Intelligent Forecasting of Electricity Losses in Urban Distribution Networks Using ANN and SOM

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Keywords: Electric Power Industry, Artificial Neural Networks, Self-Organizing Maps, Clustering, Principal Component Analysis, Forecasting.

Abstract: This paper proposes an intelligent framework for analyzing and forecasting operating parameters of urban electric networks in Tashkent. Monthly data (84 observations, 2018-2024) on electricity purchase, technological losses, planned and actual indicators were preprocessed using interpolation for missing values, outlier smoothing based on the interquartile range, and min-max normalization to the range [0, 1]. To reveal heterogeneous operating regimes, clustering based on self-organizing maps (SOM) was applied, while Principal Component Analysis (PCA) was used for factor analysis and visualization. For forecasting excess electrical energy losses, three approaches were compared: autoregressive parametric stochastic systems (ARPSS), a multilayer perceptron neural network (ANN/MLP), and a combined model integrating several expert MLP networks. The comparative evaluation shows that the ARPSS model produces high prediction errors, whereas intelligent models significantly improve accuracy. The average relative error equals 42.8% for ARPSS, 6.1% for ANN, and 3.7% for the combined model. The proposed approach can support operational decision-making in urban distribution networks by improving the reliability of loss forecasting.

1 INTRODUCTION

The digital transformation of the electric power industry has significantly expanded the possibilities for analyzing and managing power systems [1], [2]. Modern electric power markets require energy marketing organizations to ensure transparency of operating parameters, reduce electric energy losses, and improve forecasting accuracy [3]-[8]. AI-based optimization methods are also actively applied in power-supply systems, for example for reactive power compensation in nonlinear traction networks [9].

The increasing complexity of electric networks and the growing volume of heterogeneous data require the use of artificial intelligence and intelligent data processing methods [10]. Neural network technologies, clustering methods, and dimensionality reduction techniques enable effective modeling of nonlinear dependencies in electric load and loss dynamics [5], [11].

The purpose of this study is to develop and evaluate an intelligent approach to analyzing and forecasting technological parameters of urban electric networks in Tashkent.

The use of intelligent learning systems capable of accumulating the expertise of operational personnel, combined with modern digital information processing tools, creates the prerequisites for improving the efficiency of electric power calculations. This makes it possible to ensure the required level of accuracy and reliability when modeling the operating modes of electrical networks in conditions of increasing operational requirements [12].

2 MATERIALS AND METHODS

2.1 Data Description and Preprocessing

The dataset used in this study includes monthly data on electric energy purchase, technological losses, planned and actual implementation, and total electricity consumption (TEC) for urban electric networks of Tashkent for the period 2018-2024.

The dataset consists of 84 monthly observations.

Data preprocessing included:

- removal of missing values using linear interpolation;
- detection and smoothing of outliers based on the interquartile range method;
- normalization of input parameters using min-max scaling to the range [0, 1].

Experimental setup. The dataset was split chronologically into training and test subsets: the first 80% of observations were used for training and the remaining 20% for testing. Forecasting was performed with a one-step-ahead (1-month) horizon. Model accuracy was evaluated on the test set using MAPE (mean absolute percentage error) [12].

2.2 Methodological Foundations of Analysis and Forecasting

Currently, several key areas of application of modern information and intelligent technologies have been formed in the electric power industry, including: methods of processing uncertain and fuzzy information used in the construction of intelligent control systems; neural network algorithms used to create self-learning control systems and data analysis; evolutionary modeling methods designed to optimize parameters and adjust membership functions in fuzzy systems; multi-agent approaches underlying distributed intelligent control systems.

The results of numerous theoretical and applied studies show that among the listed technologies, artificial neural networks have become the most widespread in the electric power industry. A variety of ways to organize neural structures and their learning mechanisms has led to the formation of a wide range of neural network models, each of which is focused on solving a specific class of tasks. The most significant types of neural networks used in the electric power industry are shown in Table 1.

