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Information and Measurement System for Electric Power Losses Accounting in Railway Transport

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Abstract

The purpose of the presented research is to minimize the loss of electricity during the operation of railway power systems. Losses are defined as an unbalance between the released and consumed electricity, which is recorded by means of commercial electricity accounting. Given that electricity losses are divided into technical and non-technical (commercial) components, there are currently no technical tools that can analyze the components of electricity losses in detail, and therefore prevent their occurrence. To achieve this goal, the factors inherent in commercial electricity accounting systems in various areas of production activity that affect the growth of electricity losses are identified. An algorithm is proposed that allows determining the presence of abnormal power losses in real time for making organizational and technical decisions to reduce them. A block diagram of the information and measurement system for accounting of power losses has been developed, which allows using the existing equipment without replacement or modernization, which allows obtaining new technical capabilities. The method of intellectualization of the process of classification of factors that cause the growth of abnormal power losses, based on artificial neural networks, is proposed. The intelligent module allows replacing the person who makes organizational and technical decisions, minimizing the consequences of abnormal situations that lead to the growth of abnormal losses, applying the proposed solutions in departments that do not have qualified specialists. The results of training an artificial neural network are considered, and the main parameters of the efficiency of the information and measurement system for loss accounting on a real railway transport object are determined.

Keywords: Power Loss; Artificial Neural Networks.

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1. Introduction

The Automated System for Commercial Accounting of Power Consumption (ASCAPC) is actively used in JSC “Russian Railways”. There are three areas of production activity in which independent ASCAPC are operated: ASCAPC of the Railway junction (RJ), ASCAPC of the Traction substation (TS), ASCAPC of the Retail electricity market (REM). These systems are developed by third-party organizations and do not have common information flows. One of the disadvantages inherent in all operated ASCAPC is the lack of detailed analysis of the factors that lead to power losses. The software allows detecting the difference (unbalance) between the released and consumed electricity at the borders of the serviced areas, which is not enough to determine the reasons for its appearance. Analysis of the causes of unbalance is usually not more frequently than once a year, and there is no detailed estimate of each component of the unbalance that does not allow obtaining a significant effect of organizational and technical measures (Zhelezko, 2003).

Accurate monitoring of the consumed and released electricity in real time will allow carrying out effective measures to minimize or eliminate the unbalance of electricity on the section. The creation of new ASCAPC or their modernization with the use of high-precision measuring devices is not an economically effective measure at the moment (Avram et al., 2017; Sauhats et al., 2015; Qi-xin et al., 2014), and the use of error correction methods for measuring devices will require the procedure of metrological certification, which will also entail significant financial costs. In this regard, it is important to determine the factors that affect the unbalance of electricity and minimize their impact without changing the metrological certified ASCAPCs that are in operation in JSC “Russian Railways”.

2. Methods and Materials of the Research

When considering the components of the unbalance of electricity, it is customary to distinguish the technical and commercial components. The technical component of the unbalance (technical losses) is caused by physical processes in the power system and its minimization, without replacing the operated equipment, is difficult. The commercial component of the unbalance (commercial losses) on the section is determined by the formula:

$$\Delta W_K = W_{re} - W_{ce} - \Delta W_T, \tag{1}$$

where W_{re} – the amount of released electricity, determined by the difference in the readings of electricity meters at the borders of the section in question;

W_{ce} – the amount of electricity consumed, determined by the readings of consumers’ electricity meters;

ΔW_T – calculated for the section the technical component of the unbalance of electricity.

For an ideal case, the amount of released electricity is equal to the amount consumed and dispersed in the elements of the power system. However, in real conditions of operation, ASCAPCs have errors, which leads to an increase in the commercial component of the unbalance. Factors affecting ASCAPC accuracy class are structural components of commercial components of the unbalance, and, consequently, the components of the unbalance of power in general (Kaczmarek and Stano, 2019; Viegas et al., 2016). There is almost linear dependence between the growth unbalance of power and an increase in errors of ASCAPC that controls the section.

