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Power Consumption in Railway Power Supply Systems with of Artificial Intelligence

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***Abstract*—The paper considers simulation of power consumption at railway facilities. The text reveals the importance and urgency of improving the accuracy of the simulation of power consumption. The results of the analysis of the laws of distribution of electric power consumption of railway transport objects are presented. The study is based on samples of various railway subdivisions in operation. Process and climatic factors are selected as influences. The results of comparison of the simulation of electric power consumption by different methods are presented. Artificial intelligence aids (artificial neural network, fuzzy neural network, support vector machine) may considerably increase the accuracy of mathematical models.**

Keywords—railway; simulation; artificial neural network; fuzzy neural network; support vector machine; artificial intelligence

I. Introduction

Russian Railways (RZD) is the backbone of the Russian economy and the most important element of its transportation system, which accounts for 45% of cargo turnover (including pipeline transport) and over 26% of passenger turnover. The holding is one of the largest consumers of fuel and energy resources in Russia. In 2015 electric energy consumption of the Russian Railways made 45.9 bln kWh (4.6% of the total consumption volume in Russia) and continues to increase [1, 2]. Therefore, electric supply is one of the most important elements of the Russian Railways operation. Power management system has been introduced at the Russian Railways since 2012. It presupposes improvement of control and dosage methods as well as managing electric energy consumption processes, which improves the use of electric energy.

Such approach presupposes the need to devise mathematical simulation models of electric power consumption for both train traction and non-traction needs. The models should ensure high accuracy of electric power consumption calculation both for short-term period (24 hours) to ensure operational management of energy consumption and for long-term perspective (month, quarter, year) for rationing and controlling electric power consumption.

The mathematical models, which are nowadays used for the simulation of electric power consumption at the railway are not perfect. The research conducted at the railway network has established that the gap between estimated and actual electric power consumption at Russian Railways facilities in many cases exceeds 20%. The gap is especially significant in rationing of electric power for non-traction needs. The inaccuracy of mathematical models and methods makes them unsuitable for operational management of electric power consumption.

The article targets at studying electric power consumption methods and conducting their comparative analysis at railway facilities in operation.

II. The Study of Distribution Laws for Electric Power Consumption Samples

When devising mathematical model of electric power consumption in electric power supply systems of the railway it is especially important to detect the distribution law of the random value of electric power consumption. To prove the hypothesis about any distribution law it is necessary to have sampling of values of electric power consumption parameters, which has been previously cleared of inaccuracy. In the case of studying electric power consumption inaccuracy may occur because of mistakes in reports, malfunctioning of electricity meters, mistakes in the locomotive driver's root and other factors.

To measure the inaccuracy a number of criteria is used [3]. In this paper we use the three sigma rule:

$$\left|x^{*} - \bar{x}\right| \; 3 \qquad ( )$$

There has been conducted the study of the distribution laws of electric power consumption random values (specific consumption) for the following railway facilities of non-traction electric power supply system: Arkaim service locomotive depot of the South-Urals Railway; SCB division of Bryansk-Lgovsky of Moscow Railway; Apatity cargo handling division of Oktyabrskaya Railway.

Pearson criterion z^2 [4-7] has been used for comparing hypothetical theoretical distribution of random value of electric power consumption with its empirical distribution.

The results of observed values and critical values of statistical criterion z^2 of electric power consumption at the chosen railway facilities of non-traction electric supply are presented in Fig.1-3 and in Table 1.

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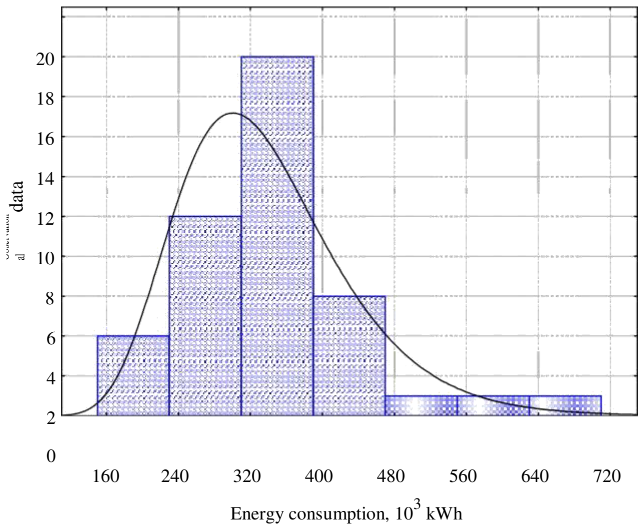

