

# Day-Ahead Short-Term Forecasting Electricity Load via Approximation

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**Abstract.** The method of short-term forecasting of a power consumption which can be applied to short-term forecasting of power consumption is offered. The offered model is based on sinusoidal function for the description of day and night cycles of power consumption. Function coefficients – the period and amplitude are set up is adaptive, considering dynamics of power consumption with use of an artificial neural network. The presented results are tested on real retrospective data of power supply company. The offered method can be especially useful if there are no opportunities of collection of interval indications of metering devices of consumers, and the power supply company operates with electrical supply points. The offered method can be used by any power supply company upon purchase of the electric power in the wholesale market. For this purpose, it is necessary to receive coefficients of approximation of sinusoidal function and to have retrospective data on power consumption on an interval not less than one year.

## 1. Introduction

Relevance of work is caused by development of the wholesale market of the electric power and capacity and need of the companies, working at it to creation of short-term models for implementation of process of forecasting of power consumption for the days ahead. From quality of such models, eventually the financial result of the company depends. Now there is a big arsenal of methods of creation of short-term forecasts, but they aren't always effective for such forecasts as they strongly depend on dynamics of power consumption. Besides, other problem characteristic of power supply companies is a lack of opportunities of collection of hourly indications of metering devices of a large number of consumers. At the same time, power supply companies are, as a rule, limited to data of the actual hourly accounting of a power consumption of clients and operate in case of creation of the forecast with data of the system operator on delivery points. On the one hand, it simplifies process of aggregation of data, on the other hand, complicates process of creation of predictive model. The offered technique allows, operating with actual data of the system operator on delivery points, to construct prognostic model which considers dynamics of power consumption. At the same time, process of power consumption is described by an approximating sine function which coefficients – the period and amplitude are with use of the device of an artificial neural network.



## 2. Research

In [1] authors the known methods of short-term forecasting of power consumption are systematized. The greatest distribution was gained by methods of the "structural models" group. First of all, it is connected with a possibility of processing of big data arrays by means of modern computing systems, and also development of intellectual algorithms and methods of formation of the training selections for them. In works [2–3] the methods based on use of the device of an artificial neural network were considered, the neural network in this case is presented to the expert in the form of a black box with inputs and outputs. In [4–6] works based on a method of the principal components, but as these methods belong to multiple-factor models and require a large number of signs for creation of the forecast, feasibility of their use isn't justified in case of absence of data of hourly accounting a large number of consumers. In the real article by authors the method of approximation of the power consumption by function of a sine, function coefficients – the period and amplitude which are selected taking into account character of power consumption, using the device of an artificial neural network is offered. Besides, the residuals of volume of a power consumption received by a difference of the actual and expected values are also predicted for the day ahead with use of the device of an artificial neural network.

If to consider the daily schedule of power consumption, according to the available data of power supply company, presented in the Figure 1a; it is possible to notice that in a form it reminds a sinusoid. Besides, the cost of the electric power can also be described sinusoidal function as in hours of the maximum power consumption and cost on the electric power will be higher. Considering power consumption in monthly scale, it is possible to notice that in this case the schedule also reminds sinusoidal function, but already with the week period. In this connection, authors have made a hypothesis of a possibility of implementation of the short-term forecast by an approximation method sinusoidal function. For extension of the approximating function for the days ahead it is required to receive her coefficients by means of which in the subsequent, it could be prolonged for an interval till 24 o'clock.

As follows from the schedule of power consumption that day and night cycles have obvious distinctions on character of power consumption, it is offered to use two sinusoidal functions which would describe separately day and night cycles of power consumption.

## 3. Experiment

The general formula of the sinusoidal function shows in Equation 1:

$$y = A \sin(kx + b) + D, \quad (1)$$

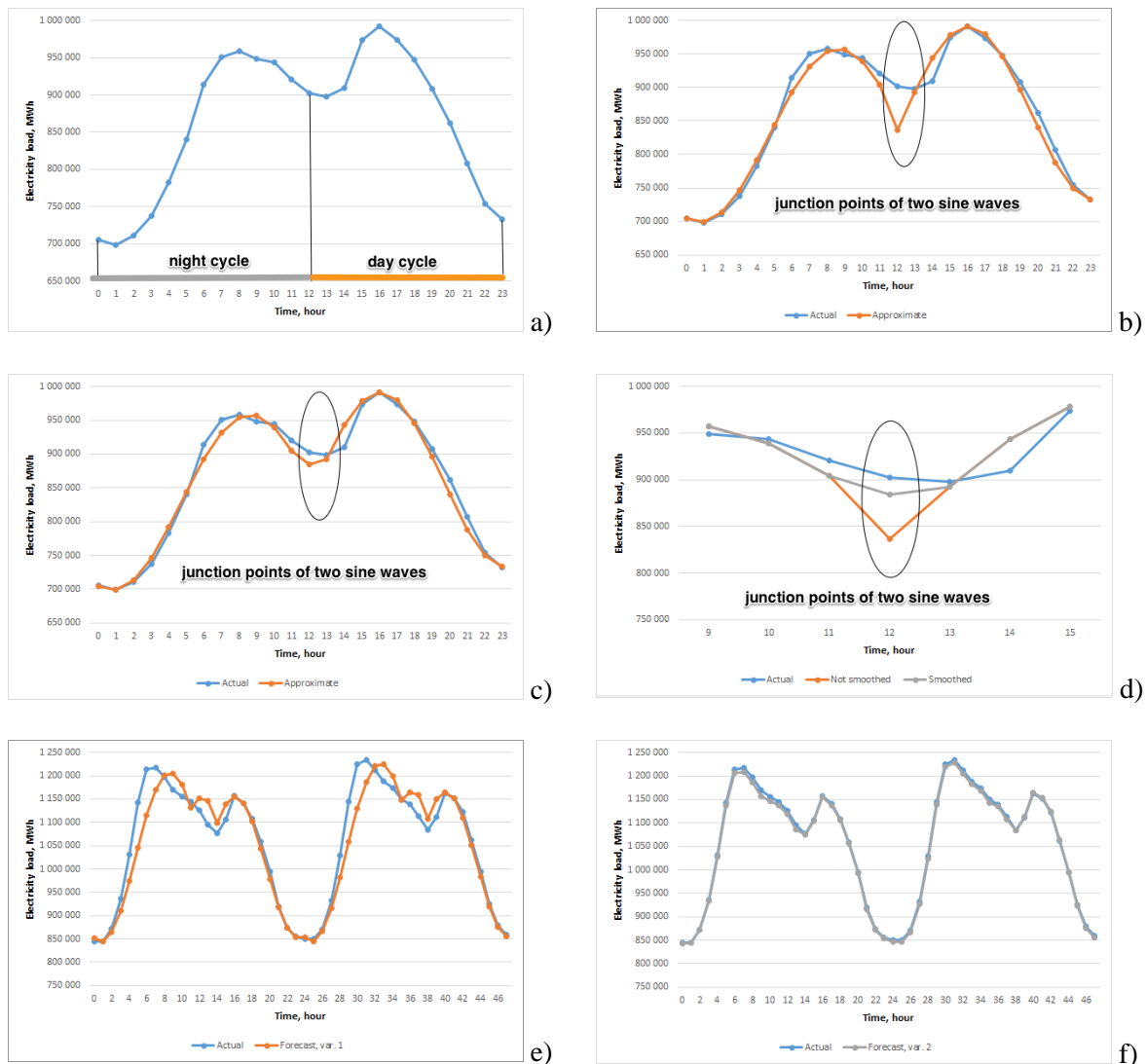
where  $y$  is the calculated electricity load, MW;  $x$  is an hour of the day;  $k$  is frequency;  $b$  is phase;

$A = \frac{\max(PC) - \min(PC)}{2}$  is amplitude;  $D = \frac{\max(PC) + \min(PC)}{2}$  offset concerning a power

consumption axis;  $\max(PC)$  and  $\min(PC)$  is the maximum and minimum power consumption on the selected time interval respectively. For determination of coefficients of  $k$  and  $b$  the least-squares method [7] was used. The received coefficients are provided in Table 1.

**Table 1.** Calculated values of parameters  $k$  and  $b$ .

Coefficient	Night cycle	Day cycle
k	0.4	0.44
b	4.4	0.8



**Figure 1.** Available data of power supply company, where a is the graph of power consumption on an interval a daily interval (24 hours); b is comparing of graph of the actual and estimated power consumption on a daily interval; c is comparing of graphs of the actual and smoothed by a polynomial of the third level estimated power consumption on a daily interval; d is comparison of actual and smoothed by a polynomial of the third degree of connection points of sinusoidal waves day and night cycles; e is actual and forecast data, the method of approximation for 24 hours; f is actual and forecast data by approximation and forecast of residues obtained by 24 hours in advance.

