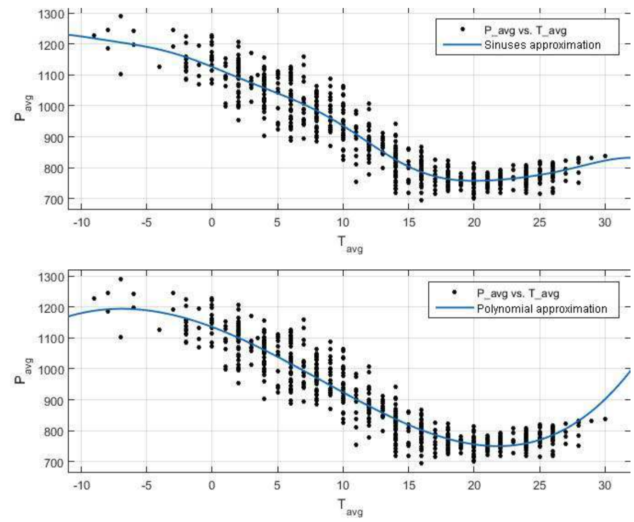

Figure 3. Approximation by using sinuses function of order 4 (upper row) and polynomial function of order 4 (bottom row)

TABLE I. SUMMARY OF TWO APPROXIMATION FUNCTIONS OF ORDER $N = 4$: (LEFT) SUM OF SINUSES $f(x) = \sum_{i=1}^{4} a_i sin(b_i x + c)$; (RIGHT) POLYNOMIAL $F(X) = P_1X^4 + P_2X^3 + P_3X^2 + P_4X + P^5$

Average load				
Sum of sinuses			**Polynomial function**	
$a_1 = 2235$	$b_1 = 0.05558$	$c_1 = 1.043$	$p_1 = 0.0002543$	$p_4 = -15.81$
$a_2 = 1355$	$b_2 = 0.08021$	$c_2 = 3.778$	$p_2 = 0.02989$	$p_5 = 1136$
$a_3 = 50.28$	$b_3 = 0.2274$	$c_3 = 0.01103$	$p_3 = -0.8584$	
$a_4 = 7.186$	$b_4 = 0.5079$	$c_4 = -3.128$		
$R^2 = 0.8961$	Corr.coeff.=	-0.9466	$R^2 = 0.8902$	Corr.coeff= -0.9435

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n} (y_{i*} - a_i)^2}}{n}, \quad R = \frac{S_{YA}}{\sqrt{S_Y S_A}} \qquad (5)$$

where

$$S_{YA} = \frac{\sum_{i=1}^{n} (y_i - \bar{y})(a_i - \bar{a})}{n-1}, \quad S_Y = \frac{\sum_{i=1}^{n} (y_{i*} - \bar{y})}{n-1} \quad S_A = \frac{\sum_{i=1}^{n} (a_i - \bar{a})}{n-1}$$

B. Results

Dependence curves of the three typical loads (Pmin, Pavg, Pmax) were estimated from the average temperature Tavg on the basis of regression analyses performed over the dataset of power loads and air temperatures for the years 2014 and 2015. Fig. 3 shows estimations of dependence curves when sinuses and polynomial functions are used. Table I summarizes the regression analyses results presenting the functions coefficients,

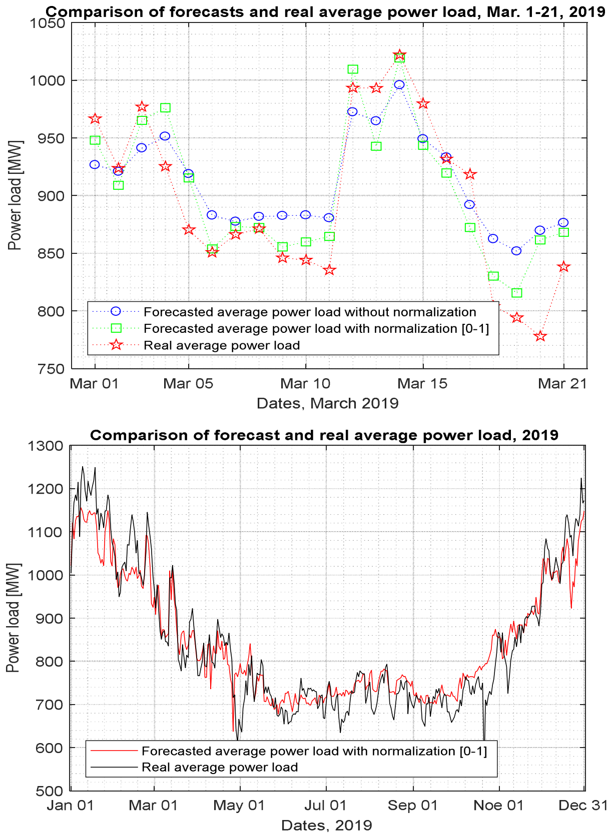

Figure 4. KNN load forecast vs real load (a) 01–21 March 2019; (b) 2019

determination coefficients (R^2) and correlation coefficients and confirms the strong negative correlation between the average power load and temperature.

Machine learning methods used for load forecast of Macedonian power system are: Bagged Trees as representative of DT methodology, Radial Kernel as representative of SVM and Exponential kernel as GPR algorithm representative. Table II and Table III present the performance results from the training dataset (years 2014–2018) and the testing dataset (2019), tested by 10-fold cross-validation. From Table II, a little better forecast accuracy is obtained when the models are trained with the Bagged trees and Exponential kernel GPR algorithms compared to Radial kernel SVM. Table 3 shows that forecast precision for testing dataset when Bagged trees and Exponential GPR are used is worse compared to the training dataset, while there is an improvement for the model trained with Radial kernel SVM. From the results, it can be concluded that in general the models trained with Radial kernel SVM give better results.

