Czech Technical University in Prague

Faculty of Electrical Engineering

Department of Economics, Management and Humanities

SHORT-TERM FORECASTING OF ELECTRICITY CONSUMPTION

Master's Thesis

Study Program: Electrical Engineering, Power Engineering and Management

Branch of study: Management of Power Engineering and Electrotechnics

Supervisor: Mgr. Sherzod Tashpulatov, M.A., Ph.D.

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MASTER'S THESIS ASSIGNMENT

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3. Application of forecasting methods for the Sibelectromotor enterprise
4. Evaluation of forecast performance of ARIMA, ANNs, CART and fuzzy logic methods
5. Economic cost of forecasting error

Bibliography / sources:

1. BROCKWELL, P., DAVIS R. Introduction to Time Series and Forecasting, New York, Springer-Verlag New York Publishing, 2005.
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3. MA, X. Using Classification and Regression Trees. 2018. North Carolina, Information Age Publishing, 2018.
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III. Assignment receipt

The student acknowledges that the master's thesis is an individual work. The student must produce her thesis without the assistance of others, with the exception of provided consultations. Within the master's thesis, the author must state the names of consultants and include a list of references.

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Abstract

There are many numbers of large electricity consumers who focuses on improving the accuracy of electricity consumption forecasts because of intensive electricity market development. Wholesale market for electricity and power require consumers to make electricity consumption forecasts at different time intervals. Increasing the accuracy of electricity consumption forecasts can significantly reduce costs. Therefore, this topic is receiving more attention. This dissertation aims to improve the economic efficiency of the enterprise by implementing forecasting system for electricity consumption at the software and hardware levels.

The result of this dissertation is day-ahead and a week-ahead forecast of electricity consumption for the Sibelectromotor Enterprise located in Tomsk, Russia. A financial analysis of the implementation of electricity consumption forecasting systems was also prepared. An automatic control system for electric drive using a fuzzy logic controller was developed during the work. The implementation of the system allows high efficiency of the electric drive within a large operational parameter range.

Dissertation is structured as follows: first I describe the Wholesale Market for Electricity and Power in Russia. Then the analysis of the enterprise load diagram is performed. The methodology for electricity consumption forecast models is presented next. In the following chapter I forecast day-ahead, week-ahead electricity consumption using Autoregressive Integrated Moving Average, Artificial Neural Networks and Classification and Regression Trees methods. Then economic evaluation of the investment decision is performed. The next chapter describes the automatic control system for an electric drive using fuzzy logic controller.

In conclusion, I can say that short-term forecasting of electricity consumption based on ANN and CART models are the best method because the key performance indicators and the cost of purchased electricity are lower.

Keywords

Forecasting of Electricity Consumption, Artificial Neural Networks, Autoregressive Integrated Moving Average, Classification and Regression Trees, Fuzzy Logic Controller

Contents

Abbreviations

ACF	Autocorrelation Function
ADF	Augmented Dickey–Fuller test
ANN	Artificial Neural Networks
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
BM	Balance Market
CART	Classification and Regression Trees
CDF	Cumulative Distribution Function
IRR	Internal Rate of Return
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MLP	Multi-Layer Perceptron
MSP	Mean Squared Error
NPV	Net Present Value
PACF	Partial Autocorrelation Function
RAO EES	Rossijskoe Akcionernoe Obshchestvo “Edinaya Energeticheskaya Sistema” (Russian Joint Stock Company “Unified Energy System”)
RBF	Radial Basis Function
RMSE	Root Mean Square Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SS	Sum of Squares
WMEP	Wholesale Market for Electricity and Power

Notation

A	Condition
a	Output neuron signals
B	Conclusion
CF_t	Cash flow
C_f	Forecast hourly power consumption
C_r	Real hourly power consumption
d	Level of differencing
C_{max}	Cost of power consumed for energy transmission services per month
C_p	Cost of electricity purchased by the consumer at the regulated electricity price per month
C_t	Cost of electricity per hour
$C_t^{+,-}$	Non-regulated electricity price on WMEP differentiated in hours of the account period
$C_{t,others}$	Payment for other services that are integral part of the electricity and capacity supply process for the billing period
$C_{t,retail}^{+,-}$	Retail markup differentiated in hours of the account period
D	Depreciation
df	Degrees of freedom
E	Quadratic loss
e	Error signal
$\dot{e}$	Derivative of error change
f	Input function
INV	Investment
$i(\tau)$	Parent node's impurity
$i(\tau_l)$	Impurity measure for left branch made
$i(\tau_r)$	Impurity measure for right branch made
k	Number of bins
L	Number of network layers
l	Layer number
m	Sample size of cross-validation
NPV	Net present value
N	Number of hours in the month
n	Number of observations in initial dataset
n_i	i-th training pattern
o	Output function
P_{BM}	Electricity price in balance market

P_{max}	Power paid by the consumer as the power consumed for energy transmission services
P_p	Peak load power
P_{WMEP}	Electricity price in wholesale market for electricity and power
p	Order of autoregressive process
p-value	Probability of obtaining results
r_i	Discount rate
q	Order of moving average process
T	Number of periods in out-of-sample forecasting
t	Time period
U_{contr}	Control voltage
U_{set}	Setting voltage
u	Input signal
w	Weight of synapsis
X_t	True value in time period
$\hat{X}_t$	Forecasting value in time period
x	Input vectors
y	Output vectors
W_t	Energy consumption per hour
W_t^+	The increase of the actual electric energy capacity on the planned capacity
W_t^-	Increase of the planned electric energy capacity on the actual capacity
Z	Random variable
Z_t	White noise
z	Possible value
α	Significance level
η	Learning rate
φ_j	Activation function
χ^2	Chi-square
Δ	Degree of impurity reduction
Δ^d	Difference operator

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1. Introduction

The electricity consumption is increasing every year. It is important for energy producers to match electricity generated and consumed because electricity cannot be stored. Consequently, accurate forecast of electricity consumption is essential for a reliable energy supply. The electricity market establishes requirements on consumers and forces enterprises to plan energy consumption in order to reduce energy costs [1]. The forecasting energy consumption is broad-based discussed in the literature.

Accurate forecasting of electricity consumption by large consumers (over 670 kW) is required due to the establishment of the Wholesale Market for Electricity and Power in Russia. Market participants must provide requests for maximum hourly capacity to the Trading System Administrator and the System Operator of the Unified Energy System 24 hours before the electricity supply for excessing the Wholesale Electricity Market. The total cost of electricity includes actual capacity consumed and the deviation fee when the company enters the balancing electricity market. An additional fee is imposed for the purchase (sale) of missing (excess) electrical energy. Therefore, accurate forecast of electricity consumption must be prepared to prevent a company's entering a balancing energy market and to reduce additional energy costs. Reducing the forecasting error allows a company to significantly reduce operating costs without purchasing additional equipment. [2, 3].

The liberalized trading sector, on the one hand, allows the enterprise to participate in competitive tenders and purchase electricity at prices lower than approved by the regional energy committee. On the other hand, there is a risk of compensation for deviations due to the impossibility of accurately forecasting energy consumption [1].

The amount of energy consumed by a certain enterprise depends on the specifics of its operation, such as the enterprise load, temperature regime, illumination level, etc. Therefore, the forecasting of electricity consumption process which can help to minimize costs is determined on a case-by-case basis. Forecasting allows both a financial analysis and the modification of equipment operating modes.

The implementation of forecasting of electricity consumption system is reviewed at the Russian company Sibelectromotor. Day-ahead and week-ahead forecasts of electricity consumption were made in Statistica, based on the actual electricity consumption data provided by Eugene Shutov [4].

The first step was to forecast day-ahead electricity consumption using Autoregressive Integrated Moving Average and Artificial Neural Networks models. The actual consumption of the enterprise was implemented for the hourly forecast of electricity consumption. The training dataset set consists of data for 20 Mondays (480 observations; from May 14, 2016, to November 1, 2016). The test dataset consists of data for 1 day (24 observations; November 8, 2016). Next, I forecast electricity consumption for the week-ahead in a similar way, but there was more input dataset. Next, I compared alternatives economically and evaluated the feasibility of implementing electricity forecasting system.

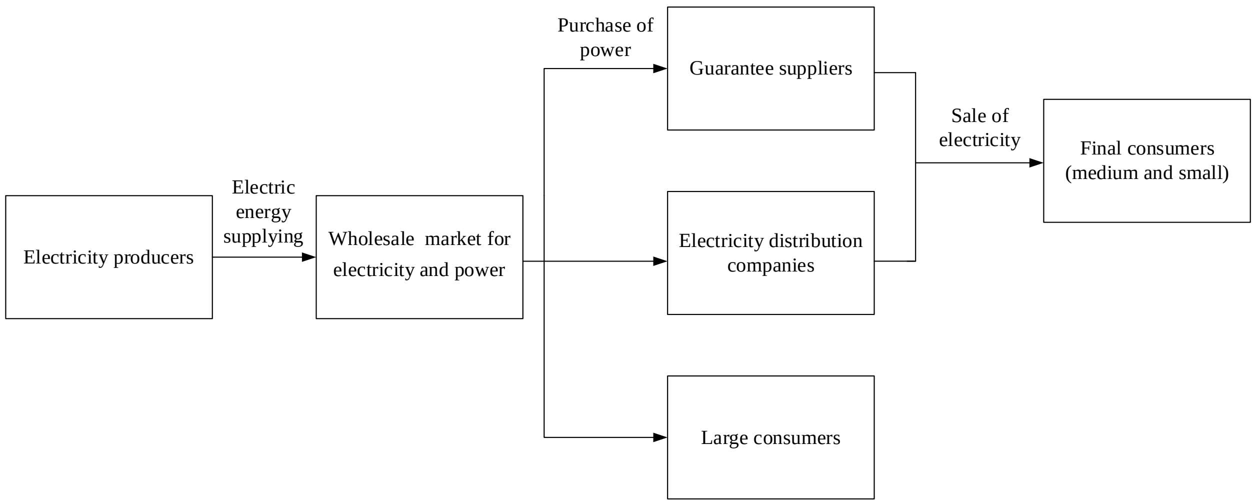
The following section I describe the medium-term forecast of electricity consumption. This model does not only include information on electricity consumed in the previous interval, but also the total production. Next, I developed automatic control system of electric drive using fuzzy logic controller to achieve high-energy efficiency of electric drive in a large operating parameter range.

2. Analysis of Electricity Market in Russia

Forecasting electricity consumption is an important part of research in the power industry for most developed countries. Wholesale Market for Electricity and Power (WMEP) require the consumer to forecast electricity consumption at various time intervals. Accurate forecasting can significantly reduce energy costs because electricity cannot be stored in stock. Therefore, when buying excess electrical power, costs can increase either by selling it on the balancing energy market or by maintaining reserve capacity. If the purchasing power is insufficient, the costs increase is due to the purchase of additional capacity [1].

2.1. Description of Wholesale Market for Electricity and Power in Russia

Figure 1 presents the current model of the electricity market. There are two products traded on the Wholesale Market for Electricity and Power - electricity and power.



Note: Author's illustration based on description in [1].

Figure 1. Structure of Wholesale Market for Electricity and Power manage by RAO "EES of Russia"

Currently, large enterprises (factories) can purchase electricity from guaranteeing suppliers (or power supply companies) or can directly participate in the tender on an equal footing with guaranteeing suppliers and power supply companies. A company is classified as large if the total connected capacity of its power consumption equipment is more than 670 kW. Every company is trying to minimize its production costs. One way is purchasing electricity from the Wholesale Market for Electricity and Power. Optimization of electricity purchase costs is achieved by organizational measures, e.g., implementation of electricity forecasting system [1].

A large enterprise can enter the Wholesale Electricity and Capacity Market if the following requirements are fulfilled:

- The enterprise is contracted with a grid organization for the transmission of electricity;
- The enterprise is contracted to participate in the trading system;

- The company is equipped with automated system of commercial accounting of electricity consumption [5].

If forecast electricity consumption deviates from actual electricity consumption, the cost of electricity can increase because the company enters the balance market (BM). If excess capacity is purchased, costs can increase either by selling it on the balancing market or by maintaining excess reserve capacity. If there is insufficient capacity, costs increase by using emergency power plants or by purchasing additional capacity. Combinations of prices and electricity consumption are presented in Table 1 [6].

Table 1. Combinations of prices and hourly consumption of electricity [6]

Price	**Power consumption**	**Market operation**	**Total price**	**Note**
$P_{BM} > P_{WMEP}$	$C_f > C_r$	Sale min (P_{BM}; P_{WMEP})	P_{WMEP}	Excess electricity is sold at a lower price (as compared to the purchase price), therefore the company suffers losses
$P_{BM} > P_{WMEP}$	$C_f < C_r$	Purchase max (P_{BM}; P_{WMEP})	P_{BM}	Shortfall of electricity is purchased at the same price (as compared to the purchase price), therefore, the company does not suffer losses.
$P_{BM} < P_{WMEP}$	$C_f > C_r$	Sale min (P_{BM}; P_{WMEP})	P_{BM}	Excess electricity is sold at the same price (as compared to the purchase price), therefore the company does not suffer losses
$P_{BM} < P_{WMEP}$	$C_f < C_r$	Purchase max (P_{BM}; P_{WMEP})	P_{WMEP}	Shortfall of electricity is purchased at a higher price (compared to the purchase price); therefore, the company suffers losses

where P_{BM} is electricity price in the BM;
P_{WMEP} is electricity price in the WMEP;
C_f is forecast hourly power consumption;
C_r is real hourly power consumption;

There are six electricity price categories. The first and second electricity price categories are integral, i.e., the total amount of electricity is determined by multiplying the price by the total amount of electricity consumed in the period. The third to sixth electricity price categories are recommended for companies because they are interval (hourly accounting) and they are more profitable for companies. If the total capacity of enterprises is higher than 670 kW, it is recommended to use the fourth or the sixth electricity price categories [7]:

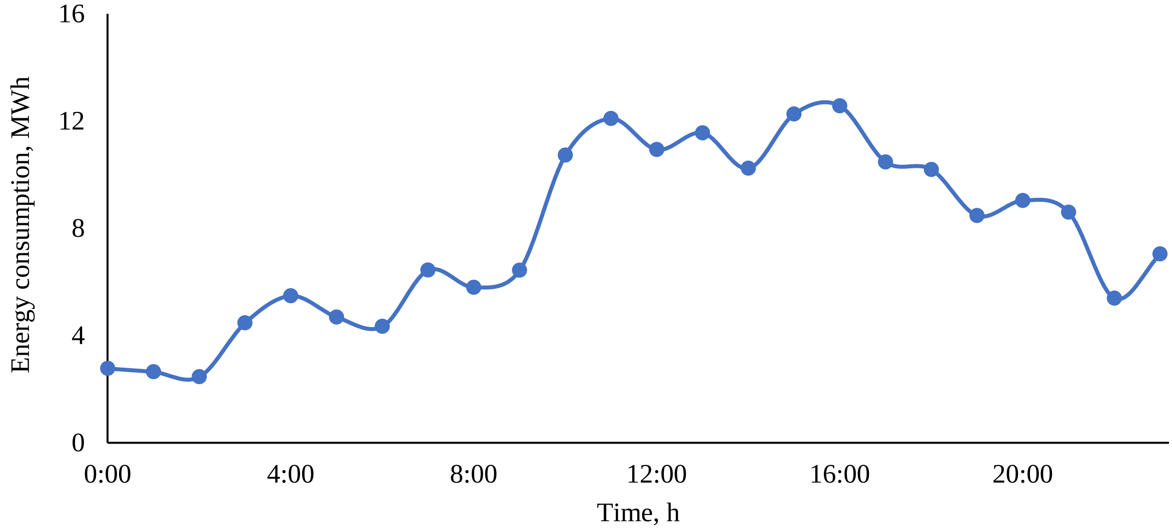
- The fourth electricity price category is appropriate for purchasing electricity where hourly electricity consumption is accounted for in the billing period, but there is no hourly forecasting of electricity consumption. The cost of electricity transmission services is determined by a two-part tariff;

- The sixth electricity price category is appropriate for purchasing electricity where hourly electricity consumption is accounted for and forecasted in the billing period. The cost of electricity transmission services is determined by a two-part tariff;

Since this case requires hourly forecasting of electricity consumption, I use the sixth electricity price category.

2.2. Analysis of Load Diagram of The Sibelectromotor Enterprise

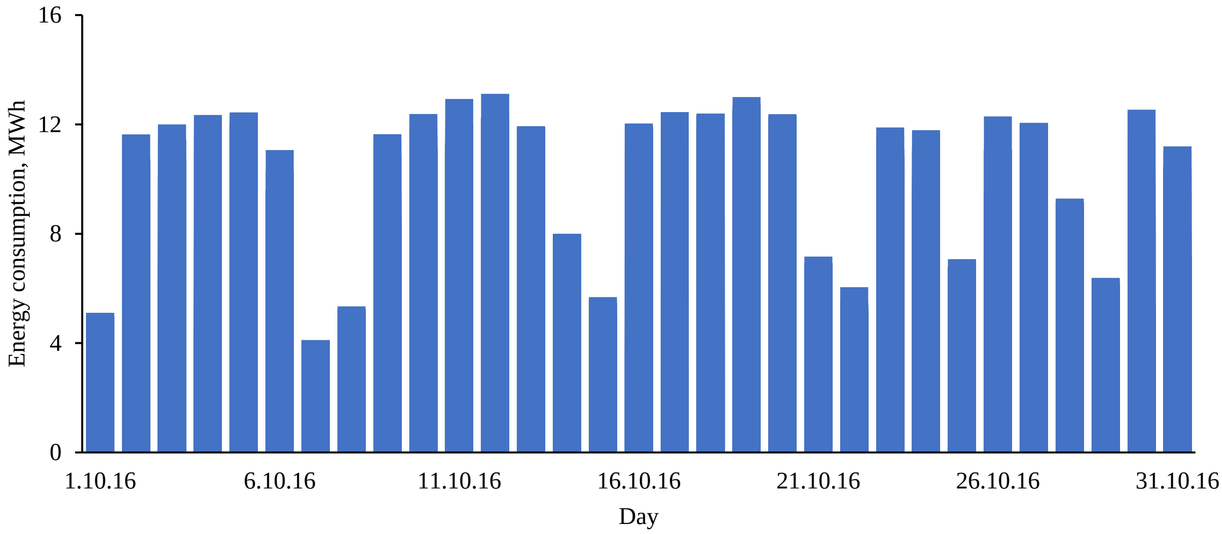
The actual electricity consumption dataset provided by Eugene Shutov [4]. The initial dataset is electricity consumption for 2015–2017. Information is presented as hourly and daily consumption. Therefore, the analysis is divided into two phases. The first stage is focused on investigating daily electricity consumption deviations. The main objective of the second stage is to forecast electricity consumption over a longer period (month). This forecast will be less accurate. In other words, the first step is based on hourly consumption and the second step on daily consumption. Figure 2 presents time series reflecting the hourly electricity consumption per day (24 observations). Figure 2 illustrates the variation of electricity consumption depending on the time of day (morning and afternoon peak demand and night-time minimum demand).



Note: Author's illustration based on initial dataset in [4].

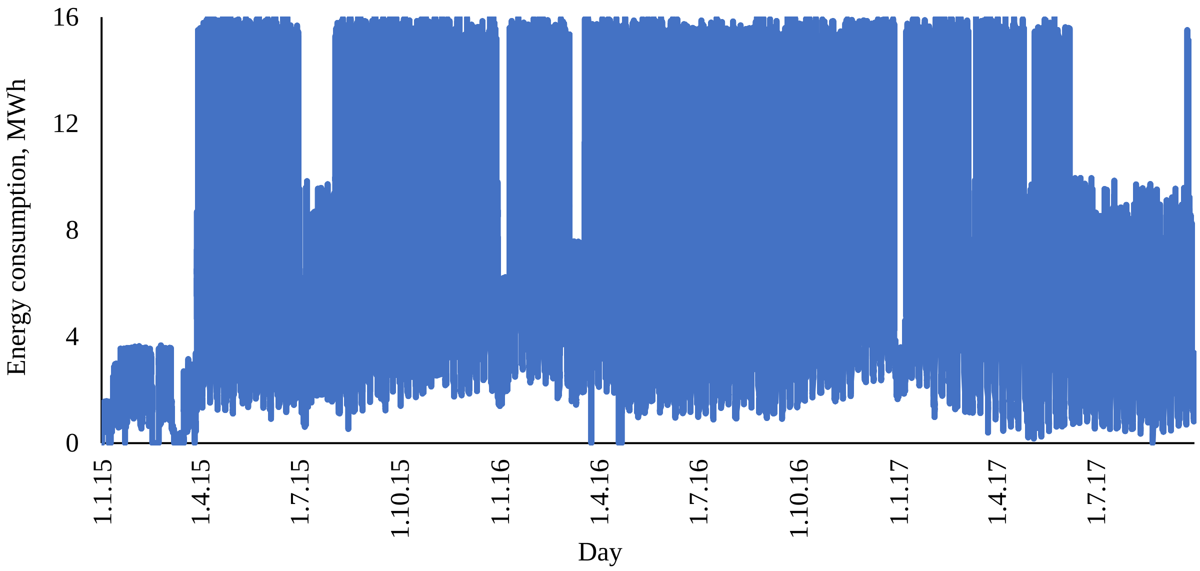
Figure 2. Intra-daily electricity consumption

Figure 3 illustrates time series reflecting the dynamics of daily energy consumption over a month (720 observations). The graph indicates a cycle corresponding to a week (it is possible to notice the change in load over the weekend). Figure 4 illustrates the variation of electricity consumption during 2015–2017.



Note: Author's illustration based on initial dataset in [4].

Figure 3. Daily electricity consumption during October 2016



Note: Author's illustration based on initial dataset in [4].

Figure 4. Electricity consumption during 2015–2017

Discriptive statistics of initial dataset:

- Mean is 5.4896
- Median is 4.8940
- Minimum is 0.00000
- Maximum is 16.000
- Standard deviation is 3.7410
- Skewness is 0.93609
- Excess kurtosis is 0.55929

A histogram is prepared by using Gretl program and is presented in Figure 5. The observed range of variation of active power is divided into intervals of equal length, and the relative frequency of each interval is defined to be the proportion of observed values of the active power that lie in that interval. Figure 5(a) describes a histogram of active power where optimal number of bins is determined by Sturges' rule according to [8] and presents below (1):

$$k = 1 + 3.322 \cdot \log(n) = 1 + 3.322 \cdot \log(24072) \approx 16, \qquad (1)$$

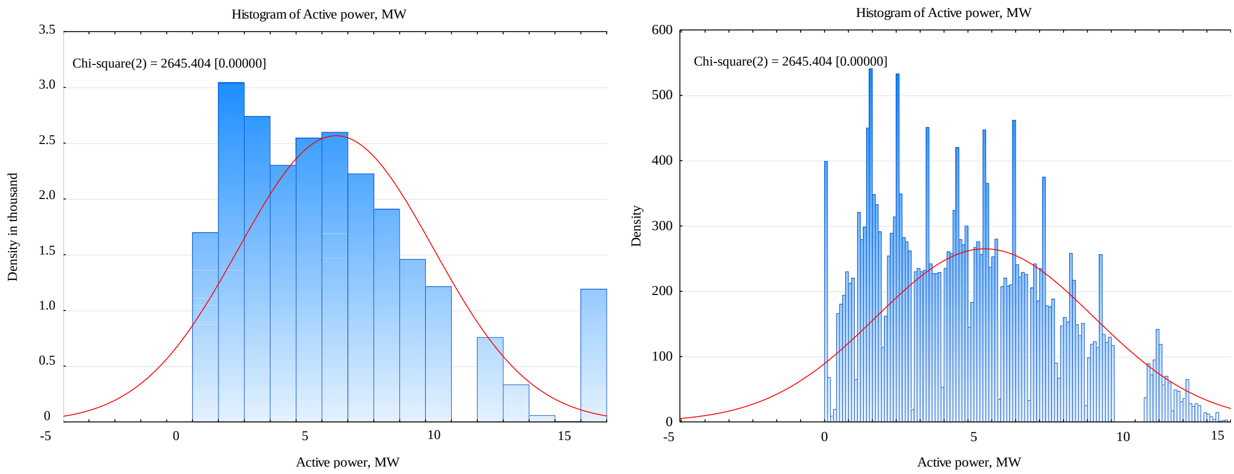
where n is the number of observations in the initial dataset.

Figure 5(b) describes a histogram of active power where optimal number of bins is determined by square root method according to [8] and presents below (2):

$$k = \sqrt{n} = \sqrt{24072} \approx 155, \qquad (2)$$

where n is the number of observations in the initial dataset.

The sequence of plotting histograms in the Statistica software is presented in Appendix A.1.



(a) Number of bins is 16 (b) Number of bins is 155

Figure 5. Empirical and fitted normal distributions of active power

There are the following hypotheses:

- The null hypothesis of the normality test (H_0) assumes that the dataset of electricity consumption follows continuous normal distribution;
- The alternative hypothesis (H_1) assumes that the dataset of electricity consumption does not follow continuous normal distribution.

The Chi-square goodness of fit test (χ^2) compares a histogram of dataset with a function of probability distribution (for discrete variables) or probability density (for continuous variables) [8].

Test for null hypothesis of normal distribution performed with Gretl program:

$$\chi^2 = 2645.404 \text{ with } p\text{-value } 0.00000$$

where p-value is the probability of test value.

Critical Chi-square (χ^2) value associated with a given (right-tail) probability level and the degrees of freedom (*df*):

$$\chi^2_{0.05}(df = 2) = 5.99146 < \chi^2 = 2645.404\,,$$

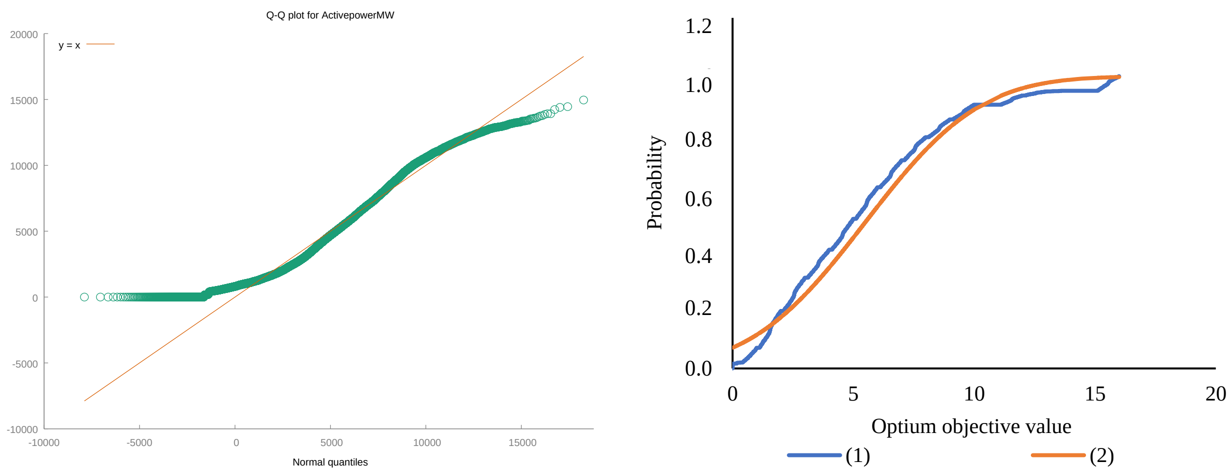
Critical Chi-square (χ^2) value associated with a given (left-tail) probability level and the degrees of freedom (*df*):

$$\chi^2_{0.95}(df = 2) = 0.102587 < \chi^2 = 2645.404$$

The null hypothesis of normality is rejected, because the test value is in the tail (i.e., rejection area). The sequence of Chi-square goodness of fit test performance in the Gretl software is presented in Appendix A.2.

The initial dataset is analyzed and presented in Figure 6. Figure 6(a) is presented normal quantile-quantile plot which was plotted for checking of normal distribution. The values are not normally distributed because there is a deviation from the straight line. The sequence of plotting normal quantile-quantile plot in the Gretl software is presented in Appendix A.3.

Figure 6(b) is presented cumulative distribution function (CDF) which was created for checking of normal distribution. CDF describes the probability that a random variable *Z* with a given probability distribution will be found at a value less than or equal to *z* (possible value). The normal CDF was compared with sample CDF. The sample cumulative distribution function almost coincides with normal CDF.



a) Normal quantile-quantile plot of active power

(b) Cumulative distribution function of active power

Figure 6. Comparison of empirical distribution to the normal distribution

The Kolmogorov-Smirnov test is a non-parametric test which compare sample CDF to the normal CDF with mean variance. Value of the Kolmogorov-Smirnov test is the maximum absolute difference between two functions. Via the Statistica program test for normality of active power is performed [9].

The value of the Kolmogorov-Smirnov test is 0.07113, with corresponding *p*-value < 0.01. The Kolmogorov-Smirnov test rejects the null hypothesis of univariate normality of initial dataset [9].

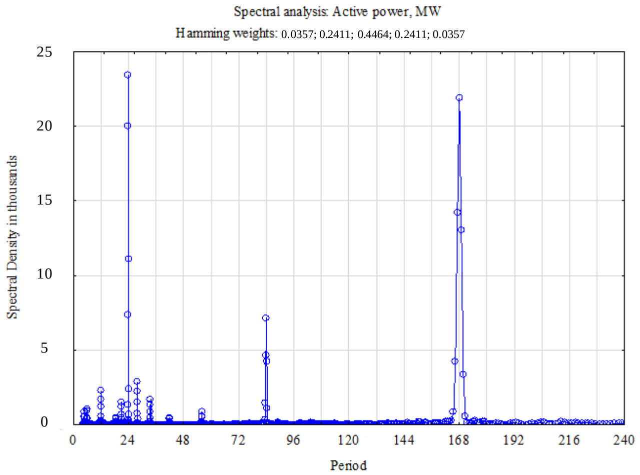
The Augmented Dickey-Fuller (ADF) unit root test will be used for testing stationary of time series. The existence of a unit root means that the time series is not stationary. In addition, the number of unit roots included in a series is equivalent to the number of differentiation operations needed to make a series stationary. Via the Gretl program augmented Dickey-Fuller unit root test of active power is performed [9]. I initially selected 47 as the maximum number of lags. The results of the ADF test are presented in Table 2. The sequence of Augmented Dickey-Fuller unit root test performance in the Gretl software is presented in Appendix A.4.

Table 2. Augmented Dickey–Fuller test

Null hypothesis: Active power time series has a unit root				
Exogenous: constant				
Lag length: 47 (based on Akaike Information Criterion)				
ADF test statistic	-15.4554	1% Critical value	−0.517520	p-value = $1.79 \cdot 10^{-041}$
		5% Critical value	0.0259122	
		10% Critical value	−0.0606817	

The H_0 for ADF tests is that the dataset is not stationary. A p-value of less than α = 0.05 therefore the time series is not stationary. α is called as significance level,

A periodogram is used to identify the dominant periods (or frequencies) of a time series (identifying the dominant cyclical behavior in a series). The precondition for the implementation of the forecast of electricity consumption is the availability of dataset periodicity. Figure 7 presents a period graph with allows to determine seasonality.



Note: 24 corresponds to a daily frequency and168 corresponds to a weekly frequency.

Figure 7. Periodogram of active power

On the periodogram, there are two obvious peaks, where the period is corresponding to 24 and 168 hours (day and week) and one smaller peak, equal to where the period is 84 hours. I could not apply logarithm transformation, because of zero values. The sequence of plotting periodogram plot in the Statistica software is presented in Appendix A.5.

3. Methodology

This chapter focuses on Autoregressive Integrated Moving Average Method, Artificial Neural Networks Method, Classification and Regression Trees Method and Fuzzy Logic models.

3.1. Autoregressive Integrated Moving Average Method

One of forecasting methods is the autoregressive integrated moving average (ARIMA) method, which describes non-stationary series. It is possible to achieve stationarity of a series (set the order of integration) by using a sufficient number of consecutive differences [10].

The model of ARMA(p, d, q) has the following components:

- The Autoregressive (AR) process of order p [11]:

y_t is AR process according to [11] and presents below (4):

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \, , \tag{4}$$

where c is a constant;

$\phi_1, \phi_2, ..., \phi_p$ are autoregressive parameters;

ε_t is iid (white) noise;

This is similar to multiple regression, but the lagged values of y_t are used as predictors.

- The Moving average (MA) process of order q [11]:

y_t is MA process according to [11] and presents below (5):

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \, , \tag{5}$$

where c is a constant;

$\theta_1, \theta_2, ..., \theta_q$ are moving average parameters;

ε_t is iid (white) noise;

Definition of ARIMA means that y_t satisfies a differential equation of the form and presents below (6):

$$\begin{pmatrix} (1 - \phi_1 B - ... - \phi_p B_p) \\ \uparrow \\ AR(p) \end{pmatrix} \begin{pmatrix} (1 - B)^d \\ \uparrow \\ d \text{ differences} \end{pmatrix} y_t = c + \begin{pmatrix} (1 + \theta_1 B + \cdots + \theta_q B^q) \\ \uparrow \\ \text{MA}(q) \end{pmatrix} \varepsilon_t \, , \tag{6}$$

where d is level of differencing;

B is backward shift operator.

Backwards shift operator is used to deal with lags in a time series according to [11] and presents below (7):

$$By_t = y_{t-1} \tag{7}$$

The backward shift operator is useful for describing the differencing process. The backward shift operator according to [11] and presents below (8):

$$\left.\begin{aligned} y_t' &= y_t - y_{t-1} = y_t - By_t = (1-B)^1 y_t; \\ y_t'' &= y_t - y_{t-1} + y_{t-2} = (1-2B+B^2)y_t = (1-B)^2 y_t; \end{aligned}\right| \rightarrow \\ \rightarrow (y_t')^d = (1-B)^d y_t \tag{8}$$

A seasonal ARIMA (SARIMA) model is established by adding seasonal members to the ARIMA models. The SARIMA model is ARIMA (*p*, *d*, *q*) (*P*, *D*, *Q*). The SARIMA model is as follows (9):

$$\begin{pmatrix} (1-\phi_p B) \\ \uparrow \\ \text{Non-seasonal } AR(p) \end{pmatrix} \begin{pmatrix} (1-\Phi_P B^m) \\ \uparrow \\ \text{Seasonal } AR(P) \end{pmatrix} \begin{pmatrix} (1-B)^d \\ \uparrow \\ \text{Non-seasonal } d \end{pmatrix} \begin{pmatrix} (1-B^m) \\ \uparrow \\ \text{Seasonal } D \end{pmatrix} y_t = \\ = \begin{pmatrix} (1+\theta_q B) \\ \uparrow \\ \text{Non-seasonal } MA(q) \end{pmatrix} \begin{pmatrix} (1+\Theta_Q B^m) \\ \uparrow \\ \text{Seasonal } MA(Q) \end{pmatrix} \varepsilon_t , \tag{9}$$

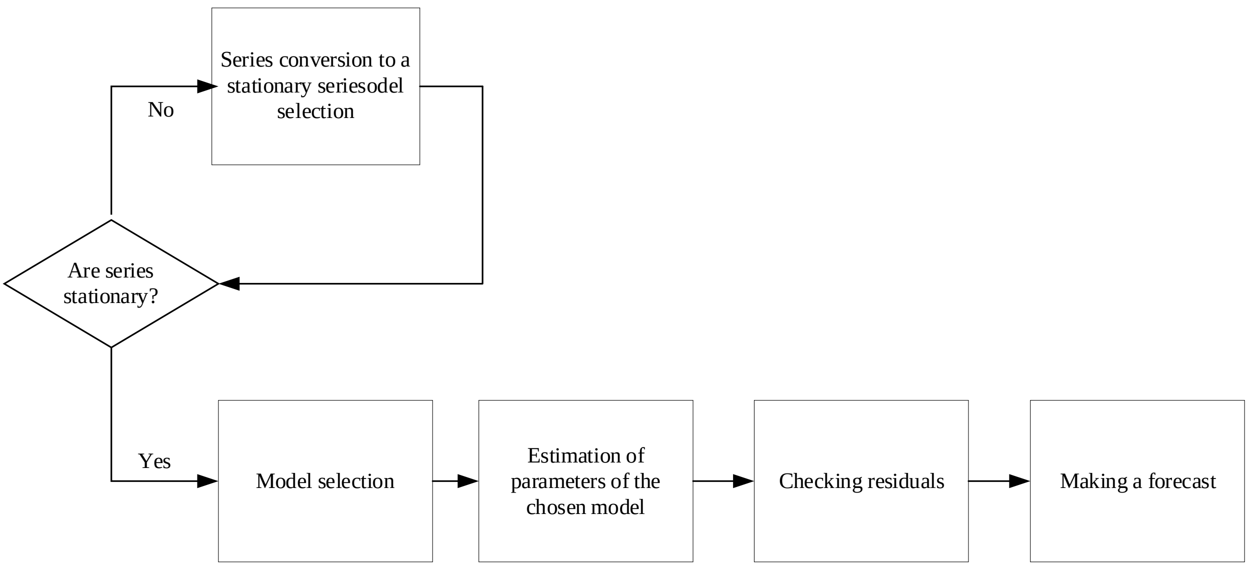
where $\Phi_1, \Phi_2, ..., \Phi_P$ are seasonal autoregressive parameters;

$\Theta_1, \Theta_2, ..., \Theta_Q$ are moving average parameters;

m is seasonality of data.

An Iterative Approach to Model Building

An iterative approach to model building is presented in Figure 8. The design of this type of model to describe the dependency structure in the observed time series is usually best achieved through a three-step iterative procedure based on identification, estimation, and diagnostic verification [12].



Note: Author's illustration based on description in [12].

Figure 8. Three-step model building methodology.

A three-step iterative procedure [12]:

1. By identification, I mean using dataset and any information about how the series was created to offer a subclass of the best model worthy of attention. Identification and estimation overlap. Thus, I can evaluate the parameters of the model, which is more complex than the one I expect to use to decide at what point simplification is possible.
2. Evaluation refers to the efficient use of the dataset in order to make conclusions about the parameters determined by the adequacy of the model.
3. By diagnostic validation, I mean checking whether the model selected matches the dataset to identify model inconsistencies and thus improve the model.

3.2. Artificial Neural Networks Method

The artificial neural networks (ANN) are an analogue of the biological neural network, which is a complex, non-linear system of information processing. Structure of ANN is presented in Figure 9.

The model consists of neurons (processing elements), which are connected among themselves with weights (coefficients). A neuron is a structural unit of the neural network which is necessary for information processing. The functional unit between two neurons is a synapsis characterized by its weight (w). [13]

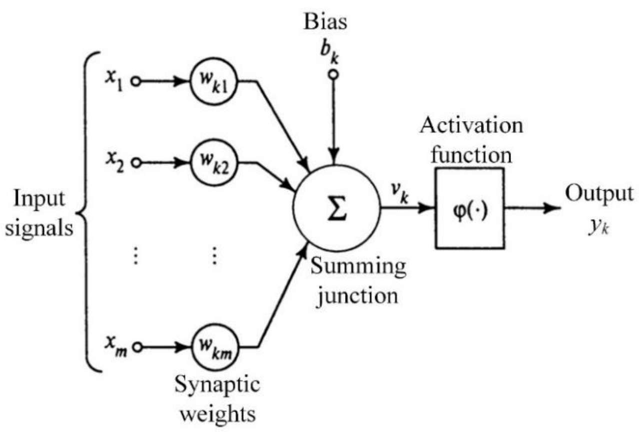


Figure 9. Artificial neural network [13]

The parameters are describing a neuron [14]:

1. Inputs: x_1, x_2, …, x_n which weights are bounded to the input connections: w_1, w_2, …, w_n.
2. Input functions f where $f(x, w)$ is usually the summation function. At this stage, the aggregated net input signal $u = f(x, w)$ to the neuron is calculated.
3. An activation function (s) is used as a function of the interrelation between input and output neuron signals: $a = s(u)$;
4. An output function (o) permits to calculate the value of output signal emitted through the neural axon (output): $o = g(a)$.

ANN are usually defined by the following parameters [14]:

1. Type of neurons (nodes): input, hidden, and output nodes.

2. Connectionist architecture is organization of connections between the neurons:
    - According to the number of input/output neurons and the number of layers:
        - ✓ Autoassociative architecture is network where input neurons are the outputs;
        - ✓ Heteroassociative architecture; There are separate input and output neurons i.e., Multi-layer perceptron (MLP).
    - Depending on the feedback from the output to the input neurons:
        - ✓ Feedforward architecture; There is no feedback from the output to the input neurons therefore the network cannot remember its previous values and activation states of output neurons.
        - ✓ Feedback architecture; There is feedback from the output to the input neurons. In memory of the network is stored its previous states, the next state relies on current input signals and the previous network states.
3. Learning algorithm; Learning algorithm is an algorithm by which the network learns. The learning algorithms are currently classified into groups:
    - Supervised learning; There are the training examples which consist of input vectors (x) and the desired output vectors (y). Training is performed until the ANN "learns" to bind each input vector to its corresponding output vector y, approximation of function y = f(x) and then network encodes the training examples in its internal structure.
    - Unsupervised learning; Neural networks are supplied only with input vectors (x) and ANN learn the whole set of all input vectors and find some internal features of its.
    - Reinforcement learning (reward penalty learning); There is input vector and the ANN are allowed to calculate the corresponding output. If output is bad then the connection weights are decreased (punished), otherwise they are increased (rewarded).
4. Recall algorithm; Recall algorithm is method by which obtained knowledge is extracted from the network.