3 RESULTS

As a result of the conducted research, it has been established that the need to form an objective and detailed picture of the state of serviced electric networks of energy retail and electric grid organizations is due to the changes that have occurred in the functioning of the modern electric power market. Each participant in such a market acts as an independent element of the system of production, transmission and sale of electric energy, which implies its responsibility for analyzing its own operating parameters and technological indicators in order to ensure sustainable and cost-effective functioning. In order to obtain a reliable assessment of the state of electrical networks and make informed management decisions at the level of an energy marketing company, it is necessary to take into account a significant number of interrelated technical and economic factors characterizing both individual sections of the network and the energy district as a whole. This significantly complicates the tasks of analysis and requires the use of complex information processing methods.

The variety and complexity of the relationships between the subjects of the electric power market necessitate the use of modern methods for assessing modes and technological characteristics that enable the formation of correct management decisions in conditions of uncertainty and limited source data.

In this regard, the role of new mathematical and intellectual approaches focused on working with multi-criteria input information and incomplete data sets is increasing. The results of a number of studies [13], [14] show that a promising tool in this field is the use of self-organizing neural network models [15] that allow performing cluster analysis of mode parameters based on the principles of neural network learning. Cluster analysis methods [16] have become widely used in solving electric power problems related to the identification of electrical system states, including emergency and pre-emergency modes, diagnosing electrical equipment and verifying the reliability of measurement information.

Heterogeneities in the distribution of parameters based on clustering results can correspond to different types of operating modes of power facilities or the network as a whole and serve as indicators of potentially undesirable or emergency combinations of parameters during operation.

When analyzing electricity consumption in urban areas of Tashkent, a set of technological indicators is used that reflect the peculiarities of electricity consumption and distribution in a large metropolis. These indicators include the volume of electricity purchased, electricity consumption by end users, planned and actual sales values, as well as excess losses of electric energy.

Table 1: Application of neural network models in solving electric power problems.

Information Systems Architecture (INSA)	Types of tasks
A class of neural network models	Functional purpose in the electric power industry
Neural networks of direct distribution	Calculation and short-term forecasting of electrical load; assessment of operating parameters of the network; analysis of losses of active electricity, taking into account external factors
Self-organizing neural models	Division of the states of the electric power system into groups; identification of normal and abnormal modes; verification of the correctness of measurements and analysis of the loss structure
Dynamic neural network structures with feedbacks	Assessment of the state of electric power systems in real time; restoration of parameters from noisy data; modeling of transient processes of electric machines
Nonlinear adaptive neural network models	Identification of parameters of complex technical objects; prediction of non-stationary signals; suppression of interference and measurement noise

Table 2: Cluster analysis of sections of urban electric networks in Tashkent.

Cluster	Characteristics of sections of electrical networks	Periods of greatest loss of electrical energy
A1	Areas with a predominance of residential development and uniform load	The losses are uniform throughout the year
A2	Plots with a mixed residential and communal load	Pronounced periods of increased losses have not been identified
B1	Areas with high density of household consumers	During the year, except for the summer period
B2	Areas with pronounced seasonal load unevenness	The summer months

Excess (commercial) losses in this case are understood as losses caused by discrepancies in meter readings from household consumers, unauthorized consumption, as well as deficiencies in the organization of electricity monitoring and metering systems. In the context of the functioning of the Tashkent electric power market, the task of a comprehensive analysis of the structure of electricity consumption, taking into account the territorial heterogeneity of urban areas and differences in the nature of the load, is of particular relevance. Along with this, it is important to analyze each indicator individually, which allows us to develop measures aimed at improving the accuracy of power consumption planning, optimizing electricity purchases and reducing losses in distribution networks.

To solve this problem, it is advisable to use intelligent data processing methods that effectively analyze multidimensional arrays of information and provide a convenient interpretation of the results. Using this approach helps to form groups of areas with similar load characteristics, and also allows you to detect deviations from typical power consumption modes.

It should be noted that in practical conditions, the greatest efficiency of the analysis of operating parameters is achieved with the combined use of intelligent data processing methods and traditional statistical approaches. Within the framework of the developed data analysis methodology [17], the combined use of cluster analysis and factor analysis methods is implemented based on the Principal Component Analysis (PCA) method [18], [19]. This approach allows you to simultaneously structure the initial information and identify the key factors that have the greatest impact on changes in electricity consumption in urban electric networks in Tashkent.