KNN method is also tested independently as a representative of machine learning methods. Table IV gives the RMSE errors when a model with 30 neighbors over 2014–2018 training dataset is evaluated with 10-fold and Leave-one-out cross-validations. The results show that the errors reduce with normalization of the variables.

This case study analyses two periods: 1) 01–21 March 2019; 2) year 2019. Table V summarizes the errors of comparison of the forecasted average power loads with different algorithm and the corresponding real average power load.

TABLE II. PERFORMANCE RESULTS FROM TRAINING DATASET WITH DIFFERENT MACHINE LEARNING METHODS

Attribute:	**Measures:**	**Bagged Trees (DT)**	**Radial SVM**	**Exponential GPR**
Temperature	R	0,93	0,91	0,93
	RMSE [MW]	59,29	67,48	59,34
	MSE [MW^2]	3515,54	4553,07	3521,28
	MAE [MW]	45,78	54,69	46,11

TABLE III. PERFORMANCE RESULTS FROM TESTING DATASET WITH DIFFERENT MACHINE LEARNING METHODS

Attribute:	**Measures**	**Bagged Trees (DT)**	**Radial SVM**	**Exponential GPR**
Temperature	R	0,93	0,95	0,94
	RMSE [MW]	67,41	56,23	64,49
	MSE [MW^2]	4543,66	3162,17	4158,66
	MAE [MW]	51,30	41,54	47,80

TABLE IV. KNN MODEL CROSS VALIDATION RESULTS FOR TRAINED DATA [MW]

Cross-validation	**normalized variables**	**non-normalized variables**
10-fold	62.2467	66.4218
Leave-one-out	65.8212	62.2133

TABLE V. COMPARISON OF PERFORMANCES OF DIFFERENT MODELS (MW)

Algo-rithm	**KNN regression**		**polynomial and sinuses regressions**		
	norma-lized variabl es	**non-norma-lized variables**	**polynomi al order 4**	**sinuses order 4**	**sinuses order 4 + wavelet transfor m**
MAE	38.4046	39.1885	41.3541	40.7253	41.1778
RMSE	50.6231	51.7435	56.4752	55.3602	54.2211
R	0.9614	0.9564	0.9488	0.9523	0.9584

The graphic in Fig. 4a illustrates a comparison of forecasts of average power load (KNN with 30 neighbours) against real average power load for the period 01–21 March 2019 (Fig. 4a) and for year 2019 (Fig. 4b). The graphics show that forecasts obtained with normalized variables are very close to the real average power load.

Results obtained with application of ANN network for power load forecast are very interesting for discussion from aspect of accuracy. Fig. 5 illustrates the results obtained from testing the trained ANN on training dataset (year 2019). The figure illustrates the daily real and forecasted load [MW]. In addition, for evaluation of the numerical method efficiency, measures shown in Table VI are calculated.

The obtained results substantially and explicitly confirm the accuracy of ANN for power load forecast on a short-run. The presented implementation not only shows a high accuracy of ANN for load forecast, but also it outperforms all the other presented methods.

IV. CONCLUSION

The paper provides very useful analysis and comparison of several practical algorithms for short-term load forecast: polynomial and sinuses regression and machine learning

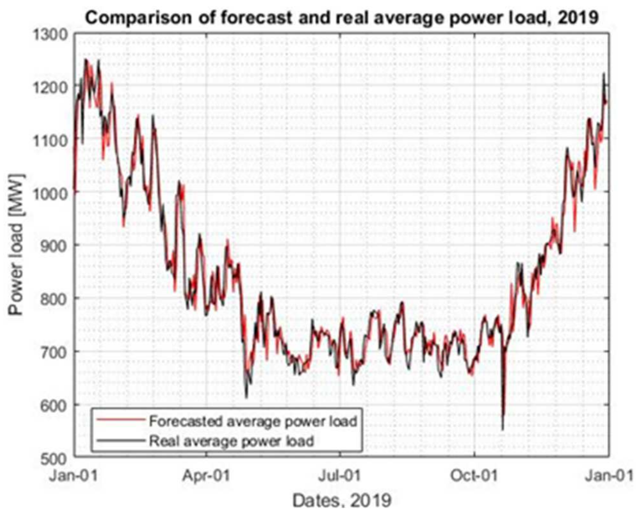

Figure 5. Load forecast for the year 2019 with ANN

TABLE VI. ANN MODEL RESULTS PERFORMANCE ILLUSTRATED ON MEASURES FOR THE TRAINING DATA

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

methods. The compared methodologies are for the first time applied on real data for power system of Republic of North Macedonia. Compared methodologies such as KNN, ANN, SVM, GPR work with all day types and simulation results are given for a wide time span. Another paper contribution is comparative analysis between mentioned methodologies. The results show that for short-term power load forecasts, the algorithms based on KNN and ANN outperforms polynomial and sinuses regressions. The presented results show that ANN demonstrates the best accuracy compared with all other presented methods. ANN based methodology has succefully introduced the usage of data for load and air temperatures in the seven past days for load forecast of the day ahead. It is illustrated in the paper that this approach gives very accurate results with ANN methodology.

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