ANN has the following general functions [14]:

1. Approximation of the function when the dataset is presented;
2. Association information storage;
3. Clusterization, categorization and conceptualization of dataset;
4. Learning and adaptation;
5. Extraction of knowledge through analysis of weights linking;
6. Accumulation of knowledge through learning (training);
7. Inserting knowledge into the structure of the network for approximate reasoning.

The process of solving problems using ANN actually consists of two main phases [13]:

1. Training phase; During this stage, the network is trained through training examples and rules are inserted in its structure.
2. Recall phase; The feedback algorithm is used to calculate the results, when dataset come to the trained network.

Multi-Layer Perceptron

Multi-layer perceptrons were introduced to overcome linear separability limitations of single-layer perceptrons [13].

A multilayer perceptron is a network of neurons that consists of [13]:

1. An input layer in which several input nodes are combined;
2. A hidden layer in which computational models of neurons are located (there may be several hidden layers);
3. Neuron output layer.

The individual neurons of layers are fully or partially linked to the neurons of the next layers depending on the network type and architecture. Neurons in MLP have continuous inputs and outputs, an input summation function and a non-linear activation function. An MLP with a hidden layer can approximate any continuous function with any desired accuracy if there are enough hidden nodes. This network allows to solve a wider range of tasks, as opposed to a single-layer perceptron. Training for this network can be performed using the back-propagation algorithm [14].

The Back-Propagation Algorithm

The back-propagation algorithm involves two passes through layers of the neural network [13]:

1. Forward pass (all synaptic weights of the network are fixed). The input vector is supplied to the input layer of the ANN and then distributed from layer to layer in the network. As a consequence of that, a set of output signals is produced (the network's actual reaction to this input signal).
2. Backward pass. All synaptic weights are corrected according to the delta rule: the actual network output is subtracted from the desired one, resulting in an error signal. This signal is propagated through the network in the opposite direction to the synaptic links. In general, the algorithm looks like this [13]:
   a. Initialization; Synaptic weights and threshold values (weights of all connections) are determined by random values.
   b. Presentation of examples of training; An input signal is supplied to the network input for which the forward and reverse passes are executed until the condition of stopping the algorithm is fulfilled (a certain error threshold value is reached or the required number of iterations is executed).
   c. Forward pass; At this stage, the functional output signal of the neuron is calculated (y_i). A signal ($x(n)$, $d(n)$) is given. $x(n)$ is a vector supplied to the input layer, $d(n)$ is the necessary response provided for error calculation.

The weighted total of the *i*-th neuron according to [13] and presents below (10):

$$\upsilon_j^{(l)}(n) = \sum_{i=0}^{m_0} \omega_{ji}^{(l)}(n) \cdot y_i^{(l-1)}(n)\,, \tag{10}$$

where n is the i-th training pattern;

i is the network neuron located on the l - 1 layer;

j is network neuron located on the l layer;

l is layer number;

$\omega_{ij}^{(l)}(n)$ is synaptic weight of the neuron (links the neuron output i to the neuron input j) on the l layer with n iterations;

$y_i^{(l-1)}(n)$ is neuron functional signal i generated on the layer l with n iterations;

Then I define the neuron signal at the layer output l according to [13] and presents below (11):

$$y_j^{(l)}(n) = \varphi_j(\upsilon_j^{(l)}(n)), \tag{11}$$

where φ_j is the activation function (describes the interrelation between input and output neuron signals);

If the neuron is in the first hidden layer, the functional signal of the neuron can be defined according to [13] and presents below (12):

$$y_j^{(1-1)}(n) = y_j^{(0)}(n) = x_j(n), \tag{12}$$

where $x_j(n)$ is the element of the input vector $x(n)$;

If the neuron is in the output layer, the functional signal of this neuron can be defined according to [13] and presents below (13):

$$y_j^{(L)}(n) = o_j(n), \tag{13}$$

where L is the number of network layers;

$o_j(n)$ is the j-th output vector element;

Then an error signal on the output layer may be calculated according to [13] and presents below (14):

$$e_j(n) = d_j(n) - y_j(n) = d_j(n) - o_j(n), \tag{14}$$

where $d_j(n)$ is j-th element of the input required response $d(n)$;

d. Backward pass. At this stage the synaptic weights are corrected and the error signal (from the output to the input layer) is calculated.

First, it is necessary to calculate the local gradient of the network according to [13] and presents below (15):

$$\delta_j(n) = -\frac{\partial E(n)}{\partial \upsilon_j(n)}, \tag{15}$$

where the quadratic loss is calculated according to [13] and presents below (16):

$$E(n) = \frac{1}{2}\sum_{j\in C} e_j^2(n), \tag{16}$$

C is all neurons of the output layer;

The gradient is calculated according to [13] and presents below (17):

$$\delta_j(n) = -\frac{\partial E(n)}{\partial \upsilon_j(n)} = -\frac{\partial E(n)}{\partial e_j(n)}\frac{\partial e_j(n)}{\partial y_j(n)}\frac{\partial y_j(n)}{\partial \upsilon_j(n)} = e_j(n)\varphi_j'(\upsilon_j(n)), \tag{17}$$

where $\frac{\partial E(n)}{\partial e_j(n)} = e_j(n)$ – is partial differentiation of equation (16);

$\frac{\partial e_j(n)}{\partial y_j(n)} = -1$ – is differentiation of equation (14);

$\frac{\partial y_j(n)}{\partial \upsilon_j(n)} = \varphi_j'(\upsilon_j(n))$ – is differentiation of equation (11);

$\varphi_j'(\upsilon_j(n))$ is activation function, differentiated by the argument;

If the neuron is in the first hidden layer, the gradient can be determined is calculated according to [13] and presents below (18):

$$\delta_j^l(n) = \varphi_j'(\upsilon_j^l(n))\sum_k \delta_k^{(l+1)}(n)\omega_{kj}^{(l+1)}(n), \tag{18}$$

where *k* is network neuron, located on the *l* + 1 layer;

$\delta_k^{(l+1)}(n)$ local gradient *l* + 1 with *n* iterations;

$\omega_{kj}^{(l+1)}(n)$ is synaptic weight of the neuron (links the neuron output *j* to the neuron input *k*) on the layer *l* + 1 with *n* iterations;

In other words, a gradient depends on a weighted total of gradients of the next layer *l* + 1.

If the neuron is in the output layer, the gradient can be determined according to [13] and presents below (19):

$$\delta_j(n) = e_j^L(n)\varphi_j'(\upsilon_j^L(n)); \tag{19}$$

Then, I correct synaptic weight according to [13] and presents below (20):

$$\Delta\omega_{ij}(n) = -\eta\frac{\partial E(n)}{\partial \omega_{ij}(n)}, \tag{20}$$

where η is learning rate;

A negative sign indicates the use of gradient descent, i.e., finding the answer in which function decreases. In other words, there is a descent from this point to the minimum one. Usually, the length of step is set proportional to the slope gradient (multiplied by learning rate) and decreases because it nears the minimum.

The gradient is determined according to [13] and presents below (21):

$$\Delta\omega_{ij}(n) = -\eta\frac{\partial E(n)}{\partial \omega_{ij}(n)} = -\eta\frac{\partial E(n)}{\partial e_j(n)}\frac{\partial e_j(n)}{\partial y_j(n)}\frac{\partial y_j(n)}{\partial \upsilon_j(n)}\frac{\partial \upsilon_j(n)}{\partial \omega_{ij}(n)} = \eta e_j(n)\varphi_j'(\upsilon_j(n))y_j(n), \tag{21}$$

where $\dfrac{\partial \upsilon_j(n)}{\partial \omega_{ij}(n)} = y_i\,(n)$ is differentiation of equation (10);

The process of gradient calculation and correction of weights is done layer by layer from output to input until all weights are corrected.

Activation Function

Since to calculate the gradient, it is necessary to calculate a derivative activate function [14]. Because such a function is quite often used sigmoidal nonlinear function (i.e., the logistic). It has the following form according to [13] and presents below (22):

$$\varphi_j(\upsilon_j(n)) = \frac{1}{1+e^{-\alpha\upsilon_j(n)}}\,, \tag{22}$$

where α is slope parameter of sigmoidal nonlinear function. This parameter, as a rule, has a positive value.

Sigmoidal nonlinear function is presented in Figure 10.

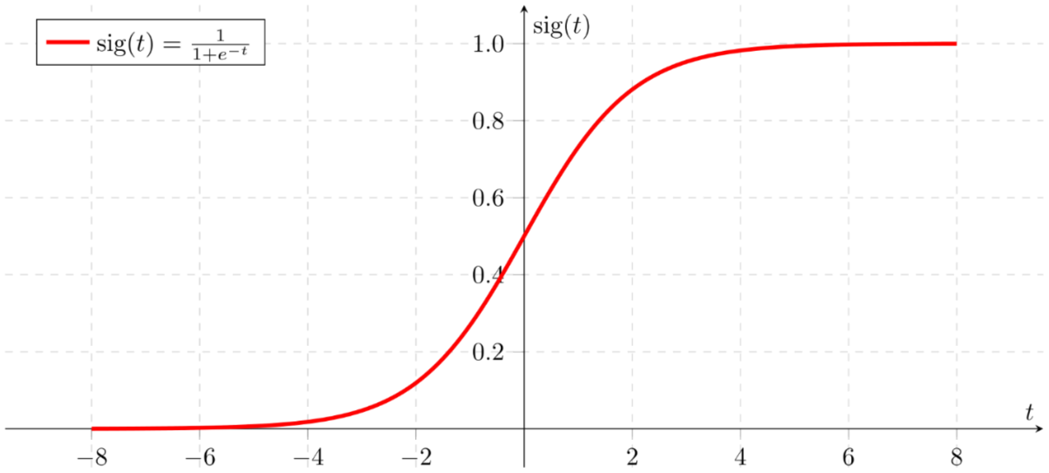


Figure 10. Sigmoidal nonlinear function [15]

Another advantage is the automatic gain control. If the signal is weak, you will notice that the curve has a stronger slope, so the gain from this function is greater (without excessive weakening). When the signal increases, the gain drops (without saturation) [13].

The derivative of this function according to [13] and presents below (23):

$$\varphi_j'(\upsilon_j(n)) = \frac{\alpha e^{-\alpha\upsilon_j(n)}}{\left(1+e^{-\alpha\upsilon_j(n)}\right)^2}\,; \tag{23}$$

From the formula (11), I can say (24) that according to [13]:

$$y_j(n) = \varphi_j(\upsilon_j(n))\,; \tag{24}$$

Then I express the variable according to [13] and presents below (25):

$$e^{-\alpha \upsilon_j(n)} = \frac{1 - y_j(n)}{y_j(n)}\ ; \tag{25}$$

Substitute (25) to (22) I can achieve (26) according to [13]:

$$\varphi_j'(\upsilon_j(n)) = \frac{\alpha e^{-\alpha \upsilon_j(n)}}{\left(1 + e^{-\alpha \upsilon_j(n)}\right)^2} = \frac{\alpha \frac{1 - y_j(n)}{y_j(n)}}{\left(1 + \frac{1 - y_j(n)}{y_j(n)}\right)^2} =$$

$$= \frac{\alpha \frac{1 - y_j(n)}{y_j(n)}}{1 + 2\frac{1 - y_j(n)}{y_j(n)} + \frac{1 - 2y_j(n) + y_j^2(n)}{y_j^2(n)}} = \frac{\alpha \frac{1 - y_j(n)}{y_j(n)}}{\frac{y_j^2(n) + 2y_j(n) - 2y_j^2(n) + 1 - 2y_j(n) + y_j^2(n)}{y_j^2(n)}} = \tag{26}$$

$$= \frac{\frac{\alpha - \alpha y_j(n)}{y_j(n)}}{\frac{1}{y_j^2(n)}} = \frac{\alpha y_j^2(n) - \alpha y_j^3(n)}{y_j(n)} = \alpha y_j(n) - \alpha y_j^2(n) = \alpha y_j(n)\left(1 - y_j(n)\right)$$

Analyzing this formula, I can say that the derivative reaches its minimum at $y_i(n) = 0$; $y_i(n) = 1$, and maximum at $y_i(n) = 0.5$.

If the neuron is in the first hidden layer, then by substituting (26) to (15), the gradient can be determined according to [13] and presents below (27):

$$\delta_j(n) = \alpha y_j(n)\left(1 - y_j(n)\right)\sum_k \delta_k(n)\omega_{kj}(n)\ ; \tag{27}$$

If the neuron is in the output layer, the gradient can be determined by substituting (14) and (26) to (15) I can obtain according to [13] and presents below (28):

$$\delta_j(n) = \left(d_j(n) - o_j(n)\right)\alpha o_j(n)\left(1 - o_j(n)\right)\ ; \tag{28}$$

The back-propagation algorithm is most often used when the input dataset volume is large and there is redundant dataset because there is an error correction for specific cases.

3.3. Classification and Regression Trees Method

Classification and regression trees (CART) are effective research statistical method. The statistical principle of the method can be described as a recursive division (the gradual division when groups of individuals are becoming smaller and smaller with increasing similarity in the dependent variable in each group with increasing differences between newly formed groups). It is a heuristic tree method that unpacks the communication between a dependent variable (result indicator) and an independent variable (group of predictors) [16].

The main advantages of classification and regression trees are [16]:

1. Simplicity of interpreted dataset because of the presentation of dataset in the form of a tree structure. The model does not contain complex mathematical equations which describe the model.
2. The system automatically sets the frame of communication between dependent and predictor variables and selects the most significant predictors (the user does not need to perform these operations);
3. Ability to use variables with missed dataset; Traditional statistical techniques often require some distributional assumptions (usually difficult to meet it in real dataset). That is why I can use method to investigate inappropriately (unfruitful) for statistical dataset sets (abnormal distributions of dataset).
4. Possibility to use any type of variables both quantitative and qualitative dataset (there is not necessary to convert them of a specific type);
5. CART can capture complex interactions and nonlinear interactions in the dataset as opposed to traditional statistical techniques. The pre-identification and modelling of interactions are not necessary for the model since it provides automatic generation of mutually exclusive groups that provide direct insight into independent variables.

Important CART functions [17]:

1. Segmentation; Aims of segmentation is identifying cases that may belong to a certain group;
2. Stratification; Aims of stratification is a distribution of cases into different categories;
3. Forecasting; The goals are to create rules for forecasting future events;
4. Interaction identification; Aims of interaction identification is an identification of relations which together define a certain group with a unique value of a dependent variable;
5. Screening variables; Aims of variable screening is a identify a small number of predictors from a large number of variables;
6. Manipulations with variables; Aims of variable manipulation is a minimizing the loss of information in the categories of predictors and continuous variables.

Algorithm of Building the Tree

The algorithm is designed to solve classification and regression problems. A tree structure is formed using the algorithm "*IF*(*A*), *THEN*(*B*)", where "*IF*(*A*)" is a logical condition, "*THEN*(*B*)"is a procedure for dividing the whole set into two parts (for one part "*IF*(*A*)" is true then for the other part is false). One of the predictors is compared to a certain threshold value [17].

In CART terminology, node is each box (representing a group or subgroup). The analysis comes from root node which is at the top of the tree. The CART analysis contains partitions on different branches (different levels). Partition means separating observations in a node into groups. When a partition is created in CART, one node creates two consequent nodes. The created nodes are called child nodes (decision nodes), and the producing node is called the parent node. Two child nodes can be distinguished by their position under the parent node (i.e., the left child node and the right child node). A leaf node means the end of growth in this part of the tree, this node cannot be further divided into child nodes. The tree grows on a level, when the root node or parent node creates child nodes. The typical structure of CART is shown in Figure 11 [16].

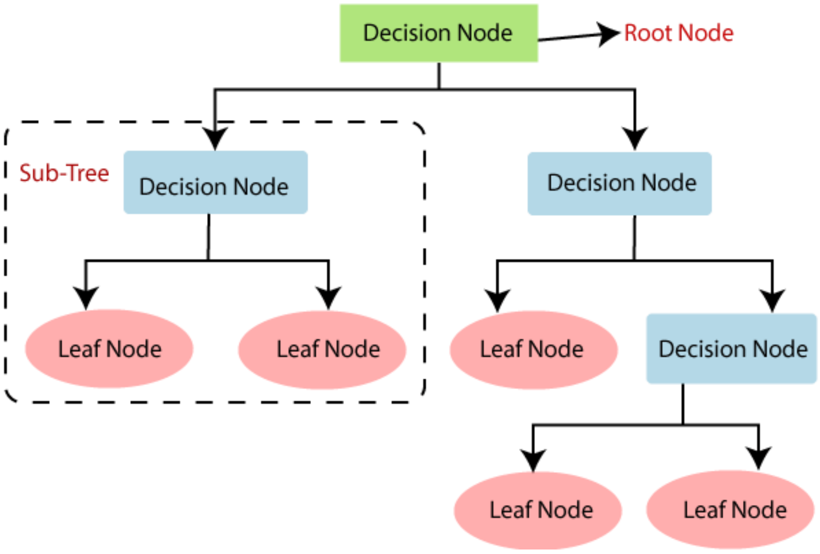


Figure 11. Classification and regression trees [18]

Growing the CART Tree

CART grows the tree based on the reduction of impurities. Starting with the root node, each independent variable is tested as a potential candidate to split the root node into two nodes. The different values (categories) of the independent variable can be used to separate the root node, and the optimal performance (best impurity reduction associated with a specific category or value) of the independent variable is recorded. The degree of impurity reduction associated with the separation of a parent node into child nodes is calculated according to [17] and presents below (29):

$$\Delta = i(\tau) - i(\tau_L)\frac{n_1}{n_1+n_2} - i(\tau_R)\frac{n_2}{n_1+n_2}, \tag{29}$$

where $i(\tau)$ is a parent node's impurity;

$i(\tau_l)$ is the impurity measure for the left branch made;

$i(\tau_r)$ is the impurity measure for the right branch made;

Coefficients associated with child nodes can usually be considered as probabilities that the case will pass to τ_l and τ_r, respectively.

Using a different stress value to separate the parent node results in a different reduction of the impurity entropy measure. After all stress values were tested for impurity reduction, the optimal stress value associated with the largest impurity reduction is determined. After all independent variables were considered, an independent variable with the largest impurity reduction is selected to divide the root node into two nodes [17].

Then procedure moves on to each of the child nodes. For the left child node, for example, the same procedure can be applied to split this node into child nodes. Thus, new branches constantly appear, each of which is guided by the reduction of a certain measure of impurities [17].

Stopping the CART Tree

A rule (called a stopping rule) is used to stop the separation process. When setting a stopping rule, caution must be taken. If the rule stops the partition too early, the resulting tree is likely to be too small to reflect the true data structure. If the rule stops the partition too late, the resulting tree will probably be too big to be stable or significant (e.g., having several options in the end nodes) [19].

One traditional approach uses verification to decide when to stop the procedure. The idea is to use a subset of dataset to grow the tree and use the rest of the dataset to check the tree. For example, according to the usual division of dataset for a work and check set, it is possible to run a CART analysis of 90% of the dataset and reserve the remaining 10% for validation purposes. The CART tree stops growing or splitting when the error in the validation dataset reaches its minimum. This general (erroneous) trend is also reflected in the CART test set with a monotonous reduction in the test error until the current set is retrained. Because of retraining, the validation error is limited backwards, as presented in Figure 12. The program should stop the tree when the check error reaches its first minimum. The line representing the first local minimum indicates where to stop tree growth (partitioning) [19].

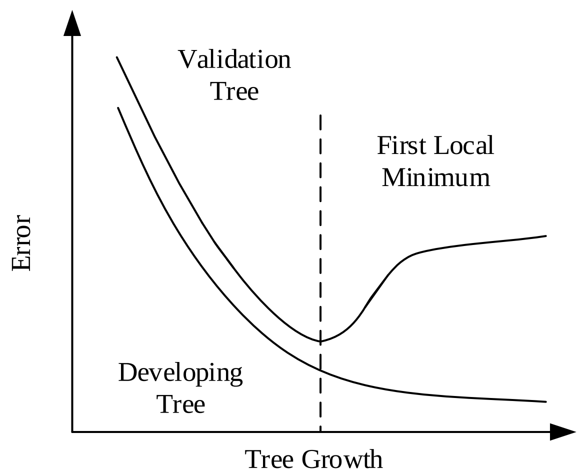


Figure 12. Relationship between error in tree structure and degree of tree development [19]

With a small sample size, a cross-validation approach is often used (called *m*-fold cross-validation). This approach generates *m* (usually *m* = 10) mutually exclusive subsets of dataset with equal sample size *n/m* (*n* is the total number of observations in the root node). Then the CART tree is increased m times after the verification procedure described above. In each of these m cases, one subset is not used for work as a check set, and the tree grows on the other subset. The average of *m* classification errors is used as a checking measure that joins the CART tree generated from all (*n*) cases to indicate its potential performance [19].

3.4. Fuzzy Logic Method

Fuzzy logic is a section of mathematics that includes the theory of sets, which describes certain sets of objects (elements), as well as classical logical theory. The control system in fuzzy logic is based on processes of associative thinking and perception of the person that allows carrying these systems to the group of artificially-intellectual. The occurrence of the given theory is connected with use of various uncertain estimations in the description of subjects, processes, systems [20].

A fuzzy system is any system in which some of variables change in states (fuzzy sets). For each variable, fuzzy sets are defined on some corresponding universal set, which often represents an interval of real numbers.

Application Field of Fuzzy Control Systems

Causes for fuzzy control algorithms proliferation in various intelligent systems are the specific features [20]:

1. The change of the controlled object parameters has insignificant influence on the control system using fuzzy logic;
2. The process of combination of fuzzy controller and control system using actual software and hardware support is easier than using traditional controllers.

The most preferable fields of application of fuzzy logic are systems, which has uncertainties (impossibility of description by traditional methods, small volume of available information about an object, system complexity), but at the same time there is information of qualitative character (for example, dataset about control actions) [19]:

1. Application in combination with traditional regulators to add adaptability properties;
2. Restoration of human-operator actions;
3. Systems, in which the model of the controlled object is described only qualitatively.

Fuzzy Controllers

Fuzzy controllers are special expert systems each of them uses the knowledge base, expressed in terms of corresponding rules of fuzzy output, and the corresponding inference mechanism to solve this control problem. Control problems range from complex tasks, which require many coordinated actions, to simple goals. Fuzzy controllers, in contrast to classical controllers, are able to use knowledge gained from human operators. This is critical for control tasks where it is difficult (or impossible) to build accurate mathematical models, or when the acquired models are expensive or difficult to use. They can arise from inherent nonlinearity, the time-varying nature of the processes under control, large unpredictable environmental disturbances or other difficulties in obtaining accurate and reliable measurements. The knowledge of an experienced human operator can be used as an alternative to an accurate controlled process model. Although this knowledge is difficult to express in precise terms, an imprecise linguistic description of the control method can usually be relatively easily formulated by the operator. This linguistic description consists of a set of control rules which use fuzzy propositions [19].

The typical form of these rules according to [19] and presents below (30):

$$"IF\ (A),\ THEN\ (B)", \tag{30}$$

where (A) is condition,

(B) is conclusion.

The simplest version of a fuzzy rule according to [19] and presents below (31):

$$"IF\ (\beta_1 \text{ IS } \alpha_1),\ THEN\ (\beta_2 \text{ IS } \alpha_2)", \tag{31}$$

A variant of the fuzzy rule using logical expressions (*"AND"*, *"OR"*, *"NOT"*) presents below (32):

$$"IF\ (\beta_1 \text{ IS } \alpha)\ AND\ (\beta_2 \text{ IS NOT } \alpha),\ THEN\ (\beta_1 \text{ IS NOT } \beta_2)", \tag{32}$$

The base of fuzzy rules can be presented in the form of a structured text agreed on the applied linguistic variables (33):

$$\begin{gathered} (1):\ IF\ \left(Condition_1\right)\ THEN\ \left(Conclusion_1\right);\ \left(F_1\right), \\ (2):\ IF\ \left(Condition_2\right)\ THEN\ \left(Conclusion_2\right);\ \left(F_2\right), \\ \dots \\ (n):\ IF\ \left(Condition_n\right)\ THEN\ \left(Conclusion_n\right);\ \left(F_n\right). \end{gathered}, \tag{33}$$

The list must be consistent, that is, only simple or compound statements can be used as conditions, and in each of them, the functions of belonging to a set of allowable values must be defined for each linguistic variable.

The general fuzzy controller consists of following modules: a fuzzy rule base, a fuzzy inference engine, and fuzziflcation/defuzzification modules. The relationship between these modules and the controlled process is shown in Figure 13 [19].

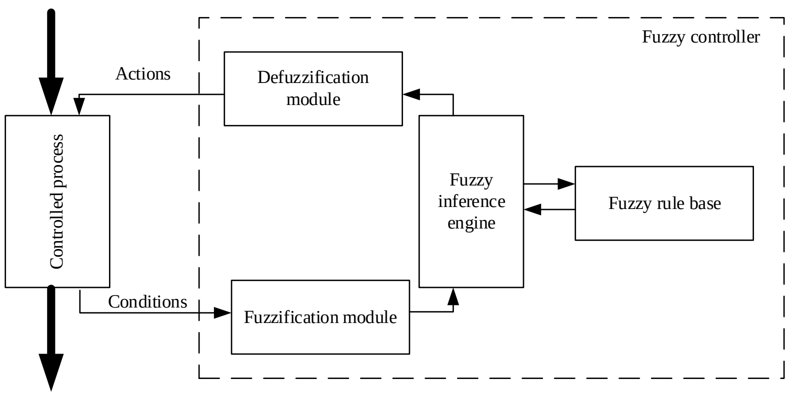


Figure 13. A general scheme of a fuzzy controller [19]

A fuzzy controller works by repeating a cycle of the following steps. First, all variables are measured which represent the corresponding conditions of the process being controlled. The next step is called fuzzification (measurements are converted into corresponding fuzzy sets for expressing measurement uncertainty). The inference engine uses the fuzzified measurements to evaluate the control rules stored in the fuzzy rules database. The result of the evaluation is one or several fuzzy sets defined in the universe of possible actions. The next step is called defuzzification it means that fuzzy set is transformed at the last step of the cycle into a single value or vector of values. defuzzied values represent the actions taken by the fuzzy controller in individual control cycles. The main steps in the design of fuzzy controllers are shown in Figure 14 [19].

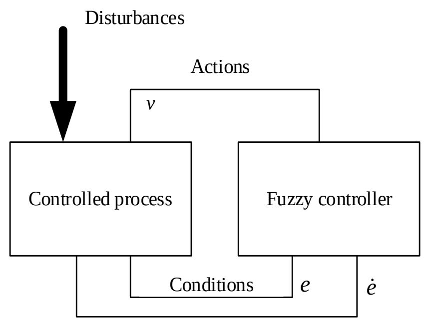


Figure 14. General scheme for controlling the desired value of a single variable [19]

The controller usually monitors two conditions: error e (the difference between the actual value of the controlled variable and its desired value) and a derivative of error change $\dot{e}$ (the rate of change error). Using the values e and $\dot{e}$, the fuzzy controller outputs the values of the manipulated variable v (the corresponding control actions) [19].

The first step: After defining the corresponding input and output controller variables and their ranges of values, I should select the significant linguistic states for each variable and express them with corresponding fuzzy sets (it can be fuzzy numbers that represent linguistic labels such as approximately zero, positive small, negative small, positive medium).

The second step: A fuzzy function is introduced for input variable to express the related measurement uncertainty. Fuzzification is a setting of correspondence between the numerical value of the input variable of the fuzzy output system and more realistic fuzzy approximations of the corresponding real numbers (linguistic terms). For each measurement, the fuzzy set enters into the output process (step 4) as a fact.

The third step: in this step, the knowledge related to this control problem is formulated in terms of a set of rules for the fuzzy inference. There are main ways to define the corresponding inference rules. The first one is to call them from experienced operators. The other way is to get them from empirical dataset by suitable training methods, usually with the help of neural networks.

The fourth step: Measurements of the input variables of the fuzzy controller must be correctly combined with the corresponding fuzzy rules to make conclusions about the output variables.

The fifth step: In this last step of the design process, the developer of a fuzzy controller must select a suitable defuzzification method. Defuzzification in fuzzy output systems is a process of transition from the function of belonging of the output linguistic variable to its clear (numerical) value. The purpose of defuzzification is to convert each output obtained by the output mechanism, which is expressed in terms of a fuzzy set, into one actual number. The resulting number, which determines the action taken by the fuzzy controller, is not arbitrary. In some sense, it must summarize the elastic limitation imposed by the fuzzy set on the possible values of the output variable.

4. Forecasting of Electricity Consumption

The energy consumption of each enterprise is a complex, random process because it depends on many factors (temperature, lighting level, quantities of products, etc.). This characteristic complicates the process of forecasting hourly electricity consumption. Moreover, electricity is not a typical product, because it cannot be stored in warehouses. Therefore, the process of forecasting electricity consumption has to be determined on a case-by-case basis.

4.1. Short-Term Forecasting from

In this section, I forecast electricity consumption using ARIMA and ANN methods. Hourly forecasts of electricity consumption are reviewed in this section. The hourly load of the enterprise is presented as the initial dataset for day-ahead electricity consumption forecast. Initial data for a day-ahead electricity consumption forecast from ARIMA and ANN is presented in Appendix B.1.

4.1.1. Autoregressive Integrated Moving Average Method

The first step is selecting the values required to forecast electricity consumption. I selected days where there is obvious pattern (no sharp spikes or sharp drops in consumption). To forecast electricity consumption, for example for a Monday, I have selected 20 Mondays. The training hourly dataset consists of data for 20 Mondays (from 14 May 2016 to 1 November 2016). The forecast of electricity consumption is prepared for Monday, 8 November 2016. The line graph of the initial data set is presented in Figure 15. The sequence of plotting in Statistica software is presented in Appendix A.6.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) allow determining the orders of AR and MA in the ARIMA model (parameters p and q). In time series analysis, the Autocorrelation Function indicates the degree of linear statistical correlation between the values of a time series. The PACF is a partial autocorrelation function to explain the partial correlation between a series and its own lags. The order of lag is approximately 25% of the initial sample and equals 120. The correlogram for active power is presented in Figure 16. The correlogram for active power is presented in Figure 16. The sequence for plotting the correlogram in Statistica software is presented in Appendix A.7. The parameters of the correlogram are presented in Appendix B.2.

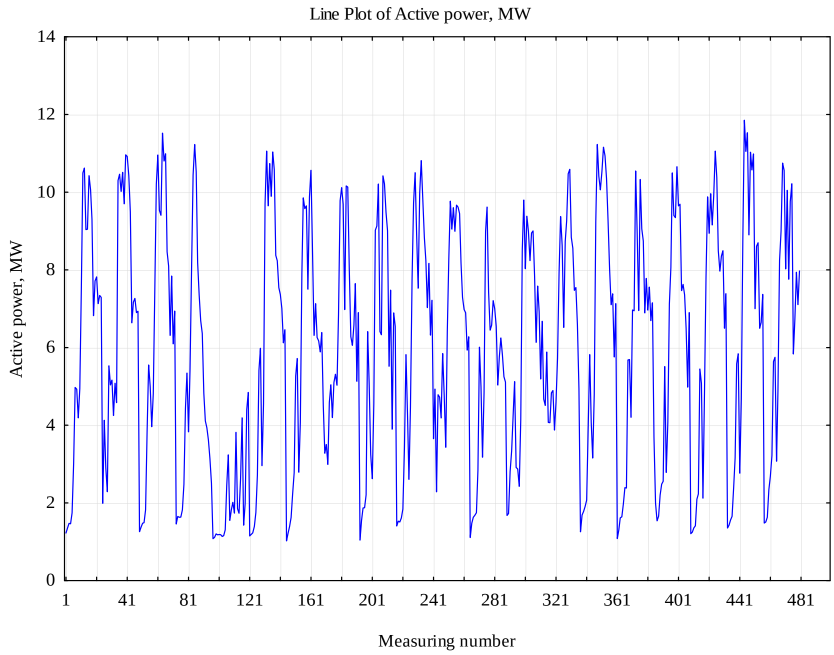


Figure 15. Line plot of initial dataset for a day-ahead forecasting of electricity consumption

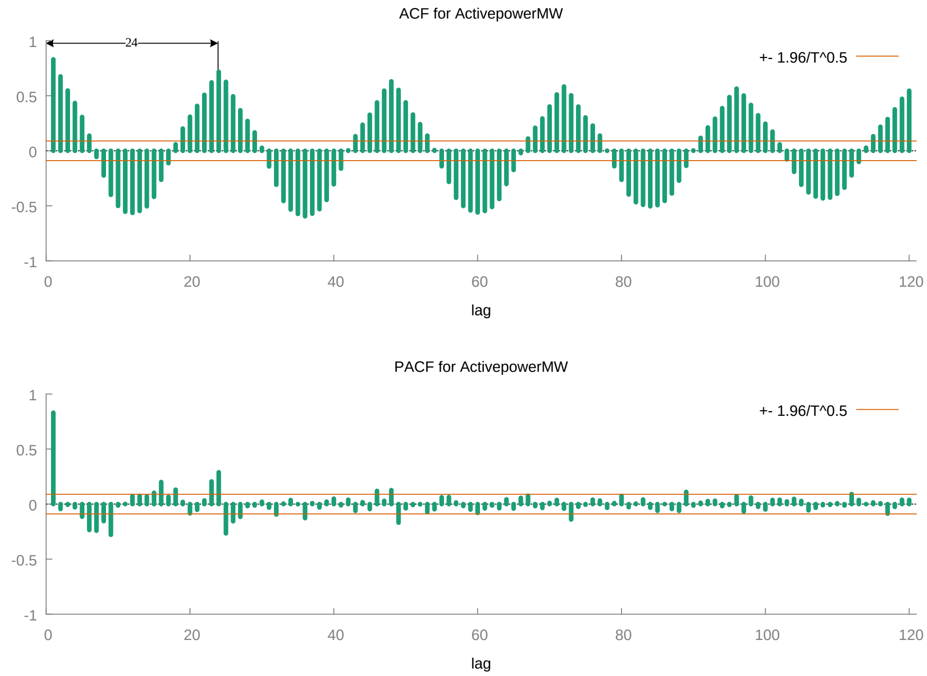


Figure 16. Correlogram for initial dataset of active power for day-ahead forecasting of electricity consumption

The ACF decreases rapidly and then increases. This variation proceeds at a shift is 24. The Autocorrelation Function indicates that model with $q = 1$; $Q = 1$ is appropriate because the ACF is reduced after the first lag and the first lag is higher than the other lags. The Partial Autocorrelation Function indicates that model with $p = 1$; $P = 1$ is appropriate because the PACF is reduced after the first lag and the first lag is higher than the other lags. Therefore, if I substitute the parameters into the ARIMA (*p*, *d*, *q*) (*P*, *D*, *Q*) model, I obtain the following ARIMA (1, 1, 1) (1, 1, 1) model.

Next, a periodogram was plotted to determine the seasonal component. The periodogram is presented in Figure 17. The sequence of periodograms in Gretl is presented in Appendix A.8. Parameters of the periodogram are presented in Appendix B.3.

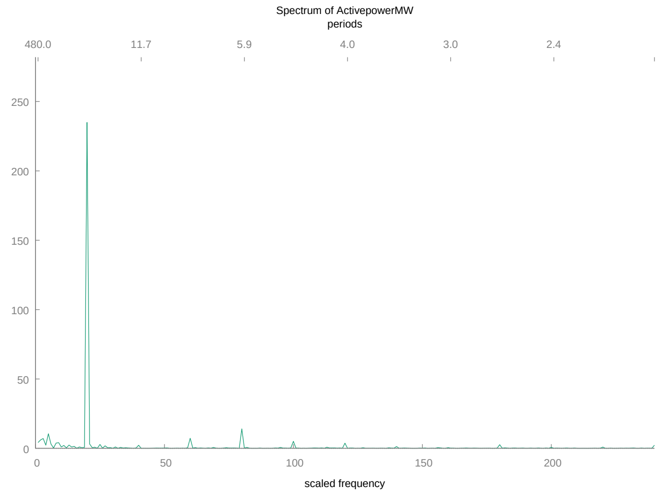


Figure 17. Periodogram for initial dataset of active power for a day-ahead forecasting of electricity consumption

The period of power consumption is 24 hours, determined by the ACF and periodogram.

The next step is smoothing the series, smoothing is performed on the first and 24th lag as determined by the ACF and periodogram. The smoothed dataset is presented in Figure 18. The procedure for obtaining smoothed data is presented in Appendix A.9. Parameters of smoothed data are presented in Appendix B.4. The smoothed data are presented from 01:00 on 21 May 2016 to 23:00 on 1 November 2016 (454 observations). The smoothed data plot indicates the smoothed time series has smaller spikes.

After the seasonality (lags) equal to one and 24 are added, I obtain a normal quantile-quantile plot and a histogram, presented in Figures 19, 20. The sequence of plotting the normal quantile-quantile plot in Statistica software is presented in Appendix A.10. The sequence for plotting the histogram and for testing the normality of the distribution is the same as in Appendix A.1.

Optimal number of bins is determined by Sturges' rule according to (1) [8]

$$k = 1 + 3.322 \cdot \log(n) = 1 + 3.322 \cdot \log(454) \approx 10$$

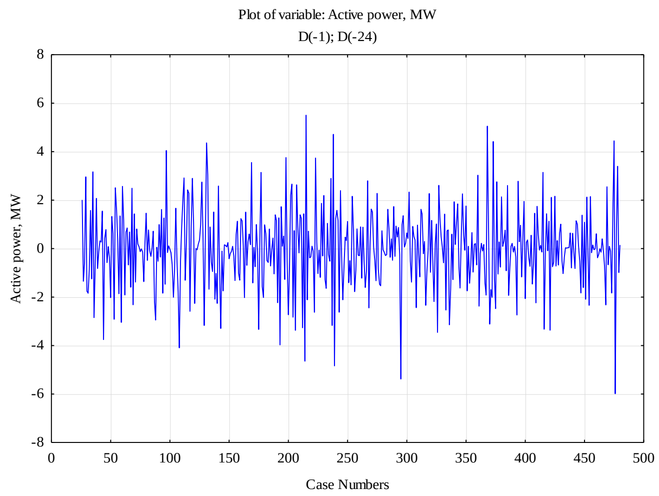


Figure 18. The smoothed data of active power for a day-ahead forecasting of electricity consumption

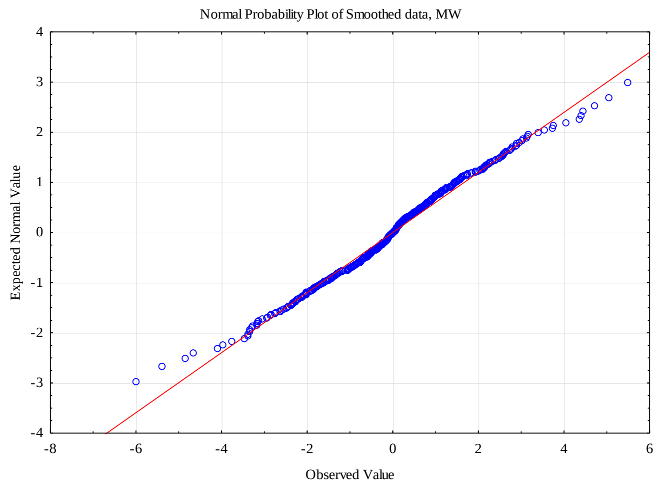
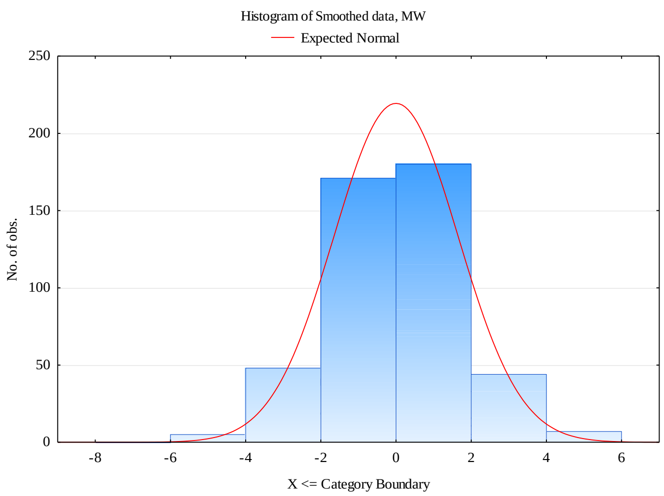


Figure 19. Normal quantile-quantile plot of active power after smoothing for a day-ahead forecasting of electricity consumption



Note: number of bins is 10.