Figure 1b shows actual and approximated sinusoidal function separately for the graphs of day and night cycles of power consumption. From a Figure 1b, it is visible that the greatest discrepancy of the actual and estimated values is watched in a point of connection of sinusoids which describe day and night cycles of power consumption. At that time, the average error of approximation on an annual interval made 4.52% (real data on a power consumption for 2015 of power supply company were used), in a point of connection of the sinusoids describing day and night cycles of a power consumption, average deviation on an annual interval made 14.52% that considerably exceeds an average error on other hour intervals. In order of reduction of value of an error of power consumption in these point different methods of approximation were tested. The received results, when using these methods, are provided in Table 2.

**Table 2.** Comparing of methods of approximation for finding of a point of connection of sinusoids for day and night cycles.

No.	Approximation method	The reliability on 1 year data interval	The reliability on 24 hours' data interval
1	Linear	0.01	0.13
2	Logarithmic	0.01	0.20
3	Exponential	0.01	0.24
4	Polynomial of degree 2	0.15	0.84
5	Polynomial of degree 3	0.15	0.92

The best result of approximation of points of connection of sinusoids by a polynomial of the third level was achieved by using two next values to the calculated points and starting and finite value of selection. For finding of values of unknown members of model it is possible to use any known method [8]. The received result of approximation is presented in a Figure 1c, peak discrepancies of the actual and estimated values of power consumption in points of connection of the sinusoids describing night and day cycles were removed. In a Figure 1d the graph of the actual power consumption and received by an approximation method before smoothing by a polynomial of the third level, and after smoothing is presented.

For implementation of the short-term forecast of a power consumption the offered method of approximation requires to find coefficients of  $A$  and  $D$  on a step of  $X+I$  where  $X$  is the current days, used a neural network [9]. The neural network consists of three full-meshed layers of neurons where all neurons of one layer are connected to neurons of the following layer. Function of activation of neurons is sigmoid. For training of a neural network Levenberga-Markvardt's algorithm was used [10]. For training of a neural network the learning selection consisting from six input and one output parameter was created. In Table 3 the selection fragment for prediction for 02/17/2016 of night and day cycles of power consumption is shown. Mathematically dependence of coefficient of  $A$  can be shown function from variables (Equation 2):

$$A_{res} = \{A, C, V_{avg}, T_{avg}, h\}, \quad (2)$$

where  $C$  is power consumption cycle (0 – night, 1 – day);  $T_{avg}$  is average daily ambient air temperature (this parameter is the major, consuming of electrical energy directly depends on it), °C;  $h$  is the sign specifying whether day is holiday or working (in case of  $h=1$  – the day off,  $h=0$  – the working day);  $t$  is an hour interval of time;  $V_{avg}$  is the consuming approximated by a sinusoid,  $A$  is the actual value of coefficient of  $A$ ,  $A_{res}$  is expected value of coefficient of  $A$ .

**Table 3.** Fragment of training sample for  $A$  forecasting coefficient on 02/17/2016.

Date	Input neural network					Output neural network	
	$A$	$C$	$V_{avg}$	$T_{avg}$	$h$	$A_{res}$ night	day
02/10/16	144062	0	921482.5	-10.9	0	135411.6	172066.8
	160350.5	1	935633.5				
02/11/16	141897.5	0	909551.3	-8.1	0	135411.6	172066.8
	153709.5	1	917336.3				
02/12/16	91956	0	820419.75	-5.3	0	135411.6	172066.8
	143566	1	868883.4				

The coefficient of  $D$  was found similarly, at the same time on an input of a neuronet the coefficient of  $D$  and as the expected  $D_{res}$  value moved. The result of approximation of a function graph by method of finding of coefficient  $t$  with use of a neural network is shown in a Figure 1e. From the

diagram, it is visible that expected values are offset rather actual diagram in this connection, the decision to realize prediction of residuals of volume of power consumption, values, received method of a difference actual and expected with use of a sine function, was made. Forecast was also carried out with use of the device of an artificial neural network. Learning selection for the forecast of residuals for a day sinusoid is presented in Table 4.

