# Power System Load Forecasting by using Sinuses Approximation and Wavelet Transform

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*Abstract* – **Power system load predictions are important factors for planning the future electrical energy consumption. One of the important factors that influence the power load is the air temperature. This paper analyses the correlation between the power system load and the air temperature. Power load forecasting is investigated by using a combination of the best fitting approximation with sum of sinuses and wavelet transform.**

*Keywords* – **Power system load, Forecast, Air temperature, Correlation, Regression, Wavelet Transform.**

## I. Introduction

Electricity is one of the most important and inseparable factors in social life. Each electricity company has a strategic goal to provide end users with reliable and stable power supply. Having in mind that it cannot be stored as it should be generated as soon as needed, electricity power system load forecasting is a key factor in the functioning of power systems. Moreover, renewable energy sources are increasingly being incorporated in power systems in an effort to reduce $CO_2$ emissions and reliance on fossil fuels. Furthermore, the use of low carbon technologies, such as electric vehicles and heat pumps, has increased in recent years. Therefore, accurate predictions are important for planning the future electrical energy consumption - they lead to significant savings in operating and maintenance costs and increased reliability of the electricity supply and delivery system.

Power load forecasting is the process of forecasting future electrical energy demand so that to cope with the growing needs. Power load forecasting would determine which power units should increase their production and which generators should be dispatched. According to the period of the load forecasting, it can be classified into three categories: short-term load forecasting (one hour to one week), mid-term load forecasting (one week to one year) and long-term load forecasting (longer than a year) [1].

Factors that play key role in forecasting of power load consumption are the air temperature, type of the day (weekday, weekend or holiday), geographical differences, people standard, demographic information, etc. This paper analyses the correlation between the power system load and the air temperature in Republic of Macedonia. In addition, forecasting of the power system load consumption is investigated. The power system load is estimated by applying a combination of best fitting function of sum of sinuses and discrete wavelet transform.

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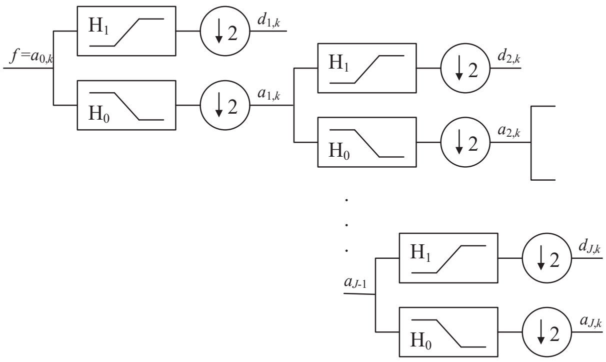


Fig. 1. Discrete wavelet transform tree.

The paper is organized as follows. After the introduction, the basic definitions of discrete wavelet transform are given in Section II. Section III gives data overview and presents regression analysis for determining the functions of variation between three typical loads and average air temperature. Section IV describes the forecasting of power system load from air temperature. The experimental results are presented in Section V. Section VI concludes the paper.

## II. Discrete Wavelet Transformation

Discrete wavelet transform (DWT) decomposes a signal into a set of orthogonal components describing the signal variation across the scale [2]. The orthogonal components are generated by dilations and translations of a prototype function $\psi$, called mother wavelet:

$$\psi_{jk}(t) = 2^{-j/2}\psi(t/2^{j} - k), \quad k, j \in Z . \tag{1}$$

The above equation means that the mother function is dilated by integer $j$ and translated by integer $k$. A signal $f$ for each discrete coordinate $t$ can be presented as a sum of an approximation plus $J$ details at the $J$th decomposed level:

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

where $\Phi_{Jk}(t)$ is scaling function. The residual term corresponds to a coarse approximation of $f(t)$ at resolution $J$. The coefficients $a_{Jk}$ and $d_{jk}$ are approximation wavelet coefficients at level $J$ and detail wavelet coefficients (or wavelet coefficients) at level $j$, respectively:

$$a_{jk} = 2^{-j/2}\int f(t)\phi(2^{-j}t - k)dt , \tag{3}$$

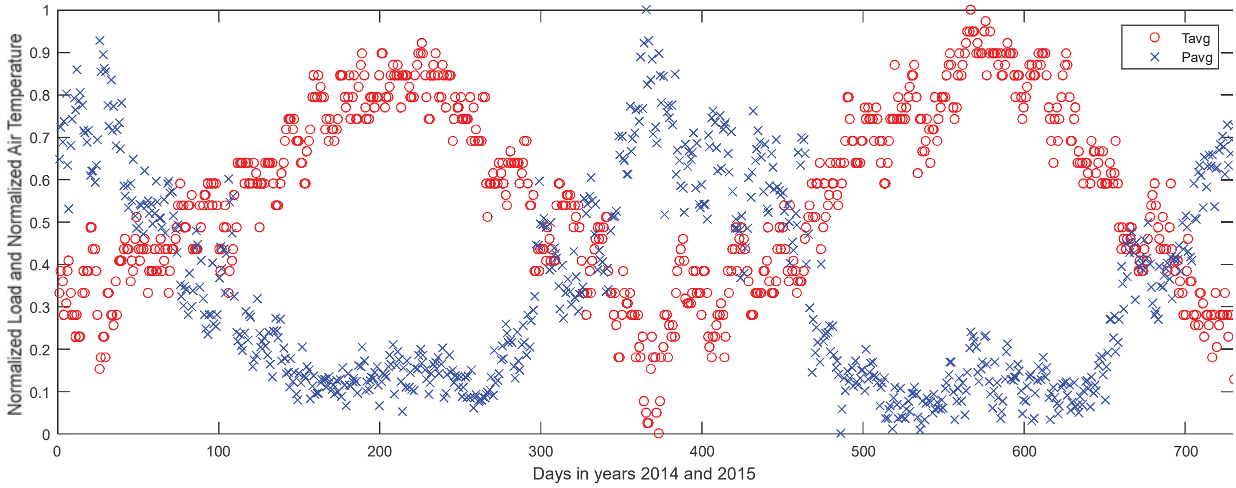


Fig. 2. Normalized daily loads and air temperatures for years 2014 and 2015.

$$d_{jk} = 2^{-j/2} \int f(t) \psi(2^{-j} t - k) dt \,. \tag{4}$$

The estimate of $d_{jk}$ and $a_{Jk}$ can be achieved via iterative algorithm for decomposition using two complementary QMF filters $h_0$ (low-pass) and $h_1$ (high-pass) [3], as it is illustrated in Fig. 1. The relation between mother and scaling functions with the QMF bank is given with an efficient recursion:

$$\psi(t) = 2\sum_{n} h_1(k)\phi(2t-k) \,, \tag{5}$$

$$\phi(t) = 2\sum_{n} h_0(k)\phi(2t-k) \,. \tag{6}$$

## III. Data Overview and Basic Statistical Analysis

Electric power load forecasting means to calculate the expected energy requirements of a system, which is important for making decisions including decisions on purchasing and generating electric power, load switching and infrastructure development. The power load forecasting relies on historical data to determine how much power customers may need. Forecasting model inputs can include day of the week, holiday calendars, weather conditions and forecasts, geographical differences, demographic information, etc. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company [1].

In this paper, the case study dataset consists of hourly power system load data for Skopje for the calendar years 2014 and 2015 [4] and the corresponding meteorological information about minimal, average and maximal air temperatures obtained from the internet [5]. An analysis of the power load data shows that it depends on the time of the year, day of the week and hour of the day.

Fig. 2 presents normalized daily average power load diagram and normalized daily air temperatures diagram for Skopje across the years of 2014 and 2015, both normalized in the interval [0 1]. It can be noticed that there is a strong negative correlation between the power load and the air temperature. There are peaks at the beginning of the graphic (January 2014), the middle of the graphic (December 2014-January 2015) and at the end of the graphic (December 2015). The highest peak for the power load for the year of 2014 corresponds to the values Pavg = 1289MW and Tavg = –7C and it was registered on 31 Dec 2014. The highest peak for the power load for the year of 2015 corresponds to the values Pavg = 1247MW and Tavg = –8C registered on 2 Feb 2015. Fig. 2 confirms what is characteristic for this region that during the winter period the electrical energy consumption is bigger. The lowest average temperature in the graphic is Tavg = –9C registered on 8 Jan 2015, when the registered average power load was Pavg = 1228MW.