Figure 20. Empirical and fitted normal distributions of active power after smoothing for a day-ahead forecasting of electricity consumption

The value of the Kolmogorov-Smirnov test is 0.05167, with corresponding *p*-value < 0.2. The Kolmogorov-Smirnov test does not reject the null hypothesis of univariate normality of initial dataset [9].

Analyzing Normal quantile-quantile plot I can tell the time series almost coincides with the straight-line value, and the experimental distribution is close to the expected normal distribution.

Next, ARIMA model (1, 1, 1) (1, 1, 1) was performed using Statistica software. *p*, *P*, *q*, *Q* were determined earlier, as well as the order of difference and seasonality. The parameters of the ARIMA (1, 1, 1) (1, 1, 1) model are presented in Table 3. The sequence of forecasting by ARIMA (1, 1, 1) (1, 1, 1) model in Statistica software is presented in Appendix A.11.

Table 3. Parameters of ARIMA (1, 1, 1) (1, 1, 1) model

Parametr	Transformations: $D(1)$, $D(24)$ Model:(1, 1, 1)(1, 1, 1) Seasonal lag: 24 MS Residual = 1.3395					
	Parametr	**Asymptote**	**Asymptote**	**p**	**Lower**	**Upper**
$p(1)$	0.231437	0.095397	2.42605	0.015655	0.043960	0.418915
$q(1)$	0.692361	0.074374	9.30915	0.000000	0.546198	0.838524
$P(1)$	0.019565	0.054965	0.35596	0.722040	-0.088454	0.127585
$Q(1)$	0.891949	0.025357	35.17602	0.000000	0.842117	0.941781

I can conclude that the coefficients $p(1)$, $q(1)$, $Q(1)$ are significant because they are greater than 10% [21]. The equation of the model is as follows:

$$(1-0.23B)(1-B)(1-B^{24})y_t = (1+0.69B)(1+0.89B^{24})\varepsilon_t$$

Next, I forecast electricity consumption for the day-ahead based on ARIMA (1, 1, 1,) (1, 1, 1) model for 24 hours. The forecast is prepared for November 8, 2016, from 00:00 to 23:00. And I have also plotted a graph to compare the initial dataset to the forecast electricity consumption values. The initial dataset and the forecast electricity consumption of the ARIMA model (1, 1, 1) (1, 1, 1) are presented in Figure 21. The sequence of electricity consumption forecast by ARIMA model (1, 1, 1) (1, 1, 1) in Statistica software is presented in Appendix A.12. The forecast and initial dataset of electricity consumption from ARIMA (1, 1, 1) (1, 1, 1) model are presented in Appendix B.5.

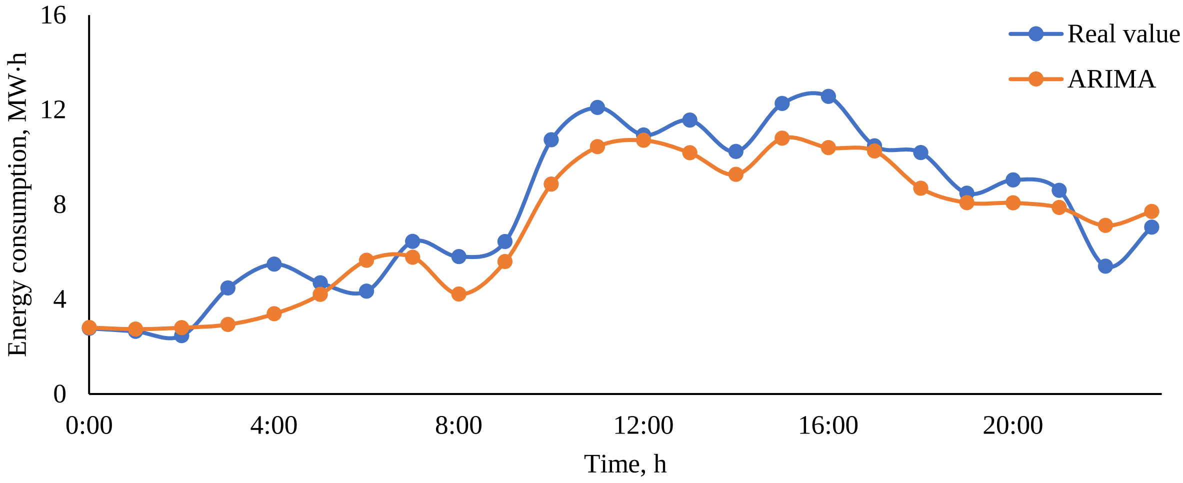


Figure 21. Day-ahead electricity consumption forecast from ARIMA (1, 1, 1) (1, 1, 1)

The accuracy of the electricity consumption forecast was estimated from the residual's distribution histogram presented in Figure 22, the normal quantile-quantile residuals diagram presented in Figure 23 and the correlogram for the residuals presented in Figure 24. The sequence of plotting is the same as in Appendices A.1., A.8., A.9. The parameters of the correlogram for the residuals are presented in Appendix B.6.

Optimal number of bins is determined by Sturges' rule according to (1) [8]

$$k = 1 + 3.322 \cdot \log(n) = 1 + 3.322 \cdot \log(244) \approx 6$$

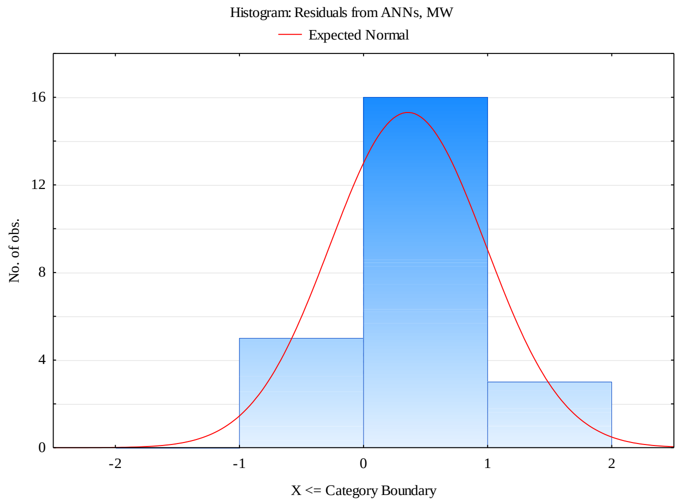


Figure 22. Histogram of residuals for day-ahead forecast of electricity consumption from ARIMA (1,1,1) (1,1,1) and fitted normal distribution

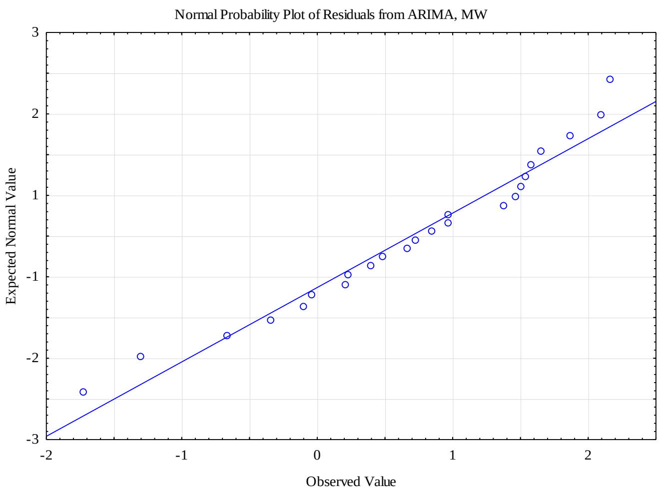


Figure 23. Normal quantile-quantile plot of residuals for day-ahead forecast of electricity consumption from ARIMA (1,1,1) (1,1,1)

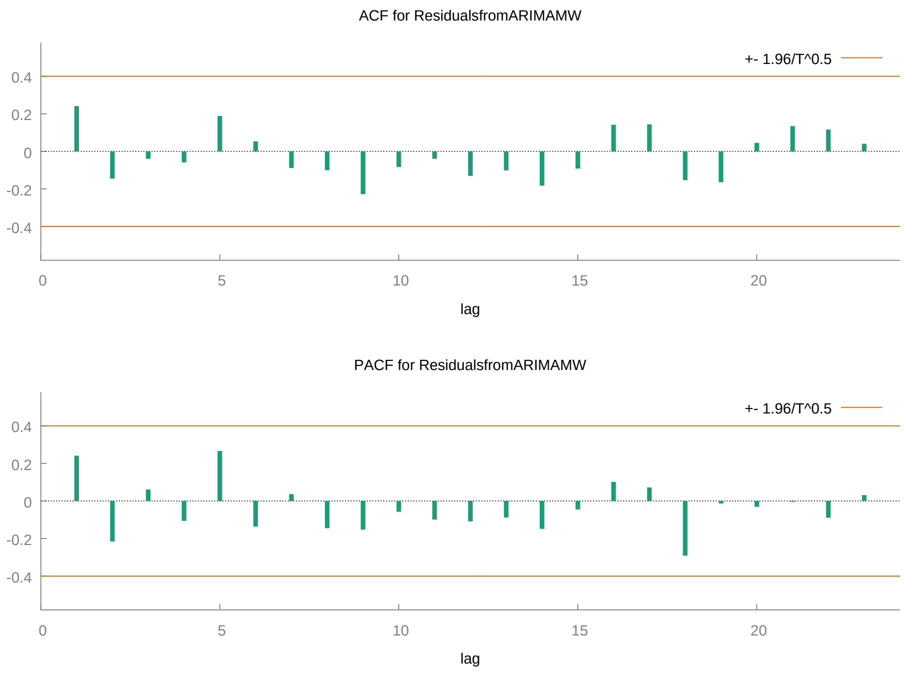


Figure 24. Correlogram for residuals for a daily forecasting of electricity consumption from ARIMA (1,1,1) (1,1,1)

The value of the Kolmogorov-Smirnov test is 0. 16167, with corresponding p-value < 0.15. The Kolmogorov-Smirnov test does not reject the null hypothesis of univariate normality of initial dataset [9].

Analyzing the correlogram, I can identify that the residuals are almost within the confidence limit. Analyzing Normal quantile-quantile plot I can tell the time series almost coincides with the straight-line value, and the experimental distribution is close to the expected normal distribution. So, the residuals are normal, it means that my assumption is valid and model inference (confidence intervals, model forecasting) is valid.

Then forecasts of electricity consumption for week-ahead was made. The actual dataset of electricity consumption of the enterprise for 20 weeks (14.05.16–07.10.16) is used to forecast electricity consumption for week-ahead. Electricity consumption forecasts are performed using the same method as the day-ahead electricity consumption forecast. All necessary graphs are presented in Appendices A.13–A.22 (electricity consumption forecast for the week-ahead). Analyzing the residuals, I can say the forecasting models were correct.

4.1.2. Artificial Neural Networks Method

Hourly forecasts of electricity consumption are reviewed in this section. The hourly load of the enterprise is presented as the initial dataset for day-ahead electricity consumption forecast. Initial data for a day-ahead electricity consumption forecast from ARIMA is presented in Appendix B.1.

I assume the variable is continuous, so the analysis is performed using time series (regression). The Radial Basis Functions are appropriate for time series forecasting, but they are less accurate and have more required input parameters compared to MLP. Therefore, a Multilayer Perceptron is used to forecast electricity consumption.

The initial dataset is divided into three groups: the training sample, which is 85% of the total sample; the test sample is equal to 15% of the initial sample and the validation sample is equal to 0% of the initial sample. The period of power consumption is 24 hours, determined by the ACF and periodogram in the previous section. The sequence of forecasting by ANN model in Statistica software is presented in Appendix A.23.

The training dataset is used to fit model parameters (e.g., weights of connections between neurons in Artificial Neural Networks). Validation dataset provides evaluation of model correspondence on the training dataset when configuring model hyperparameters (e.g., number of hidden layers). The validation dataset to detect overtraining during the training phases. The test dataset is used to evaluate the final fit of the model on the training dataset.

After the completion of MLP training, the best network in terms of performance (correlation value between the initial series and the forecasted series) was selected. The parameters of the chosen model are presented in Table 4. After selecting the most efficient electricity consumption forecast model, a time series projection spreadsheet was prepared, i.e., each value of the forecasted time series is based on the previous value of that series.

Table 4. The parameters of the ANN model

Network name	MLP 24–313–1	Output activation	Logistic	Training performance	0.938	Training error	0.541
Training algorithm	BFGS 39	Hidden activation	Logistic	Test performance	0.956	Test error	0.475
Error function				SS			

Network name is a type of network selected (MLP 24–313–1):

- MLP is topology of ANN (MLP or RBF);

- 24 is number of time steps used as inputs;
- 313–1 are two hidden layers of 313 and 1 neuron in layers.

BFGS 39 is optimization method (named after the scientists who created this method: Broyden–Fletcher–Goldfarb–Shanno algorithm), 39 is the number of cycles for determining the best network [22].

Error function is Sum of Squares (SS).

Figure 25 illustrates a comparison of the resulting forecast electricity consumption values with the real values.

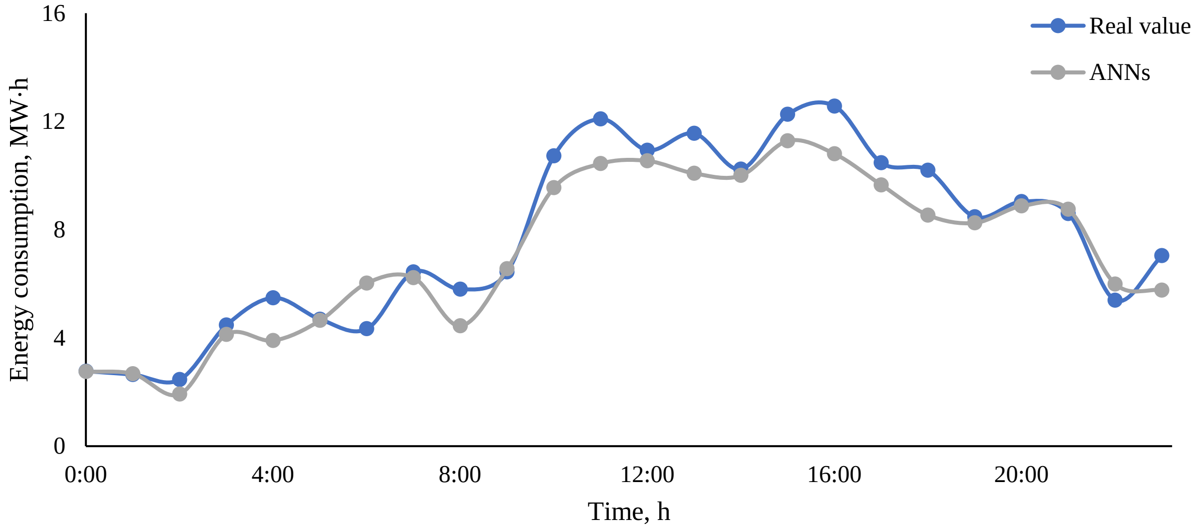


Figure 25. Day-ahead electricity consumption forecast from ANN and initial value of electricity consumption

Training, validation and test errors are the calculated error value for the training validation and test samples. The training error is smaller than the validation error, because the main objective is to reduce the output error of the network. The validation performance of this model was 94%, which is quite a high value.

The accuracy of the electricity consumption forecast was estimated from the residual's distribution histogram presented in Figure 26, the normal quantile-quantile residuals diagram presented in Figure 27 and the correlogram for the residuals presented in Figure 28. The sequence of plotting is the same as in Appendices A.1., A.8., A.9. The parameters of the correlogram for the residuals are presented in Appendix B.9.

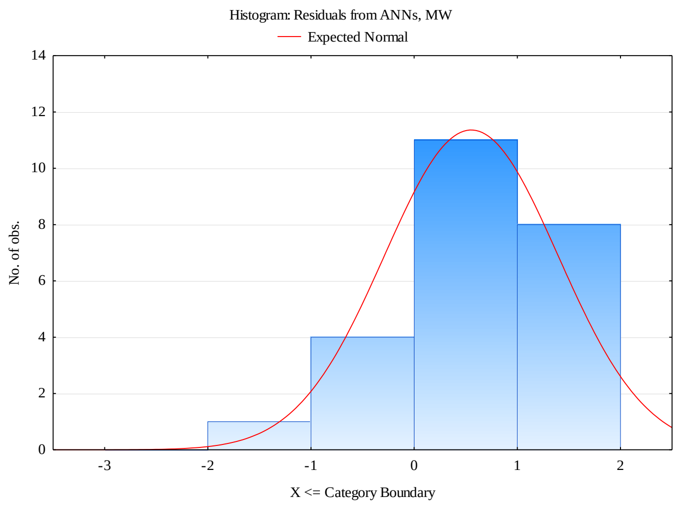


Figure 26. Histogram of residuals for day-ahead forecast of electricity consumption from ANN and fitted normal distribution

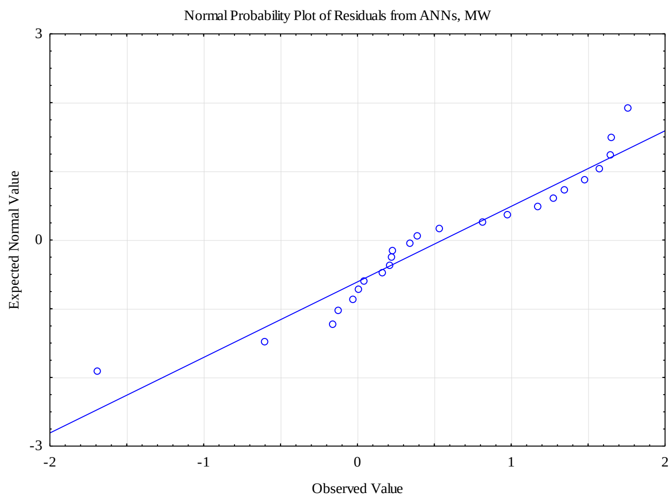


Figure 27. Normal quantile-quantile plot of residuals for day-ahead forecast of electricity consumption from ANN

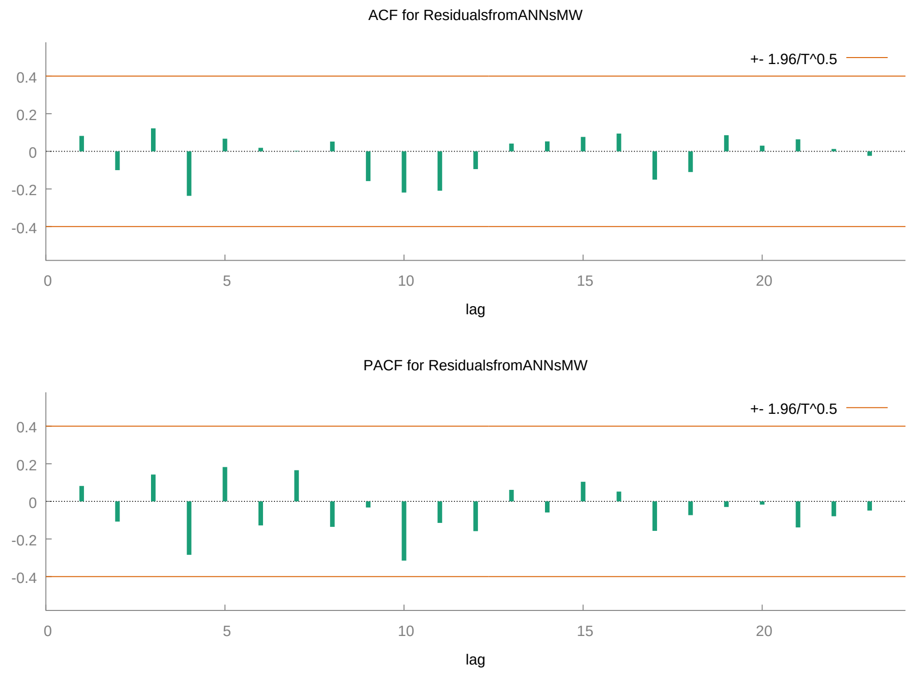


Figure 28. Correlogram for residuals for week-ahead forecast of electricity consumption from ANN

The value of the Kolmogorov-Smirnov test is 0.11822, with corresponding *p*-value > 0.2. The Kolmogorov-Smirnov test does not reject the null hypothesis of univariate normality of initial dataset [9].

Analyzing the correlogram, I can identify that the residuals are almost within the confidence limit. Analyzing Normal quantile-quantile plot I can tell the time series almost coincides with the straight-line value, and the experimental distribution is close to the expected normal distribution. So, the residuals are normal, it means that my assumption is valid and model inference (confidence intervals, model forecasting) is valid.

Then forecasts of electricity consumption for week-ahead was made. The actual dataset of electricity consumption of the enterprise for 20 weeks (14.05.16–07.10.16) is used to forecast electricity consumption for week-ahead. Electricity consumption forecasts are performed using the same method as the day-ahead electricity consumption forecast. All necessary graphs are presented in Appendices A.24–A.27; B.8. (electricity consumption forecast for the week-ahead). Analyzing the residuals, I can say the forecasting models were correct.

4.2. Mid-Term Forecasting

Multifactor forecasting allows considering a larger number of factors impacting the final result. The amount of energy consumed is influenced by the quantity of products produced. For the forecast, I used regression estimation with the help of the Classification and Regression Tree (CART). The initial dataset on the consumed power, the number of heats, and the volume of the casting products are presented in an aggregated form. Presentation of information in this way allows resolving an issue of short-term term fluctuation due to, for example, weekly periodicity. The initial dataset is presented in monthly form. The parameters used to analyze the dataset and forecast electricity consumption are presented in Table 5. "Power Consumed, GW" is used as the dependent variable and the continuous factors are: "Casting from gray cast iron - 15, t", "Casting from pig iron, t", "Centrifugal casting, t", "Number of heats". To forecast electricity consumption, 12 months of 2016 were implemented. A Classification and Regression Trees were prepared based on the initial dataset. Next, assume that enterprise has a production plan for the year-ahead, presented as values by month. Based on this plan and the CART model, a monthly forecast of electricity consumption for the year-ahead is prepared.

The sequence of forecasting by CART model in Statistica software is presented in Appendix A.28. 11 Classification and Regression Trees were prepared using Statistica software. Next, the best tree was determined using multiple V-block cross-validation. The sequence of cross-validation in Statistica software is presented in Appendix A.29. The parameters of the trees are presented in Table 6.

When preparing the models, it was determined that Tree 1 is overtrained, because the standard error of Cross-validation is practically the highest of all errors, and the classification is extremely detailed (many nodes). If the dataset is so detailed, outliers can be mistaken for patterns therefore the analysis of the new dataset can fail. It is necessary to select such an able tree to take into account this information, i.e., to be complicated enough, and on the other hand, should be simple. Statistica software was operated to determine the most efficient tree. Tree 5 was chosen for further forecasting because it has a sufficient number of nodes and the standard error of cross-validation is smaller than other trees with more nodes. This tree is presented in Table 7 and Figure 29.

Table 5. Input dataset

Month	Consumed active power, GW	Casting from gray cast iron - 15, t	Casting from pig iron, t	Centrifugal casting, t	Number of heats
31.01.2016	4.482	436.600	1020.600	1812.800	341.000
29.02.2016	4.819	610.900	940.730	2020.010	383.000
31.03.2016	3.871	452.900	558.490	1525.000	341.000
30.04.2016	4.230	619.500	961.600	2247.300	401.000
31.05.2016	4.384	662.400	1102.760	2392.300	419.000
30.06.2016	3.982	641.200	951.280	2258.900	404.000
31.07.2016	4.108	575.400	1019.000	2125.700	391.000
31.08.2016	4.368	648.600	1010.910	2338.010	420.000
30.09.2016	3.563	554.300	261.450	1322.170	225.000
31.10.2016	4.735	720.300	216.600	1564.760	264.000
30.11.2016	4.554	642.600	209.200	1514.100	247.000
31.12.2016	4.627	661.800	153.000	1513.470	264.000
Total	51.722	7226.500	8405.620	22634.520	4100.000

Table 6. Parameters of the trees

	Terminal nodes	Cross-validation cost	Cross-validation standard error	Resubstitution cost	Node complexity
Tree 1	12	0.279328	0.112904	0.000000	0.000000
Tree 2	11	0.279859	0.112854	0.000011	0.000011
Tree 3	10	0.284371	0.113018	0.000232	0.000221
Tree 4	9	0.291034	0.115925	0.000851	0.000619
Tree 5	8	0.269491	0.102739	0.002021	0.001171
Tree 6	7	0.277465	0.104536	0.003955	0.001933
Tree 7	6	0.295918	0.107484	0.008686	0.004732
Tree 8	5	0.312343	0.116784	0.015947	0.007261
Tree 9	3	0.343853	0.112421	0.054626	0.019339
Tree 10	2	0.270410	0.073615	0.077936	0.023310
Tree 11	1	0.153733	0.052518	0.128653	0.050717

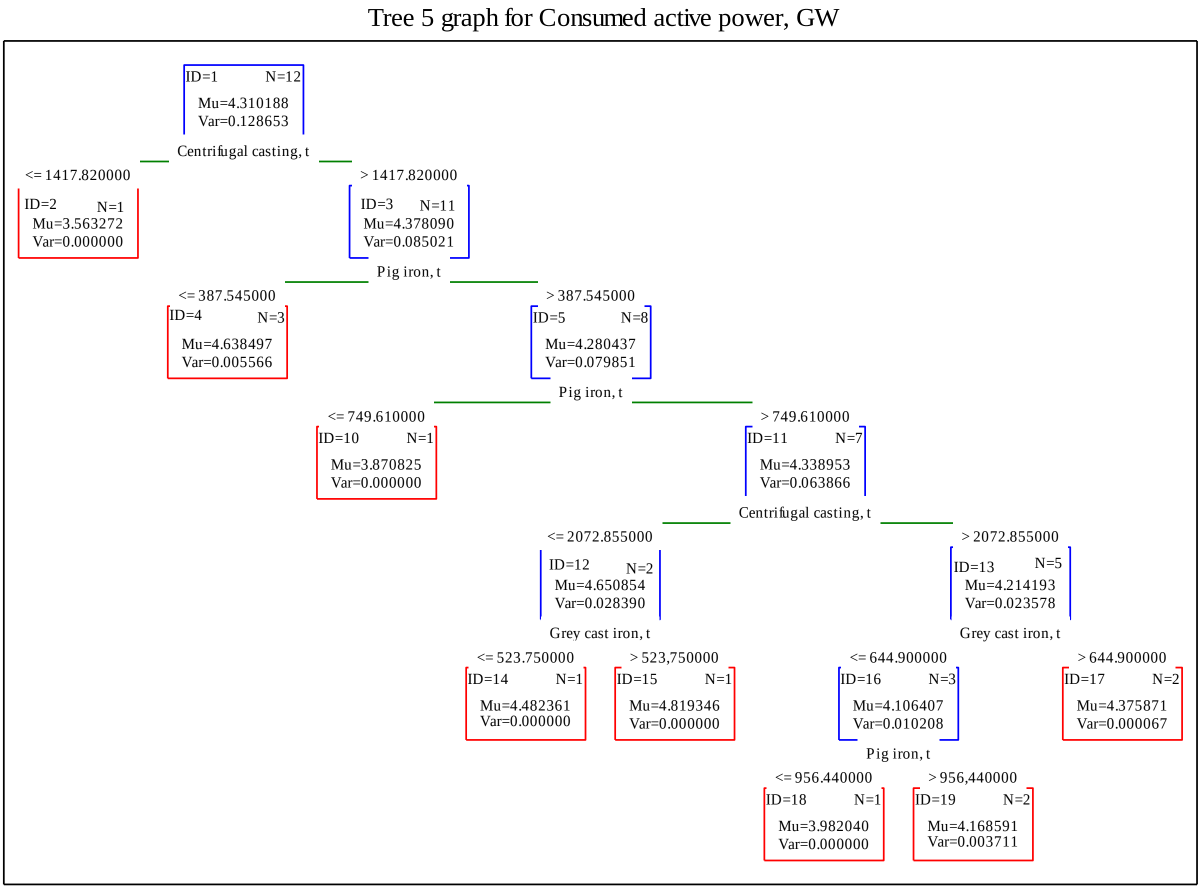


Figure 29. Classification Tree 6

Table 7. Classification Tree 6

Node	Left branch	Right branch	Size of node	Node mean	Node variance	Split variable	Split constant
1	2	3	12	4.310188	0.128653	Centrifugal casting, t	1417.820
2			1	3.563272	0.000000		
3	4	5	11	4.378090	0.085021	Pig iron, t	387.545
4			3	4.638497	0.005566		
5	10	11	8	4.280437	0.079851	Pig iron, t	749.610
10			1	3.870825	0.000000		
11	12	13	7	4.338953	0.063866	Centrifugal casting, t	2072.855
12	14	15	2	4.650854	0.028390	Grey cast iron, t	523.750
14			1	4.482361	0.000000		
15			1	4.819346	0.000000		
13	16	17	5	4.214193	0.023578	Grey cast iron, t	644.900
16	18	19	3	4.106407	0.010208	Pig iron, t	956.440
18			1	3.982040	0.000000		
19			2	4.168591	0.003711		
17			2	4.375872	0.000067		

The results included the following datasets:

1. If the output volume of centrifugal casting, t > 1417.820, pig iron, t > 387.545, pig iron, t > 749.610, centrifugal casting, t > 2072.855, grey cast iron, t <= 644.900 and pig iron, t > 956.440, then consumed active power, GW = 4.169 (number of points is 2);
2. If the output volume of centrifugal casting, t > 1417.820, pig iron, t > 387.545, pig iron, t > 749.610, centrifugal casting, t > 2072.855, grey cast iron, t <= 644.900 and pig iron, t <= 956.440, then consumed active power, GW = 3.982 (number of points is 1);
3. If the output volume of centrifugal casting, t > 1417.820, pig iron, t > 387.545, pig iron, t > 749.610, centrifugal casting, t > 2072.855 and grey cast iron, t > 644.900, then consumed active power, GW = 4.375 (number of points is 2);
4. If the output volume of centrifugal casting, t > 1417.820, pig iron, t > 387.545, pig iron, t > 749.610, centrifugal casting, t <= 2072.855 and grey cast iron, t > 523.750, then consumed active power, GW = 4.819 (number of points is 1);
5. If the output volume of centrifugal casting, t > 1417.820, pig iron, t > 387.545, pig iron, t > 749.610, centrifugal casting, t <= 2072.855 and grey cast iron, t <= 523.750, then consumed active power, GW = 4.482 (number of points is 1);
6. If the output volume of centrifugal casting, t > 1417.820, pig iron, t > 387.545 and pig iron, t <= 749.610, then consumed active power, GW = 3.871 (number of points is 1);

7. If the output volume of centrifugal casting, t > 1417.820 and pig iron, t <= 387.545 then consumed active power, GW = 4.638 (number of points is 3);
8. If the output volume of centrifugal casting, t <= 1417.820 and pig iron, then consumed active power, GW = 3.563 (number of points is 1);

Then, forecast of electricity consumption for the next year, in monthly form, can be prepared using this tree, as well as the production plan, from Excel. The results are presented in Figure 30. The accuracy of the electricity consumption forecast was estimated from the residual's distribution histogram presented in Figure 31, the normal quantile-quantile residuals diagram presented in Figure 32 and the correlogram for the residuals presented in Figure 33. The sequence of plotting is the same as in Appendices A.1., A.8., A.9. The parameters of the correlogram for the residuals are presented in Appendix B.9. The forecast was evaluated on 12 observations. Also, Figure 34 allows to determine the most important parameters that contribute to electricity consumption.

The formula for preparing forecast:

= IFS(Centrifugal casting, t <= 1417.82; 3.56; AND(Centrifugal casting, t > 1417.82; Casting from pig iron, t <= 387.55); 4.64; AND(Centrifugal casting, t > 1417.82; Casting from pig iron, t > 387.55; Casting from pig iron, t <= 749.61); 3.87; AND(Centrifugal casting, t > 1417.82; Casting from pig iron, t > 387.55; Casting from pig iron, t > 749.61; Centrifugal casting, t <= 2072.86; Casting from gray cast iron - 15, t <= 523.75); 4.48; AND(Centrifugal casting, t > 1417.82; Casting from pig iron, t > 387.55; Casting from pig iron, t > 749.61; Centrifugal casting, t <= 2072.86; Casting from gray cast iron - 15, t > 523.75); 4.82; AND(Centrifugal casting, t > 1417.82; Casting from pig iron, t > 387.55; Casting from pig iron, t > 749.61; Centrifugal casting, t >2072.86; Casting from gray cast iron - 15, t <= 644.90); 4.11; AND(Centrifugal casting, t > 1417.82; Casting from pig iron, t > 387.55; Casting from pig iron, t > 749.61; Centrifugal casting, t >2072.86; Casting from gray cast iron - 15, t > 644.90; Casting from pig iron, t <= 956.44); 3.98; AND(Centrifugal casting, t > 1417.82; Casting from pig iron, t > 387.55; Casting from pig iron, t > 749.61; Centrifugal casting, t >2072.86; Casting from gray cast iron - 15, t > 644.90; Casting from pig iron, t > 956.44); 4.17)

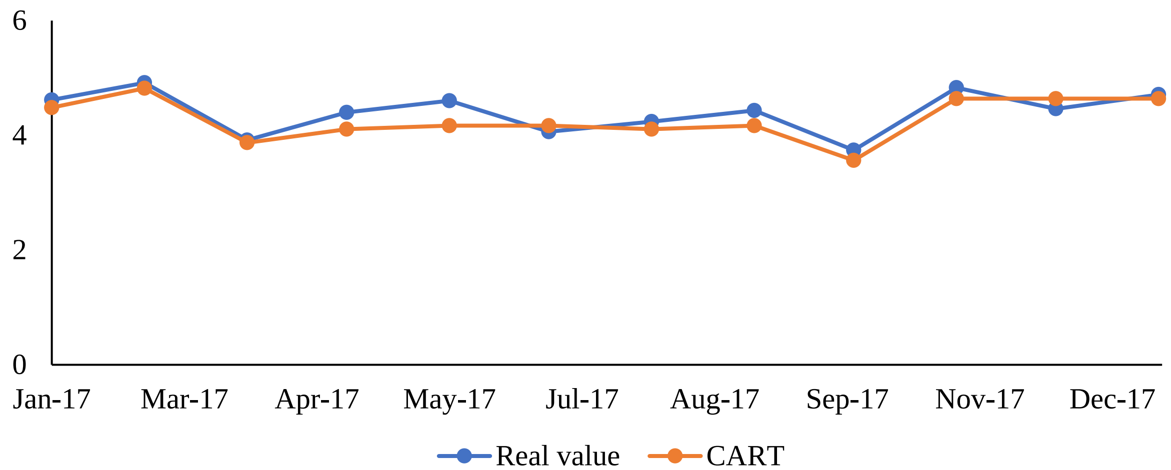


Figure 30. Actual and forecasted consumption of active power for year-ahead by CART method

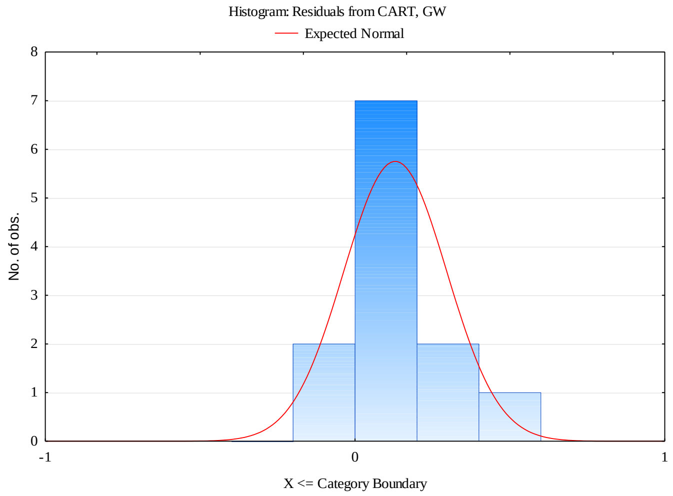


Figure 31. Histogram of residuals from CART and fitted normal distribution

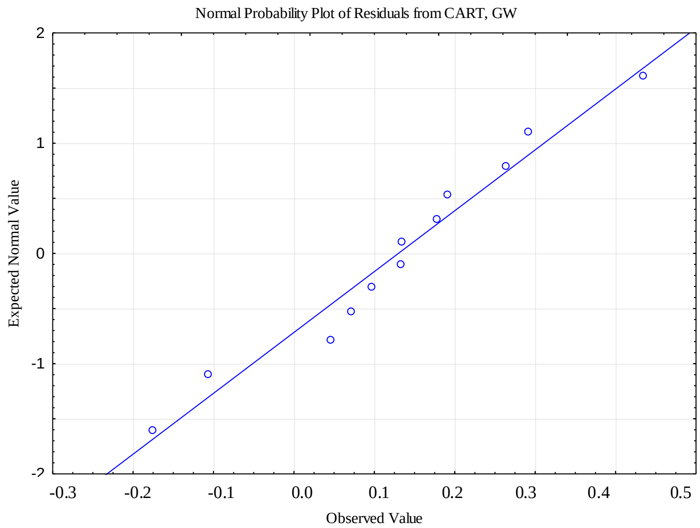


Figure 32. Normal quantile-quantile plot of residuals from CART

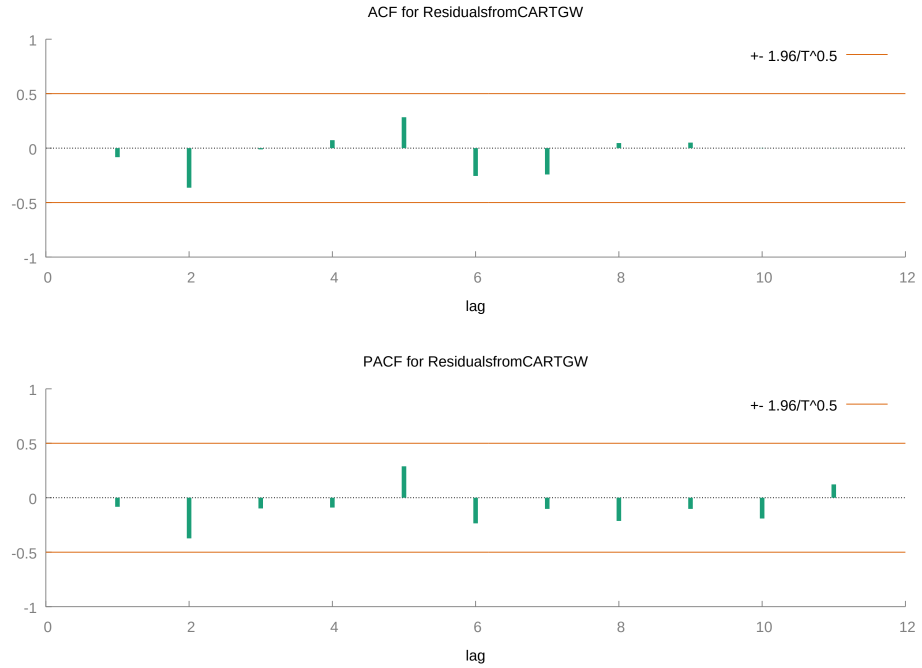


Figure 33. Correlogram for residuals for a daily forecasting of electricity consumption from CART

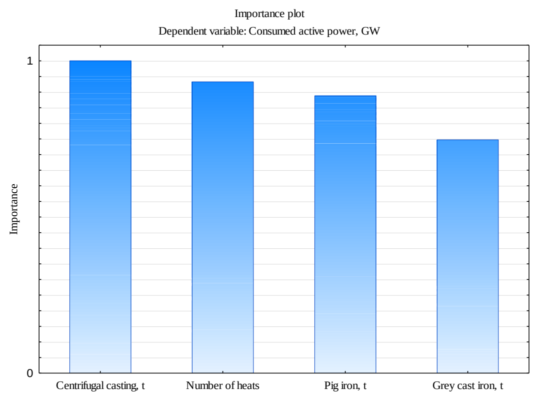


Figure 34. Parameter distribution according to importance

The value of the Kolmogorov-Smirnov test is 0.14119, with corresponding *p*-value > 0.2. The Kolmogorov-Smirnov test does not reject the null hypothesis of univariate normality of initial dataset [9].

Analyzing the correlogram, I can identify that the residuals are almost within the confidence limit. Analyzing Normal quantile-quantile plot I can tell the time series almost coincides with the straight-line value, and the experimental distribution is close to the expected normal distribution. So, the residuals are normal, it means that my assumption is valid and model inference (confidence intervals, model forecasting) is valid.