**Table 4.** Fragment of training sample for forecasting residues on 02/17/2016.

Date	Input neural network					Output neural network	
	$d$	$t$	$V$	$V_{\sin}$	$T_{avg}$	$h$	$d_{res}$
02/10/16	-2465.3	0	748703	751168.3	-10.9	0	-5256.6
	-552.5	1	744196	744748.5			-637
	-474.8	2	760511	760985.8			2800
	28913.5	3	826230	797316.5			28723
	75398.2	4	923403	848004.8			68214.1
	93778.7	5	998827	905048.3			102262.8

In Table 4 the fragment of learning data, for forecast of the residuals of volume of a power consumption received by method of a difference actual and expected (an approximation method) of power consumption volumes is shown, where  $d_{res}$  is expected value of residual, [MW];  $d$  is actual value of residual, [MW];  $t$  is an hour interval of time;  $V_{\sin}$  is value of the power consumption received by method of approximation of a sine function, [MW];  $V$  is the actual value of a power consumption, [MW].

The result is presented in Figure 1f. As it follows from the Figure 1f, the method of function approximation and residues forecasting with the use of artificial neural network brought the forecast values and the actual values together, so it possible to use this approach in compiling forecasts for Wholesale Electricity and Capacity Market (WECM).

#### 4. Result

The process of power consumption short-term forecasting by approximation in the form of a UML schema is shown in Figure 2. The power consumption process is known to be of different character on different days [11]. The realized process takes into account the specifics of forming a variety of training samples for retrospective data: filter 1 generates a data set for training sample of week days, filter 2 is for weekends and filter 3 is for holidays.

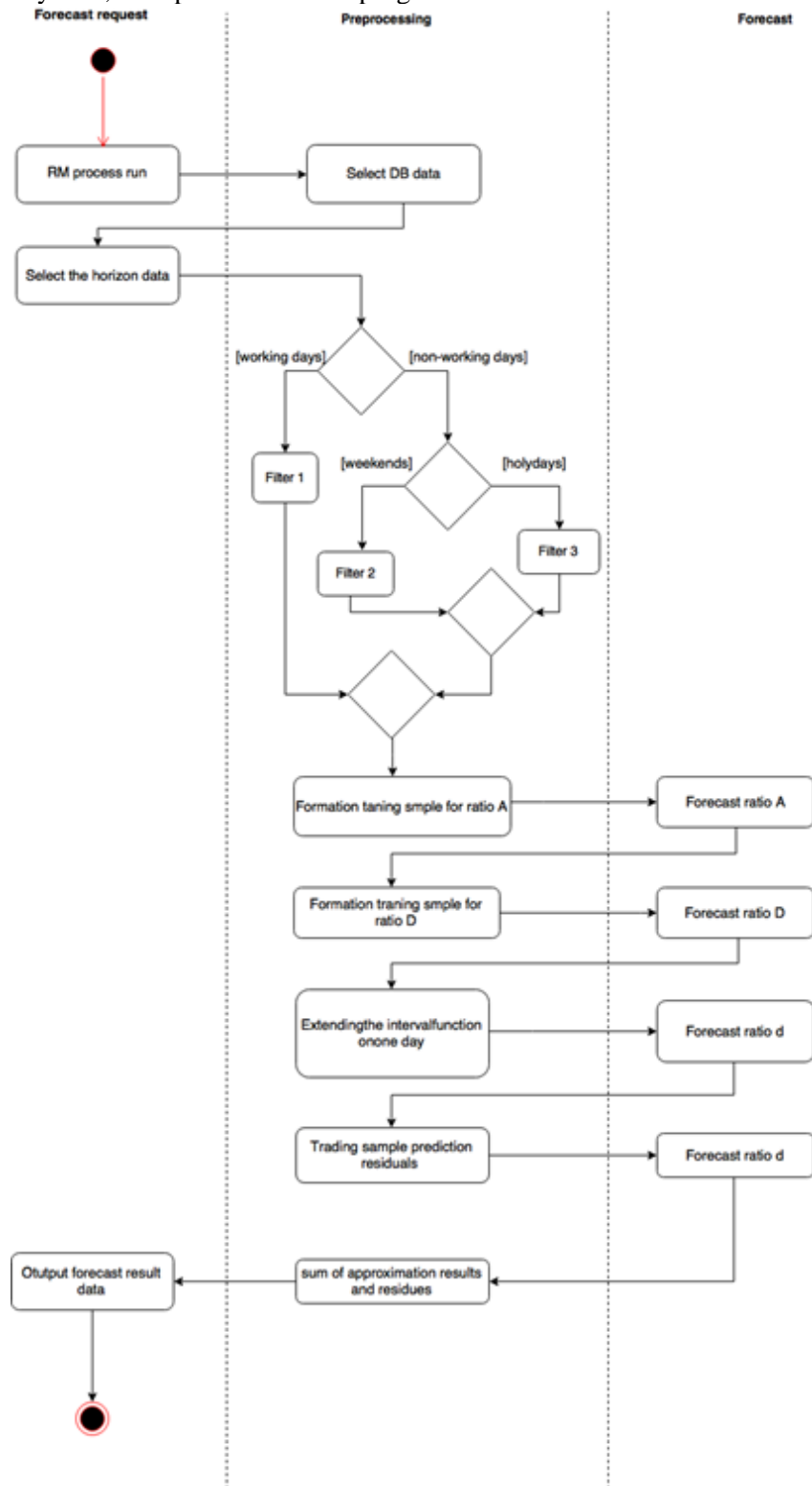
The algorithm for power consumption short-term forecasting was realized using Rapidminer analytical system. It is distributed under the LGPL (Lesser General Public License) and has a flexible customizable structure with many realized operators. If it is necessary to implement the algorithm not being available in the standard configuration of the analytical information system, it is possible to extend it through the implementation of the interface developers specific system. This is possible using JAVA programming language and integrated development environment Eclipse. The resulting extension is compiled into a library file and it connects Rapidminer platform within startup process.