Fig. 1. Bar Graph of the Distribution Law for Arkaim

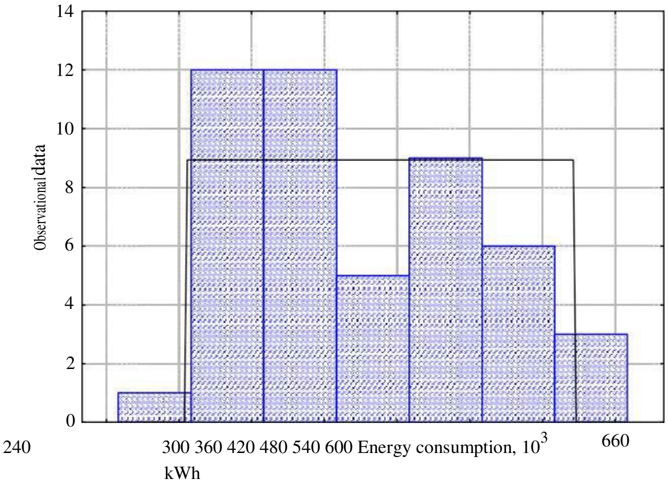

Fig. 2. Bar Graph of the Distribution Law for Bryansk-Lgovsky

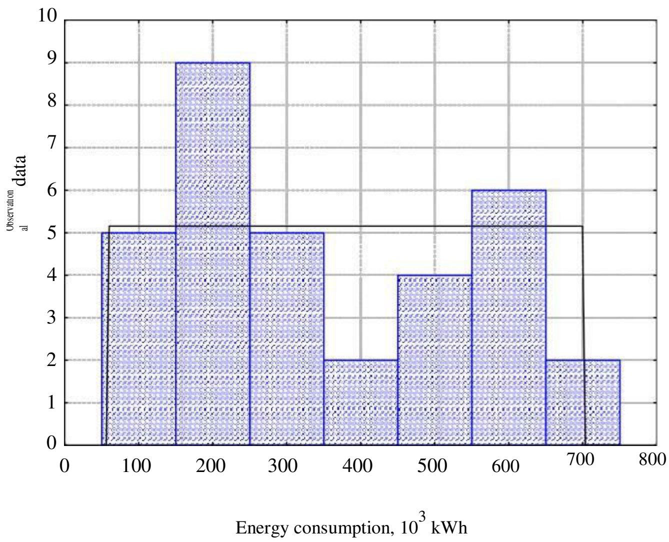

Fig. 3 Bar Graph of the Distribution Law for Apatity

TABLE 1. The Study of Electric Power Consumption Distribution Law

The Subject of Research	Distribution Law	The Value of Statistical Criterion	
		observed	critical
Arkaim	Lognormal	5.39	13.28
Bryansk-Lgovsky	Normal	4.94	13.28
Apatity	Normal	5.36	13.28

We can therefore conclude that various distribution laws including normal and lognormal occur in electric power consumption of non-traction railway devices, therefore, the hypothesis of normal distribution law is rejected.

Mathematical model of electric power consumption at railway facilities can be presented as follows:

$$W = F\,(X_1, X_2 \ldots X_m) \qquad (\;)$$

where W is electric energy consumption; $X_1, X_2 \ldots X_m$ – industrial, climatic and other factors that impact electric power consumption [8].

The task of selecting informative indicators for the mathematical model can be formalized in the following way. The initial sampling A consists of vectors of contributors values x of $1{\times}n$ size and the corresponding values of electric power consumption:

$$A = \left(x^i; W^i\right)_{i=1}^{k} \qquad (\;)$$

Among the multitude of informative factors $F = x_{i\;j=1}^{\;n}$ subaggregate must be selected.