The principal component method is used in this case as an auxiliary tool for data analysis and visualization, which makes it possible to identify correlations between various analyzed parameters. The use of PCA helps to reduce the dimension of the initial data set by selecting the most informative linear combinations of parameters characterized by the highest values of variance. This ensures a more efficient presentation of information and increases the visibility of the analysis results.

Based on this methodology, an approach to the analysis of electric energy losses in the distribution networks of Tashkent has been formed. In modern conditions, the task of correctly identifying local areas of increased losses and determining the causes of their occurrence is of particular importance, since such zones largely determine the economic losses of energy marketing organizations. A comprehensive analysis based on a combination of clustering and factor analysis methods allows us to identify the main factors leading to an increase in electric energy losses, as well as group sections of the urban electric grid into compact aggregates with similar operational characteristics.

The results of the cluster analysis make it possible to divide the urban electric grid into groups of sites that differ in the level and nature of electricity losses, and thereby localize potential "pockets" of increased losses. Factor analysis, in turn, allows us to determine the influence of seasonal, stress and organizational factors on the formation of such zones, which creates the basis for the development of targeted measures to reduce losses. The results of the cluster analysis of sections of urban electrical networks in Tashkent are shown in Table 2.

An analysis of current regulatory documents and regulatory requirements in the field of electric power industry shows that one of the key tools for reducing costs and financial risks of energy supply organizations is the effective forecasting of operating parameters and technological characteristics directly related to power consumption. In the context of the Tashkent electric power market, accuracy requirements for forecasting calculations are increasing, which makes it necessary to minimize prediction errors when estimating operating parameters of urban distribution networks [3]-[8], [11].

Moreover, with the current new market situation in the domestic electric power industry, it is becoming important to carry out systematic forecasting. The concept of such forecasting is that an energy marketing organization (EMO), having predicted the development of the situation (for example, the level of losses of electric energy (EE) in the serviced energy area), seeks to adjust its actions in order to respond in a timely manner to changes in the external environment, reduce damage or, conversely, increase possible profits.

An “intelligent” approach to forecasting using neural network technologies is proposed [20], which makes it possible to effectively solve predictive tasks in conditions of strict requirements for the accuracy of such calculations and significant "noise" of the studied parameter implementations characteristic of Uzbek electric networks. This approach consists of the following steps:

1) Selection of training data.
2) The use of nonlinear optimization algorithms, primarily simulated annealing (SA) [21] and neurogenetic selection (NGIS) [22] methods, which make it possible to examine an array of source data and, based on this, organize a “competitive” procedure for selecting the best predictive model for each individual sample.
3) Forecasting the parameters of the mode and technological characteristics of the EMO for a given lead interval based on the obtained neural network model.
4) Possible adaptation of an artificial neural network (ANN) when changing the circuit-mode parameters of the electrical network.

In addition, the conducted practical research shows that in modern conditions it is more effective to carry out forecasting within the framework of the principle of “decomposition”, according to which complex computational problems are solved by dividing them into many simpler tasks and then combining the solutions obtained. When training the obtained predictive model, computational simplicity is achieved by distributing the task among a variety of experts. Combinations of such experts form an associative machine (AM) [23]. The effectiveness of the developed approach has been confirmed by numerous experimental calculations for predicting various parameters of the regime and technological characteristics (electrical load, total electricity consumption (TEC), outdoor temperature, etc.) in electrical networks [24].

In the tasks of forecasting excess losses of electrical energy, time series are characterized by pronounced irregularity and a high level of noise, which leads to a decrease in the accuracy of traditional forecasting models.

3.1 Model Configuration

Three forecasting approaches were considered:

1) ARPSS (autoregressive parametric stochastic systems) is a class of parametric predictive models describing, among other things, non-stationary series, [25] - data from previous years were used as input values only for TEC, due to the limitation of regression models on the number of input parameters.
2) The multilayer perceptron (MLP) model had a 5-5-1 architecture, selected empirically through cross-validation to balance model complexity and generalization performance, with sigmoid activation functions in the hidden layer - chosen for its smooth gradient properties, which facilitate stable training of shallow MLP architectures - and linear activation in the output layer. MLP-type ANN (multilayer perceptron trained using the reverse error propagation method, MLP has the original properties to reproduce rather complex dependencies that accompany poorly formalized tasks) (5-5-1) - the following input

parameters were used for training: EE purchase, EE technological losses, planned EE implementation, actual EE implementation and month number. The output value of the ANN was the excess electric energy losses.