A regression analysis is performed over the dataset illustrated in Fig. 2 in order to estimate dependence curves of the three typical loads (minimal power system load Pmin, average power system load Pavg, maximal power system load Pmax) from the independent variable – the average temperature Tavg for the two years 2014 and 2015. The used approximation function is the sum of sinuses function of order $n = 4$ given by:

$$f(x) = \sum_{i=1}^{n} a_i \sin(b_i x + c_i). \tag{7}$$

Fig. 3 shows the estimation of dependence curves of Pavg, Pmax and Pmin from Tavg, respectively, for the years 2014 and 2015. Table I summarizes the regression analyses presenting the equations coefficients, determination coefficients ($R^2$) and correlation coefficients. The determination coefficient shows the proportion of the variance in the dependent variable that is predictable from the independent variable (it ranges from 0 to 1, the coefficient 0 means the dependent variable cannot be predicted from the independent variable, while 1 means the dependent variable can be predicted without error from the independent variable) [6]. According to the Table I, the determination coefficients of the maximum, average and minimum daily load due to the

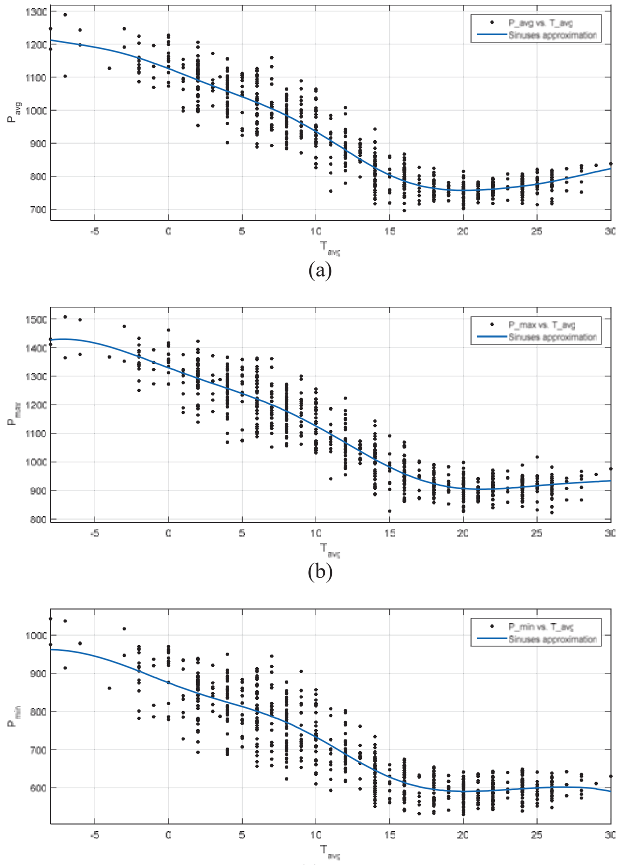


Fig. 3. Estimated approximation of power load from air temperatures by using the sum of sinuses function (7) of order 4: (a) averaged load, (b) maximal load, (c) minimal load.

TABLE I
SUMMARY OF THE APPROXIMATION FUNCTION (7) OF ORDER $n = 4$, PRESENTING THE FUNCTION COEFFICIENTS $a_i$, $b_i$, $c_i$, DETERMINATION COEFFICIENTS ($R^2$) AND CORRELATION COEFFICIENTS.