Presently, there are a lot of approaches to this task [9–11], which include filter methods (information gain method, mutual information method, etc.), cover method (exponential, forward and backward greedy algorithms and randomized search algorithms) and built-in methods.

Forward and backward greedy algorithms have been chosen among the above-mentioned methods for further research. The advantages of these approaches are in their high convergence, speed and accuracy.

Principal component analysis (PCA) based on constructing the indicators can serve as an alternative to the above-mentioned approaches. The main idea of the method is in uniting several correlated variables into one, which becomes a linear combination of initial variables [12]. In this case new variables marked as F_1, F_2 etc. emerge.

The following factors of influence such as production volume V; air temperature t, °C; the length of light day T, c; cloud coverage Cl, %; wind F_w, м/c; snow, Sn. have been taken into account. 'Snow' factor is considered as the ratio between the number of days during the period of time when

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precipitation in the form of snow occurred and the total number of days and is measured in relative units.

To collect the information on climatic factors open Internet sources (‘Weather Archive’ section of rp5.ru portal) have been used.

The course of the experiment was as follows. Initial sampling was randomly divided into training and test samples and the ratio made 80%/20%. After that regression model of electric power consumption for various methods of factors selection has been devised based on the training sampling. The case when the model includes all the factors was studied separately.

Then all the indicators that characterize the devised models were defined. Based on the training sampling correlation and determination coefficients were calculated, and the following indicators were calculated based on the test sampling [8]:

Mean absolute percentage error *(MAPE):*

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|W_{act} - W_{mod}\right|}{W_{act}}100\%, \qquad (\ )$$

Root mean squared error *(RMSE):*

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(W_{act} - W_{mod}\right)^2}, \qquad (\ )$$

Coefficient of variation *(CV):*

$$CV = \frac{RMSE}{\overline{W}_{act}}, \qquad (\ )$$

where W_{act} – actual consumption of electric power; W_{mod} – electric power consumption, which has been simulated by using the model based on the same set of factors of influence; $\overline{W}_{act}$ – arithmetic mean of actual electric power consumption; n – the sample volume.

The accuracy rates of the devised mathematical models for various methods of factors selection are presented in Tables 2-4.

Various methods prove more or less efficient for various facilities. PCA proved to be the best for Arkaim, though it has rather high average ratio error of 17.56%, but a lower variation coefficient of 0.18. The method proved the most efficient for Apatity as its accuracy indicators ($MAPE$ = 19.66%, CV = 0.19) considerably exceed other methods.

However, forward greedy algorithm, which allowed to use only 3 factors instead of 6 and resulted in higher accuracy indicators ($MAPE$ = 6.08%, CV = 0.07), proved the most efficient for Bryansk-Lgovsky.

TABLE 2. Accuracy Indicators of Regression Models for Arkaim

Methods of Feature Selection	**Correlation coefficient r_{xy}**	**R-squared r_{xy}^2**	***MAPE*, %**	***RMSE*, kWh**	***CV***
All features	0.85	0.73	16.06	65.56	0.22
Forward greedy algorithm (V, t)	0.85	0.72	17.23	65.75	0.22
Backward greedy algorithm (V, t)	0.85	0.72	17.23	65.75	0.22
PCA (F_1, F_2)	0.61	0.38	17.56	60.43	0.18

TABLE 3. Accuracy Indicators of Regression Models for Bryansk-Lgovsky

Methods of feature selection	**Correlation coefficient r_{xy}**	**R-squared r_{xy}^2**	***MAPE*, %**	***RMSE*, kWh**	***CV***
All features	0.96	0.92	6.63	33.05	0.08
Forward greedy algorithm (t, T, Sn)	0.96	0.92	6.08	30.44	0.07
Backward greedy algorithm (t)	0.95	0.90	8.01	39.79	0.10
PCA (F_1, F_2)	0.93	0.87	8.15	48.76	0.12