5. Evaluation of Forecast Performance

Accuracy forecast of electricity consumption is an essential aspect. The accuracy of forecasts affects the cost of electricity. For this purpose, I used a measure of forecast performance, called the forecast percentage error. In this chapter, you can identify the results of comparing the performance of the forecasts of electricity consumption. The evaluation of forecast performance is performed based on the following models: ARIMA, ANN, CART.

5.1. Mean Absolute Error

The Mean Absolute Error (MAE) measures the average value of errors in the forecast set (average absolute values of individual forecast errors for all items in the test set) regardless of their direction. It measures precision for continuous variables [23].

The equation of MAE according to [24] and presents below (34):

$$MAE = \frac{1}{T} \cdot \sum_{t=1}^{T} \left| X_t - \hat{X}_t \right| \tag{34}$$

where X_t is the true value in time period t;

$\hat{X}_t$ is the forecasting value in time period t;

T is the number of periods in out-of-sample forecasting;

t is time period.

In other words, MAE is the average of a test sample of absolute values of differences between forecast and the corresponding supervision. MAE is a linear estimate, which illustrates that all the individual differences in the average are weighted equally [23].

5.2. Mean Squared Error

Mean Squared Error (MAE) is a model evaluation metric which is often used with regression models. A model mean square error in relation to a set of tests is the average of forecast error squares for all instances in a set of tests. Forecast error is the difference between a true value and forecasted value for an instance [23].

The equation of MSE according to [24] and presents below (35):

$$MSE = \frac{1}{T} \cdot \sum_{t=1}^{T} \left(X_t - \hat{X}_t \right)^2 \tag{35}$$

where X_t is the true value in time period t;

$\hat{X}_t$ is the forecasting value in time period t;

T is the number of periods in out-of-sample forecasting;

t is time period.

MSE is sensitive to outliers, and given several examples with the same attributes input values, the best forecast would be mean target value. This should be compared to MAE where the optimal forecast is the median. Thus, MSE is good to use if the target dataset resulting from the input dataset is usually distributed around the mean value and when it is important to severely punish the emissions [23].

MAE values or MSE values, a more accurate forecast model; conversely, the higher the value, the more inaccurate the model. The main drawback of MAE and MSE forecasting values is that they do not take into account the value of actual values [23].

5.3. Mean Absolute Percent Error

The Mean Absolute Percentage Error (MAPE) is the average or average of absolute percentage error forecasts. The error is determined as an actual (observable) value minus forecast value. The error percentage is summed up without the sign for MAPE calculation [25].

The equation of MAPE according to [24] and presents below (36):

$$MAPE = \frac{1}{T} \cdot \sum_{t=1}^{T} \left| \frac{X_t - \hat{X}_t}{X_t} \right| \cdot 100\% \tag{36}$$

where X_t is the true value in time period t;

$\hat{X}_t$ is the forecasting value in time period t;

T is the number of periods in out-of-sample forecasting;

t is time period.

As with the MAE and MSE performance metrics, the lower the MAPE, the more precise the forecast model is. The scale for estimating the accuracy of the model on the basis of MAPE was developed by Lewis and is presented in Table 8. MAPE, the value and application of the Lewis scale, provides some basis for model evaluation. But depending on the dataset, whether there is a significant trend or seasonal component, MAPE may underestimate or overestimate the model's accuracy [25].

Table 8. A scale of judgment of forecast accuracy [25]

MAPE	Judgment of Forecast Accuracy	MAPE	Judgment of Forecast Accuracy
Less than 10%	Highly accurate	21% to 50%	Reasonable forecast
11% to 20%	Good forecast	51% or more	Inaccurate forecast

5.4. Mean Absolute Scaled Error

Mean Absolute Scaled Error (MASE) is a scaleless error metric that provides each error as a ratio to the base line average error [26].

The equation of MASE according to [24] and presents below (37):

$$MASE = \frac{\frac{1}{T} \cdot \sum_{t=1}^{T} \left| X_t - \hat{X}_t \right|}{\frac{1}{T-1} \cdot \sum_{t=2}^{T} \left| X_t - X_{t-1} \right|} \tag{37}$$

where X_t is the true value in time period t;

$\hat{X}_t$ is the forecasting value in time period t;

T is the number of periods in out-of-sample forecasting;

t is time period.

The advantage of MASE is that it never gives undefined or infinite values and is therefore a good choice for intermittent demand series (which occur when there are periods of zero demand in the forecast). It can be used for a single series or as a tool to compare multiple series [26].

5.5. Root Mean Square Error

Root Mean Square Error (RMSE) is the standard deviation of residues (forecast errors). Residues are a measure of how far from the dataset points of the regression line; RMSE is a measure of how far these residues are scattered. It shows how much dataset is concentrated around the best fit line [23].

The equation of RMSE according to [24] and presents below (38):

$$RMSE = \sqrt{\frac{1}{T} \cdot \sum_{t=1}^{T} \left(X_t - \hat{X}_t \right)^2} \tag{38}$$

where X_t is the true value in time period t;

$\hat{X}_t$ is the forecasting value in time period t;

T is the number of periods in out-of-sample forecasting;

t is time period.

The difference between the forecast and the observed values is erected in a square and then averaged in the sample. Finally, the square root is extracted from the average. Since errors are squared before averaging, RMSE gives relatively high weight to large errors. This means that RMSE is most useful when large errors are particularly undesirable [23].

5.6. Calculating of forecast error

After preparing the forecasts of electricity consumption with ARIMA, ANN and CART, the following key performance indicators were calculated: Mean Absolute Error, Mean Squared Error, Mean Absolute Percentage Error, Mean Absolute Scaled Error, Root Mean Square Error. The analysis of these indicators allows us to evaluate which model is the best. The results are also estimated based on the length of the obtained results, i.e., how the values change depending on the size of the model (24 observations or 168 observations). Table 9 presents the Key Performance Indicators for each model.

Table 9. Key Performance Indicators

Type of forecast model	Length of forecast model	Model	Key Performance Indicators				
			MAE	MSE	MAPE, %	MASE	RMSE
Short-term electricity consumption forecast	Day-ahead forecast	ARIMA (1,1,1) (1,1,1)	1.04	1.49	14.51	0.83	1.22
		ANN	**0.77**	**0.99**	**10.54**	**0.49**	**0.99**
	Week-ahead forecast	ARIMA (1,1,1) (1,1,1)	1.51	3.33	31.18	1.36	1.82
		ANN	**0.95**	**1.41**	**15.57**	**0.86**	**1.19**
Mid-term electricity consumption forecast	Month-ahead forecast	**CART**	**0.18**	**0.04**	**3.98**	**0.04**	**0.21**

Example of calculation of the MAE for ARIMA (1,1,1) (1,1,1):

$$MAE = \frac{1}{24} \cdot \left(|2.769 - 2.805| + |2.643 - 2.739| + |2.461 - 2.800| + ... + |7.039 - 7.704| \right) = \frac{24.907}{24} = 1.038$$

Example of calculation of the MSE for ARIMA (1,1,1) (1,1,1):

$$MSE = \frac{1}{24} \cdot \left((2.769 - 2.805)^2 + (2.643 - 2.739)^2 + (2.461 - 2.800)^2 + ... + (7.039 - 7.704)^2 \right) = 1.491$$

Example of calculation of the MAPE for ARIMA (1,1,1) (1,1,1):

$$MAPE = \frac{1}{24} \cdot \begin{pmatrix} \left| \frac{2.769 - 2.805}{2.769} \right| \cdot 100\% + \left| \frac{2.643 - 2.739}{2.643} \right| \cdot 100\% + \\ + \left| \frac{2.461 - 2.800}{2.461} \right| \cdot 100\% + ... + \left| \frac{7.039 - 7.704}{7.039} \right| \cdot 100\% \end{pmatrix} = \frac{348.27}{24} = 14.511\%$$

Example of calculation of the MASE for ARIMA (1,1,1) (1,1,1):

$$MASE = \frac{\frac{1}{24} \cdot \left(|2.769 - 2.805| + |2.643 - 2.739| + |2.461 - 2.800| + ... + |7.039 - 7.704| \right)}{\frac{1}{23} \cdot \left(|2.643 - 2.769| + |2.461 - 2.643| + |4.473 - 2.461| + ... + |5.391 - 7.039| \right)} = \frac{1.256}{1.038} = 0.826$$

Example of calculation of the RMSE for ARIMA (1,1,1) (1,1,1):

$$RMSE = \sqrt{\frac{1}{24} \cdot \left((2.769 - 2.805)^2 + (2.643 - 2.739)^2 + (2.461 - 2.800)^2 + ... + (7.039 - 7.704)^2 \right)} = \sqrt{\frac{35.78}{24}} = 1.221$$

The most interpretable indicator is MAPE because it defines a percentage. It allows a more straightforward determination of the accuracy of the model. Analyzing the indicators, ANN models are more accurate. The length of the model also affects the accuracy of the forecast of electricity consumption. I can conclude that the forecast error increases when the length of the model increases. I can additionally note that the forecast of electricity consumption using the CART model proved to be the most accurate.

6. Impact of Forecasting Performance on Electricity Cost

The cost of electricity per day will be determined by the formula according to [27] and presents bellow (39):

$$C_e = \sum_{t=1}^{24} W_t \cdot C_t + \frac{P_p \cdot C_p}{N} + \frac{P_{max} \cdot C_{max}}{N} + \sum_{t=1}^{24} W_t \cdot C_{t,others} + \sum_{t=1}^{24} W_t^+ \cdot C_{t,retail}^+ + \sum_{t=1}^{24} W_t^- \cdot C_{t,retail}^- + \\ + \sum_{i=1}^{24} W_i^- \cdot C_t^+ + \sum_{t=1}^{24} W_t^+ \cdot C_t^+ + \sum_{t=1}^{24} W_t^- \cdot C_t^- \to \min \tag{39}$$

where t is time period;

W_t is energy consumption per hour, MWh;

C_t is cost of electricity per hour, $\frac{\mathrm{EUR}}{\mathrm{MWh}}$;

N is number of hours in the month;

P_p is power paid on the WMEP (the peak load power), MWh;

C_p is cost of electricity purchased by the consumer at the regulated electricity price per month, $\frac{\mathrm{EUR}}{\mathrm{MWh}}$;

P_{max} is power paid by the consumer as the power consumed for energy transmission services, MW (determined as the maximum power from the planned peak load hours approved by the System Operator of the Unified Power System, depending on the price zone of the consumer), MWh;

C_{max} is cost of power consumed for energy transmission services per month, $\frac{\mathrm{EUR}}{\mathrm{MWh}}$;

$C_{t,others}$ – Payment for other services that are integral part of the electricity and capacity supply process for the billing period, $\frac{\mathrm{EUR}}{\mathrm{MWh}}$;

W_t^+ is the increase of the actual electric energy capacity on the planned capacity, MWh;

$C_{t,retail}^+$ is the retail markup differentiated in hours of the account period, which is applied to the non-regulated electricity price on WMEP determined based on the results of the competitive procedure of selecting bids for system balancing in regard to the increase of the actual electric energy capacity on the planned capacity, $\frac{\mathrm{EUR}}{\mathrm{MWh}}$;

W_t^- is the increase of the planned electric energy capacity on the actual capacity, MWh;

$C_{t,retail}^-$ is the retail markup differentiated in hours of the account period, which is applied to the non-regulated electricity price on WMEP determined based on the results of the competitive procedure of selecting bids for system balancing in regard to the increase of the planned electric energy capacity on the actual capacity, $\frac{\mathrm{EUR}}{\mathrm{MWh}}$;

C_t^+ is the non-regulated electricity price on WMEP differentiated in hours of the account period, which is determined by the commercial operator of the wholesale market based on the results of the competitive procedure of selecting bids for system balancing in regard to the increase of the actual electric energy capacity on the planned capacity per hour (t) of the account period, $\frac{\text{EUR}}{\text{MWh}}$;

C_t^- is the non-regulated electricity price on WMEP differentiated in hours of the account period, which is determined by the commercial operator of the wholesale market based on the results of the competitive procedure of selecting bids for system balancing in regard to the increase of the planned electric energy capacity on the actual capacity per hour (t) of the account period, $\frac{\text{EUR}}{\text{MWh}}$.

Analyzing the formula (36), I can conclude that any deviation of the forecasted value of electricity consumption from the actual value results in a loss for the enterprise. Therefore, one of the objectives was reducing the relative error and, as a result, the overpayments.

The next step involved calculating the electricity purchase costs for the forecasts produced by ARIMA and ANN using the formula (39). Forecast models with various relative errors were used to determine the value of cost reductions when the error is decreased. Two forecast models were used for the comparison: ARIMA (1,1,1) (1,1,1) and ANN.

For the calculation the data on the maximum levels of non-regulated electricity price on WMEP and the electricity sales mark-up estimated by the supplier for the enterprise of the sixth price category with a maximum capacity of power consumption equipment from 670 kW to 10 MW for November 2016 [28]. The details of prices are presented in the Appendix B.11.

An example of a calculation for 08.10.16 00:00–01:00 performed using the ARIMA method is presented below:

$$C_e = C_e = \sum_{t=1}^{24} W_t \cdot C_t + \frac{P_p \cdot C_p}{N} + \frac{P_{max} \cdot C_{max}}{N} + \sum_{t=1}^{24} W_t \cdot C_{t,others} +$$

$$+\sum_{t=1}^{24} W_t^+ \cdot C_{t,retail}^+ + \sum_{t=1}^{24} W_t^- \cdot C_{t,retail}^- + \sum_{i=1}^{24} W_i^- \cdot C_t^+ + \sum_{t=1}^{24} W_t^+ \cdot C_t^+ + \sum_{t=1}^{24} W_t^- \cdot C_t^- =$$

$$= 2.805 \cdot 11.417 + \frac{15.000 \cdot 6199.380}{30 \cdot 24} + \frac{807.955 \cdot 7061.451}{30 \cdot 24} +$$

$$+2.805 \cdot 1.231 + 0.036 \cdot 0.302 + 0.036 \cdot 0.037 = 12225 \text{ EUR}$$

Similarly, the electricity purchase costs for each hour on 08.10.16 were estimated and the results were summed up. The total cost of purchasing electricity per day was 12225 EUR. For the year, the consumption was 11002664 EUR.

Next, the total costs for each model were determined in a similar way. The results are presented in the table 10.

Table 10. The results of the calculations performed

Forecasting algorithm	ARIMA (1,1,1) (1,1,1)	ANN
MAPE, %	14.51	10.54
Total cost per day, EUR	12225	10672
Total cost per month, EUR	366755	320172
Total cost per year, EUR	11002664	9605151

Based on the analysis of the results I can conclude that there is a significant reduction in electricity purchase costs with accuracy of electricity forecasting. When the calculation error is reduced, the costs of purchasing (selling) missing (excess) electricity are reduced, as well as the energy supply mark-ups are reduced. If the error is reduced by 4%, the electricity purchase costs are reduced by 14.55%, which is about 1.4 million EUR per year. In other words, an error reduction of about 1% saves the company about 140,000 EUR per year. The reduction in the cost of electricity is only achieved by implementing forecasting system and requires minimal investment.

7. Inputs for economic model

There is no cash inflow from the current project. Thus, the NPV for each possible alternative will be calculated on the basis of the initial investment and the annual cost of buying electricity, staff salaries, taking into account annual cost increases, inflation rates and the lifetime of the project. Since the NPV calculation is only based on expenditure, the NPV for all alternatives considered will be negative, and the higher NPV will represent the more profitable alternative. I will use the same economic model to calculate each project alternative, the investment, maintains and employee salaries will be the same for each project because both models were prepared in software. The difference between these projects is the cost of purchasing licensed software and the cost of buying electricity per year.

7.1. Investments

The initial investment is the purchase of a computer to operate the forecasting system. For most desktop PCs, average lifespan is five years. Since the lifespan of the computer is 10 years, I have to renovate the computer, resulting in an additional investment after tenth years. Also, the investment includes the cost of delivering the installation of the computer. The investment will be the same because both models are prepared in software requiring the same PC. The investments are presented in Table 11.

Table 11. Investments

№	Model	Cost of computer, RUB	Delivered, RUB	Installation, RUB	Total investment, RUB	Total investment, EUR
1.	ANN	49649	490	1000	51139	552
2.	ARIMA	49649	490	1000	51139	552

7.2. Inflation

Inflation is sustained increase in the general level of prices for goods and services. The money is depreciating, the purchasing ability of the community is decreasing. Generally, inflation rates vary from one economic sector to another.

The growth rates of parameters such as the cost of software licenses and the price of purchasing electricity will be correlated with the rate of inflation in this project. To determine inflation, I used the inflation rate for the Russian Federation over the last 10 years. The historical inflation data is presented in Table 12. The inflation rate is 6.49% [30].

Table 12. The historical inflation data

Year	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010
Inflation in Russia	3.22%	4.47%	2.88%	3.68%	7.04%	15.53%	7.82%	6.75%	5.08%	8.44%	6.85%

7.3. Depreciation

Depreciation is the systematic reduction of a fixed asset's value until the asset's value becomes zero or insignificant [29]. According to Russian accounting standards, there are four main methods of calculating depreciation for fixed assets:

- The linear method. The annual depreciation amount is determined on taking into account the initial cost of the fixed asset and the depreciation rate calculated on the basis of the lifetime of the fixed asset. The current residual value is determined by deducting the total accumulated depreciation of the fixed asset from its initial cost;
- Decreasing balance method. The annual amount of depreciation is determined based on the residual value of the fixed asset at the beginning of the accounting year and the depreciation rate calculated according to the lifetime of the fixed asset and the coefficient specified by the organization. Each year, depreciation is added to the residual value at the beginning of the year;
- The method of deducting the cost in proportion to the volume of production. Depreciation charges are based on the natural volume of production in the reporting period and the ratio of the initial cost of the fixed asset to the estimated volume of production for the total lifetime of the fixed asset.
- The depreciation method is based on the sum of the years of lifetime. The annual amount of depreciation charges is determined based on the initial cost of fixed assets and a ratio where the numerator is the number of years remaining until the end of the lifetime denominator is the sum of the number of years of the lifetime of the asset [30].

Russian law allows a firm to decide how to calculate depreciation. The method chosen in this dissertation is straight-line depreciation, which is the most common method in accounting. [32]. The equation of straight-line depreciation according to [29] and presents bellow (40):

$$D = \frac{INV}{n}, \tag{40}$$

where INV is Investment;

n is the number of periods.

7.4. Discount rate

The discount rate is the interest rate used to convert future cash flows into present value. The discount rate is used in determining the discounted value of future cash flows [29]. The discount rate takes into account the time value of money as well as the risk or uncertainty of future cash flows. For this project (low-risk project), I take the discount rate as the risk-free rate of Russian Government Bond. The discount rate is 7.16% [34].

7.5. Operational costs

Annual computer maintenance includes: diagnostics and repair of computer faults, cleaning, dusting, temperature monitoring and upgrading of PC equipment. The cost of computer maintenance and repairs is 6.5 euros per inspection [35]. The maintenance of the computer will be performed once every 4 months, i.e., 3 times a year. An increase in maintenance costs of 1% per year was also taken into account. An employee's salary has to be included as well. I have assumed that the employee's salary is 430 euros per month. Also, the electricity purchase cost calculated in the previous chapter for each model is included in the calculations. The operating costs will increase in the future due to inflation. The annual purchase of licensed software is included in this item [36]. The data are presented in Table 13.

Table 13. Operational costs

Maintenance, EUR	**Cost of licensed software for ARIMA model, EUR**	**Cost of purchasing electricity using ARIMA model, EUR**
19	324	118819
Employee salaries, EUR	**Cost of licensed software for ANN model, EUR**	**Cost of purchasing electricity using ANN model, EUR**
5184	378	104317

8. Financial analysis

This chapter provides an economic comparison of two models for forecasting electricity consumption: ARIMA (1, 1, 1) (1, 1, 1) and ANN. The main objective is not only estimation of economic benefit of each option, but also identifying the investment required implement each alternative. Furthermore, it is necessary to consider possible changes in the basic values, for example an increase in the cost of electricity. Evaluation of the investment efficiency of projects generally focuses on the evaluation of such indicator as Net Present Value (NPV).

8.1. Net Present Value

Net Present Value is difference between the sum of the discounted cash flow and cost of project. The equation of NPV according to [31] and presents bellow (41):

$$NPV = \sum_{t=0}^{n} \frac{CF_t}{(1+r_i)^t} = \sum_{t=1}^{n} \frac{CF_t}{(1+r_i)^t} - INV, \tag{41}$$

where CF_t is Cash flow in time period t;

r_i is Discount rate;

INV is Investment;

n is the number of periods;

t is time period.

The project approval criterion is a positive NPV value. If there are two or more possible projects for selection, the higher net present value of the project is to be preferred.

8.2. Economic model calculation of Net Present Value

The previous sections provide all necessary data for the economic analysis. The next step is to calculate the NPV for each alternative. The results of economic analysis are presented in Table 14.

Table 14. Economic calculation

	The first alternative (ARIMA)	**The second alternative (ANN)**
NPV, EUR	-1117938	-986830

I compared the alternatives according to the NPV calculations and chose the highest one. I can conclude that electricity consumption forecasting model based on ANN is the best.

8.3. Sensitivity analysis

Sensitivity analysis is a method for determining the impact of input independent parameters on the dependent variable. Sensitivity analysis is important for planning a long-term project. Some parameters can change significantly over the lifetime of the project. Therefore, it is necessary to evaluate these changes and determine their impact on the profitability of the project.

I perform a sensitivity analysis using the tornado diagram for the second alternative (ANN), when the initial parameters are changed by 20%. The tornado diagram is presented in Figure 35.

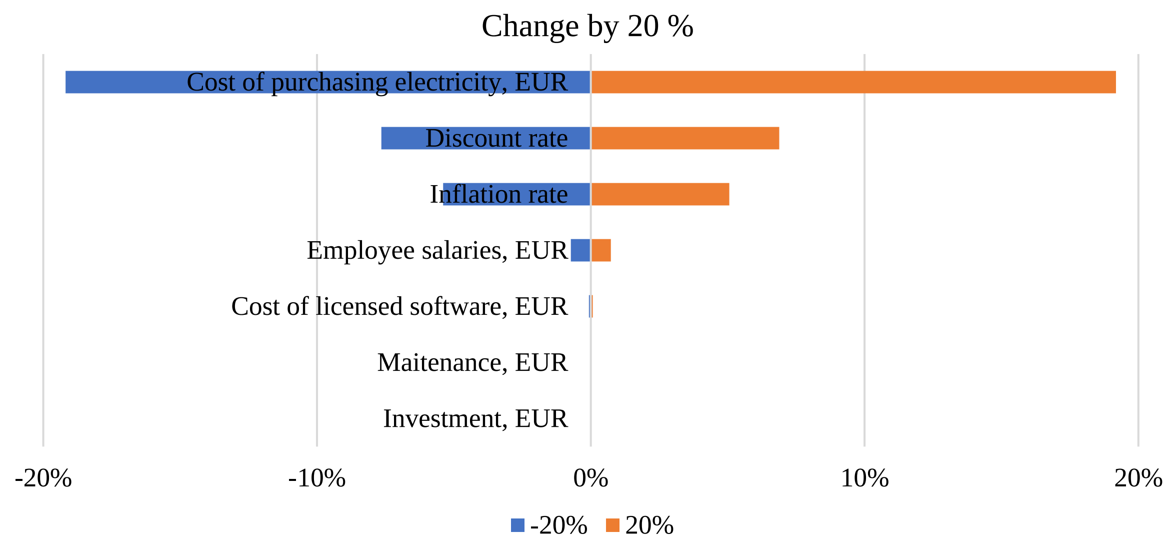


Figure 35. The tornado diagram

It can be observed that the change in the NPV is most strongly influenced by such parameters as cost of purchasing electricity, discount rate and inflation rate. A sensitivity analysis is performed for these parameters.

Let consider the impact of changing the discount rate on the NPV for each alternative. The dependence of NPV on the discount rate is presented in Figure 36. The value of the discount rate varies by 20%, either positively or negatively. Because the discount rate increases, the NPV increases. However, changing the discount rate has no impact on the decision. For all alternatives, the NPV increases proportionally. The curve form is explained by the negative cash flows.

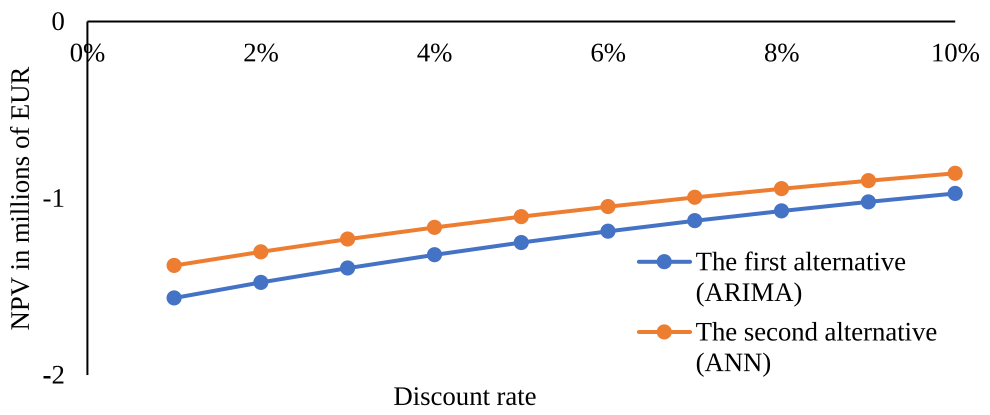


Figure 36. The dependence of NPV on the discount rate

Let consider the impact of changing the inflation rate on the NPV for each alternative. The dependence of NPV on the inflation rate is presented in Figure 37. The value of the inflation rate varies by 20%, either positively or negatively. Because the inflation rate increases, the NPV decreases. However, changing the inflation rate has no impact on the decision. For all alternatives, the NPV decreases proportionally. The NPV is decreasing because there is an increase in enterprise expenditure due to increasing inflation.

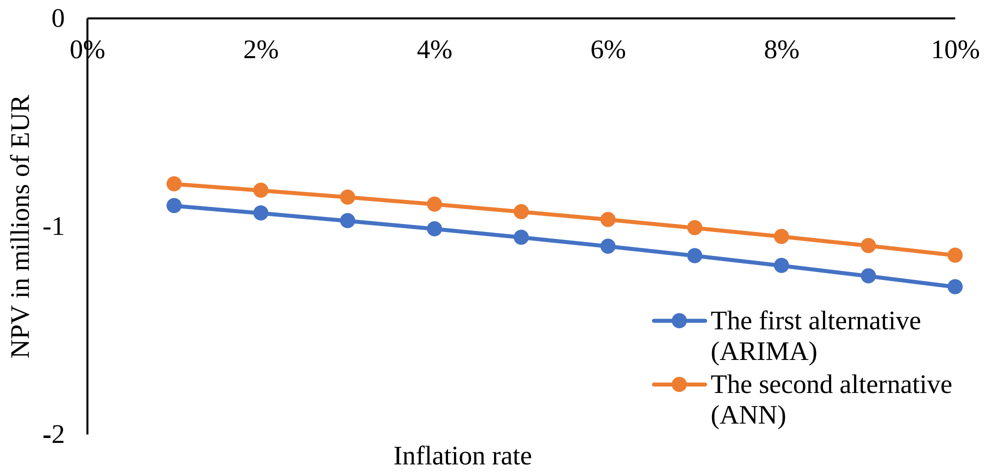


Figure 37. The dependence of NPV on the inflation rate

Let consider the impact of changing the cost of purchasing electricity on the NPV for each alternative. The dependence of NPV on the cost of purchasing electricity is presented in Figure 38. The value of the cost of purchasing electricity varies by 20%, either positively or negatively. Because the cost of purchasing electricity increases, the NPV decreases. However, changing the cost of purchasing electricity has no impact on the decision. For all alternatives, the NPV decreases proportionally. The curves are almost identical in this case, because the other input parameters, except for the cost of the licensed software, are the same.

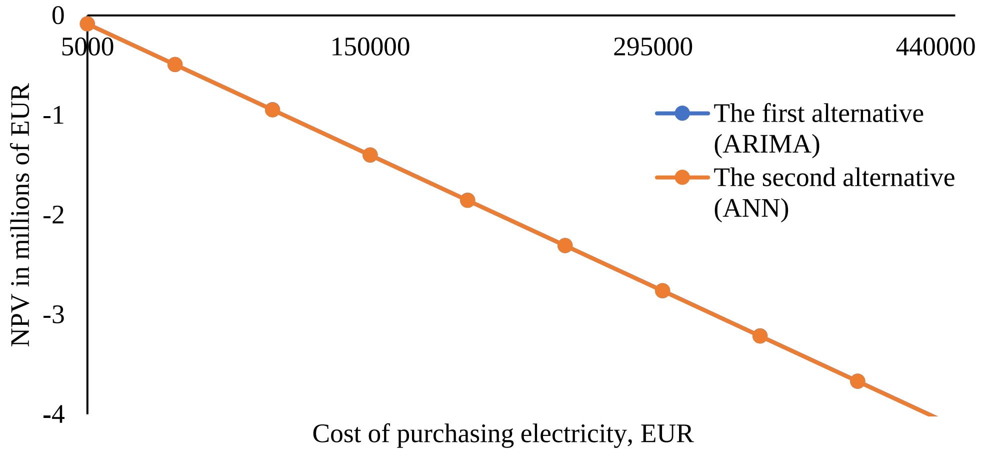
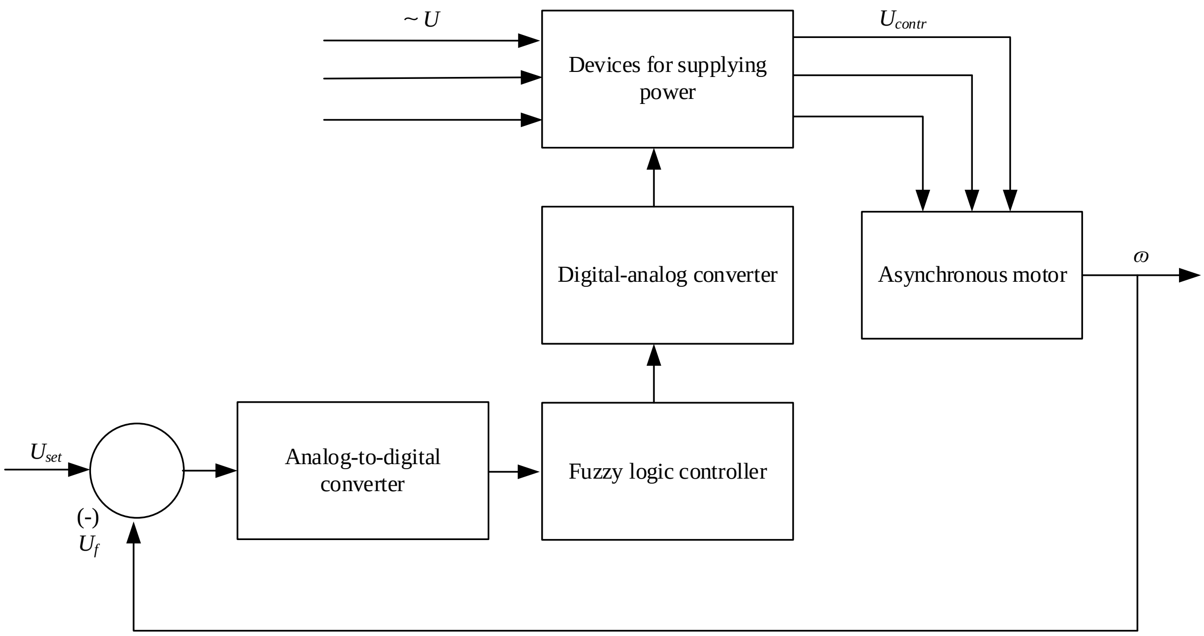


Figure 38. The dependence of NPV on the inflation rate

9. Fuzzy Logic Controller

Function chart of the automatic control system of electric drive is presented in Figure 39.



Note: Author's illustration base on description in [37]

Figure 39. Function chart of the automatic control system of electric drive using fuzzy logic controller

The simulation model of vector control of electric driver with the classical speed governor is presented in Figure 40. Subsystems of this model are presented in Appendices A.30−A.35.

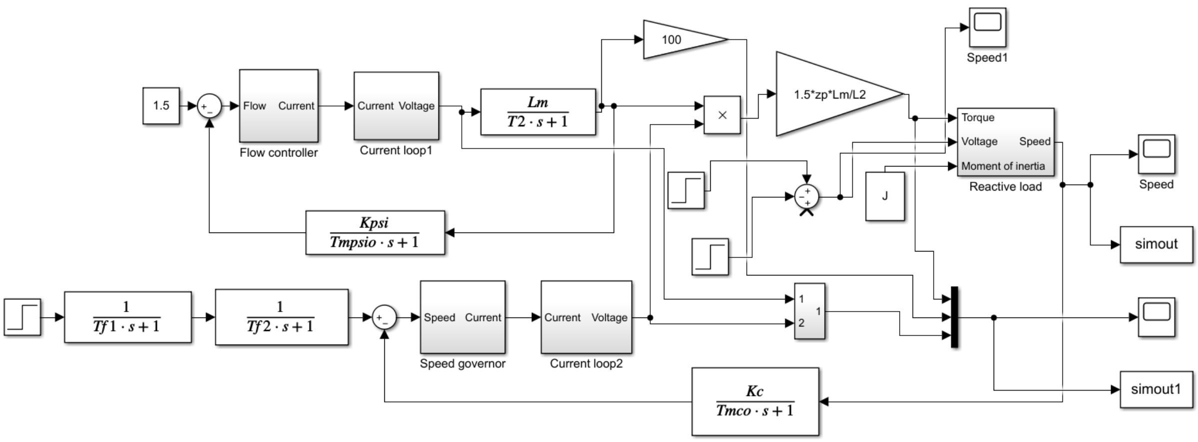


Figure 40. The simulation model of vector control of electric driver with the classical speed governor

The motor is controlled by two independent control channels: the automatic control system of the flux linkage which is presented in Appendix A.30 and the automatic control system of the speed governor which is presented in Appendix A.32. The input actions on the circuits are constant control voltages U_{contr}

supplied to the summator of flux linkage controller and speed governor filters. First the control voltage is applied to the flux linkage controller, and only then to the speed governor. This is due to the greater inertia of the speed loop.

The Automatic Control System of The Flux Linkage

The control voltage is supplied from the adder to the input of the Proportional-Integral (PI) controller of the rotor current loop, which provides a setting in the loop close to the optimum. Current loop simulation model is presented in Figure A.31.

At the input of the automatic control system of the flux linkage, the control voltage is amplified by the transmission factor of the controller, thus forming the setpoint voltage for the internal current loop.

The setpoint voltage is supplied to the PI current regulator, which provides a provides a setting in the loop close to the optimum. At the input of the current regulator the control voltage is amplified by the transmission factor of the regulator, thus forming the reference voltage to the controlled inverter. The inverter forms the supply voltage of stator winding, which is used to limit the stator current along the d-axis. Accordingly, the stator winding transfer function forms the stator current along the d-axis.

In order to control the stator current on the d-axis, it is necessary to remove the feedback signal (these feedbacks are inertial). The resulting stator current signal on the d-axis is supplied to the transfer function of stator current loop feedback and then to the adder with a "-" sign. The feedback signal is subtracted from the stator current loop input on the d-axis, and then the resulting signal is fed to the automatic control system of the flux linkage.

The output of the current loop is the stator current on the d-axis. It enters the transfer function to form the rotor current loop, and the rotor current loop appears. The flux-circuit current flows to the feedback transfer function of the flux-circuit feedback loop, and then to the adder at the input of the flux-circuit current loop.

Thus, the automatic control system of the flux linkage provides independent subordinate regulation of the rotor flux of the motor and consists of an internal circuit of the stator current along the d-axis and an external circuit of the rotor flux-limit loop. This the automatic control system of the flux linkage is characterized by fast transients with small overshoot on control and disturbance and negligible static error on the disturbing influence.

The Automatic Control System of The Speed Governor

The control voltage is supplied to the input filters of the speed loop. This is due to the need for precise astatic control of the motor speed under disturbance and, as a consequence, to limit speed overshoot in a system with a PI speed controller. Accordingly, the filters convert the original control signal into the desired speed loop reference signal, which enters the speed loop adder.

The control voltage is supplied from the adder to the input of the PI speed regulator, which provides in the loop a setting close to the optimum.

At the input of the speed governor, the setpoint voltage is amplified by the transmission factor of the governor, thereby forming the setpoint voltage for the internal current loop.

The further signal transformation is identical to the automatic control system of the flux linkage, because the automatic control system of the speed governor also contains an internal stator current loop, only along the q-axis.

At the output of the current loop the stator current appears on the q-axis. It enters the signal multiplier. The same multiplier receives the rotor current loop signal from the automatic control system of the speed governor. The product of these signals goes to the torque generator amplifier, thus forming the electromagnetic torque of the motor. This in turn goes to the first input of the mechanical system, represented by the reactive load in Appendix A.33. The second input is the input for applying and removing the static load torque. The third input sets the moment of inertia of the motor rotor. At the output of the mechanical one, the motor rotation speed is formed, the signal of which by feedback enters the feedback transfer function of the speed loop, and after that it enters the adder at the input of the speed loop.

Thus, the speed control system provides a subordinate regulation of the rotor flux-limit and consists of an internal stator current loop along the q-axis and an external speed loop, the feedback of which depends on the automatic control system of the speed governor. This automatic control system of the speed governor is characterized by fast transients with small overshoot on control and disturbance and absence of static error on the disturbing action.

All the received transient signals can be evaluated by oscilloscope. In order to estimate the root-mean-square current value of stator current, it is required to calculate it from the vector sum of stator current components along the d and q axes, multiplied by half the square root. This algorithm is presented in Appendix A.34.

The first oscilloscope is designed to monitor the motor speed. The second oscilloscope monitors the motor torque, the rotor flux ratio and the root-mean-square current of stator. The signals of the second oscilloscope are input to the same coordinate system via a multiplexer, and the rotor flux-circuit signal is also input via a scaling factor.

The simulation model of vector control of electric drive with fuzzy regulator is presented in Figure 41. The simulated block diagram of the fuzzy speed regulator is presented in the Appendix A.35. The sequence of preparing fuzzy in MATLAB software is presented in the Appendix A.36.

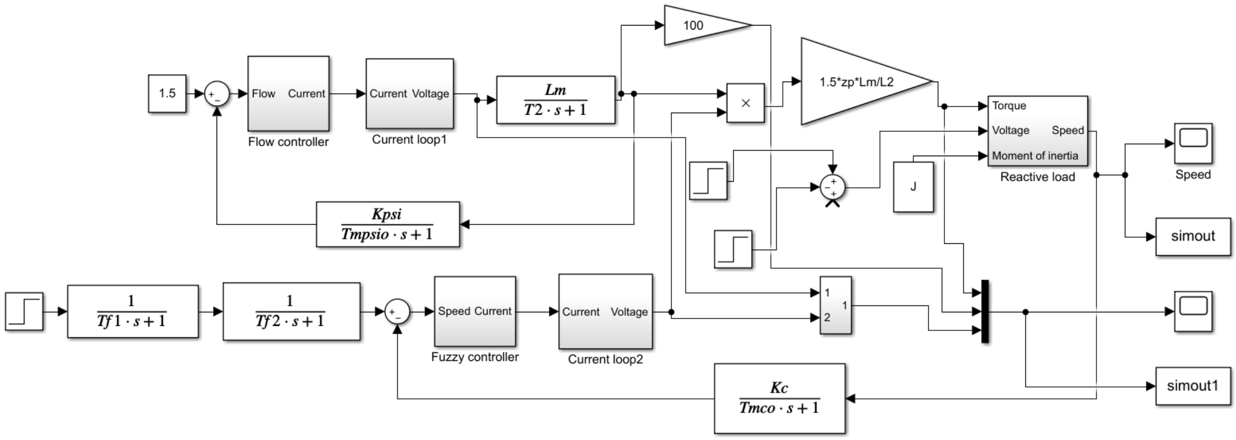


Figure 41. Simulation model of electric drive with fuzzy speed controller

Figures 42−44 present transient plots (diagrams of speed, rotor current, moment of inertia and stator current) at a reference voltage of U_{set} = 1.5 V, for a system with classical and fuzzy speed controllers. Figures 45, 46 present plots of speed and current changes after engine start. Figures 47−49 present plots of speed and current changes during load decrease and increase.