| | | |
|---|---|---|
| Averaged load: | | |
| Function coefficients: | | |
| $a_1 = 2235$ | $b_1 = 0.05558$ | $c_1 = 1.043$ |
| $a_2 = 1355$ | $b_2 = 0.08021$ | $c_2 = 3.778$ |
| $a_3 = 50.28$ | $b_3 = 0.2274$ | $c_3 = 0.01103$ |
| $a_4 = 7.186$ | $b_4 = 0.5079$ | $c_4 = -3.128$ |
| Goodness of fit: $R^2$: 0.8961, Correlation coefficient: –0.9466. | | |
| Maximal load: | | |
| Function coefficients: | | |
| $a_1 = 3193$ | $b_1 = 0.0472$ | $c_1 = 0.6216$ |
| $a_2 = 2278$ | $b_2 = 0.06366$ | $c_2 = 3.367$ |
| $a_3 = 19.29$ | $b_3 = 0.3514$ | $c_3 = -1.542$ |
| $a_4 = -1.558$ | $b_4 = 0.4358$ | $c_4 = 0.557$ |
| Goodness of fit: $R^2$: 0.8874, Correlation coefficient: –0.9420. | | |
| Minimal load: | | |
| Function coefficients: | | |
| $a_1 = 2719$ | $b_1 = 0.06857$ | $c_1 = 0.9005$ |
| $a_2 = 2023$ | $b_2 = 0.08394$ | $c_2 = 3.797$ |
| $a_3 = 30.43$ | $b_3 = 0.2781$ | $c_3 = -0.7307$ |
| $a_4 = 5.246$ | $b_4 = 0.4954$ | $c_4 = -2.71$ |
| Goodness of fit: $R^2$: 0.8223, Correlation coefficient: –0.9068. | | |

average daily temperature are 88.74%, 89.61% and 82.23%, respectively. The regression analysis shows high prediction degree of the daily typical loads from the air temperature.

The correlation coefficient is a statistical measure that calculates the strength of the relationship between two variables [6]. Coefficients of correlation can have values in range from −1 (negative relation) to 1 (positive relation). There is not a significant relation if the correlation coefficient is less than 0.3. The correlation is with practical importance when the correlation coefficient is between 0.5 and 0.7. Correlation coefficient between 0.7 and 0.9 shows close correlation, while correlation coefficient greater than 0.9 shows very close correlation. According to the results presented in Table I, the correlation coefficients have values in a range from –0.90 to –0.95 what implies very close negative relation between all the combinations of typical daily loads and air temperatures.

The determination and correlation coefficients presented in Table 1 are higher than corresponding coefficients obtained when polynomial functions are used [8].

## IV. POWER SYSTEM LOAD FORECASTING

The main idea is to forecast electrical power system load by analysing and processing the dataset of temperatures and corresponding power loads from Section III by applying a combination of the best fitting approximation in the least squares sense (Section IV) and the discrete wavelet transform (Section II). First, from the given dataset, the average air temperatures and the average power loads are used to estimate the best fitting function (7). This function is applied over a set of forecasted air temperatures in order to obtain the corresponding power loads. However, it should be kept in mind that the power system load of a specific day depends on not only the current air temperature, but also the weather conditions in the previous days affect the current power load. Therefore, the output (power load) from the best fitting function (7) should be related to the previous values of the air temperatures/power loads. For this reason, the wavelet transform at level ($j$) is applied over the output values from the function and as a result, approximation coefficients at level ($j$) (low-pass version) and detail coefficients at levels (1), (2), …, ($j$) (high-pass versions) are obtained. Finally, the inverse wavelet transform is applied over the approximation coefficients at level ($j$). The result is predicted power load. The procedure is illustrated with the block diagram in Fig. 4.

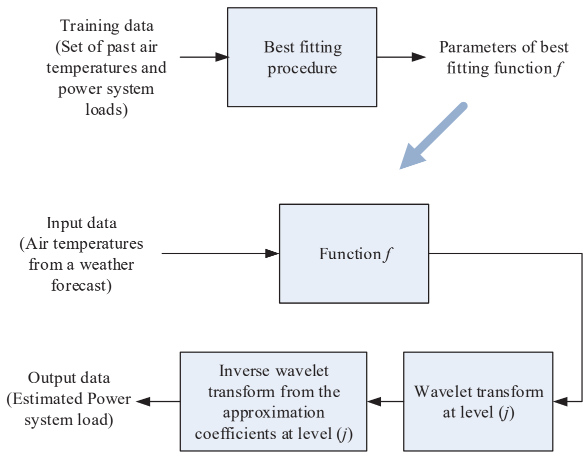


Figure 4. Block diagram of estimation of power system load.