TABLE 4. Accuracy Indicators of Regression Models for Apatity

Methods of feature selection	**Correlation coefficient r_{xy}**	**R-squared r_{xy}^2**	***MAPE*, %**	***RMSE*, kWh**	***CV***
All features	0.87	0.75	19.61	90.72	0.25
Forward greedy algorithm (V, t, Sn)	0.86	0.74	21.61	83.82	0.23
Backward greedy algorithm (t)	0.82	0.67	36.05	107.04	0.34
PCA (F_1, F_2)	0.83	0.69	19.66	65.49	0.19

Accuracy indicators of mathematical models based on regression analysis are relatively low. Mean absolute percentage error in most cases exceeds 10% and in many cases 15%. Variation coefficients for most facilities exceed 0.15. Therefore, statistical methods based on regression analysis are not applicable for creating mathematical models of electric power consumption at railway facilities in all cases. Other variants of mathematical models creation particularly artificial intelligence methods have to be considered.

IV. Simulation of Electric Power Consumption with the Help of Artificial Intelligence Method

Among the methods based on artificial intelligence theory are support vector machine, method of nearest neighbour, Bayesian classification, neural networks, fuzzy neural networks, genetic algorithms, etc. Let us look at the main approaches that are used in the simulation of electric power consumption.

1. Artificial neural networks (ANN) is a mathematical model, which includes its software and hardware solutions that imitate the structure and properties of the nervous system of living organisms. The method displays good results in the simulation of complex non-linear processes including electric load [13-22]. For training and validation of the ANN by the order of the Russian Railways the authors have developed specialized software package 'Neural Network Forecasting for Rail Transport'.

ANN training is performed by the backpropagation algorithm. Learning speed varies from 30 to 60 in increments of 5, and the feedback gain is changed from 0 to 0.5 in increments of 0.2. At the same time tested three types of activation functions: tanh, exponential and logistic. The parameter of the exponential function a ranges from 0.04 to 0.2 in increments of 0.2 and 0.03 to 0.6 in increments of 0.08.

2. Fuzzy neural networks (FNN) make conclusions based on fuzzy logic instrument, but corresponding parameters are fine-tuned with the help of ANN training algorithms [23-27]. The study of mathematical models of electric power consumption process has been conducted with the help of *ANFIS Editor* and graphic *Fuzzy Logic Toolbox* of *MATLAB*.

3. Support Vector Machine (SVM) is a type of boundary methods and is used for classification as well as for regression models construction. SVM was first studied in the paper by Vapnik in 1995 [28]. Unlike traditional regression model the method demonstrates good results when simulating non-linear relations between the target value and factors of influence. As [29] shows SVM method demonstrates high accuracy in forecasting electric power consumption.

The above-mentioned methods have been used for creating mathematical model of electric power consumption for the chosen facilities.

V. Results

The methods based on artificial intelligence theory have been used for devising the model of electric power consumption at the chosen railway facilities. The obtained results suggest that in all cases accuracy indicators proved to be
higher than when regression models are applied (**Table 5-7**).

ANN ($MAPE$ = 13.66%) proved the most efficient for Arkaim while FNN ($MAPE$ = 3.34% and 10.25%) for Bryansk-Lgovsky and Apatity.

The obtained results suggest that artificial intelligence methods allow to increase the accuracy of electric power consumption models and improve the power management of the railway.

Table 5. The Comparison of the Accuracy of Various Models of Electric Power Consumption for Arkaim

Simulation method	*MAPE*, %	*RMSE*, kWh	*CV*
Regression	17.56	60.43	0.18
ANN	13.66	45.12	0.15
FNN	17.45	60.07	0.18
SVM	16.39	55.10	0.17

Table 6. The Comparison of the Accuracy of Various Models of Electric Power Consumption for Bryansk-Lgovsky

Simulation method	*MAPE*, %	*RMSE*, kWh	*CV*
Regression	6.08	30.44	0.07
ANN	5.85	31.03	0.07
FNN	3.34	17.23	0.04
SVM	5.04	26.91	0.06

Table 7. The Comparison of the Accuracy of Various Models of Electric Power Consumption for Apatity

Simulation method	*MAPE*, %	*RMSE*, kWh	*CV*
Regression	19.66	65.49	0.19
ANN	10.38	45.56	0.12
FNN	10.25	45.02	0.11
SVM	14.84	56.20	0.15

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