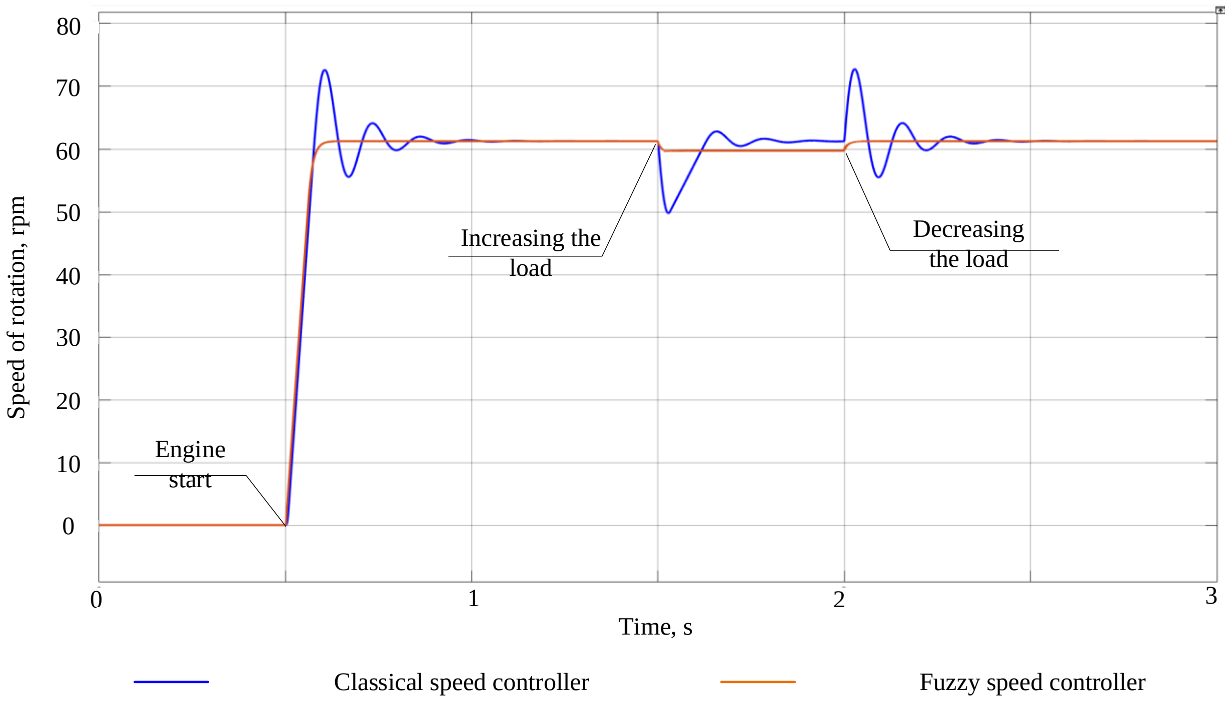


Figure 42. Rotation speed diagram

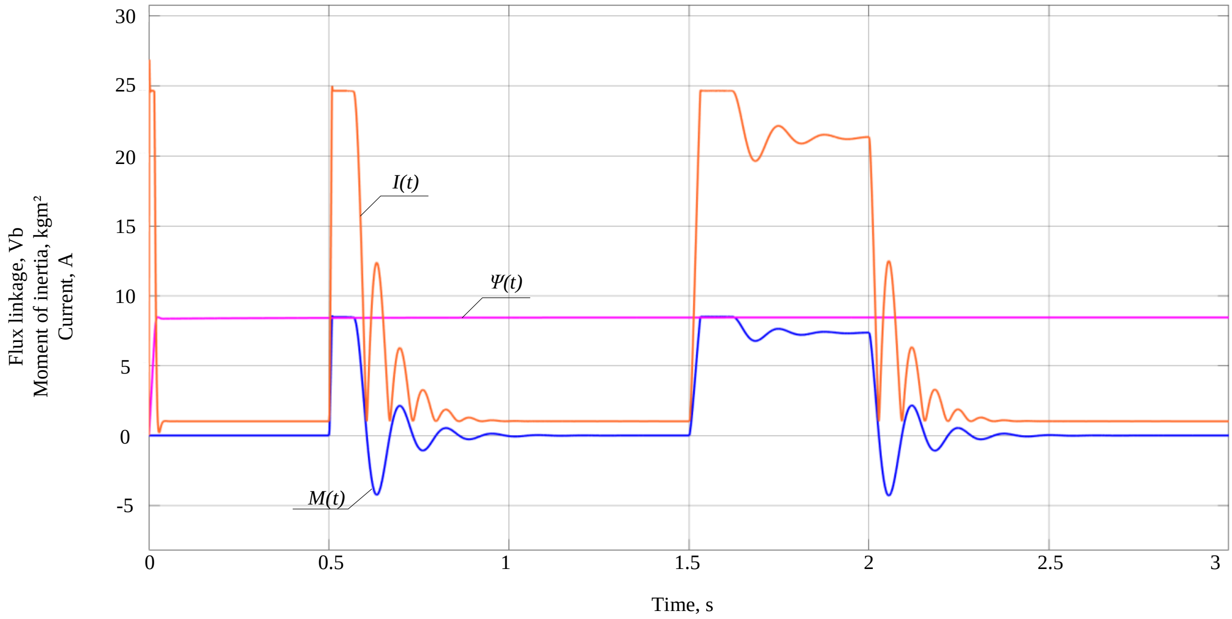


Figure 43. Diagrams of rotor flux, moment of inertia and stator current (classical speed controller)

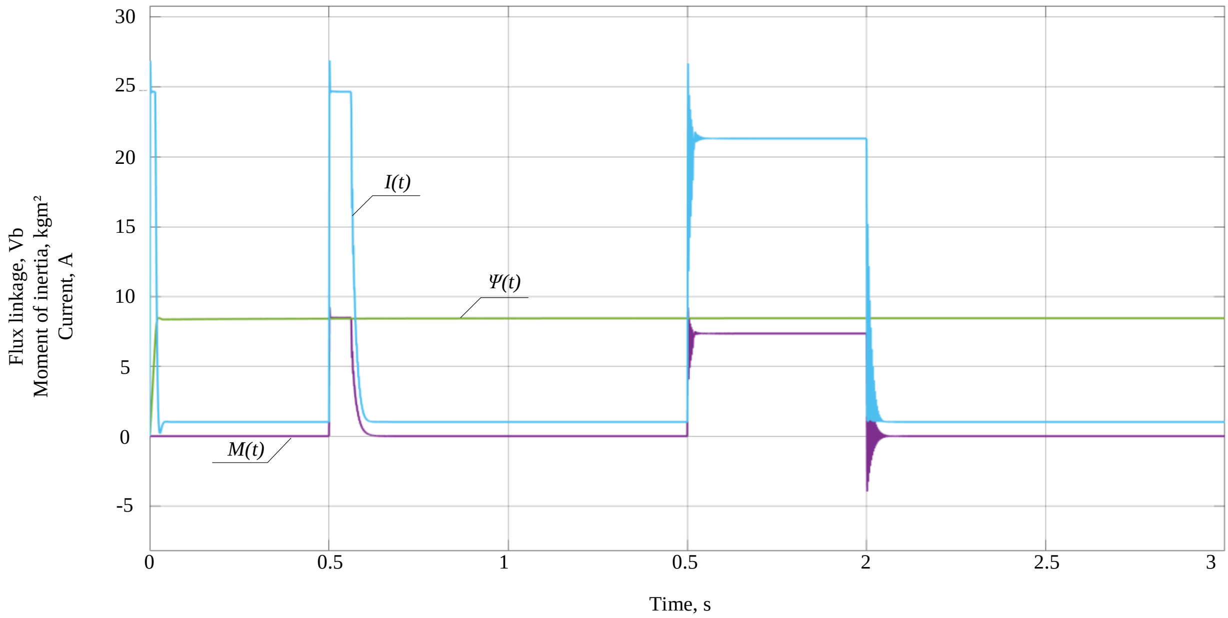


Figure 44. Diagrams of rotor flux, moment of inertia and stator current (fuzzy speed controller)

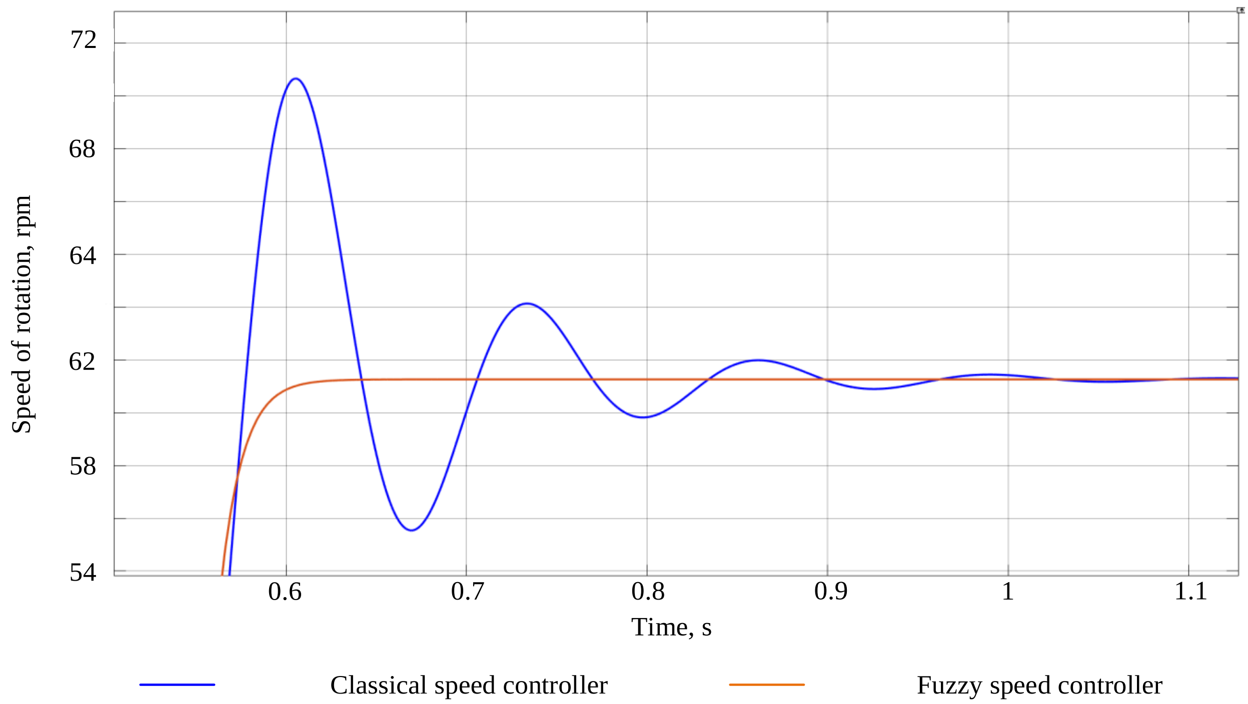


Figure 45. Rotation speed diagram after engine start

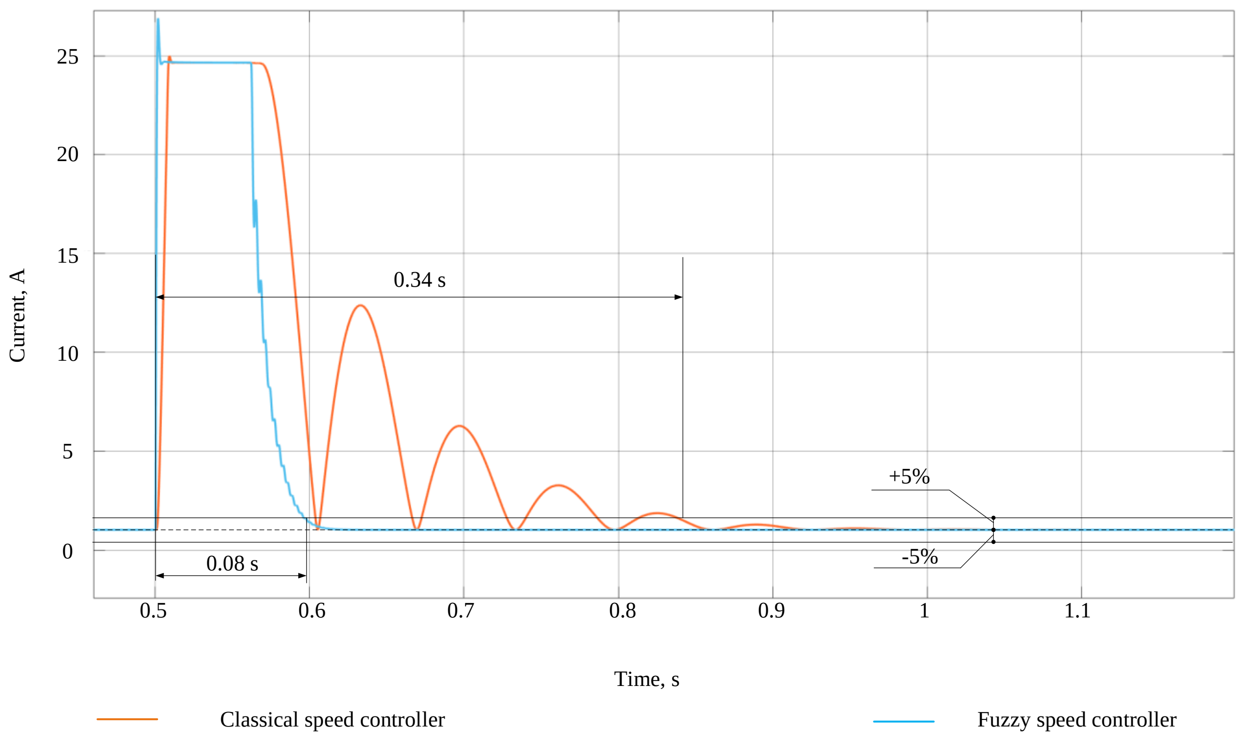


Figure 46. Current of rotor diagram after engine start

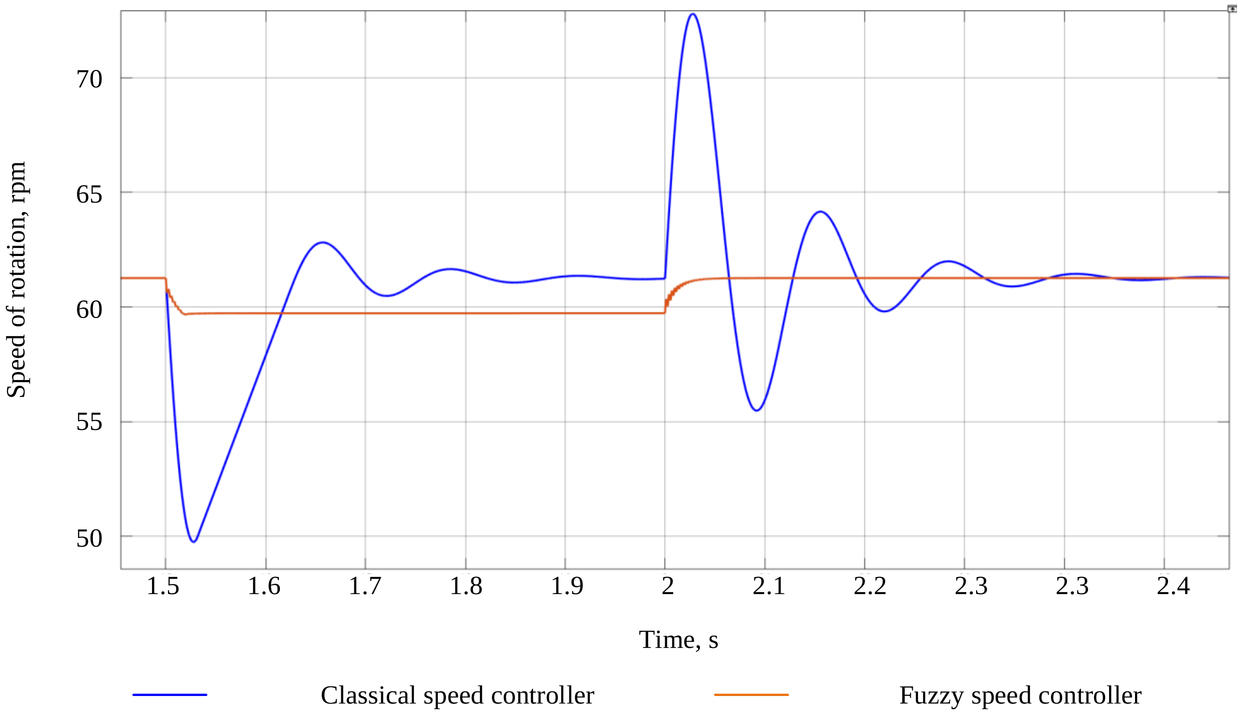


Figure 47. Rotation speed diagram after decreasing and increasing load

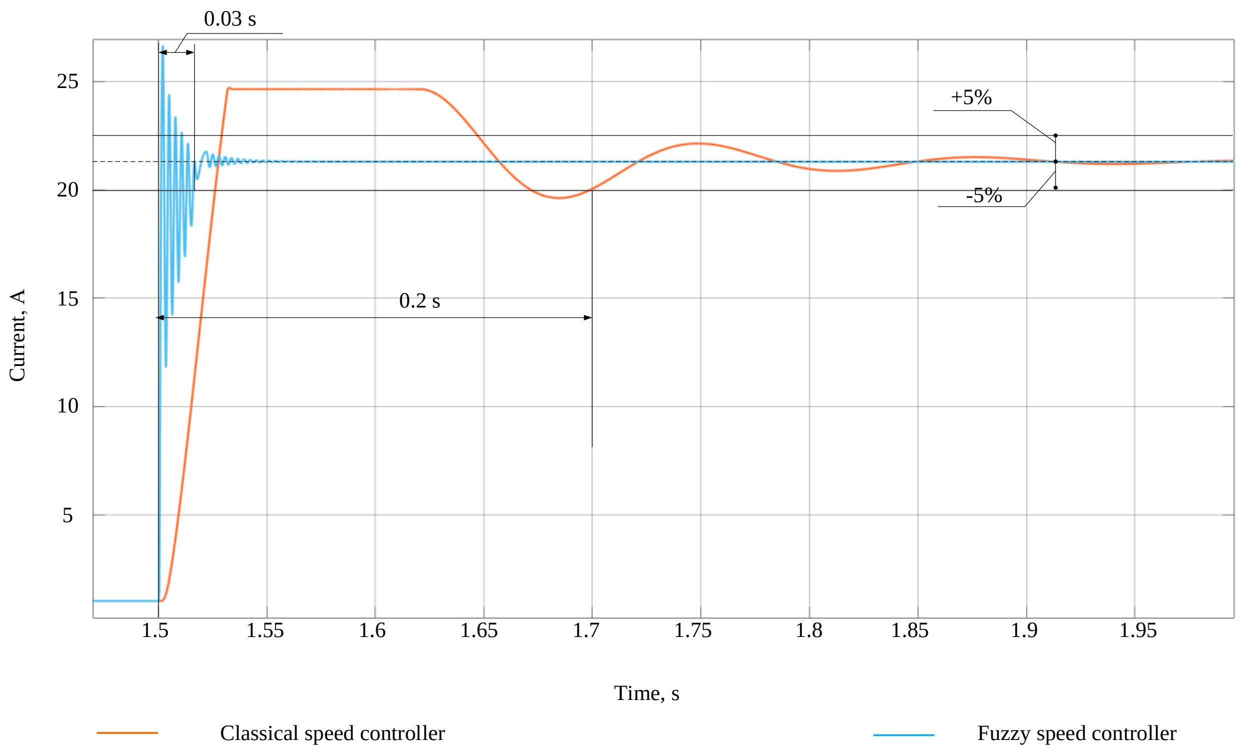


Figure 48. Current of rotor diagram after increasing load

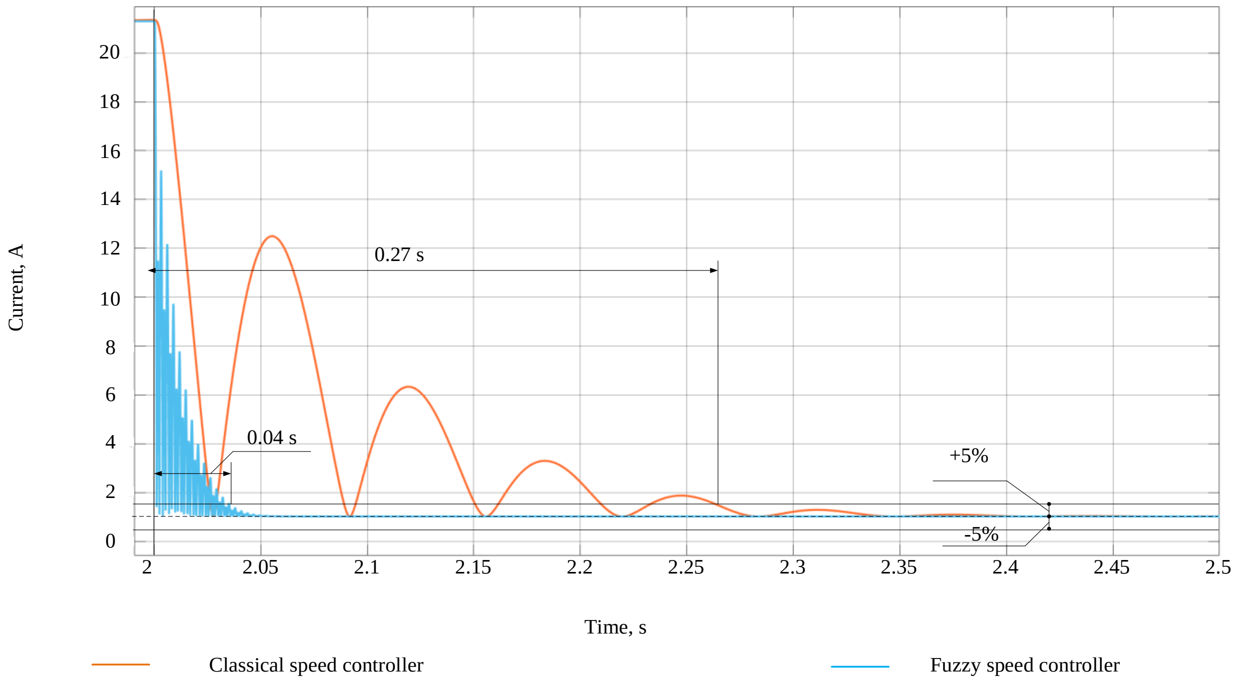


Figure 49. Current of rotor diagram after decreasing load

To control an electric drive using a classical controller, the transient is aperiodic with a significant over-regulation. I can conclude that by increasing or decreasing the load, the duration of the transient process with a classical controller is longer compared to a fuzzy controller. To control the system with fuzzy controller the transient process is asymptotic without over-regulation. The diagrams illustrate that experiments carried out on a vector control system have confirmed the effectiveness of fuzzy logic methods in controlling an induction motor.

The diagrams illustrate the effectiveness of fuzzy logic methods in controlling an asynchronous motor. When the load is increased or decreased, the system more effectively compensates for disturbing dynamic action and contributes a statistical error that does not exceed 3% of the steady-state rotation speed value.

The fuzzy control system is the most advantageous because the duration of the transient process is smaller and the system is not over-regulated. Increasing the influence of high currents and its duration on the system increases the thermal load, therefore reducing the equipment's service life.

If the load varies frequently or if there are frequent starts of engine, the impact of transients must be reduced by the use of regulators. It can also be achieved by purchasing additional cooling equipment, which will increase the cost.

The advantages of using fuzzy control to achieve automation problems compared to classical control systems are following:

- These models are appropriate for use in complex systems to formalise using classical methods of mathematical modelling;
- Increase the efficiency of filtering information received from sensor data processing;
- Reducing the probability of erroneous decisions in the operation of control algorithms;

- Ability to maintain a constant speed, thereby increasing the service life of the equipment and the economical usage of the equipment;
- Improved energy efficiency, as the reduction in speed recovery time, reduces energy consumption.

Despite many advantages, these systems have disadvantages:

- The statistical error, which is low but still present;
- The performance of the system is not increased.

Therefore, application of fuzzy electric drive control models is most beneficial in highly dynamic systems that require high accuracy, stability and speed of control signal, but do not require a fast response time.

Conclusion

This dissertation compares the effectiveness of electricity consumption forecasting methods. Improvement of economic efficiency of the enterprise through implementation of this system on software and hardware levels and their adaptation to the conditions of Sibelectromotor Enterprise.

The market economy in Russia has made possible the opening of a free trade sector in the Federal Wholesale Electricity Market. The free trade sector, on the one hand, allows companies to participate in competitive tendering and purchase electricity at prices lower than those approved by the regional energy commission. But on the other hand, there is a risk of variance compensation, which is due to the impossibility of accurately planning the energy consumption.

Analysis of the electricity market indicates that consumers have to focus on improving the accuracy of electricity consumption forecast. Optimization of forecasts can significantly reduce the cost of purchasing electricity, as electricity cannot be stored. Therefore, if excess electricity is purchased, costs may increase either by selling it on the balancing energy market or by maintaining reserve capacity. If the purchased capacity is insufficient, the costs increase by buying additional capacity.

This dissertation focuses on Autoregressive Integrated Moving Average Method, Artificial Neural Networks Method, Classification and Regression Trees Method. ARIMA is a common forecast method. The stationary series is obtained by differencing the time series. ARIMA is relatively frequently used for the analysis of initial dataset, where periods of operation are visible. Therefore, this method requires the sampling of a typical time series. An ANN consists of multiple input/output neurons interacting with each other through synapses. Such networks can be trained, i.e., it is possible to identify patterns and integrate background information. In addition, ANN allows the processing of noisy input signals. Classification and Regression Trees allow examination of data in the existence of several initial parameters. This allows a more specific taught model and provides a more extensive forecast because a variety of conditions contribute to the formation of the dependent variable.

The application of forecast electricity consumption models at the industrial production level provides a benefit. Based on the analysis of the results, I can conclude:

- The short-term ANN-based electricity consumption forecasting model is the best, as the forecasted error and the cost of purchasing electricity are lower in comparison to other methods. This result is achieved by the ability to train neural networks consuming stochastic input data;
- For medium-term forecasting of electricity consumption, the most accurate method is Regression and Classification Tree. This is because the initial dataset is based not only on the values of previous measurements but also on the volume of production. The volume of production receives a significant impact on the electricity consumption of the company.
- When the calculation error is reduced, the costs of purchasing (selling) missing (excess) electricity are reduced, as well as the energy supply mark-ups are reduced. If the error is reduced by 4%, the electricity purchase costs are reduced by 14.55%, which is about 1.4

million EUR per year. In other words, an error reduction of about 1% saves the company about 140,000 EUR per year.

The application of the forecasting system at the hardware level allows achieving the following benefits:

- These models are appropriate for use in complex systems to formalize using classical methods of mathematical modelling;
- Improved energy performance;
- Increased efficiency in filtering information from sensor data processing;
- Reduction of the probability of erroneous decisions in the operation of control algorithms;
- Increase of service life of technological equipment, as well as increase of economic efficiency of equipment usage.

To sum up, I can make a conclusion that the short-term forecasting of electricity consumption based on Artificial Neural Networks is the most effective, because ANN have the ability to learn. For medium-term forecasting of electricity consumption, the most effective are CART models, which allow to take into account the volume of manufactured products. Application of fuzzy electric drive control models is most beneficial in highly dynamic systems that require high accuracy, stability and speed of control signal, but do not require a fast response time.

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E-mail address: Eugene Shutov iom@elti.tpu.ru

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Appendices

Appendix A – Figures

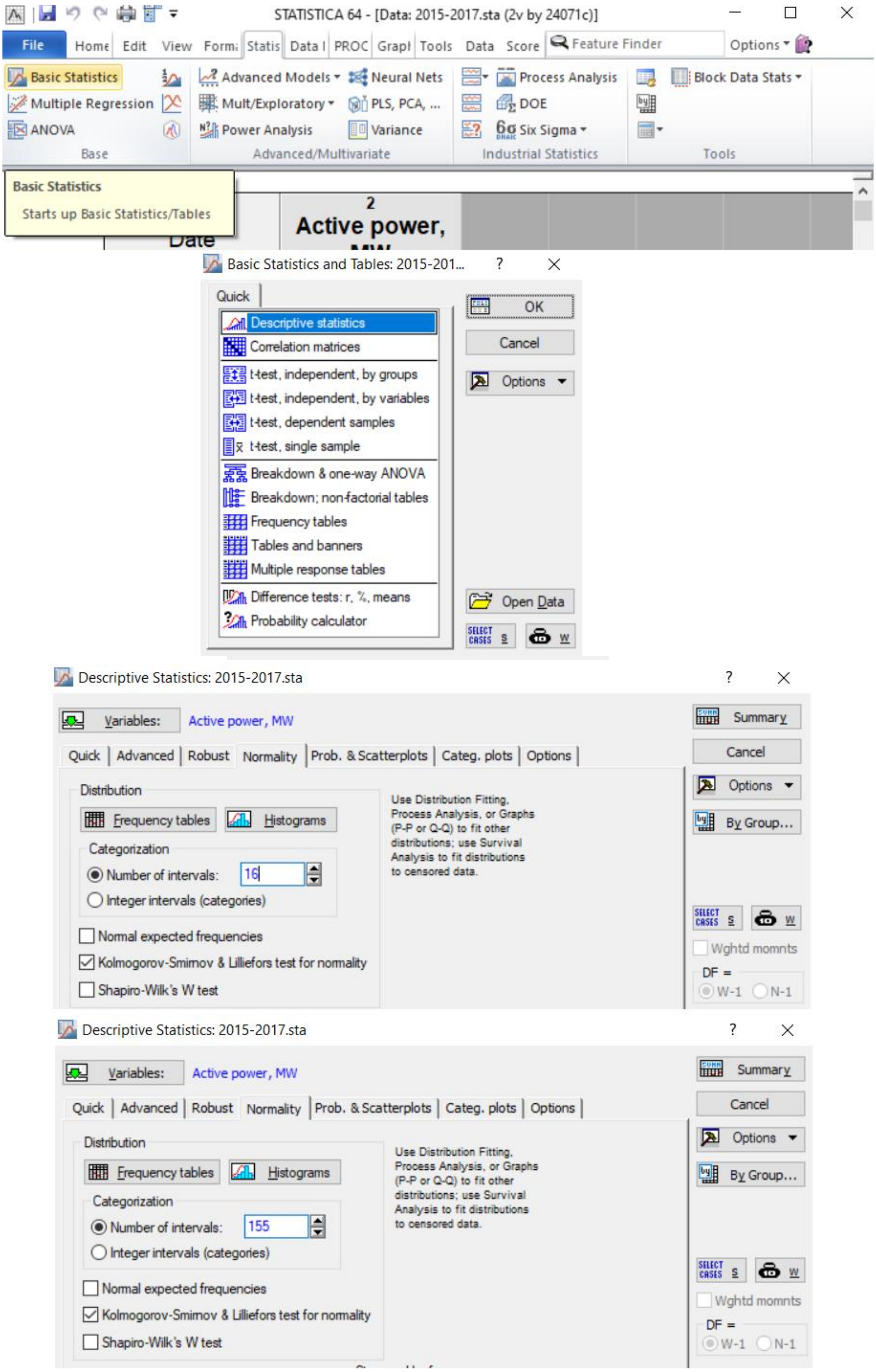


Figure A.1. The sequence of plotting histograms in the Statistica software

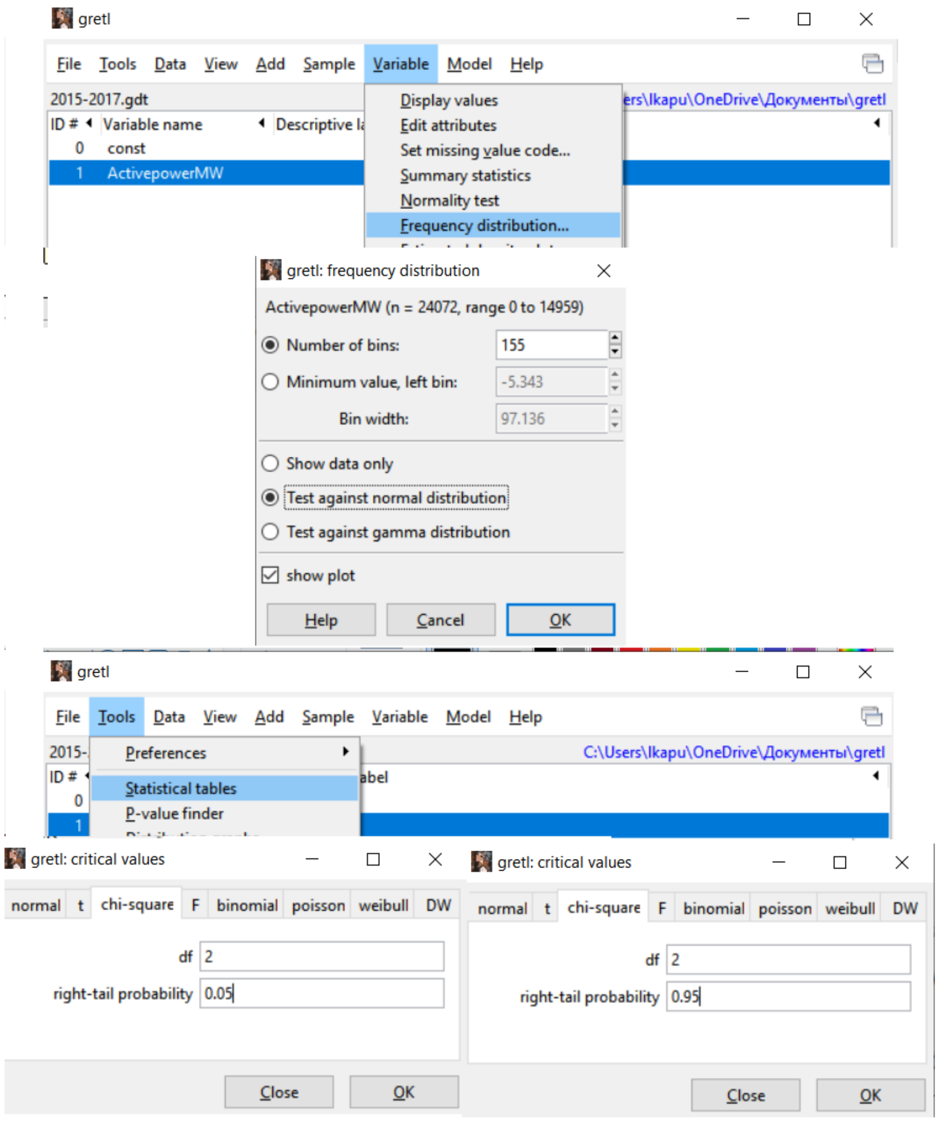


Figure A.2. The sequence of Chi-square goodness of fit test performance in the Gretl software

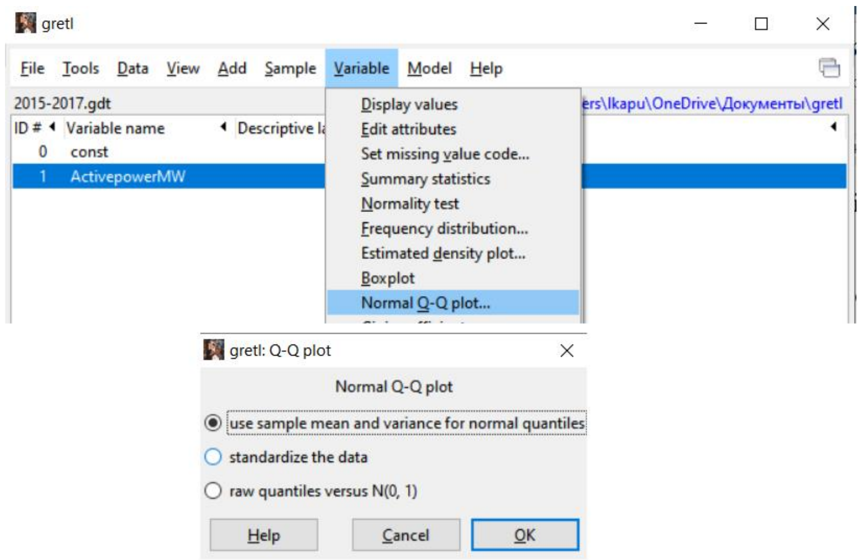


Figure A.3. The sequence of plotting normal quantile-quantile plot in the Gretl software

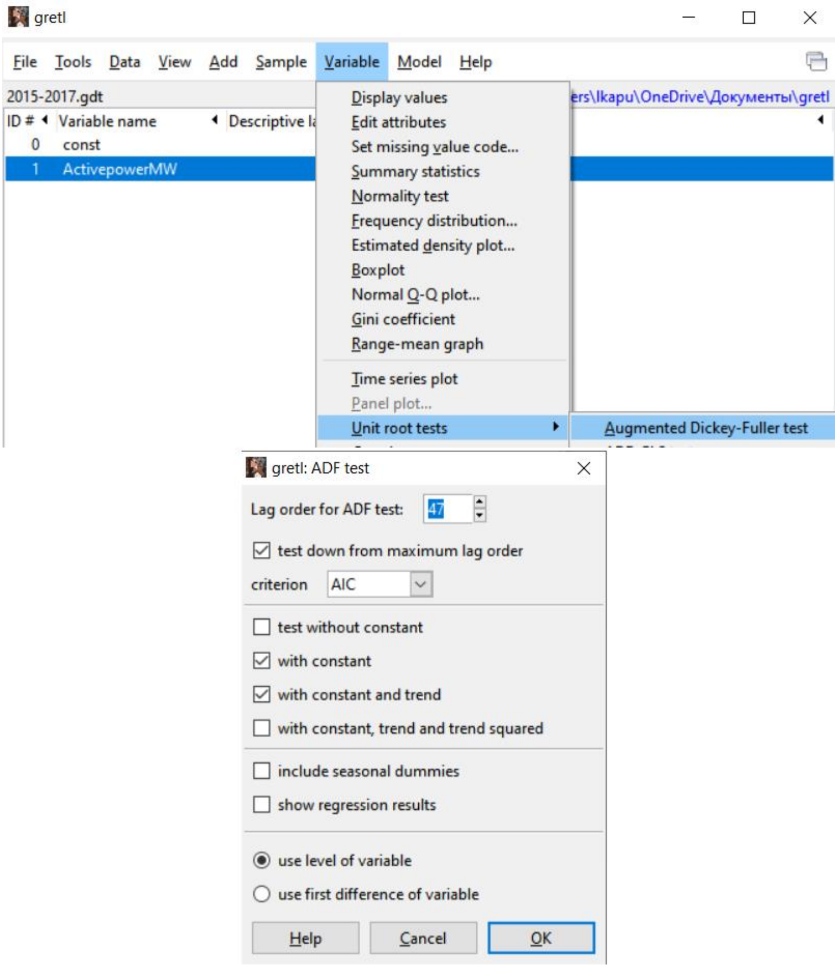


Figure A.4. The sequence of Augmented Dickey-Fuller unit root test performance in the Gretl software