TABLE II

WEATHER FORECAST FOR THE PERIOD 01-21 MAR. 2019.

| | | | | | | |
|---|---|---|---|---|---|---|
| 1 Mar | 2 Mar | 3 Mar | 4 Mar | 5 Mar | 6 Mar | 7 Mar |
| $3^0$C | $4^0$C | $11^0$C | $10^0$C | $16^0$C | $18^0$C | $14^0$C |
| 8 Mar | 9 Mar | 10 Mar | 11 Mar | 12 Mar | 13 Mar | 14 Mar |
| $12^0$C | $17^0$C | $18^0$C | $20^0$C | $22^0$C | $19^0$C | $22^0$C |
| 15 Mar | 16 Mar | 17 Mar | 18 Mar | 19 Mar | 20 Mar | 21 Mar |
| $22^0$C | $20^0$C | $6^0$C | $12^0$C | $8^0$C | $14^0$C | $19^0$C |

TABLE III

ESTIMATED POWER LOAD IN [MW] FOR THE PERIOD 01-21 MAR. 2019.

| | | | | | | |
|---|---|---|---|---|---|---|
| 1 Mar | 2 Mar | 3 Mar | 4 Mar | 5 Mar | 6 Mar | 7 Mar |
| 1061.7 | 1060.9 | 955.6 | 878.3 | 829.0 | 772.2 | 803.2 |
| 8 Mar | 9 Mar | 10 Mar | 11 Mar | 12 Mar | 13 Mar | 14 Mar |
| 810.7 | 794.7 | 784.9 | 770.9 | 758.0 | 746.3 | 734.2 |
| 15 Mar | 16 Mar | 17 Mar | 18 Mar | 19 Mar | 20 Mar | 21 Mar |
| 816.7 | 873.9 | 905.7 | 944.4 | 854.3 | 798.6 | 777.5 |

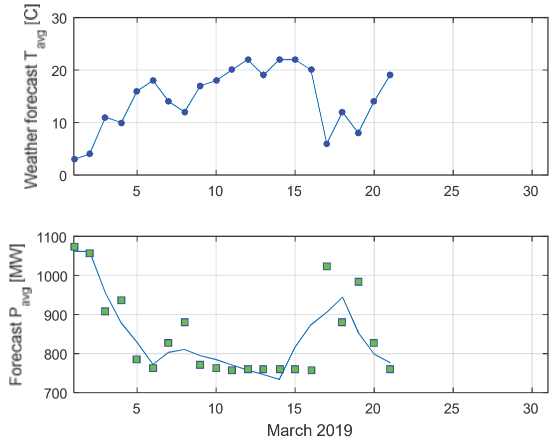


Fig. 5. (a) Weather forecast (air temperatures); (b) Forecasted average power load for period Mar 01-21 2019.

## V. EXPERIMENTAL RESULTS

This Section presents the results obtained by experiments performed over the average power load hourly values for Skopje for years 2014 and 2015 that are used as training data for the model parameters optimization. The air temperatures for the period March 01–21 2019 (Table II, Fig. 5) from the weather forecast [7] serve as test data set for model performance assessment. A number of experiments for approximating the power load are made with best fitting polynomial functions of order 3, 4, 5 [8] and functions defined as sum of sinuses (7) of order 3, 4, 5 over the data of air temperatures and power loads for the years of 2014 and 2015. The results of these experiments show that the approximations with the sums of sinuses outperform the polynomial approximations in sense of higher determination coefficients $R^2$ and higher correlation coefficients. In addition, the experiments show that the order $n = 4$ for the function (7) gives satisfactory results (Fig. 3, Table I). The result of applying the proposed algorithm over the air temperatures from Table II is illustrated in Fig. 5. The squares denote the power loads as output from the function (7), while the solid line depicts the forecasted loads after applying the wavelet transform in two levels with db2 function used (Table III).

## VI. CONCLUSION

Power load forecasting is a key factor in the functioning of power systems. It would determine which power units should increase their production and which generators should be dispatched. This paper analyses the relation between the power load and the air temperature in Republic of Macedonia. The correlation coefficients imply very strong negative relation between all combinations of typical daily loads and air temperatures. Regression analysis shows high prediction degree of daily typical loads from air temperature.

Power load forecasting is proposed as a combination of best fitting approximation and wavelet transform. A better load prediction can be achieved if more years are incorporated in estimating the approximation function.

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