The fragment process of power consumption approximation using Rapidminer analysis system is shown in Figure 3.

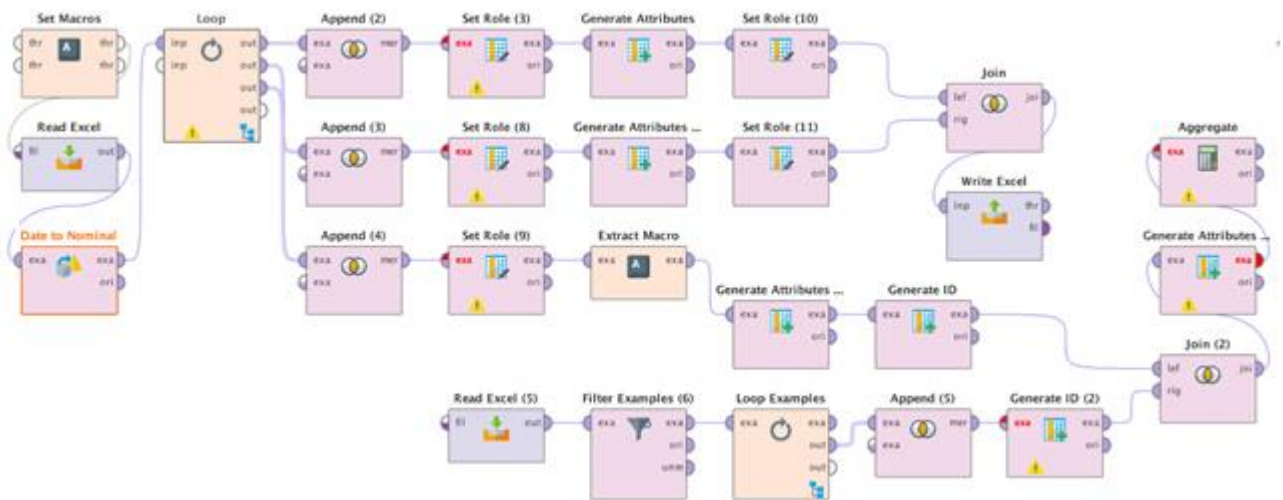
#### 5. Conclusion

The offered method approximation by a sine function, coefficients – amplitude and the period which are set up with use of an artificial neural network and the residuals of volume of a power consumption received by a difference of the actual and expected values, also predicted with use of an artificial neural network allowed, based on retrospective data on a power consumption separately to the taken power supply company, to provide the accuracy of 1.5% on an annual interval of data. This method can be used by the subject of the wholesale market of the electric power, not only power supply

company, but also the industrial enterprise. For this purpose, it is necessary to enumerate coefficients of  $k$ ,  $b$ ,  $A$ ,  $D$  sine function of approximation by the offered method. The algorithm can be realized with use of analytical system, or is presented in the program form.



**Figure 2.** UML-diagram of electricity load short-term forecasting by approximation method.



**Figure 3.** Fragment algorithm of approximation of electricity load implemented in analytical system Rapidminer.

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