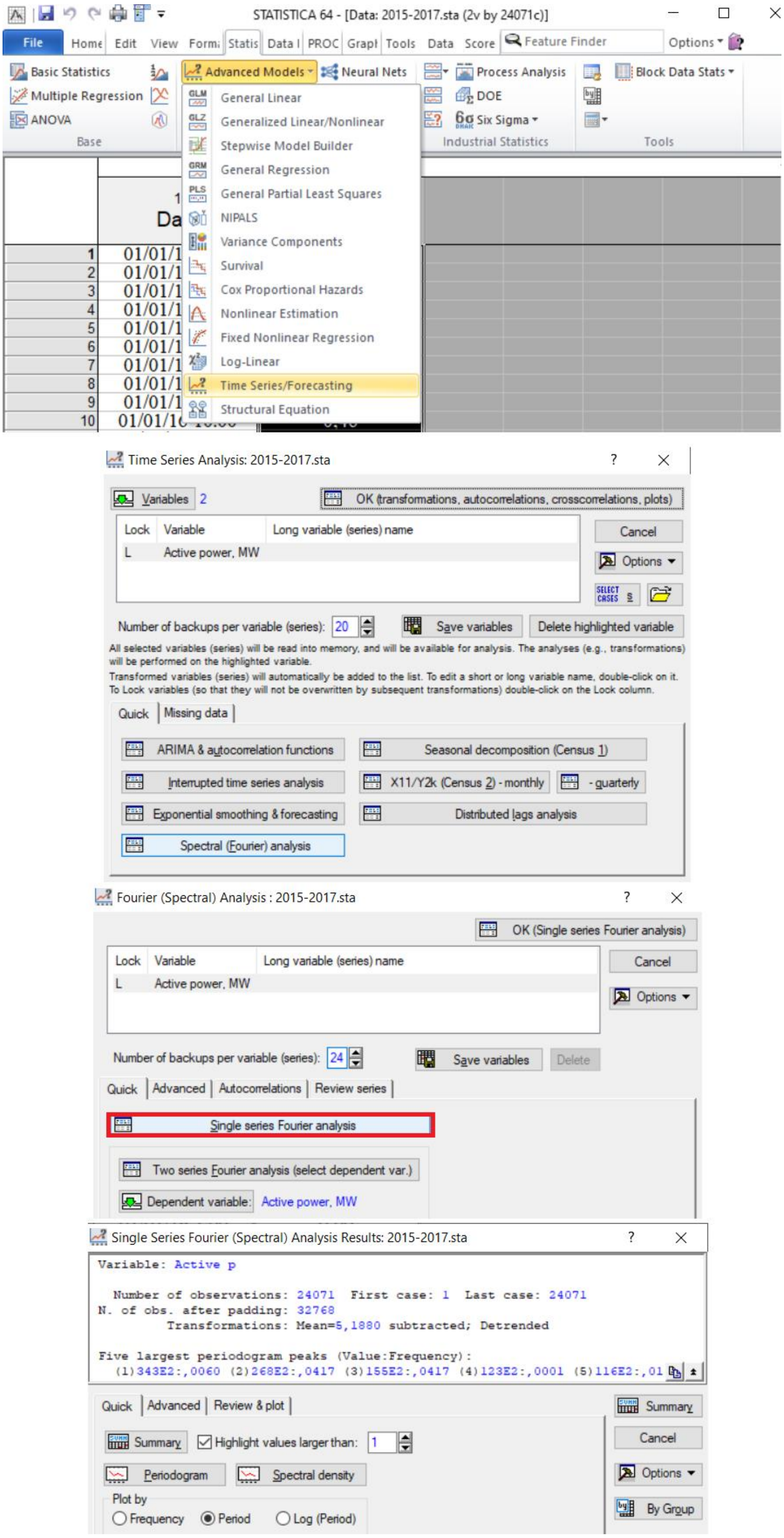


Figure A.5. The sequence of plotting periodogram plot in the Statistica software

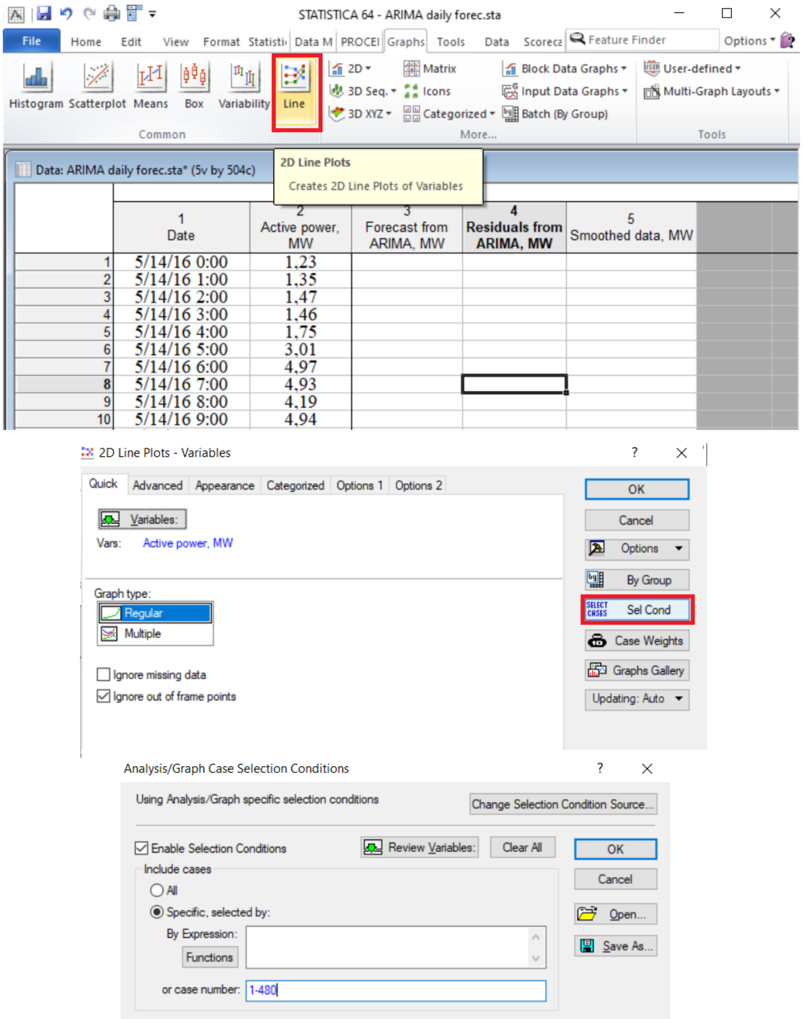


Figure A.6. The sequence of plotting within the Statistica software

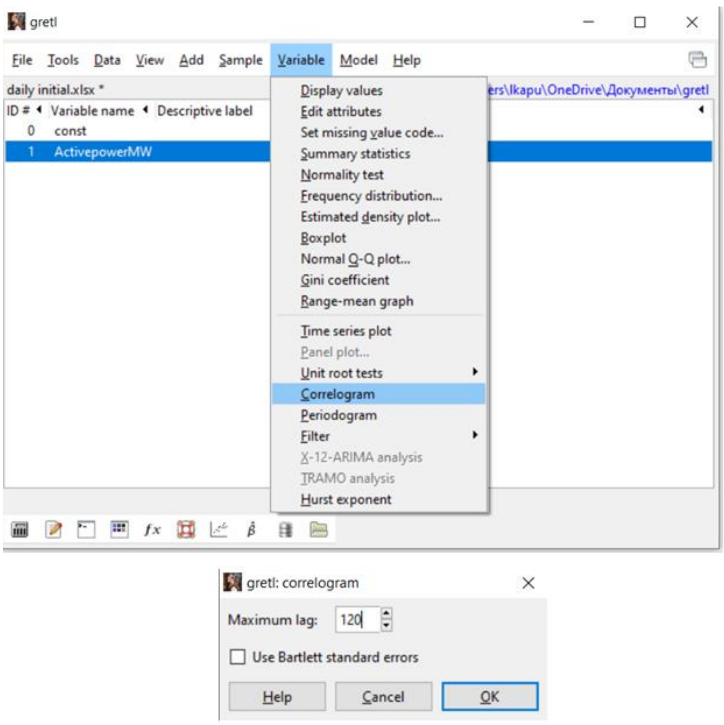


Figure A.7. The sequence of plotting a correlogram within the Statistica software

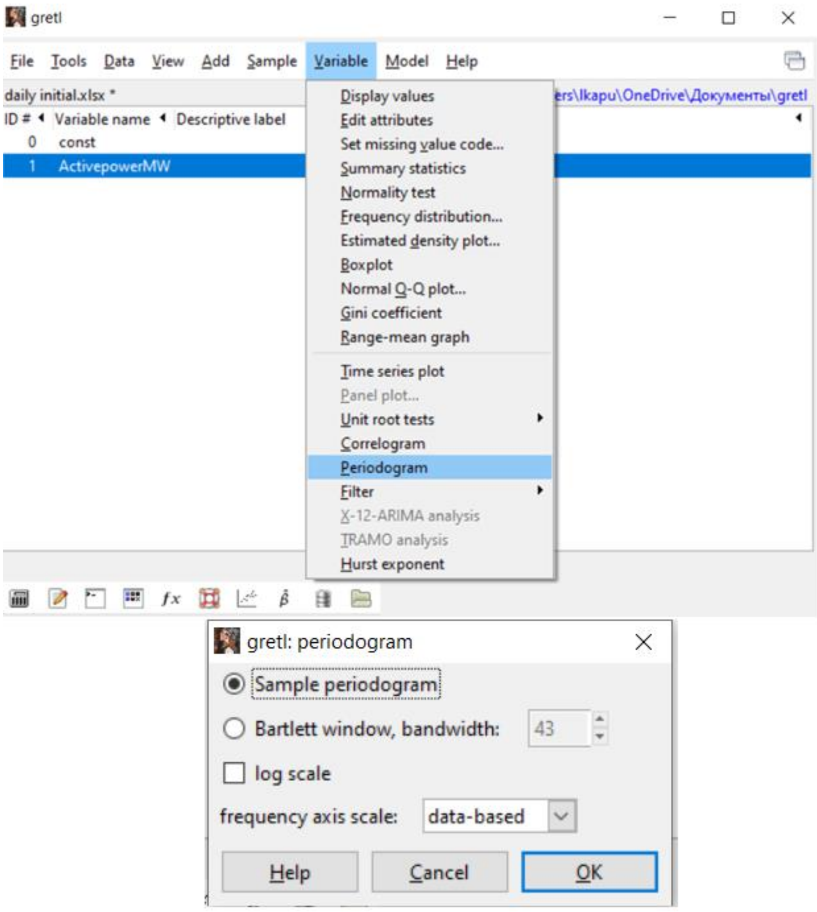


Figure A.8. The sequence of plotting a periodogram within the Statistica software

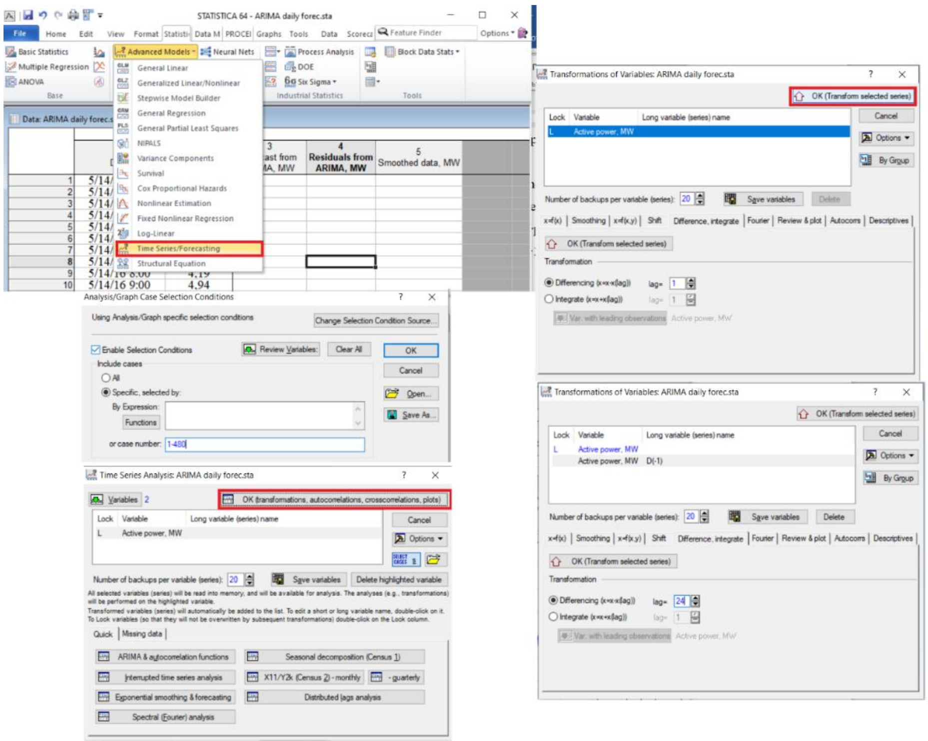


Figure A.9. Procedure for obtaining smoothed data within the Statistica software

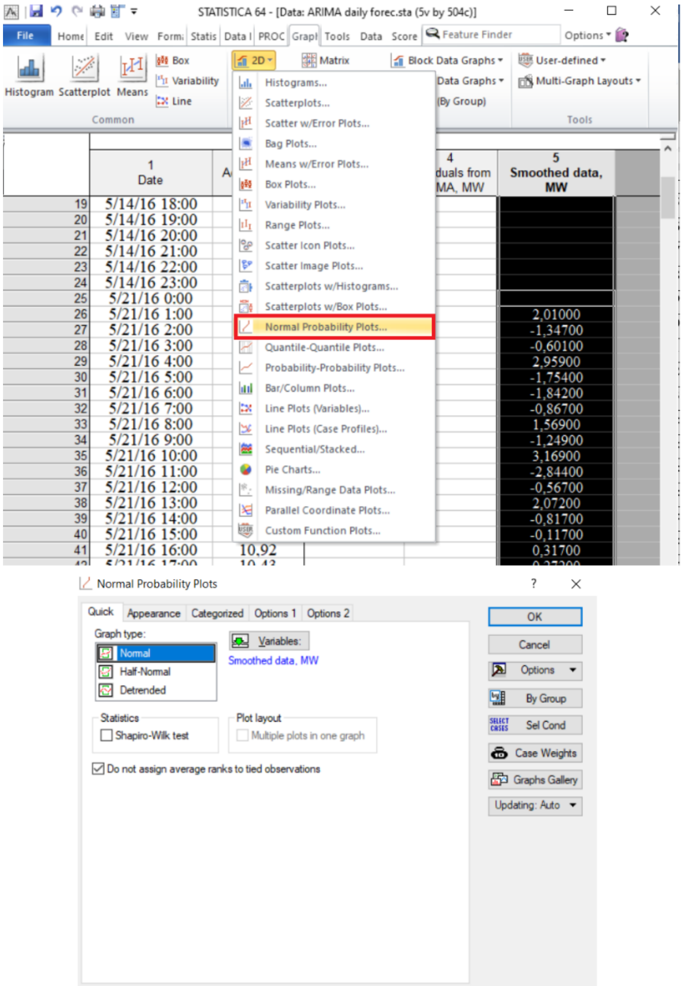


Figure A.10. The sequence of plotting a normal quantile- quantile plot in the Statistica software

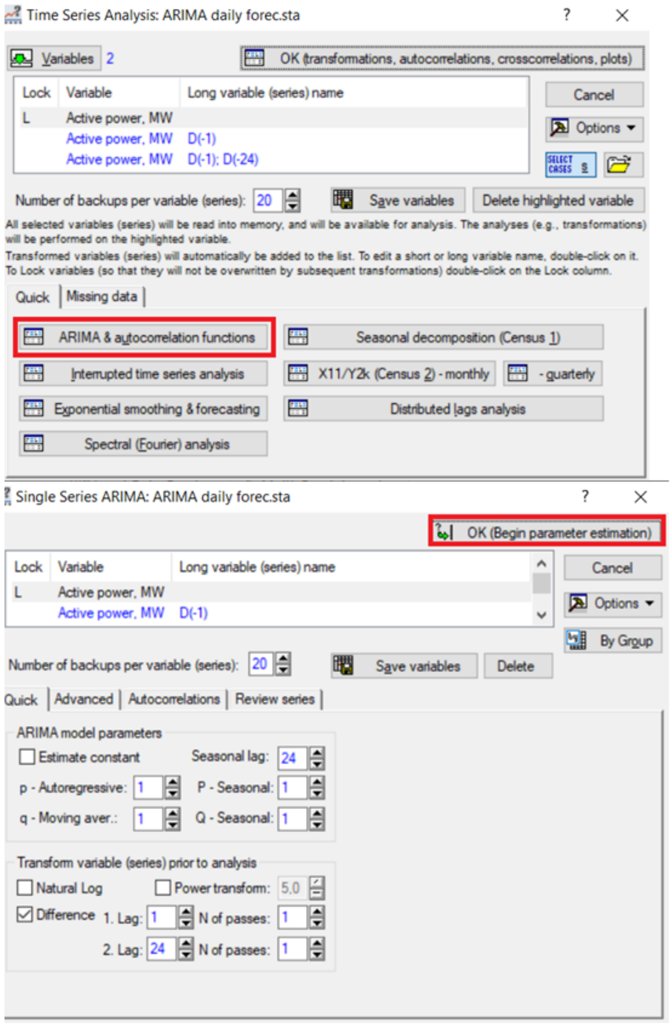


Figure A.11. The sequence of preparing ARIMA (1, 1, 1) (1, 1, 1) model in the Statistica software

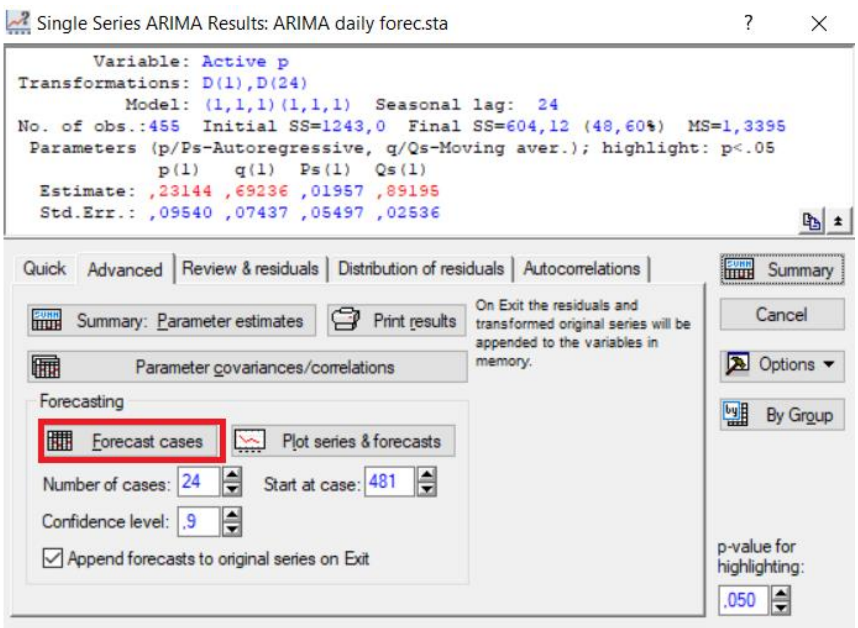


Figure A.12. The sequence of forecasting by ARIMA (1, 1, 1) (1, 1, 1) model in Statistica software

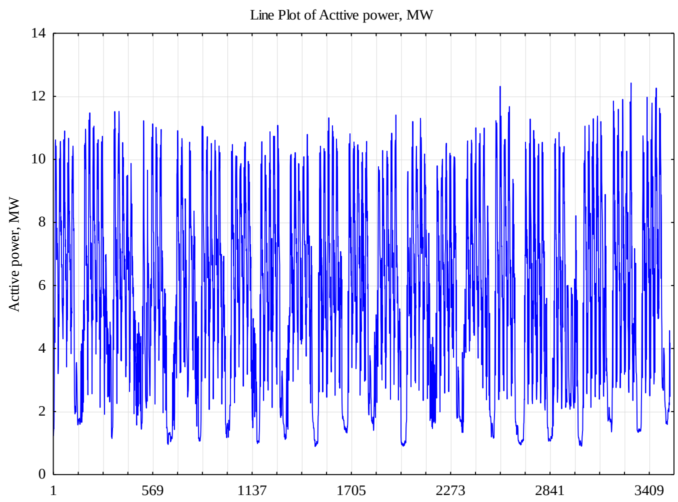


Figure A.13. Line plot of initial dataset for a week-ahead forecasting of electricity consumption

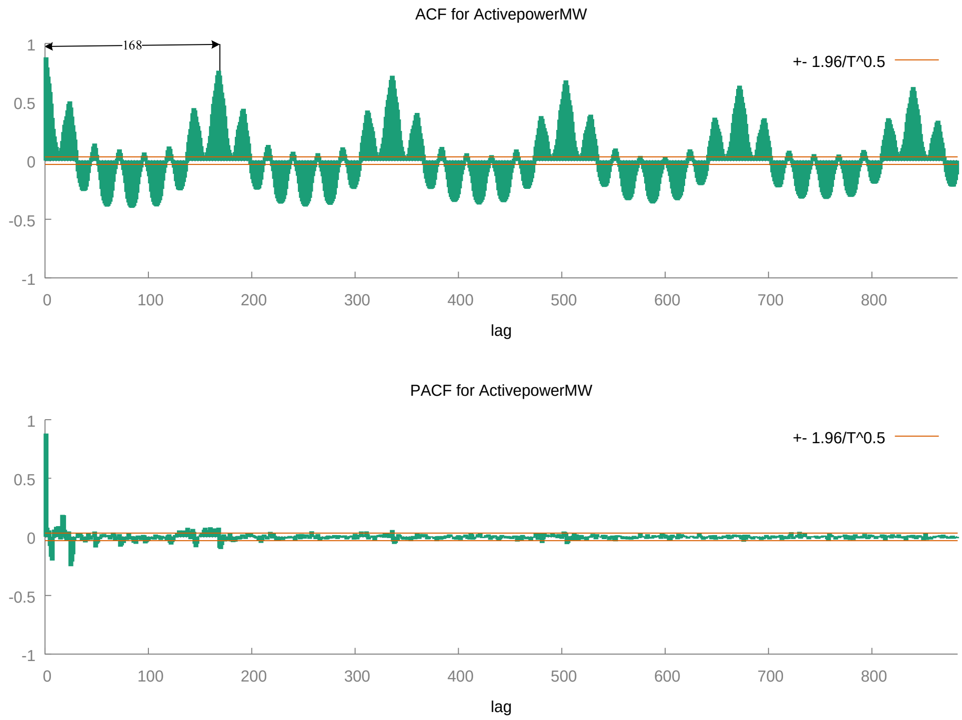


Figure A.14. Correlogram for initial dataset of active power for a week-ahead forecasting of electricity consumption

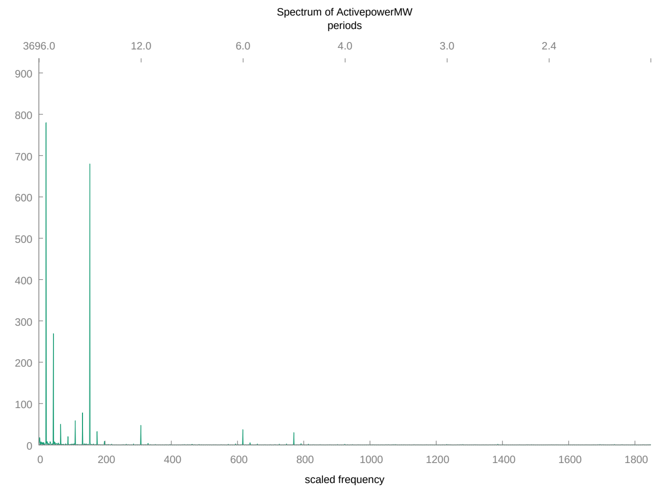


Figure A.15. Periodogram for initial dataset of active power for a week-ahead forecasting of electricity consumption

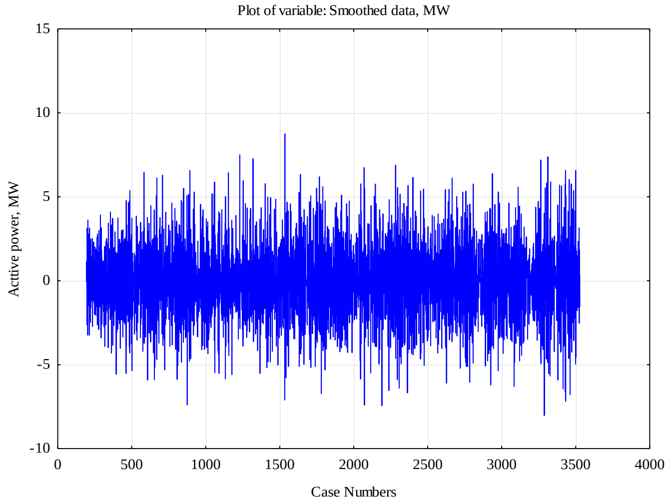


Figure A.16. The smoothed data of active power for a week-ahead forecasting of electricity consumption

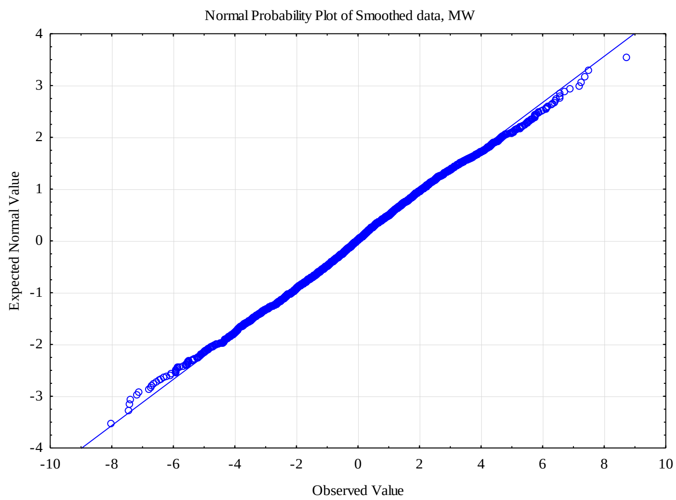
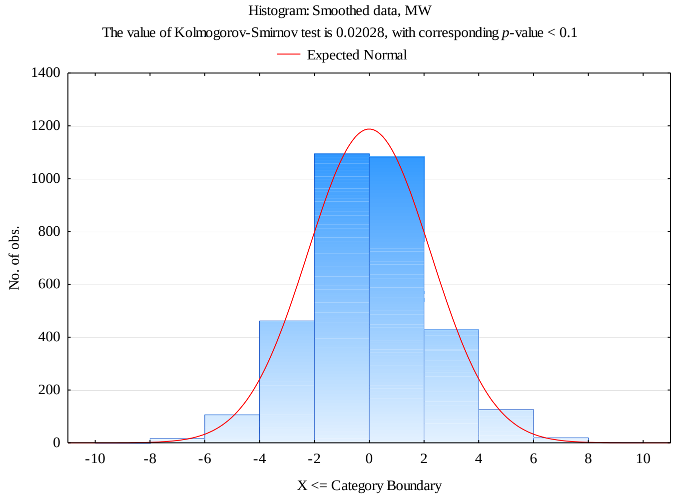


Figure A.17. Normal quantile-quantile plot of active power after smoothing for a week-ahead forecasting of electricity consumption



Note: number of bins is 13.

Figure A.18. Empirical and fitted normal distributions of active power after smoothing for a week-ahead forecasting of electricity consumption

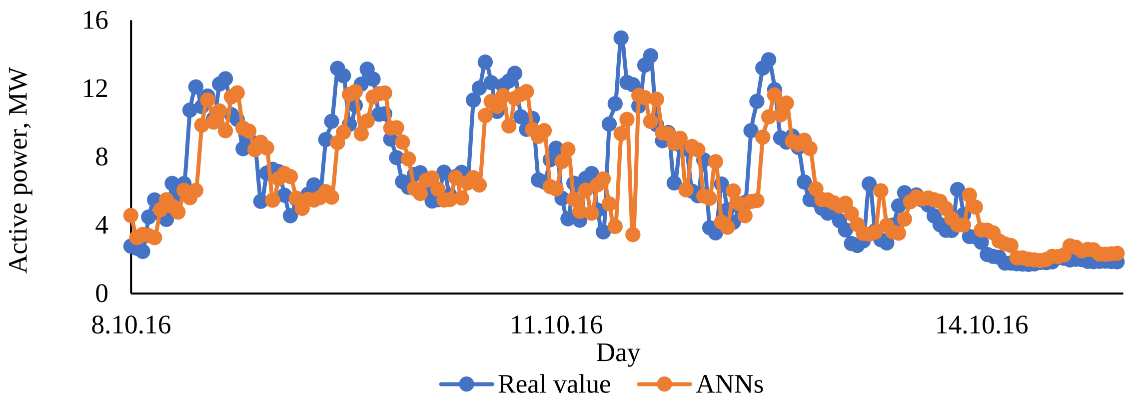


Figure A.19. Week-ahead electricity consumption forecast from ARIMA and initial value of electricity consumption

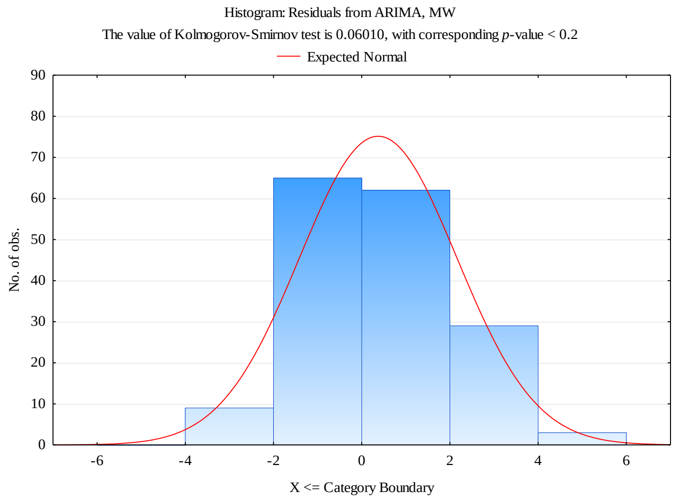


Figure A.20. Histogram of residuals for week-ahead forecast of electricity consumption from ARIMA and fitted normal distribution

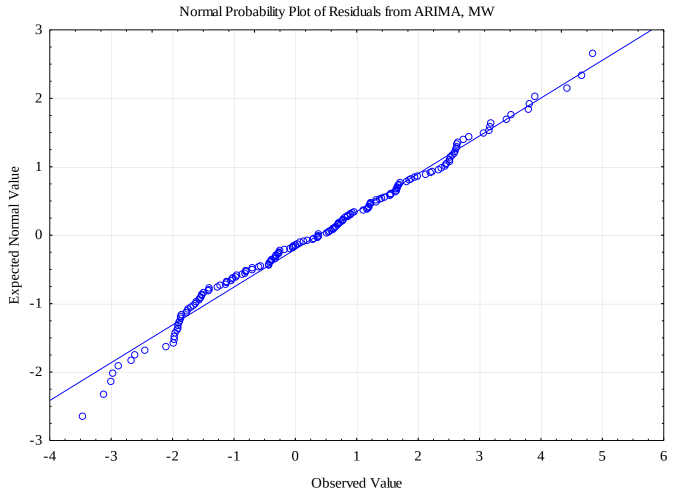


Figure A.21. Normal quantile-quantile plot of residuals for week-ahead forecast of electricity consumption from ARIMA

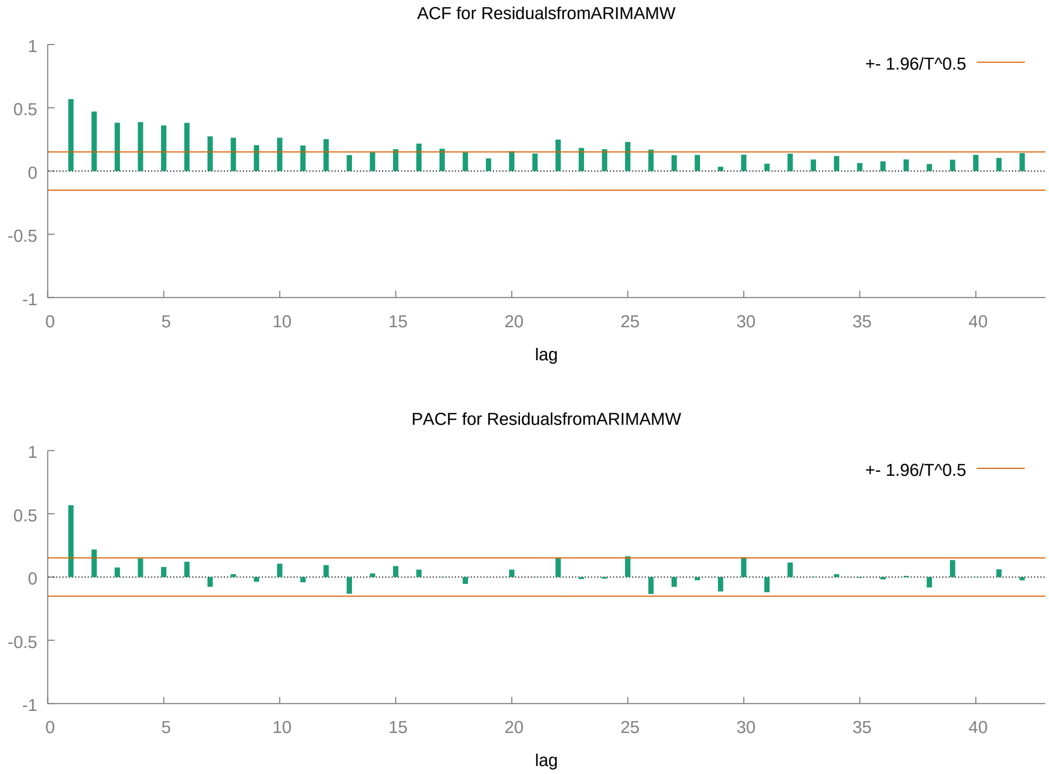


Figure A.22. Correlogram for residuals for week-ahead forecast of electricity consumption from ARIMA

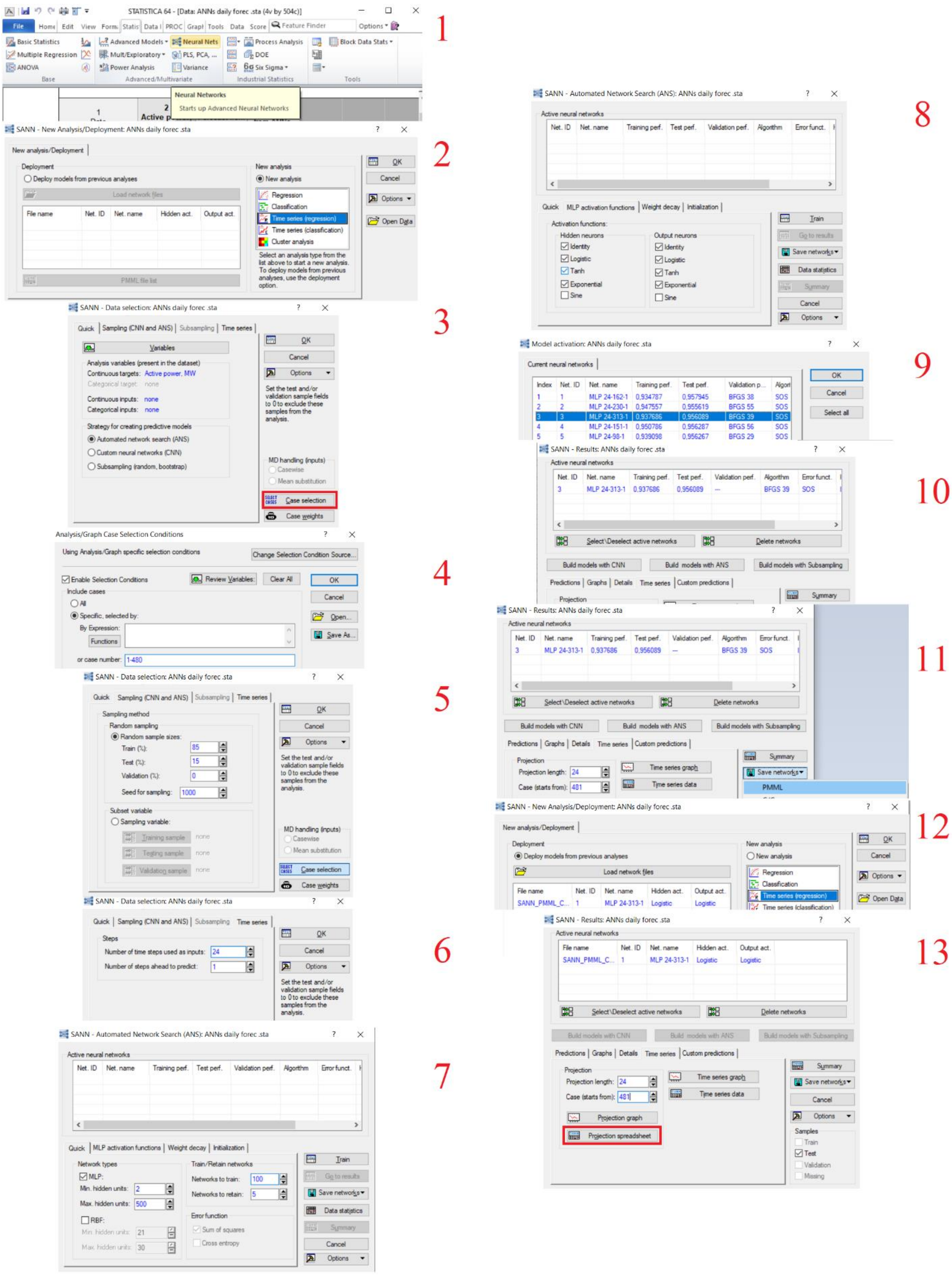


Figure A.23. The sequence of forecasting by ANN model in Statistica software

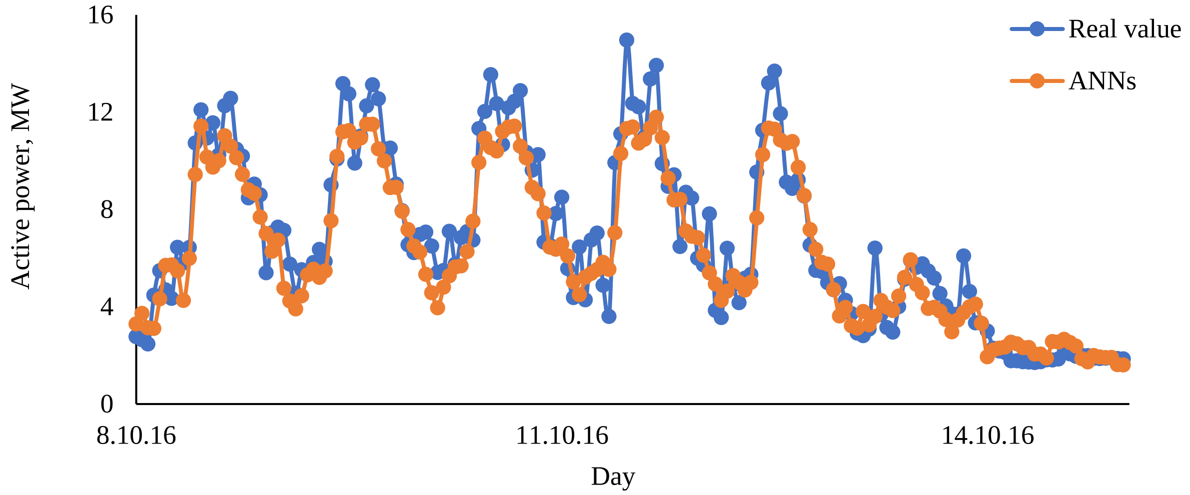


Figure A.24. Week-ahead electricity consumption forecast from ANN and initial value of electricity consumption

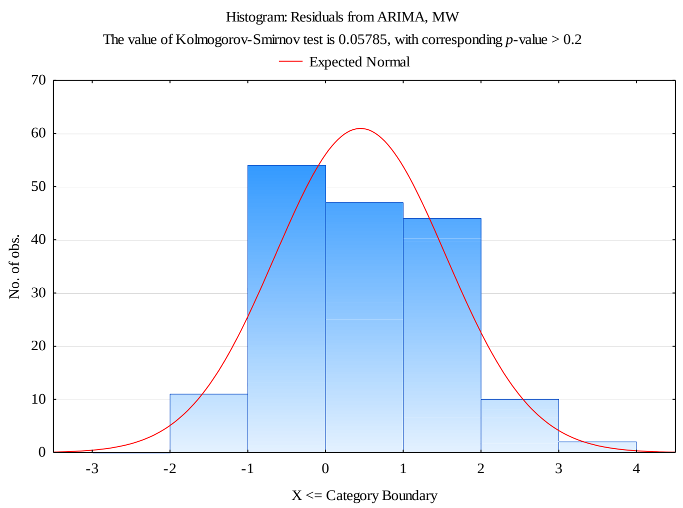


Figure A.25. Histogram of residuals for week-ahead forecast of electricity consumption from ANN and fitted normal distribution

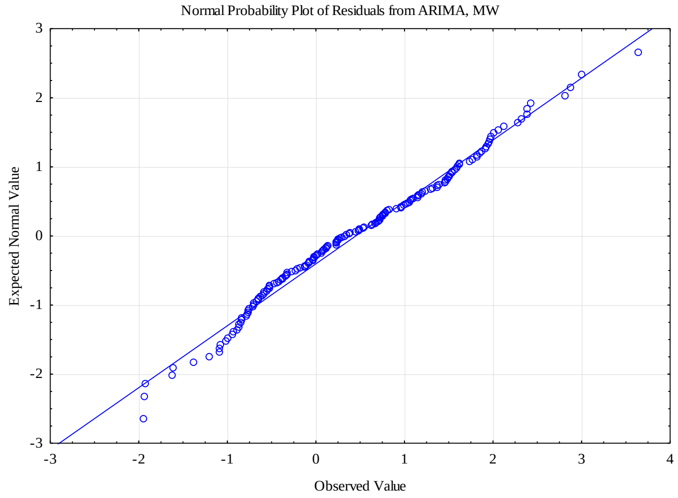


Figure A.26. Normal quantile-quantile plot of residuals for week-ahead forecast of electricity consumption from ANN