The analysis of ASCAPC on railway transport is carried out to identify and classify the types of equipment in use and identify factors that affect the unbalance of electricity (Viegas et al., 2016). All operated ASCAPCs use microprocessor-based electricity meters with interfaces for interfacing with modern packet data transmission systems. On a number of sections, significant indicators of unbalance of electricity reaching 15-25% are periodically recorded. Figure 1 shows the results of analysis for the presence of factors that affect the growth of losses, typical for certain areas of use on the railway transport. The error of each of these factors should not exceed 5% of the total amount of electricity consumed, but at the same time the sum of all errors should not be more than 5% (normalized losses).

Factors	ASCAPC of wholesale electricity market (provider of electricity)	ASCAPC REM (the directorate of energy)	ASCAPC RJ (structural units of Russian Railways)	ASCAPC TS (Traction substations)
Power loss due to measurement errors	☑	☑	☑	☑
Under-accounting of electricity	☑		☑	☑
Theft of electricity		☑		
Repair of equipment	☑	☑	☑	☑
Climatic factor	☑	☑	☑	☑
Seasonality	☑	☑	☑	☑
Under-loading/ overloading		☑	☑	☑
Low accuracy class			☑	☑

Fig. 1. Results of analysis of the Kuibyshev railway polygon for errors caused by external factors affecting the growth of power losses.

Despite the fact that the considered ASCAPCs do not have a single database, are built on different element bases, and operate under the control of their own software, there are technical possibilities for combining the received measurement information into a single information space (Arturo et al., 2020; Tyugashev et al., 2019).

A method has been developed that allows detecting abnormal losses in a timely manner. The flowchart of the algorithm, implementation of the method, is shown in figure 2. At the initial moment of time t, the abnormal losses are calculated conditionally from the first section of the power network. Next, we check whether the section K belongs to the array M (M is an array of sections that require additional control over the growth of abnormal losses). If the section is not in this array, then we check the abnormal losses greater than δ_1. If not, we check this section again in a day and check the following sections. If it is in the range from δ_1 to δ_2, then enter in the array M and check the section in an hour. If more than δ_2, then it is necessary to conduct an intelligent analysis to identify the factors that led to an increase in abnormal losses. When checking sections from the array M, we need to calculate D as the difference between the abnormal losses of the section with a difference of 1 hour. If D is less than δ_3, then we remove the area from control. If it is in the range from δ_3 to δ_4, we check the section again in 30 minutes. If D is less than δ_4, then we connect the intelligent analysis based on the artificial neural networks, which after its operation signals the decision-maker about possible factors for increasing power losses.