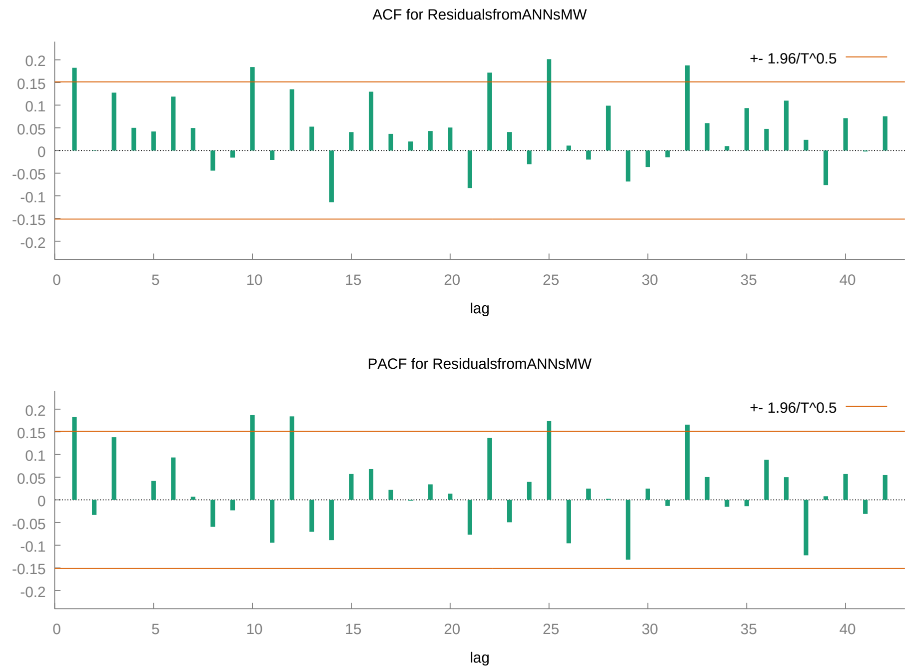


Figure A.27. Correlogram for residuals for week-ahead forecast of electricity consumption from ANN

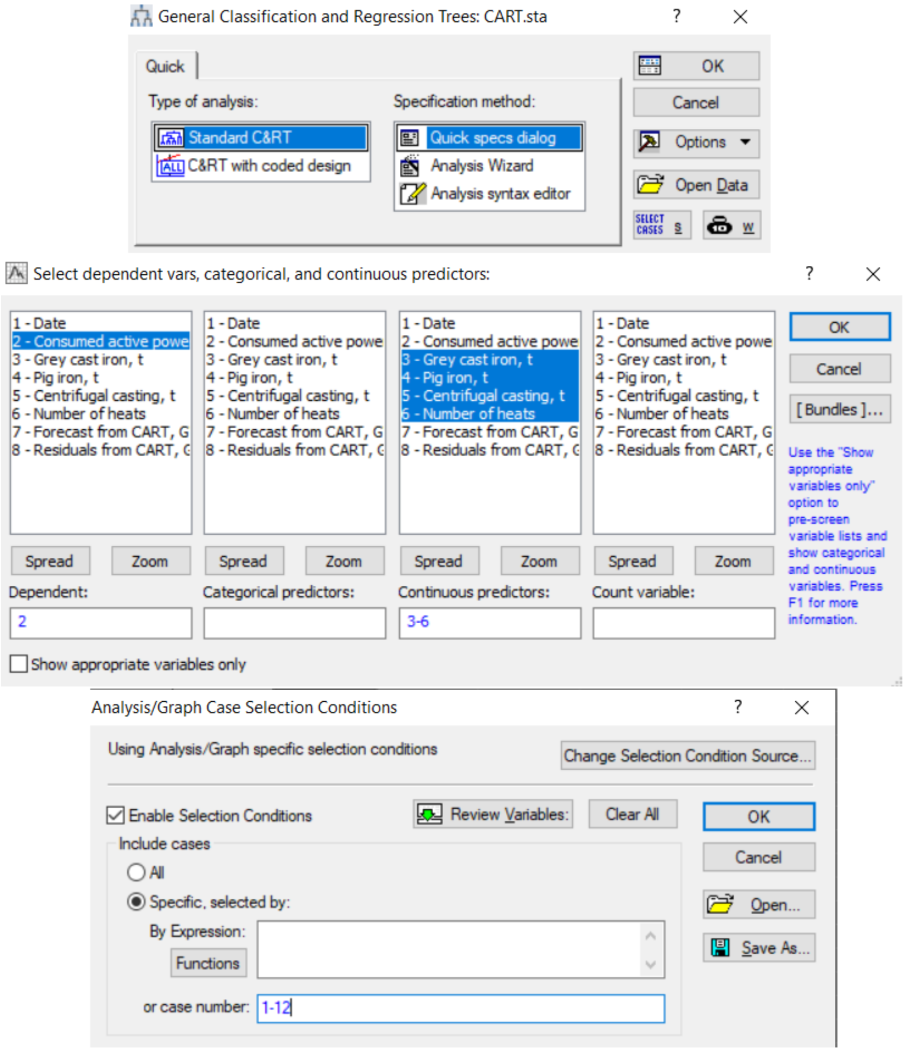


Figure A.28. The sequence of preparing a CART model in Statistica software

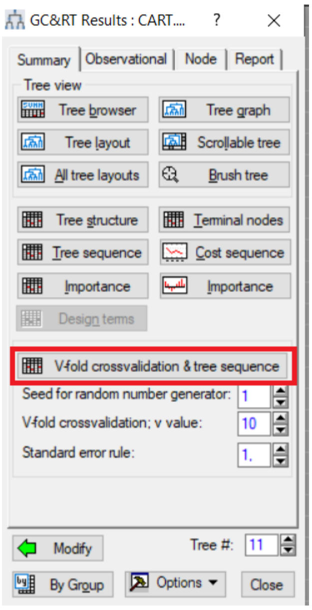


Figure A.29. The sequence of cross-validation in Statistica software

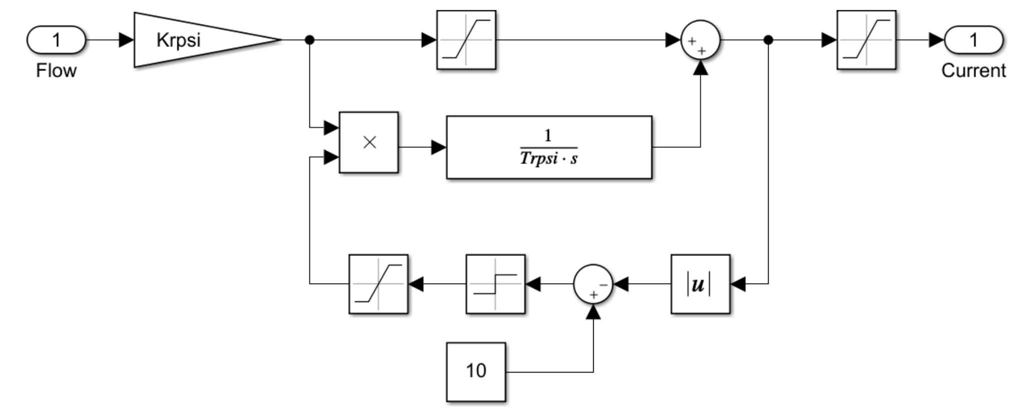


Figure A.30. Simulation model of the flux linkage controller

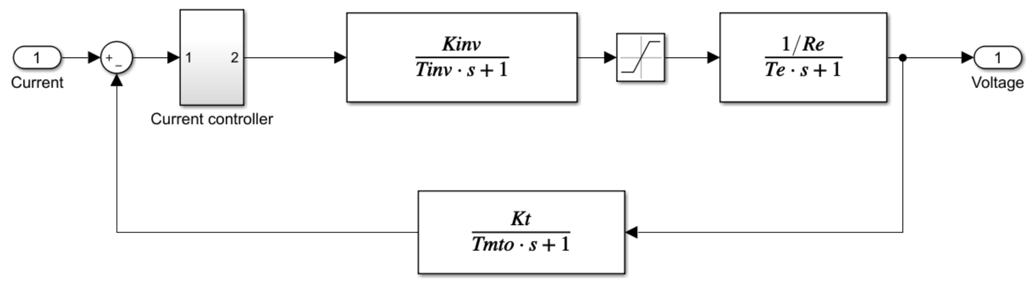


Figure A.31. Current loop simulation model

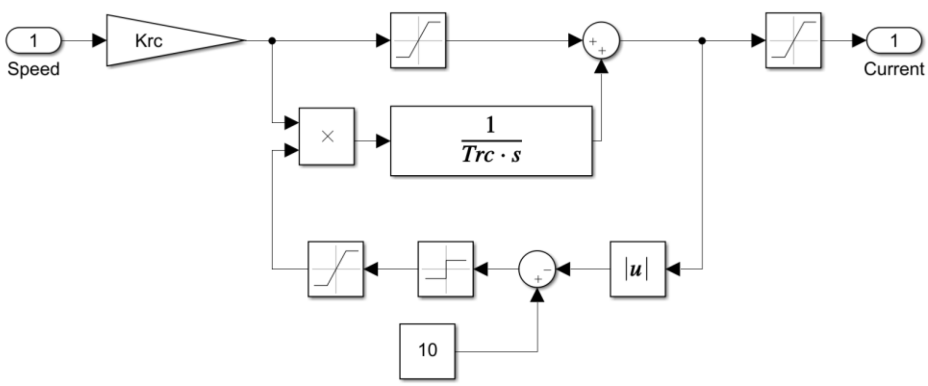


Figure A.32. Speed governor simulation model

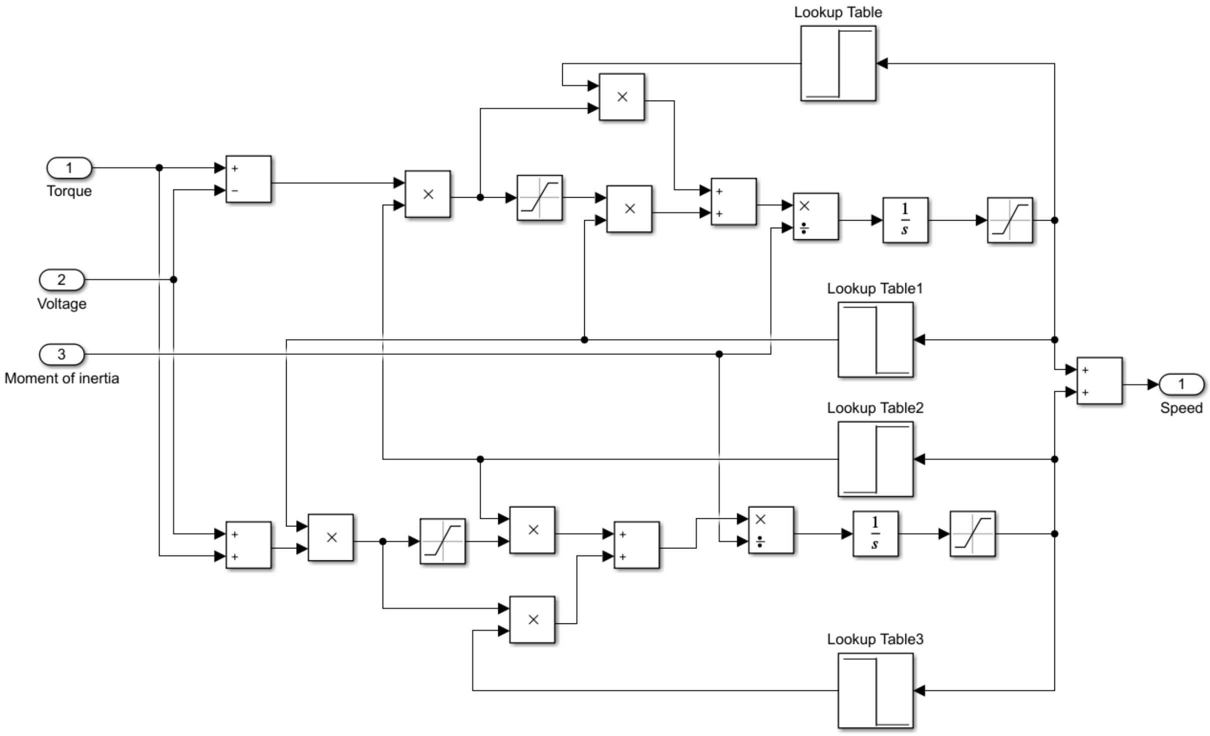


Figure A.33. Reactive load simulation model

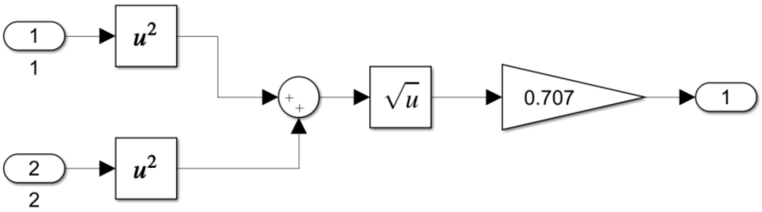


Figure A.34. Simulation model of the phase current calculation unit

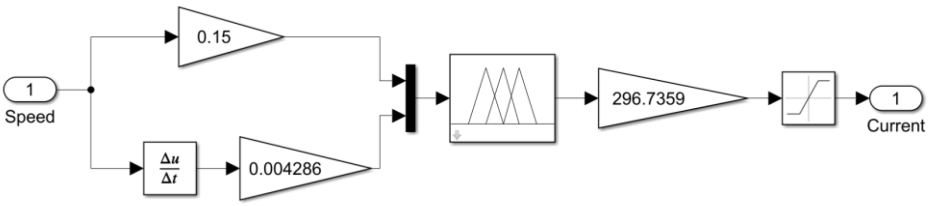


Figure A.35. Fuzzy logic controller simulation model

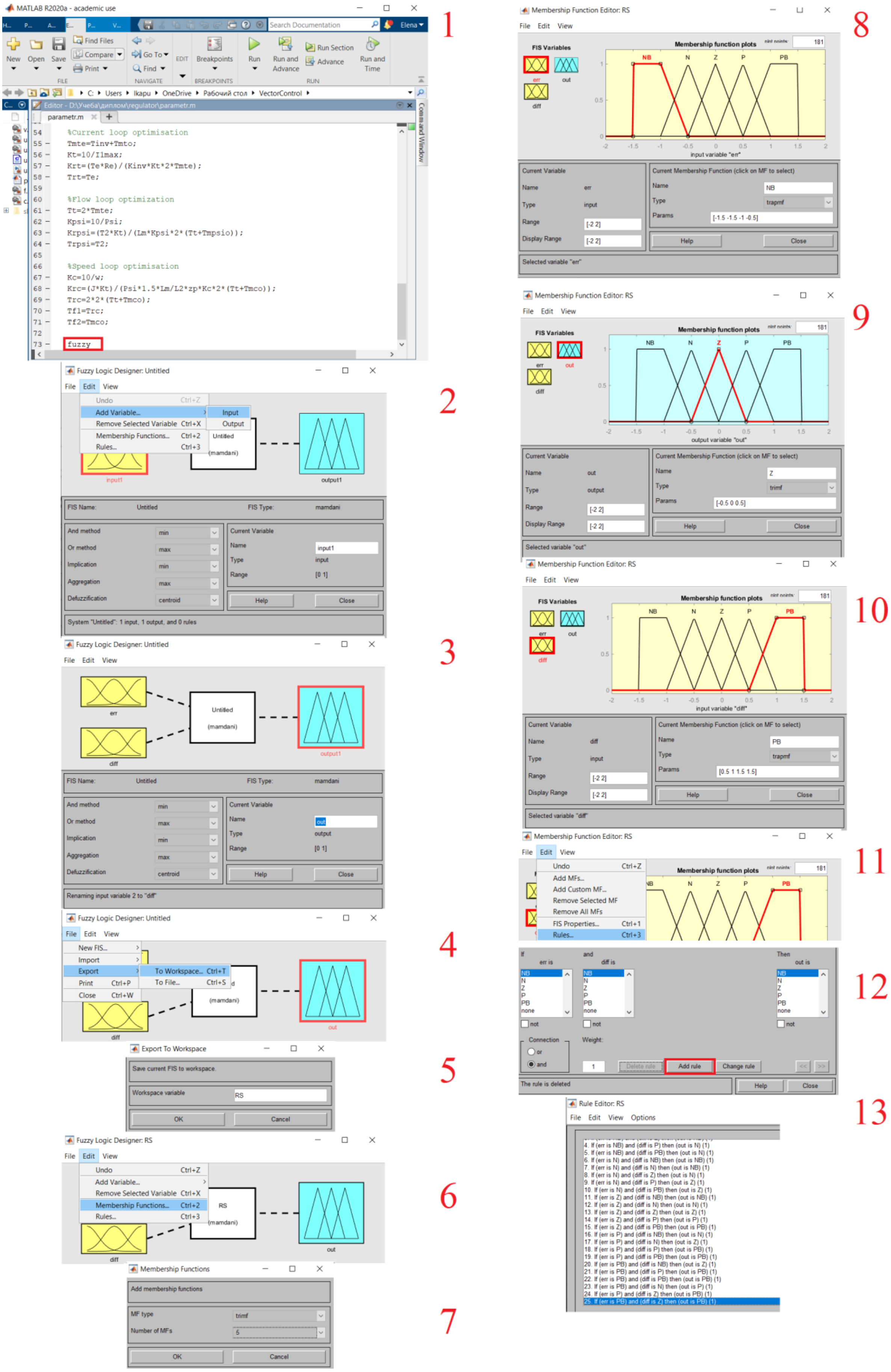


Figure A.36. The sequence of preparing fuzzy in MATLAB software

Appendix B – Tables

Table B.1. Initial data for a day-ahead electricity consumption forecast from ARIMA

№	**Time**	**Active power, MW**	**№**	**Time**	**Active power, MW**	**№**	**Time**	**Active power, MW**
1	14.05.2016 0:00	1.226	161	02.07.2016 16:00	10.564	321	20.08.2016 8:00	4.592
2	14.05.2016 1:00	1.353	162	02.07.2016 17:00	8.476	322	20.08.2016 9:00	5.726
3	14.05.2016 2:00	1.474	163	02.07.2016 18:00	6.314	323	20.08.2016 10:00	7.923
4	14.05.2016 3:00	1.462	164	02.07.2016 19:00	7.13	324	20.08.2016 11:00	9.375
5	14.05.2016 4:00	1.746	165	02.07.2016 20:00	6.26	325	20.08.2016 12:00	8.621
6	14.05.2016 5:00	3.007	166	02.07.2016 21:00	6.17	326	20.08.2016 13:00	6.517
7	14.05.2016 6:00	4.972	167	02.07.2016 22:00	5.889	327	20.08.2016 14:00	8.737
8	14.05.2016 7:00	4.928	168	02.07.2016 23:00	6.388	328	20.08.2016 15:00	9.264
9	14.05.2016 8:00	4.191	169	09.07.2016 0:00	4.501	329	20.08.2016 16:00	10.473
10	14.05.2016 9:00	4.94	170	09.07.2016 1:00	3.279	330	20.08.2016 17:00	10.588
11	14.05.2016 10:00	7.49	171	09.07.2016 2:00	3.503	331	20.08.2016 18:00	8.84
12	14.05.2016 11:00	10.495	172	09.07.2016 3:00	2.991	332	20.08.2016 19:00	8.559
13	14.05.2016 12:00	10.621	173	09.07.2016 4:00	4.593	333	20.08.2016 20:00	7.474
14	14.05.2016 13:00	9.038	174	09.07.2016 5:00	5.041	334	20.08.2016 21:00	7.544
15	14.05.2016 14:00	9.046	175	09.07.2016 6:00	4.198	335	20.08.2016 22:00	6.59
16	14.05.2016 15:00	10.424	176	09.07.2016 7:00	5.101	336	20.08.2016 23:00	4.932
17	14.05.2016 16:00	10.065	177	09.07.2016 8:00	5.313	337	27.08.2016 0:00	1.257
18	14.05.2016 17:00	9.298	178	09.07.2016 9:00	5.031	338	27.08.2016 1:00	1.688

19	14.05.2016 18:00	6.82	179	09.07.2016 10:00	6.845	339	27.08.2016 2:00	1.783
20	14.05.2016 19:00	7.713	180	09.07.2016 11:00	9.779	340	27.08.2016 3:00	1.907
21	14.05.2016 20:00	7.819	181	09.07.2016 12:00	10.117	341	27.08.2016 4:00	2.072
22	14.05.2016 21:00	7.131	182	09.07.2016 13:00	9.692	342	27.08.2016 5:00	3.916
23	14.05.2016 22:00	7.341	183	09.07.2016 14:00	6.977	343	27.08.2016 6:00	5.819
24	14.05.2016 23:00	7.293	184	09.07.2016 15:00	10.162	344	27.08.2016 7:00	4.066
25	21.05.2016 0:00	1.99	185	09.07.2016 16:00	10.13	345	27.08.2016 8:00	3.157
26	21.05.2016 1:00	4.127	186	09.07.2016 17:00	8.009	346	27.08.2016 9:00	4.784
27	21.05.2016 2:00	2.901	187	09.07.2016 18:00	6.281	347	27.08.2016 10:00	9.24
28	21.05.2016 3:00	2.288	188	09.07.2016 19:00	6.057	348	27.08.2016 11:00	11.23
29	21.05.2016 4:00	5.531	189	09.07.2016 20:00	6.58	349	27.08.2016 12:00	10.41
30	21.05.2016 5:00	5.038	190	09.07.2016 21:00	7.646	350	27.08.2016 13:00	10.061
31	21.05.2016 6:00	5.161	191	09.07.2016 22:00	5.133	351	27.08.2016 14:00	10.538
32	21.05.2016 7:00	4.25	192	09.07.2016 23:00	6.901	352	27.08.2016 15:00	11.158
33	21.05.2016 8:00	5.082	193	16.07.2016 0:00	1.043	353	27.08.2016 16:00	10.937
34	21.05.2016 9:00	4.582	194	16.07.2016 1:00	1.548	354	27.08.2016 17:00	10.35
35	21.05.2016 10:00	10.301	195	16.07.2016 2:00	1.871	355	27.08.2016 18:00	9.262
36	21.05.2016 11:00	10.462	196	16.07.2016 3:00	1.877	356	27.08.2016 19:00	8.015
37	21.05.2016 12:00	10.021	197	16.07.2016 4:00	2.208	357	27.08.2016 20:00	7.104
38	21.05.2016 13:00	10.51	198	16.07.2016 5:00	6.411	358	27.08.2016 21:00	7.384

39	21.05.2016 14:00	9.701	199	16.07.2016 6:00	5.076	359	27.08.2016 22:00	5.76
40	21.05.2016 15:00	10.962	200	16.07.2016 7:00	3.251	360	27.08.2016 23:00	7.131
41	21.05.2016 16:00	10.92	201	16.07.2016 8:00	2.624	361	03.09.2016 0:00	1.081
42	21.05.2016 17:00	10.425	202	16.07.2016 9:00	4.549	362	03.09.2016 1:00	1.303
43	21.05.2016 18:00	9.495	203	16.07.2016 10:00	9.023	363	03.09.2016 2:00	1.616
44	21.05.2016 19:00	6.638	204	16.07.2016 11:00	9.129	364	03.09.2016 3:00	1.641
45	21.05.2016 20:00	7.17	205	16.07.2016 12:00	10.209	365	03.09.2016 4:00	1.973
46	21.05.2016 21:00	7.265	206	16.07.2016 13:00	6.413	366	03.09.2016 5:00	2.394
47	21.05.2016 22:00	6.9	207	16.07.2016 14:00	6.33	367	03.09.2016 6:00	2.383
48	21.05.2016 23:00	6.933	208	16.07.2016 15:00	10.42	368	03.09.2016 7:00	5.68
49	28.05.2016 0:00	1.26	209	16.07.2016 16:00	10.214	369	03.09.2016 8:00	5.691
50	28.05.2016 1:00	1.377	210	16.07.2016 17:00	9.488	370	03.09.2016 9:00	4.204
51	28.05.2016 2:00	1.477	211	16.07.2016 18:00	9.008	371	03.09.2016 10:00	6.966
52	28.05.2016 3:00	1.492	212	16.07.2016 19:00	5.519	372	03.09.2016 11:00	6.947
53	28.05.2016 4:00	1.819	213	16.07.2016 20:00	7.477	373	03.09.2016 12:00	10.545
54	28.05.2016 5:00	3.836	214	16.07.2016 21:00	3.9	374	03.09.2016 13:00	8.95
55	28.05.2016 6:00	5.551	215	16.07.2016 22:00	6.893	375	03.09.2016 14:00	6.952
56	28.05.2016 7:00	4.993	216	16.07.2016 23:00	6.547	376	03.09.2016 15:00	10.327
57	28.05.2016 8:00	3.963	217	23.07.2016 0:00	1.406	377	03.09.2016 16:00	9.057
58	28.05.2016 9:00	4.808	218	23.07.2016 1:00	1.53	378	03.09.2016 17:00	8.743

59	28.05.2016 10:00	7.484	219	23.07.2016 2:00	1.509	379	03.09.2016 18:00	6.893
60	28.05.2016 11:00	10.211	220	23.07.2016 3:00	1.614	380	03.09.2016 19:00	7.781
61	28.05.2016 12:00	10.957	221	23.07.2016 4:00	1.842	381	03.09.2016 20:00	6.964
62	28.05.2016 13:00	9.533	222	23.07.2016 5:00	3.418	382	03.09.2016 21:00	7.556
63	28.05.2016 14:00	9.404	223	23.07.2016 6:00	5.818	383	03.09.2016 22:00	6.693
64	28.05.2016 15:00	11.518	224	23.07.2016 7:00	4.259	384	03.09.2016 23:00	7.151
65	28.05.2016 16:00	10.801	225	23.07.2016 8:00	2.605	385	10.09.2016 0:00	3.699
66	28.05.2016 17:00	10.99	226	23.07.2016 9:00	4.465	386	10.09.2016 1:00	1.991
67	28.05.2016 18:00	8.468	227	23.07.2016 10:00	7.754	387	10.09.2016 2:00	1.539
68	28.05.2016 19:00	8.1	228	23.07.2016 11:00	9.725	388	10.09.2016 3:00	1.658
69	28.05.2016 20:00	6.314	229	23.07.2016 12:00	10.501	389	10.09.2016 4:00	2.204
70	28.05.2016 21:00	7.84	230	23.07.2016 13:00	8.896	390	10.09.2016 5:00	2.483
71	28.05.2016 22:00	6.097	231	23.07.2016 14:00	7.529	391	10.09.2016 6:00	2.558
72	28.05.2016 23:00	6.939	232	23.07.2016 15:00	9.979	392	10.09.2016 7:00	5.512
73	04.06.2016 0:00	1.459	233	23.07.2016 16:00	10.813	393	10.09.2016 8:00	2.785
74	04.06.2016 1:00	1.652	234	23.07.2016 17:00	9.832	394	10.09.2016 9:00	4.077
75	04.06.2016 2:00	1.63	235	23.07.2016 18:00	8.835	395	10.09.2016 10:00	7.122
76	04.06.2016 3:00	1.634	236	23.07.2016 19:00	8.238	396	10.09.2016 11:00	8.067
77	04.06.2016 4:00	1.821	237	23.07.2016 20:00	7.028	397	10.09.2016 12:00	10.496
78	04.06.2016 5:00	2.478	238	23.07.2016 21:00	8.166	398	10.09.2016 13:00	9.399

79	04.06.2016 6:00	4.439	239	23.07.2016 22:00	6.321	399	10.09.2016 14:00	9.344
80	04.06.2016 7:00	5.343	240	23.07.2016 23:00	7.217	400	10.09.2016 15:00	10.655
81	04.06.2016 8:00	3.829	241	30.07.2016 0:00	3.653	401	10.09.2016 16:00	9.647
82	04.06.2016 9:00	5.444	242	30.07.2016 1:00	4.93	402	10.09.2016 17:00	9.689
83	04.06.2016 10:00	8.031	243	30.07.2016 2:00	2.287	403	10.09.2016 18:00	7.466
84	04.06.2016 11:00	10.44	244	30.07.2016 3:00	4.785	404	10.09.2016 19:00	7.625
85	04.06.2016 12:00	11.227	245	30.07.2016 4:00	4.726	405	10.09.2016 20:00	7.358
86	04.06.2016 13:00	10.521	246	30.07.2016 5:00	4.188	406	10.09.2016 21:00	6.487
87	04.06.2016 14:00	8.188	247	30.07.2016 6:00	5.847	407	10.09.2016 22:00	4.982
88	04.06.2016 15:00	7.356	248	30.07.2016 7:00	4.756	408	10.09.2016 23:00	6.899
89	04.06.2016 16:00	6.693	249	30.07.2016 8:00	3.434	409	17.09.2016 0:00	1.209
90	04.06.2016 17:00	6.362	250	30.07.2016 9:00	6.413	410	17.09.2016 1:00	1.245
91	04.06.2016 18:00	4.83	251	30.07.2016 10:00	8.296	411	17.09.2016 2:00	1.356
92	04.06.2016 19:00	4.113	252	30.07.2016 11:00	9.767	412	17.09.2016 3:00	1.413
93	04.06.2016 20:00	3.937	253	30.07.2016 12:00	9.049	413	17.09.2016 4:00	2.095
94	04.06.2016 21:00	3.624	254	30.07.2016 13:00	9.602	414	17.09.2016 5:00	2.232
95	04.06.2016 22:00	3.14	255	30.07.2016 14:00	8.994	415	17.09.2016 6:00	5.45
96	04.06.2016 23:00	2.511	256	30.07.2016 15:00	9.667	416	17.09.2016 7:00	5.078
97	11.06.2016 0:00	1.078	257	30.07.2016 16:00	9.616	417	17.09.2016 8:00	2.122
98	11.06.2016 1:00	1.113	258	30.07.2016 17:00	9.448	418	17.09.2016 9:00	4.851

99	11.06.2016 2:00	1.203	259	30.07.2016 18:00	8.18	419	17.09.2016 10:00	7.805
100	11.06.2016 3:00	1.179	260	30.07.2016 19:00	7.292	420	17.09.2016 11:00	9.879
101	11.06.2016 4:00	1.189	261	30.07.2016 20:00	6.978	421	17.09.2016 12:00	8.942
102	11.06.2016 5:00	1.184	262	30.07.2016 21:00	6.896	422	17.09.2016 13:00	9.959
103	11.06.2016 6:00	1.137	263	30.07.2016 22:00	5.935	423	17.09.2016 14:00	9.157
104	11.06.2016 7:00	1.158	264	30.07.2016 23:00	6.278	424	17.09.2016 15:00	9.905
105	11.06.2016 8:00	1.309	265	06.08.2016 0:00	1.11	425	17.09.2016 16:00	11.057
106	11.06.2016 9:00	2.453	266	06.08.2016 1:00	1.475	426	17.09.2016 17:00	10.381
107	11.06.2016 10:00	3.238	267	06.08.2016 2:00	1.629	427	17.09.2016 18:00	8.488
108	11.06.2016 11:00	1.551	268	06.08.2016 3:00	1.681	428	17.09.2016 19:00	7.969
109	11.06.2016 12:00	1.819	269	06.08.2016 4:00	1.747	429	17.09.2016 20:00	8.356
110	11.06.2016 13:00	2.017	270	06.08.2016 5:00	2.839	430	17.09.2016 21:00	8.493
111	11.06.2016 14:00	1.739	271	06.08.2016 6:00	6.009	431	17.09.2016 22:00	6.498
112	11.06.2016 15:00	3.819	272	06.08.2016 7:00	4.983	432	17.09.2016 23:00	7.387
113	11.06.2016 16:00	1.852	273	06.08.2016 8:00	3.177	433	24.09.2016 0:00	1.355
114	11.06.2016 17:00	1.734	274	06.08.2016 9:00	4.831	434	24.09.2016 1:00	1.426
115	11.06.2016 18:00	2.622	275	06.08.2016 10:00	8.991	435	24.09.2016 2:00	1.56
116	11.06.2016 19:00	4.191	276	06.08.2016 11:00	9.618	436	24.09.2016 3:00	1.655
117	11.06.2016 20:00	1.429	277	06.08.2016 12:00	7.43	437	24.09.2016 4:00	2.379
118	11.06.2016 21:00	1.987	278	06.08.2016 13:00	6.449	438	24.09.2016 5:00	3.16

119	11.06.2016 22:00	4.4	279	06.08.2016 14:00	6.578	439	24.09.2016 6:00	5.584
120	11.06.2016 23:00	4.845	280	06.08.2016 15:00	7.206	440	24.09.2016 7:00	5.841
121	18.06.2016 0:00	1.151	281	06.08.2016 16:00	7.002	441	24.09.2016 8:00	2.765
122	18.06.2016 1:00	1.19	282	06.08.2016 17:00	6.548	442	24.09.2016 9:00	4.676
123	18.06.2016 2:00	1.229	283	06.08.2016 18:00	5.034	443	24.09.2016 10:00	8.778
124	18.06.2016 3:00	1.393	284	06.08.2016 19:00	5.765	444	24.09.2016 11:00	11.852
125	18.06.2016 4:00	1.753	285	06.08.2016 20:00	6.247	445	24.09.2016 12:00	11.05
126	18.06.2016 5:00	2.716	286	06.08.2016 21:00	5.808	446	24.09.2016 13:00	11.531
127	18.06.2016 6:00	5.413	287	06.08.2016 22:00	5.249	447	24.09.2016 14:00	8.901
128	18.06.2016 7:00	5.981	288	06.08.2016 23:00	5.111	448	24.09.2016 15:00	11.028
129	18.06.2016 8:00	2.961	289	13.08.2016 0:00	1.678	449	24.09.2016 16:00	10.573
130	18.06.2016 9:00	4.546	290	13.08.2016 1:00	1.726	450	24.09.2016 17:00	10.984
131	18.06.2016 10:00	9.693	291	13.08.2016 2:00	2.808	451	24.09.2016 18:00	7.002
132	18.06.2016 11:00	11.056	292	13.08.2016 3:00	3.337	452	24.09.2016 19:00	8.608
133	18.06.2016 12:00	9.65	293	13.08.2016 4:00	4.271	453	24.09.2016 20:00	8.699
134	18.06.2016 13:00	10.737	294	13.08.2016 5:00	5.125	454	24.09.2016 21:00	6.498
135	18.06.2016 14:00	9.895	295	13.08.2016 6:00	2.914	455	24.09.2016 22:00	6.65
136	18.06.2016 15:00	11.036	296	13.08.2016 7:00	2.874	456	24.09.2016 23:00	7.368
137	18.06.2016 16:00	10.579	297	13.08.2016 8:00	2.427	457	01.10.2016 0:00	1.482
138	18.06.2016 17:00	8.375	298	13.08.2016 9:00	4.148	458	01.10.2016 1:00	1.509

139	18.06.2016 18:00	8.234	299	13.08.2016 10:00	8.526	459	01.10.2016 2:00	1.632
140	18.06.2016 19:00	7.545	300	13.08.2016 11:00	9.798	460	01.10.2016 3:00	2.339
141	18.06.2016 20:00	7.365	301	13.08.2016 12:00	8.031	461	01.10.2016 4:00	2.686
142	18.06.2016 21:00	7.003	302	13.08.2016 13:00	9.381	462	01.10.2016 5:00	3.222
143	18.06.2016 22:00	6.122	303	13.08.2016 14:00	8.993	463	01.10.2016 6:00	5.64
144	18.06.2016 23:00	6.461	304	13.08.2016 15:00	8.239	464	01.10.2016 7:00	5.749
145	02.07.2016 0:00	1.023	305	13.08.2016 16:00	8.95	465	01.10.2016 8:00	3.073
146	02.07.2016 1:00	1.217	306	13.08.2016 17:00	9.002	466	01.10.2016 9:00	4.888
147	02.07.2016 2:00	1.392	307	13.08.2016 18:00	7.839	467	01.10.2016 10:00	8.248
148	02.07.2016 3:00	1.625	308	13.08.2016 19:00	6.134	468	01.10.2016 11:00	8.999
149	02.07.2016 4:00	2.233	309	13.08.2016 20:00	7.582	469	01.10.2016 12:00	10.749
150	02.07.2016 5:00	2.777	310	13.08.2016 21:00	6.916	470	01.10.2016 13:00	10.561
151	02.07.2016 6:00	5.269	311	13.08.2016 22:00	5.192	471	01.10.2016 14:00	8.025
152	02.07.2016 7:00	5.72	312	13.08.2016 23:00	6.677	472	01.10.2016 15:00	10.048
153	02.07.2016 8:00	2.792	313	20.08.2016 0:00	4.671	473	01.10.2016 16:00	7.761
154	02.07.2016 9:00	4.071	314	20.08.2016 1:00	4.509	474	01.10.2016 17:00	9.755
155	02.07.2016 10:00	7.901	315	20.08.2016 2:00	5.883	475	01.10.2016 18:00	10.216
156	02.07.2016 11:00	9.854	316	20.08.2016 3:00	4.073	476	01.10.2016 19:00	5.835
157	02.07.2016 12:00	9.579	317	20.08.2016 4:00	4.065	477	01.10.2016 20:00	6.743
158	02.07.2016 13:00	9.647	318	20.08.2016 5:00	4.834	478	01.10.2016 21:00	7.939

159	02.07.2016 14:00	7.502	319	20.08.2016 6:00	4.894	479	01.10.2016 22:00	7.105
160	02.07.2016 15:00	9.881	320	20.08.2016 7:00	3.877	480	01.10.2016 23:00	7.972

Table B.2. The parameters of the correlogram of initial data for a day-ahead electricity consumption forecast from ARIMA

LAG	ACF	PACF	Q-stat.	p-value	LAG	ACF	PACF	Q-stat.	p-value
1	0.8302	0.8302	332.9177	0.000	61	-0.5471	-0.0394	5858.0491	0.000
2	0.6755	-0.0443	553.7725	0.000	62	-0.5110	-0.0126	6002.5777	0.000
3	0.5470	-0.0060	698.9056	0.000	63	-0.4376	-0.0373	6108.8264	0.000
4	0.4338	-0.0289	790.3533	0.000	64	-0.3015	0.0431	6159.3870	0.000
5	0.3073	-0.1145	836.3360	0.000	65	-0.1740	-0.0403	6176.2572	0.000
6	0.1371	-0.2353	845.5128	0.000	66	-0.0208	0.0566	6176.4993	0.000
7	-0.0559	-0.2415	847.0401	0.000	67	0.1108	0.0764	6183.3811	0.000
8	-0.2244	-0.1543	871.7254	0.000	68	0.2091	-0.0185	6207.9225	0.000
9	-0.4006	-0.2786	950.5492	0.000	69	0.2936	-0.0345	6256.4408	0.000
10	-0.5009	-0.0123	1074.0452	0.000	70	0.4021	0.0107	6347.6883	0.000
11	-0.5540	0.0020	1225.4482	0.000	71	0.5116	0.0379	6495.7320	0.000
12	-0.5642	0.0736	1382.8018	0.000	72	0.5836	-0.0413	6688.8802	0.000
13	-0.5463	0.0747	1530.6751	0.000	73	0.5041	-0.1399	6833.3077	0.000
14	-0.5045	0.0703	1657.0627	0.000	74	0.4019	-0.0242	6925.3334	0.000
15	-0.4185	0.1031	1744.1989	0.000	75	0.3030	-0.0054	6977.7715	0.000
16	-0.2634	0.2008	1778.7958	0.000	76	0.2289	0.0400	7007.7661	0.000
17	-0.1123	0.0659	1785.0925	0.000	77	0.1378	0.0319	7018.6648	0.000
18	0.0588	0.1310	1786.8233	0.000	78	0.0005	-0.0338	7018.6650	0.000
19	0.2021	0.0201	1807.3283	0.000	79	-0.1400	0.0091	7029.9742	0.000
20	0.3096	-0.0837	1855.5334	0.000	80	-0.2640	0.0752	7070.2768	0.000
21	0.4077	-0.0521	1939.3221	0.000	81	-0.3972	-0.0277	7161.7453	0.000
22	0.5080	0.0333	2069.6867	0.000	82	-0.4674	0.0048	7288.7321	0.000
23	0.6214	0.2061	2265.1686	0.000	83	-0.4909	0.0415	7429.1618	0.000
24	0.7169	0.2892	2525.9023	0.000	84	-0.5047	-0.0324	7577.9907	0.000
25	0.6260	-0.2659	2725.1697	0.000	85	-0.4939	-0.0609	7720.8527	0.000
26	0.4946	-0.1559	2849.8409	0.000	86	-0.4555	0.0005	7842.7026	0.000
27	0.3681	-0.1153	2919.0259	0.000	87	-0.3884	-0.0442	7931.5046	0.000
28	0.2709	-0.0177	2956.5800	0.000	88	-0.2712	-0.0615	7974.9296	0.000
29	0.1666	-0.0127	2970.8191	0.000	89	-0.1370	0.1110	7986.0378	0.000