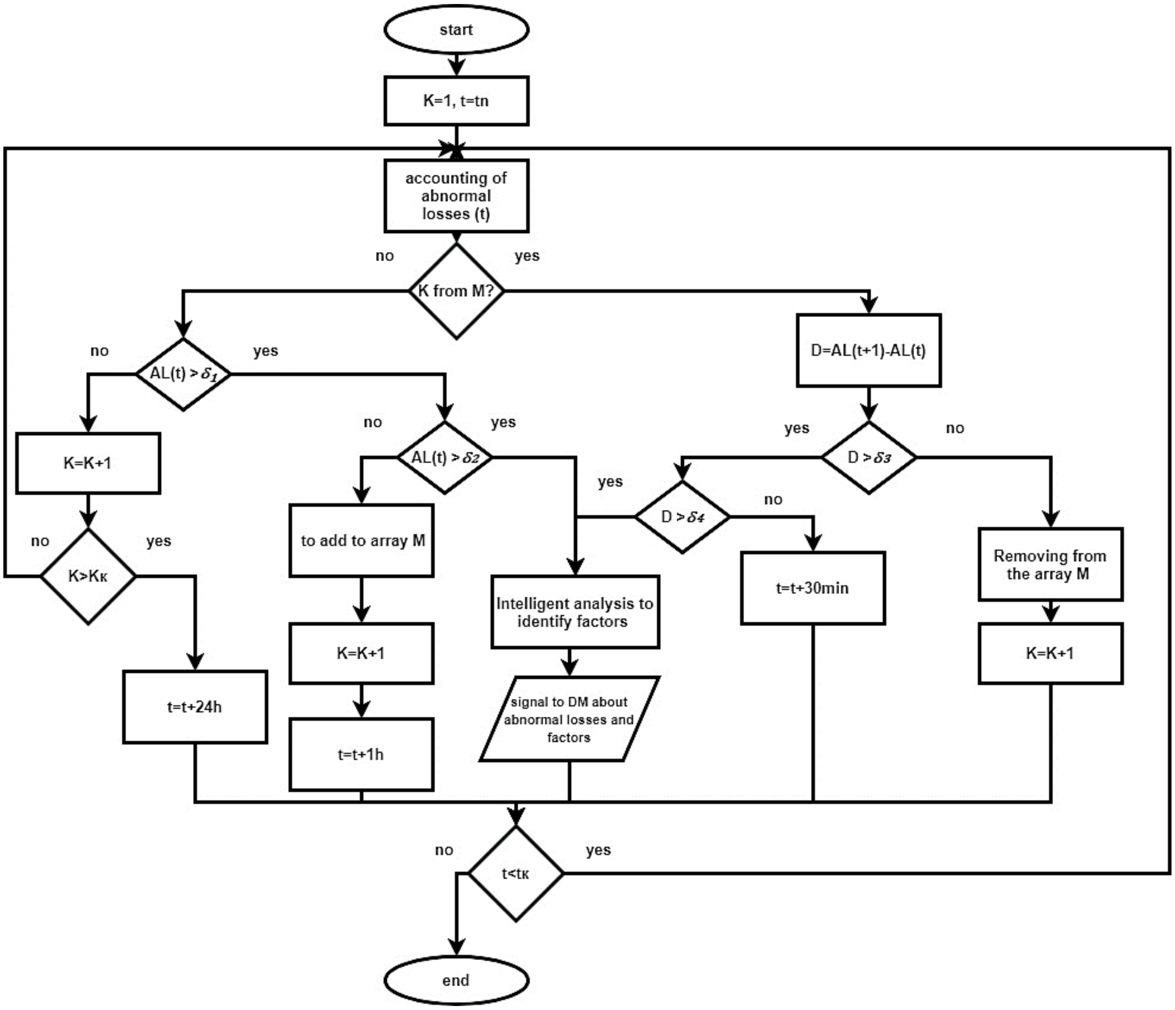

Fig. 2. Block diagram of the algorithm for monitoring the presence of an abnormal component of electricity losses in geographically distributed independent sections of the power system using artificial intelligence.

The growth of abnormal losses - is a poorly formalized task, in which the decision-maker (DM) uses experience, knowledge and intuition to assess possible factors that affect the growth of abnormal losses and make management decisions (Orlov and Vasilchenko, 2016). The decision of similar tasks is 20% of his time. Figure 3 shows the location of the electricity meter values as the difference between the readings at the beginning and at the end of the sections when analyzing the object under study.

The DM expert verbally explained the appearance of the values in the area A1 as the impact of a low accuracy class of operated ASCAPC for the area B1 is caused by under-loading/overloading of the network, i.e. the operation of the ASCAPC outside the normalized values. The reasons for the appearance of values in the A2 area are determined as seasonal factors, and for the B2 area - climate factors. It was more difficult for DM to classify factors for areas A2 and B2. The graph also shows values that go beyond the A2 and B2 areas. These values belong to the field of weakly formalized knowledge and their classification is difficult without an experienced DM (expert). The process of classifying the causes of electricity unbalance can be automated by transferring and preserving the expert's experience and knowledge through the use of artificial intelligence technologies. The main problem arises when trying to describe the classification rules for weakly formalized data, since the classification rules obtained from the DM often cover the simplest cases. The optimal approach is to use artificial neural network (ANN) technology with training (Das et al., 2020; Velaso et al., 2020). This will allow creating elements of intellectualization without the need to fully formalize all possible cases, but based on the experience of an expert in analyzing the causes of unbalance.

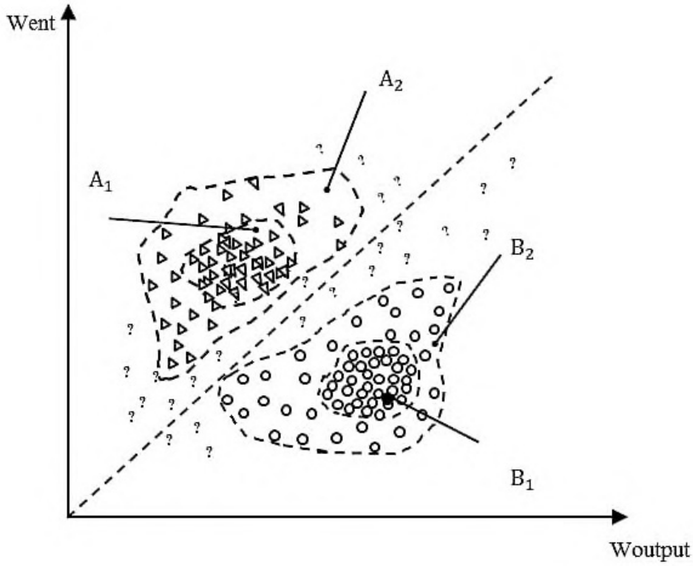

Fig. 3. Location of electricity meter values as the difference between the readings at the beginning and at the end of the section.

When analyzing the causes of unbalance, the expert calculates the standards for power losses, taking into account the equipment used on the site. When identifying factors that differ from the estimated standards of losses from the actual data obtained from the ASCAPC, the expert prepares a report. The performed traffic schedule is analyzed to identify the fact that an electric locomotive passes through this section (this factor is identified as important for this technological process as a result of analyzing the causes of power losses in railway transport). The factor that affects the deviation from the standard losses may be overload, i.e. going beyond the limits of the values in which the ASCAPC retains the accuracy class, or under-loading the section due to low train turnover. Additional factors may include the schedule of repairs and the type of work that is being performed, which may indicate that the equipment is not connected correctly. These factors form the signature of the event that caused the unbalance.

Each section of the railway power system has certain factors that affect the amount of power loss. Different variations of these factors may indicate the presence of abnormal losses. Only an expert can determine that current losses are justified or they are caused by external factors and require corrective measures.

Figure 4 shows a block diagram of the information and measurement system for accounting for power losses (AMIS APL). To build the AMIS APL, the information flows of independent ASCAPC are combined. The experience of analyzing the components of the unbalance of electricity at the Kuibyshev railway polygon was used in the development of the AMIS APL (Orlov and Vasilchenko, 2016). The input signal from the power system of the traction substation goes to the current transformer CT and the voltage transformer VT. The electricity meter registers the values and forms a signal for the data transmission device (UPD). Depending on the model, the data transmission device can use wired channels of the data network or wireless channels of cellular operators. In any case, a data packet is generated over the IP Protocol. The ultimate goal of data packets is the ASCAPC server, which stores the received information in a database for long-term storage. Then the data is uploaded to XML80020 format and a timestamp is set for further synchronization. After the verification algorithm, the data is sent to the artificial neural network ANN, and the result is output to the graphical user interface GUI. Based on these data, the DM forms a management decision to eliminate the causes of power losses in the presence of abnormal losses. The expert analysis block is necessary for forming a training selection, as well as for further training of the neural network and attracting a specialist to solve an atypical problem.