30	0.0272	0.0214	2971.1981	0.000	90	0.0032	-0.0134	7986.0440	0.000
31	-0.1423	-0.0319	2981.6367	0.000	91	0.1172	0.0121	7994.2133	0.000
32	-0.3084	-0.0946	3030.7634	0.000	92	0.2117	0.0274	8020.9430	0.000
33	-0.4562	0.0051	3138.4953	0.000	93	0.2917	0.0306	8071.8048	0.000
34	-0.5338	0.0369	3286.3065	0.000	94	0.3873	-0.0176	8161.7198	0.000
35	-0.5735	-0.0007	3457.3208	0.000	95	0.4879	-0.0068	8304.7495	0.000
36	-0.5948	-0.1275	3641.7028	0.000	96	0.5648	0.0719	8496.9755	0.000
37	-0.5715	0.0088	3812.2510	0.000	97	0.5025	-0.0668	8649.4815	0.000
38	-0.5305	-0.0305	3959.5481	0.000	98	0.4162	0.0591	8754.4191	0.000
39	-0.4465	0.0226	4064.1451	0.000	99	0.3228	-0.0244	8817.6855	0.000
40	-0.3047	0.0494	4112.9695	0.000	100	0.2459	-0.0483	8854.4966	0.000
41	-0.1624	-0.0107	4126.8673	0.000	101	0.1747	0.0379	8873.1290	0.000
42	0.0041	0.0398	4126.8763	0.000	102	0.0580	0.0396	8875.1881	0.000
43	0.1322	-0.0612	4136.1223	0.000	103	-0.0779	0.0246	8878.9092	0.000
44	0.2367	0.0176	4165.8587	0.000	104	-0.1914	0.0475	8901.4594	0.000
45	0.3273	-0.0449	4222.8312	0.000	105	-0.3086	0.0285	8960.2164	0.000
46	0.4394	0.1198	4325.7764	0.000	106	-0.3777	-0.0567	9048.4815	0.000
47	0.5462	0.0293	4485.1581	0.000	107	-0.4154	-0.0333	9155.4991	0.000
48	0.6307	0.1269	4698.1995	0.000	108	-0.4324	-0.0099	9271.7870	0.000
49	0.5529	-0.1684	4862.3016	0.000	109	-0.4256	-0.0067	9384.7305	0.000
50	0.4396	-0.0384	4966.2851	0.000	110	-0.3906	0.0076	9480.1520	0.000
51	0.3289	-0.0080	5024.6262	0.000	111	-0.3351	-0.0123	9550.5789	0.000
52	0.2418	-0.0023	5056.2365	0.000	112	-0.2230	0.0914	9581.8450	0.000
53	0.1375	-0.0728	5066.4850	0.000	113	-0.1013	0.0377	9588.3132	0.000
54	0.0069	-0.0469	5066.5113	0.000	114	0.0278	0.0005	9588.8010	0.000
55	-0.1407	0.0617	5077.2885	0.000	115	0.1322	0.0153	9599.8732	0.000
56	-0.2820	0.0641	5120.6771	0.000	116	0.2180	0.0074	9630.0913	0.000
57	-0.4266	0.0148	5220.2261	0.000	117	0.2879	-0.0861	9682.9287	0.000
58	-0.5019	-0.0172	5358.3087	0.000	118	0.3764	-0.0254	9773.4855	0.000
59	-0.5421	-0.0495	5519.7830	0.000	119	0.4720	0.0392	9916.2852	0.000
60	-0.5604	-0.0799	5692.7865	0.000	120	0.5455	0.0383	10107.5183	0.000

Table B.3. The parameters of the periodogram of initial data for a day-ahead electricity consumption forecast from ARIMA

Omega	**Scaled frequency**	**Periods**	**Spectral density**	**Omega**	**Scaled frequency**	**Periods**	**Spectral density**
0.01309	1	480	4.1529	1.58389	121	3.97	0.017206

0.02618	2	240	6.0778	1.59698	122	3.93	0.20683
0.03927	3	160	7.0575	1.61007	123	3.9	0.21755
0.05236	4	120	2.2756	1.62316	124	3.87	0.007813
0.06545	5	96	10.482	1.63625	125	3.84	0.074177
0.07854	6	80	3.0938	1.64934	126	3.81	0.033575
0.09163	7	68.57	0.22796	1.66243	127	3.78	0.44899
0.10472	8	60	3.7872	1.67552	128	3.75	0.051337
0.11781	9	53.33	4.0737	1.68861	129	3.72	0.073014
0.1309	10	48	0.97274	1.7017	130	3.69	0.068383
0.14399	11	43.64	2.0677	1.71479	131	3.66	0.08753
0.15708	12	40	0.31553	1.72788	132	3.64	0.031281
0.17017	13	36.92	2.3434	1.74097	133	3.61	0.061086
0.18326	14	34.29	0.94366	1.75406	134	3.58	0.087207
0.19635	15	32	1.4201	1.76715	135	3.56	0.069669
0.20944	16	30	0.059009	1.78024	136	3.53	0.003686
0.22253	17	28.24	0.96839	1.79333	137	3.5	0.40215
0.23562	18	26.67	0.50664	1.80642	138	3.48	0.17601
0.24871	19	25.26	0.67309	1.81951	139	3.45	0.11077
0.2618	20	24	234.97	1.8326	140	3.43	1.2778
0.27489	21	22.86	3.1207	1.84569	141	3.4	0.077024
0.28798	22	21.82	0.4895	1.85878	142	3.38	0.10224
0.30107	23	20.87	0.80736	1.87187	143	3.36	0.21792
0.31416	24	20	0.068506	1.88496	144	3.33	0.12443
0.32725	25	19.2	2.7924	1.89805	145	3.31	0.076448
0.34034	26	18.46	0.16086	1.91114	146	3.29	0.003601
0.35343	27	17.78	1.7904	1.92423	147	3.27	0.002255
0.36652	28	17.14	0.41406	1.93732	148	3.24	0.012398
0.37961	29	16.55	0.52834	1.95041	149	3.22	0.16455
0.3927	30	16	0.051472	1.9635	150	3.2	0.037996
0.40579	31	15.48	0.98545	1.97659	151	3.18	0.23453
0.41888	32	15	0.01665	1.98968	152	3.16	0.005405
0.43197	33	14.55	0.6981	2.00277	153	3.14	0.060561
0.44506	34	14.12	0.24149	2.01586	154	3.12	0.089069
0.45815	35	13.71	0.42879	2.02895	155	3.1	0.00431
0.47124	36	13.33	0.24951	2.04204	156	3.08	0.51098
0.48433	37	12.97	0.12234	2.05513	157	3.06	0.32891
0.49742	38	12.63	0.026474	2.06822	158	3.04	0.039521
0.51051	39	12.31	0.23916	2.08131	159	3.02	0.016231
0.5236	40	12	2.1963	2.0944	160	3	0.50005
0.53669	41	11.71	0.006415	2.10749	161	2.98	0.13414

0.54978	42	11.43	0.033292	2.12058	162	2.96	0.12389
0.56287	43	11.16	0.024503	2.13367	163	2.94	0.015296
0.57596	44	10.91	0.023472	2.14675	164	2.93	0.011494
0.58905	45	10.67	0.052652	2.15984	165	2.91	0.082996
0.60214	46	10.43	0.085439	2.17293	166	2.89	0.10521
0.61523	47	10.21	0.1722	2.18602	167	2.87	0.23191
0.62832	48	10	0.12899	2.19911	168	2.86	0.11236
0.64141	49	9.8	0.1407	2.2122	169	2.84	0.06671
0.6545	50	9.6	0.18054	2.22529	170	2.82	0.15515
0.66759	51	9.41	0.32683	2.23838	171	2.81	0.10874
0.68068	52	9.23	0.013854	2.25147	172	2.79	0.061685
0.69377	53	9.06	0.006649	2.26456	173	2.77	0.032482
0.70686	54	8.89	0.061766	2.27765	174	2.76	0.065855
0.71995	55	8.73	0.085713	2.29074	175	2.74	0.067549
0.73304	56	8.57	0.029024	2.30383	176	2.73	0.09395
0.74613	57	8.42	0.11403	2.31692	177	2.71	0.004584
0.75922	58	8.28	0.031148	2.33001	178	2.7	0.015113
0.77231	59	8.14	0.43484	2.3431	179	2.68	0.12443
0.7854	60	8	7.2583	2.35619	180	2.67	2.6093
0.79849	61	7.87	0.17565	2.36928	181	2.65	0.066615
0.81158	62	7.74	0.51642	2.38237	182	2.64	0.35759
0.82467	63	7.62	0.072935	2.39546	183	2.62	0.18082
0.83776	64	7.5	0.27232	2.40855	184	2.61	0.018184
0.85085	65	7.38	0.093225	2.42164	185	2.59	0.19531
0.86394	66	7.27	0.01681	2.43473	186	2.58	0.21756
0.87703	67	7.16	0.30747	2.44782	187	2.57	0.072851
0.89012	68	7.06	0.051701	2.46091	188	2.55	0.098551
0.90321	69	6.96	0.65235	2.474	189	2.54	0.1898
0.9163	70	6.86	0.15133	2.48709	190	2.53	0.032834
0.92939	71	6.76	0.001251	2.50018	191	2.51	0.04535
0.94248	72	6.67	0.030037	2.51327	192	2.5	0.16211
0.95557	73	6.58	0.20124	2.52636	193	2.49	0.048816
0.96866	74	6.49	0.46336	2.53945	194	2.47	0.052342
0.98175	75	6.4	0.21142	2.55254	195	2.46	0.23337
0.99484	76	6.32	0.19503	2.56563	196	2.45	0.067614
1.00793	77	6.23	0.23468	2.57872	197	2.44	0.009279
1.02102	78	6.15	0.16935	2.59181	198	2.42	0.21016
1.03411	79	6.08	0.024619	2.6049	199	2.41	0.021268
1.0472	80	6	13.985	2.61799	200	2.4	0.70991
1.06029	81	5.93	0.18176	2.63108	201	2.39	0.037005

1.07338	82	5.85	0.67466	2.64417	202	2.38	0.14244
1.08647	83	5.78	0.072999	2.65726	203	2.36	0.089943
1.09956	84	5.71	0.003456	2.67035	204	2.35	0.029275
1.11265	85	5.65	0.015907	2.68344	205	2.34	0.09808
1.12574	86	5.58	0.007775	2.69653	206	2.33	0.22312
1.13883	87	5.52	0.17718	2.70962	207	2.32	0.051493
1.15192	88	5.45	0.004804	2.72271	208	2.31	0.05844
1.16501	89	5.39	0.020387	2.7358	209	2.3	0.19854
1.1781	90	5.33	0.049791	2.74889	210	2.29	0.018985
1.19119	91	5.27	0.01149	2.76198	211	2.27	0.007745
1.20428	92	5.22	0.049693	2.77507	212	2.26	0.026824
1.21737	93	5.16	0.24799	2.78816	213	2.25	0.013197
1.23046	94	5.11	0.15182	2.80125	214	2.24	0.007887
1.24355	95	5.05	0.67081	2.81434	215	2.23	0.037551
1.25664	96	5	0.15578	2.82743	216	2.22	0.046222
1.26973	97	4.95	0.183	2.84052	217	2.21	0.096193
1.28282	98	4.9	0.076083	2.85361	218	2.2	0.021736
1.29591	99	4.85	0.25452	2.8667	219	2.19	0.11341
1.309	100	4.8	5.0238	2.87979	220	2.18	0.87596
1.32209	101	4.75	0.17173	2.89288	221	2.17	0.011433
1.33518	102	4.71	0.14456	2.90597	222	2.16	0.00125
1.34827	103	4.66	0.005869	2.91906	223	2.15	0.10475
1.36136	104	4.62	0.068456	2.93215	224	2.14	0.006036
1.37445	105	4.57	0.000646	2.94524	225	2.13	0.018659
1.38754	106	4.53	0.087743	2.95833	226	2.12	0.030448
1.40063	107	4.49	0.11952	2.97142	227	2.11	0.082893
1.41372	108	4.44	0.28866	2.98451	228	2.11	0.035268
1.42681	109	4.4	0.225	2.9976	229	2.1	0.10488
1.4399	110	4.36	0.13818	3.01069	230	2.09	0.074927
1.45299	111	4.32	0.2964	3.02378	231	2.08	0.15823
1.46608	112	4.29	0.009672	3.03687	232	2.07	0.22761
1.47917	113	4.25	0.78316	3.04996	233	2.06	0.015421
1.49226	114	4.21	0.27238	3.06305	234	2.05	0.011667
1.50535	115	4.17	0.27164	3.07614	235	2.04	0.19794
1.51844	116	4.14	0.30921	3.08923	236	2.03	0.00382
1.53153	117	4.1	0.11672	3.10232	237	2.03	0.089108
1.54462	118	4.07	0.26589	3.11541	238	2.02	0.084501
1.55771	119	4.03	0.017297	3.1285	239	2.01	0.044749
1.5708	120	4	3.7053	3.14159	240	2	2.2411

Table B.4. The smoothed data

№	Time	The smoothed data, MW	№	Time	The smoothed data, MW	№	Time	The smoothed data, MW
26	21.05.2016 1:00	2.01000	178	09.07.2016 9:00	-1.56100	330	20.08.2016 17:00	0.06300
27	21.05.2016 2:00	-1.34700	179	09.07.2016 10:00	-2.01600	331	20.08.2016 18:00	-0.58500
28	21.05.2016 3:00	-0.60100	180	09.07.2016 11:00	0.98100	332	20.08.2016 19:00	1.42400
29	21.05.2016 4:00	2.95900	181	09.07.2016 12:00	0.61300	333	20.08.2016 20:00	-2.53300
30	21.05.2016 5:00	-1.75400	182	09.07.2016 13:00	-0.49300	334	20.08.2016 21:00	0.73600
31	21.05.2016 6:00	-1.84200	183	09.07.2016 14:00	-0.57000	335	20.08.2016 22:00	0.77000
32	21.05.2016 7:00	-0.86700	184	09.07.2016 15:00	0.80600	336	20.08.2016 23:00	-3.14300
33	21.05.2016 8:00	1.56900	185	09.07.2016 16:00	-0.71500	337	27.08.2016 0:00	-1.66900
34	21.05.2016 9:00	-1.24900	186	09.07.2016 17:00	-0.03300	338	27.08.2016 1:00	0.59300
35	21.05.2016 10:00	3.16900	187	09.07.2016 18:00	0.43400	339	27.08.2016 2:00	-1.27900
36	21.05.2016 11:00	-2.84400	188	09.07.2016 19:00	-1.04000	340	27.08.2016 3:00	1.93400
37	21.05.2016 12:00	-0.56700	189	09.07.2016 20:00	1.39300	341	27.08.2016 4:00	0.17300
38	21.05.2016 13:00	2.07200	190	09.07.2016 21:00	1.15600	342	27.08.2016 5:00	1.07500
39	21.05.2016 14:00	-0.81700	191	09.07.2016 22:00	-2.23200	343	27.08.2016 6:00	1.84300
40	21.05.2016 15:00	-0.11700	192	09.07.2016 23:00	1.26900	344	27.08.2016 7:00	-0.73600
41	21.05.2016 16:00	0.31700	193	16.07.2016 0:00	-3.97100	345	27.08.2016 8:00	-1.62400
42	21.05.2016 17:00	0.27200	194	16.07.2016 1:00	1.72700	346	27.08.2016 9:00	0.49300
43	21.05.2016 18:00	1.54800	195	16.07.2016 2:00	0.09900	347	27.08.2016 10:00	2.25900
44	21.05.2016 19:00	-3.75000	196	16.07.2016 3:00	0.51800	348	27.08.2016 11:00	0.53800

45	21.05.2016 20:00	0.42600	197	16.07.2016 4:00	-1.27100	349	27.08.2016 12:00	-0.06600
46	21.05.2016 21:00	0.78300	198	16.07.2016 5:00	3.75500	350	27.08.2016 13:00	1.75500
47	21.05.2016 22:00	-0.57500	199	16.07.2016 6:00	-0.49200	351	27.08.2016 14:00	-1.74300
48	21.05.2016 23:00	0.08100	200	16.07.2016 7:00	-2.72800	352	27.08.2016 15:00	0.09300
49	28.05.2016 0:00	-0.37000	201	16.07.2016 8:00	-0.83900	353	27.08.2016 16:00	-1.43000
50	28.05.2016 1:00	-2.02000	202	16.07.2016 9:00	2.20700	354	27.08.2016 17:00	-0.70200
51	28.05.2016 2:00	1.32600	203	16.07.2016 10:00	2.66000	355	27.08.2016 18:00	0.66000
52	28.05.2016 3:00	0.62800	204	16.07.2016 11:00	-2.82800	356	27.08.2016 19:00	-0.96600
53	28.05.2016 4:00	-2.91600	205	16.07.2016 12:00	0.74200	357	27.08.2016 20:00	0.17400
54	28.05.2016 5:00	2.51000	206	16.07.2016 13:00	-3.37100	358	27.08.2016 21:00	0.21000
55	28.05.2016 6:00	1.59200	207	16.07.2016 14:00	2.63200	359	27.08.2016 22:00	-0.67000
56	28.05.2016 7:00	0.35300	208	16.07.2016 15:00	0.90500	360	27.08.2016 23:00	3.02900
57	28.05.2016 8:00	-1.86200	209	16.07.2016 16:00	-0.17400	361	03.09.2016 0:00	-2.37500
58	28.05.2016 9:00	1.34500	210	16.07.2016 17:00	1.39500	362	03.09.2016 1:00	-0.20900
59	28.05.2016 10:00	-3.04300	211	16.07.2016 18:00	1.24800	363	03.09.2016 2:00	0.21800
60	28.05.2016 11:00	2.56600	212	16.07.2016 19:00	-3.26500	364	03.09.2016 3:00	-0.09900
61	28.05.2016 12:00	1.18700	213	16.07.2016 20:00	1.43500	365	03.09.2016 4:00	0.16700
62	28.05.2016 13:00	-1.91300	214	16.07.2016 21:00	-4.64300	366	03.09.2016 5:00	-1.42300
63	28.05.2016 14:00	0.68000	215	16.07.2016 22:00	5.50600	367	03.09.2016 6:00	-1.91400
64	28.05.2016 15:00	0.85300	216	16.07.2016 23:00	-2.11400	368	03.09.2016 7:00	5.05000

65	28.05.2016 16:00	-0.67500	217	23.07.2016 0:00	0.71700	369	03.09.2016 8:00	0.92000
66	28.05.2016 17:00	0.68400	218	23.07.2016 1:00	-0.38100	370	03.09.2016 9:00	-3.11400
67	28.05.2016 18:00	-1.59200	219	23.07.2016 2:00	-0.34400	371	03.09.2016 10:00	-1.69400
68	28.05.2016 19:00	2.48900	220	23.07.2016 3:00	0.09900	372	03.09.2016 11:00	-2.00900
69	28.05.2016 20:00	-2.31800	221	23.07.2016 4:00	-0.10300	373	03.09.2016 12:00	4.41800
70	28.05.2016 21:00	1.43100	222	23.07.2016 5:00	-2.62700	374	03.09.2016 13:00	-1.24600
71	28.05.2016 22:00	-1.37800	223	23.07.2016 6:00	3.73500	375	03.09.2016 14:00	-2.47500
72	28.05.2016 23:00	0.80900	224	23.07.2016 7:00	0.26600	376	03.09.2016 15:00	2.75500
73	04.06.2016 0:00	0.19300	225	23.07.2016 8:00	-1.02700	377	03.09.2016 16:00	-1.04900
74	04.06.2016 1:00	0.07600	226	23.07.2016 9:00	-0.06500	378	03.09.2016 17:00	0.27300
75	04.06.2016 2:00	-0.12200	227	23.07.2016 10:00	-1.18500	379	03.09.2016 18:00	-0.76200
76	04.06.2016 3:00	-0.01100	228	23.07.2016 11:00	1.86500	380	03.09.2016 19:00	2.13500
77	04.06.2016 4:00	-0.14000	229	23.07.2016 12:00	-0.30400	381	03.09.2016 20:00	0.09400
78	04.06.2016 5:00	-1.36000	230	23.07.2016 13:00	2.19100	382	03.09.2016 21:00	0.31200
79	04.06.2016 6:00	0.24600	231	23.07.2016 14:00	-1.28400	383	03.09.2016 22:00	0.76100
80	04.06.2016 7:00	1.46200	232	23.07.2016 15:00	-1.64000	384	03.09.2016 23:00	-0.91300
81	04.06.2016 8:00	-0.48400	233	23.07.2016 16:00	1.04000	385	10.09.2016 0:00	2.59800
82	04.06.2016 9:00	0.77000	234	23.07.2016 17:00	-0.25500	386	10.09.2016 1:00	-1.93000
83	04.06.2016 10:00	-0.08900	235	23.07.2016 18:00	-0.51700	387	10.09.2016 2:00	-0.76500
84	04.06.2016 11:00	-0.31800	236	23.07.2016 19:00	2.89200	388	10.09.2016 3:00	0.09400

85	04.06.2016 12:00	0.04100	237	23.07.2016 20:00	-3.16800	389	10.09.2016 4:00	0.21400
86	04.06.2016 13:00	0.71800	238	23.07.2016 21:00	4.71500	390	10.09.2016 5:00	-0.14200
87	04.06.2016 14:00	-2.20400	239	23.07.2016 22:00	-4.83800	391	10.09.2016 6:00	0.08600
88	04.06.2016 15:00	-2.94600	240	23.07.2016 23:00	1.24200	392	10.09.2016 7:00	-0.34300
89	04.06.2016 16:00	0.05400	241	30.07.2016 0:00	1.57700	393	10.09.2016 8:00	-2.73800
90	04.06.2016 17:00	-0.52000	242	30.07.2016 1:00	1.15300	394	10.09.2016 9:00	2.77900
91	04.06.2016 18:00	0.99000	243	30.07.2016 2:00	-2.62200	395	10.09.2016 10:00	0.28300
92	04.06.2016 19:00	-0.34900	244	30.07.2016 3:00	2.39300	396	10.09.2016 11:00	0.96400
93	04.06.2016 20:00	1.61000	245	30.07.2016 4:00	-0.28700	397	10.09.2016 12:00	-1.16900
94	04.06.2016 21:00	-1.83900	246	30.07.2016 5:00	-2.11400	398	10.09.2016 13:00	0.49800
95	04.06.2016 22:00	1.25900	247	30.07.2016 6:00	-0.74100	399	10.09.2016 14:00	1.94300
96	04.06.2016 23:00	-1.47100	248	30.07.2016 7:00	0.46800	400	10.09.2016 15:00	-2.06400
97	11.06.2016 0:00	4.04700	249	30.07.2016 8:00	0.33200	401	10.09.2016 16:00	0.26200
98	11.06.2016 1:00	-0.15800	250	30.07.2016 9:00	1.11900	402	10.09.2016 17:00	0.35600
99	11.06.2016 2:00	0.11200	251	30.07.2016 10:00	-1.40600	403	10.09.2016 18:00	-0.37300
100	11.06.2016 3:00	-0.02800	252	30.07.2016 11:00	-0.50000	404	10.09.2016 19:00	-0.72900
101	11.06.2016 4:00	-0.17700	253	30.07.2016 12:00	-1.49400	405	10.09.2016 20:00	0.55000
102	11.06.2016 5:00	-0.66200	254	30.07.2016 13:00	2.15800	406	10.09.2016 21:00	-1.46300
103	11.06.2016 6:00	-2.00800	255	30.07.2016 14:00	0.75900	407	10.09.2016 22:00	-0.64200
104	11.06.2016 7:00	-0.88300	256	30.07.2016 15:00	-1.77700	408	10.09.2016 23:00	1.45900

105	11.06.2016 8:00	1.66500	257	30.07.2016 16:00	-0.88500	409	17.09.2016 0:00	-2.23800
106	11.06.2016 9:00	-0.47100	258	30.07.2016 17:00	0.81300	410	17.09.2016 1:00	1.74400
107	11.06.2016 10:00	-1.80200	259	30.07.2016 18:00	-0.27100	411	17.09.2016 2:00	0.56300
108	11.06.2016 11:00	-4.09600	260	30.07.2016 19:00	-0.29100	412	17.09.2016 3:00	-0.06200
109	11.06.2016 12:00	-0.51900	261	30.07.2016 20:00	0.89600	413	17.09.2016 4:00	0.13600
110	11.06.2016 13:00	0.90400	262	30.07.2016 21:00	-1.22000	414	17.09.2016 5:00	-0.14200
111	11.06.2016 14:00	2.05500	263	30.07.2016 22:00	0.88400	415	17.09.2016 6:00	3.14300
112	11.06.2016 15:00	2.91200	264	30.07.2016 23:00	-0.55300	416	17.09.2016 7:00	-3.32600
113	11.06.2016 16:00	-1.30400	265	06.08.2016 0:00	-1.60400	417	17.09.2016 8:00	-0.22900
114	11.06.2016 17:00	0.21300	266	06.08.2016 1:00	-0.91200	418	17.09.2016 9:00	1.43700
115	11.06.2016 18:00	2.42000	267	06.08.2016 2:00	2.79700	419	17.09.2016 10:00	-0.09100
116	11.06.2016 19:00	2.28600	268	06.08.2016 3:00	-2.44600	420	17.09.2016 11:00	1.12900
117	11.06.2016 20:00	-2.58600	269	06.08.2016 4:00	0.12500	421	17.09.2016 12:00	-3.36600
118	11.06.2016 21:00	0.87100	270	06.08.2016 5:00	1.63000	422	17.09.2016 13:00	2.11400
119	11.06.2016 22:00	2.89700	271	06.08.2016 6:00	1.51100	423	17.09.2016 14:00	-0.74700
120	11.06.2016 23:00	1.07400	272	06.08.2016 7:00	0.06500	424	17.09.2016 15:00	-0.56300
121	18.06.2016 0:00	-2.26100	273	06.08.2016 8:00	-0.48400	425	17.09.2016 16:00	2.16000
122	18.06.2016 1:00	0.00400	274	06.08.2016 9:00	-1.32500	426	17.09.2016 17:00	-0.71800
123	18.06.2016 2:00	-0.05100	275	06.08.2016 10:00	2.27700	427	17.09.2016 18:00	0.33000
124	18.06.2016 3:00	0.18800	276	06.08.2016 11:00	-0.84400	428	17.09.2016 19:00	-0.67800

125	18.06.2016 4:00	0.35000	277	06.08.2016 12:00	-1.47000	429	17.09.2016 20:00	0.65400
126	18.06.2016 5:00	0.96800	278	06.08.2016 13:00	-1.53400	430	17.09.2016 21:00	1.00800
127	18.06.2016 6:00	2.74400	279	06.08.2016 14:00	0.73700	431	17.09.2016 22:00	-0.49000
128	18.06.2016 7:00	0.54700	280	06.08.2016 15:00	-0.04500	432	17.09.2016 23:00	-1.02800
129	18.06.2016 8:00	-3.17100	281	06.08.2016 16:00	-0.15300	433	24.09.2016 0:00	-0.34200
130	18.06.2016 9:00	0.44100	282	06.08.2016 17:00	-0.28600	434	24.09.2016 1:00	0.03500
131	18.06.2016 10:00	4.36200	283	06.08.2016 18:00	-0.24600	435	24.09.2016 2:00	0.02300
132	18.06.2016 11:00	3.05000	284	06.08.2016 19:00	1.61900	436	24.09.2016 3:00	0.03800
133	18.06.2016 12:00	-1.67400	285	06.08.2016 20:00	0.79600	437	24.09.2016 4:00	0.04200
134	18.06.2016 13:00	0.88900	286	06.08.2016 21:00	-0.35700	438	24.09.2016 5:00	0.64400
135	18.06.2016 14:00	-0.56400	287	06.08.2016 22:00	0.40200	439	24.09.2016 6:00	-0.79400
136	18.06.2016 15:00	-0.93900	288	06.08.2016 23:00	-0.48100	440	24.09.2016 7:00	0.62900
137	18.06.2016 16:00	1.51000	289	13.08.2016 0:00	1.73500	441	24.09.2016 8:00	-0.12000
138	18.06.2016 17:00	-2.08600	290	13.08.2016 1:00	-0.31700	442	24.09.2016 9:00	-0.81800
139	18.06.2016 18:00	-1.02900	291	13.08.2016 2:00	0.92800	443	24.09.2016 10:00	1.14800
140	18.06.2016 19:00	-2.25800	292	13.08.2016 3:00	0.47700	444	24.09.2016 11:00	1.00000
141	18.06.2016 20:00	2.58200	293	13.08.2016 4:00	0.86800	445	24.09.2016 12:00	0.13500
142	18.06.2016 21:00	-0.92000	294	13.08.2016 5:00	-0.23800	446	24.09.2016 13:00	-0.53600
143	18.06.2016 22:00	-3.29400	295	13.08.2016 6:00	-5.38100	447	24.09.2016 14:00	-1.82800
144	18.06.2016 23:00	-0.10600	296	13.08.2016 7:00	0.98600	448	24.09.2016 15:00	1.37900

145	02.07.2016 0:00	-1.74400	297	13.08.2016 8:00	1.35900	449	24.09.2016 16:00	-1.60700
146	02.07.2016 1:00	0.15500	298	13.08.2016 9:00	0.06700	450	24.09.2016 17:00	1.08700
147	02.07.2016 2:00	0.13600	299	13.08.2016 10:00	0.21800	451	24.09.2016 18:00	-2.08900
148	02.07.2016 3:00	0.06900	300	13.08.2016 11:00	0.64500	452	24.09.2016 19:00	2.12500
149	02.07.2016 4:00	0.24800	301	13.08.2016 12:00	0.42100	453	24.09.2016 20:00	-0.29600
150	02.07.2016 5:00	-0.41900	302	13.08.2016 13:00	2.33100	454	24.09.2016 21:00	-2.33800
151	02.07.2016 6:00	-0.20500	303	13.08.2016 14:00	-0.51700	455	24.09.2016 22:00	2.14700
152	02.07.2016 7:00	-0.11700	304	13.08.2016 15:00	-1.38200	456	24.09.2016 23:00	-0.17100
153	02.07.2016 8:00	0.09200	305	13.08.2016 16:00	0.91500	457	01.10.2016 0:00	0.14600
154	02.07.2016 9:00	-0.30600	306	13.08.2016 17:00	0.50600	458	01.10.2016 1:00	-0.04400
155	02.07.2016 10:00	-1.31700	307	13.08.2016 18:00	0.35100	459	01.10.2016 2:00	-0.01100
156	02.07.2016 11:00	0.59000	308	13.08.2016 19:00	-2.43600	460	01.10.2016 3:00	0.61200
157	02.07.2016 12:00	1.13100	309	13.08.2016 20:00	0.96600	461	01.10.2016 4:00	-0.37700
158	02.07.2016 13:00	-1.01900	310	13.08.2016 21:00	-0.22700	462	01.10.2016 5:00	-0.24500
159	02.07.2016 14:00	-1.30300	311	13.08.2016 22:00	-1.16500	463	01.10.2016 6:00	-0.00600
160	02.07.2016 15:00	1.23800	312	13.08.2016 23:00	1.62300	464	01.10.2016 7:00	-0.14800
161	02.07.2016 16:00	1.14000	313	20.08.2016 0:00	1.42700	465	01.10.2016 8:00	0.40000
162	02.07.2016 17:00	0.11600	314	20.08.2016 1:00	-0.21000	466	01.10.2016 9:00	-0.09600
163	02.07.2016 18:00	-2.02100	315	20.08.2016 2:00	0.29200	467	01.10.2016 10:00	-0.74200
164	02.07.2016 19:00	1.50500	316	20.08.2016 3:00	-2.33900	468	01.10.2016 11:00	-2.32300

165	02.07.2016 20:00	-0.69000	317	20.08.2016 4:00	-0.94200	469	01.10.2016 12:00	2.55200
166	02.07.2016 21:00	0.27200	318	20.08.2016 5:00	-0.08500	470	01.10.2016 13:00	-0.66900
167	02.07.2016 22:00	0.60000	319	20.08.2016 6:00	2.27100	471	01.10.2016 14:00	0.09400
168	02.07.2016 23:00	0.16000	320	20.08.2016 7:00	-0.97700	472	01.10.2016 15:00	-0.10400
169	09.07.2016 0:00	3.55100	321	20.08.2016 8:00	1.16200	473	01.10.2016 16:00	-1.83200
170	09.07.2016 1:00	-1.41600	322	20.08.2016 9:00	-0.58700	474	01.10.2016 17:00	1.58300
171	09.07.2016 2:00	0.04900	323	20.08.2016 10:00	-2.18100	475	01.10.2016 18:00	4.44300
172	09.07.2016 3:00	-0.74500	324	20.08.2016 11:00	0.18000	476	01.10.2016 19:00	-5.98700
173	09.07.2016 4:00	0.99400	325	20.08.2016 12:00	1.01300	477	01.10.2016 20:00	0.81700
174	09.07.2016 5:00	-0.09600	326	20.08.2016 13:00	-3.45400	478	01.10.2016 21:00	3.39700
175	09.07.2016 6:00	-3.33500	327	20.08.2016 14:00	2.60800	479	01.10.2016 22:00	-0.98600
176	09.07.2016 7:00	0.45200	328	20.08.2016 15:00	1.28100	480	01.10.2016 23:00	0.14900
177	09.07.2016 8:00	3.14000	329	20.08.2016 16:00	0.49800			

Table B.5. Day-ahead electricity consumption forecast from ARIMA and initial data of electricity consumption during 08.10.2016

Case No.	Time	Active power, MW	Forecast, MW	Std.Err.
481	0:00	2.769	2.80467	1.157374
482	1:00	2.643	2.73893	1.314832
483	2:00	2.461	2.79957	1.406852
484	3:00	4.473	2.93136	1.48388
485	4:00	5.480	3.38405	1.555111
486	5:00	4.688	4.20406	1.622781
487	6:00	4.337	5.63919	1.687642
488	7:00	6.436	5.7727	1.75008
489	8:00	5.796	4.21268	1.810361
490	9:00	6.434	5.58883	1.868697

491	10:00	10.727	8.85909	1.925266
492	11:00	12.091	10.43797	1.98022
493	12:00	10.933	10.70599	2.033689
494	13:00	11.557	10.18036	2.085788
495	14:00	10.234	9.26697	2.136617
496	15:00	12.260	10.79368	2.186265
497	16:00	12.563	10.39717	2.23481
498	17:00	10.470	10.258	2.282322
499	18:00	10.191	8.68195	2.328866
500	19:00	8.472	8.07598	2.374497
501	20:00	9.035	8.0674	2.419268
502	21:00	8.595	7.8681	2.463225
503	22:00	5.391	7.11294	2.506411
504	23:00	7.039	7.7035	2.548866

Table B.6. The parameters of the correlogram for residuals for a day-ahead electricity consumption forecast from ARIMA

LAG	ACF	PACF	Q-stat.	p-value
1	0.2410	0.2410	1.5758	0.209
2	-0.1449	-0.2155	2.1717	0.338
3	-0.0395	0.0612	2.2180	0.528
4	-0.0583	-0.1060	2.3241	0.676
5	0.1882	0.2660	3.4872	0.625
6	0.0533	-0.1368	3.5857	0.733
7	-0.0888	0.0363	3.8751	0.794
8	-0.0999	-0.1448	4.2644	0.833
9	-0.2275	-0.1528	6.4179	0.697
10	-0.0829	-0.0576	6.7244	0.751
11	-0.0395	-0.0987	6.7993	0.815
12	-0.1304	-0.1085	7.6831	0.809
13	-0.1010	-0.0878	8.2621	0.826
14	-0.1826	-0.1487	10.3432	0.737
15	-0.0913	-0.0450	10.9214	0.758
16	0.1415	0.1019	12.4841	0.710
17	0.1438	0.0720	14.3278	0.644
18	-0.1532	-0.2915	16.7693	0.539
19	-0.1644	-0.0132	20.1409	0.386
20	0.0454	-0.0309	20.4622	0.429
21	0.1345	-0.0047	24.2244	0.282
22	0.1160	-0.0894	28.4259	0.162

23	0.0405	0.0311	29.4512	0.166

Table B.7. The parameters of the correlogram for residuals for a day-ahead electricity consumption forecast from ANN

LAG	**ACF**	**PACF**	**Q-stat.**	**p-value**
1	0.0819	0.0819	0.1822	0.670
2	-0.1000	-0.1075	0.4660	0.792
3	0.1223	0.1427	0.9102	0.823
4	-0.2366	-0.2842	2.6568	0.617
5	0.0671	0.1825	2.8048	0.730
6	0.0187	-0.1279	2.8169	0.831
7	0.0025	0.1658	2.8171	0.901
8	0.0521	-0.1355	2.9229	0.939
9	-0.1581	-0.0326	3.9624	0.914
10	-0.2190	-0.3151	6.1009	0.807
11	-0.2093	-0.1145	8.2038	0.695
12	-0.0944	-0.1583	8.6674	0.731
13	0.0413	0.0613	8.7642	0.791
14	0.0528	-0.0590	8.9380	0.835
15	0.0766	0.1041	9.3445	0.859
16	0.0944	0.0521	10.0397	0.865
17	-0.1503	-0.1567	12.0532	0.797
18	-0.1101	-0.0733	13.3132	0.773
19	0.0857	-0.0299	14.2304	0.770
20	0.0301	-0.0173	14.3715	0.811
21	0.0639	-0.1386	15.2206	0.812
22	0.0125	-0.0790	15.2693	0.850
23	-0.0240	-0.0490	15.6278	0.871

Table B.8. The parameters of the model for forecasting energy consumption for week-ahead

Network name	MLP 168-65-1	Output activation	Logistic	Training performance	0.949	Training error	0.426
Training algorithm	BFGS 179	Hidden activation	Logistic	Test performance	0.941	Test error	0.476
Error function				SS			

Table B.9. The parameters of the correlogram for residuals for a year-ahead electricity consumption forecast from CART

LAG	**ACF**	**PACF**	**Q-stat.**	**p-value**

1	-0.0831	-0.0831	0.1055	0.745
2	-0.3635	-0.3729	2.3247	0.313
3	-0.0115	-0.0982	2.3272	0.507
4	0.0733	-0.0900	2.4399	0.655
5	0.2838	0.2888	4.3726	0.497
6	-0.2555	-0.2353	6.2004	0.401
7	-0.2418	-0.1023	8.1655	0.318
8	0.0465	-0.2130	8.2564	0.409
9	0.0507	-0.1024	8.4004	0.494
10	0.0020	-0.1908	8.4008	0.590
11	-0.0009	0.1226	8.4009	0.677

Table B.10. The details of prices during 08.10.2016

Time	W_t, MWh	C_t, EUR/MWh	P_p, MWh	C_p, EUR/MWh	P_{max}, MWh	C_{max}, EUR/MWh	$C_i^{+}{}_{retail}$, EUR/MWh	$C_i^{-}{}_{retail}$, EUR/MWh	$C_{t,others}$, EUR/MWh	C_i^+, EUR/MWh	C_i^-, EUR/MWh
0:00	2.805	11.417	15.000	6199.380	807.955	7061.451	0.302	0.000	1.231	0.061	0.000
1:00	2.739	11.728					0.173	0.000	1.267	0.035	0.000
2:00	2.800	11.856					0.234	0.440	1.282	0.048	0.001
3:00	2.931	12.131					0.697	0.000	1.315	0.142	0.000
4:00	3.384	12.316					1.106	0.000	1.335	0.225	0.000
5:00	4.204	13.566					1.022	0.000	1.478	0.208	0.000
6:00	5.639	13.623					0.880	1.760	1.485	0.179	0.004
7:00	5.773	13.662					1.375	0.000	1.489	0.279	0.000
8:00	4.213	14.453					0.539	0.000	1.580	0.110	0.000
9:00	5.589	14.509					0.355	0.000	1.586	0.072	0.000
10:00	8.859	14.182					0.000	18.470	1.549	0.000	0.038
11:00	10.438	14.193					0.000	86.080	1.550	0.000	0.177
12:00	10.706	13.924					0.095	12.130	1.519	0.019	0.025
13:00	10.180	14.185					0.179	5.580	1.548	0.036	0.011
14:00	9.267	14.624					0.000	35.770	1.599	0.000	0.074
15:00	10.794	14.595					0.000	36.620	1.595	0.000	0.075
16:00	10.397	14.510					0.000	64.540	1.585	0.000	0.133
17:00	10.258	14.233					0.000	23.280	1.553	0.000	0.048
18:00	8.682	14.112					0.000	95.050	1.540	0.000	0.196
19:00	8.076	13.803					0.000	150.440	1.505	0.000	0.310
20:00	8.067	13.087					0.000	192.180	1.423	0.000	0.395
21:00	7.868	12.721					0.000	430.330	1.382	0.000	0.885
22:00	7.113	12.084					0.000	688.020	1.310	0.000	1.415
23:00	7.704	11.543					0.000	635.430	1.247	0.000	1.307