The technical result is to expand the functionality of the operated ASCAPC and reduce power losses due to the timely detection of abnormal power losses.

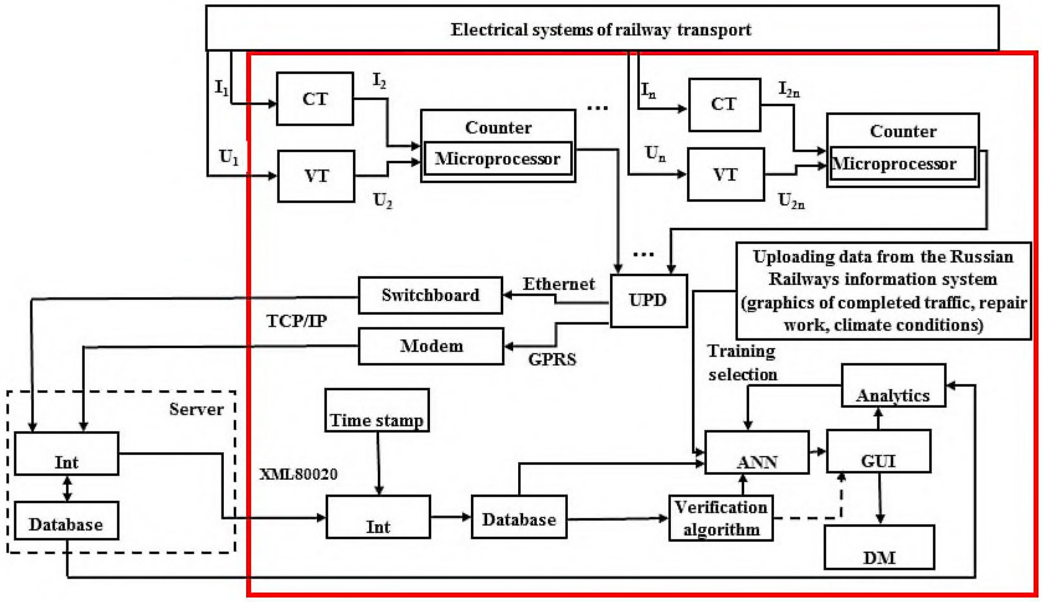

Fig. 4. Block diagram of the AMIS APL on railway transport.

For ANN training, a training selection was prepared based on the ASCAPC readings. For each fact that there is an unbalance, the expert determines the reasons for their occurrence. So, specialist of operations department of ASCAPC of Kuibyshev directorate on power supply, acting as an expert, has determined that for the considered period on the traction substation were carried out equipment replacement of ASCAPC, and CTs are working in the field of low currents, outside the lower border of the working range, which leads to increased errors. As a result of training, the ANN must determine whether there is an unbalance of electricity on the section that exceeds the calculated values for this section.

For training the neural network, an array of data is prepared that shows the electricity consumption in the boundaries of the section, the marker, fixing the presence in a given period of time at the section of a train with electric traction (the data are taken from the graphics of full of motion), and a marker for the presence of non-normalized unbalance.

The training selection for the ANN can be presented as follows:

$$P_i(t) = \{W_{ient}, W_{ioutput}, h_i, m_i, n, a, p, k_i\},\ i = 1...I, \tag{2}$$

where $P_i(t)$ – is the presence of unbalance of power in excess of normalized values; t –time of calculation of the unbalance; W_{ient} – readings of electricity meters at the entrance of the section; $W_{ioutput}$ - meter readings of electricity on the output of the section; hi – marker of repair work on the section; mi - is the marker for the presence of trains on the section; the n – set for the section standards of the unbalance; a - marker characterizing the membership of the ASCAPC to productive activity; p – the ambient temperature in the calculation period; k_i - is a marker set by an expert that characterizes the presence of an excess unbalance of electricity (k_i=0 under $W_{nb} \leq n$ and k_i=1 for $W_{nb} > n$).

3. Research Results

The process of learning the ANN took the 225 epochs. The standard error during verification of the results was 0.00501. The correlation coefficient R for training is 0.9873, the check set R=0.9905, the test set R=0.9939, and all sets R=0.9887. The average value of the correlation coefficient R=0.9499. What characterizes the high accuracy of the classification results performed by the ANN.

Indicators of unbalance of electricity at the object in question averaged 20%, when using the AMIS APL, the fact of abnormal losses can be detected within 30 minutes. This will allow quick start of organizational measures to eliminate or minimize losses. When analyzing the energy consumption of one of the catches of the power system, it is possible to reduce the unbalance by up to 5% when using the AMIS APL.

4. Results Discussion

Accurate monitoring and accounting of power losses is one of the ways to improve the efficiency of the power network. The specific nature of railway transport allows identifying factors that do not depend on the technical features of the used equipment, which make a large contribution to the final values of electricity losses. Operational control of these factors allows making effective decisions to eliminate them. Despite the complexity of identifying situations where there are no pronounced signs of ANN, trained on the actions of an experienced expert, can issue acceptable recommendations. The direction of intellectualization of the power system, in particular with the use of ANN, is currently promising in many areas, not only transport.

For the construction of the AMIS APL, the analysis of the current state of the electric power accounting system of railway transport power facilities was carried out and the factors affecting the growth of electric power losses inherent in certain technological processes in railway transport were determined. A block diagram of the AMIS APL is developed using artificial intelligence methods, which implements an algorithm for detecting the presence of excess values of the unbalance of electricity. The use of the developed approach makes it possible to increase the adequacy and efficiency of management decisions when detecting the presence of abnormal power losses, and to increase the economic and operational efficiency of the power system of JSC “Russian Railways”.

References

Arturo, et al., 2020. Distribution networks nontechnical power loss estimation: A hybrid data-driven physics model-based framework. Electric Power Systems Research 186.

Avram, et al., 2017. Design and development of an electricity Meter Test Equipment. International Conference on Optimization of Electrical and Electronic Equipment (OPTIM) & 2017 Intl Aegean Conference on Electrical Machines and Power Electronics (ACEMP). DOI: 10.1109/OPTIM.2017.7974954.

Das, et al., 2020. Neural Compression: A machine learning approach to compress high frequency measurements in smart grid. Applied Energy 257.

Kaczmarek, Stano, 2019. Proposal for extension of routine tests of the inductive current transformers to evaluation of transformation accuracy of higher harmonics. International Journal of Electrical Power & Energy Systems 113, 842-849.

Orlov, Vasilchenko, 2016. Intelligent measuring system for testing and failure analysis of electronic devices. XIX IEEE Int. Conf. on Soft Computing and Measurements 1, 401-403.

Qi-xin, et al., 2014. Research on the accounting property of digital electricity meter. China International Conference on Electricity Distribution (CICED). DOI: 10.1109/CICED.2014.6991860.

Sauhats, et al., 2015. Analysis and prediction of electricity consumption using smart meter data. IEEE 5th International Conference on Power Engineering, Energy and Electrical Drives (POWERENG). DOI: 10.1109/PowerEng.2015.7266290.

Tyugashev, et al., 2019. Methods and tools of electricity accounting information and measurement system accuracy increasing. 2019 International Conference on Industrial Engineering, Applications and Manufacturing, ICIEAM 2019.

Velasco, et al., 2020. Deep Learning loss model for large-scale low voltage smart grids, International Journal of Electrical Power & Energy Systems 121.

Viegas, et al., 2016. Classification of new electricity customers based on surveys and smart accounting data. Energy 107, 804-817.

Zhelezko, 2003. Calculation of technological losses of electricity in electrical networks. Energetic 2, 29-33.