3) The combined model (CM) consisted of three MLP expert networks integrated using a weighted averaging mechanism.

As can be seen from Table 3, the ARPSS model has a very high prediction error. At the same time, the forecast using the CM structure is almost 2 times more accurate than the forecast of a “single” ANN. In addition, the forecast result, within the framework of the proposed approach, can be clarified based on a pre-performed analysis of the predicted data using the self-organizing map (SOM) [15] and Principal Component Analysis (PCA) method [19].

To evaluate the effectiveness of various predictive approaches, a comparative analysis of the accuracy of forecasting excess electrical energy losses using traditional parametric models and intelligent neural network structures was performed. The main comparison criterion was the relative forecast error for the months of the analyzed period. The results of the comparative analysis are shown in Table 3.

For example, when analyzing electric energy losses in certain districts of Tashkent using factor analysis based on the PCA method, it was found that some sections of the urban electric grid are characterized by an increase in loss levels in the summer. This feature is associated with a seasonal increase in load and a change in the structure of electricity consumption.

This circumstance affects the accuracy of forecasting excess losses of electrical energy, especially when using traditional and basic neural network models. To increase the accuracy of the forecast within the framework of the intelligent approach, an additional input parameter was introduced into the training sample of the neural network model, characterizing the contribution of the dominant factor identified by the PCA method.

The application of adjustments to the forecast model, taking into account the results of factor and cluster analysis, made it possible to increase the stability of forecasting and significantly reduce the calculation error during periods of seasonally increased losses. This confirms the expediency of using clustering and factor analysis methods together when solving problems of forecasting electric energy losses in urban electric networks in Tashkent.

4 DISCUSSION

The principle of building “intelligent” software and computing complexes for solving electric power problems.

The development and complexity of electric power industry systems, especially at the lower levels of the hierarchy, necessitate the use of a sophisticated data analysis apparatus based on the use of modern mathematical methods and approaches. Unfortunately, existing specialized software and computing complexes (SCC) focused on solving problems of the electric power industry, as a rule, use a limited set of mathematical techniques, which does not allow to fully take into account the features and specifics of the functioning of electric power systems.

Despite a number of significant advantages of specialized Russian SCCs, such as RAP-95 and “PROGNOZ” [26], which implement both traditional approaches and modern information technologies, the principles of their operation in information processing do not fully reflect the current economic requirements and operating conditions of the electric power market. As a rule, such SCCs are highly specialized in nature.

Table 3: Forecast of excess electric energy losses by various forecasting models.

Predictive model	Relative error in months												Average error, %
	1	2	3	4	5	6	7	8	9	10	11	12	
ARPSS	43.9	43.5	49.1	42.9	45.8	35.9	35.6	43.8	40.1	44.1	40.1	49.3	42.8
ANN	2.3	0.4	2.5	4.9	8.3	8.3	30.0	12.5	1.2	0.5	1.4	1.3	6.1
CM	1.0	1.5	2.8	3.9	4.3	4.6	16.5	8.1	0.6	0.3	0.2	1.2	3.7

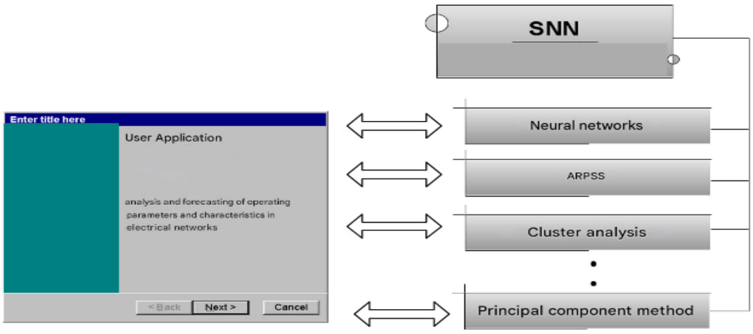

Figure 1: The block diagram of the specialized software and computing complex "ANAPRO" in the framework of the concept of macro applications.

One of the possible ways to solve this problem is to create a specialized software and computing complex based on macro applications of independent software modules that implement sequences of commands and functions and, as a rule, are developed using the Visual Basic language. Within the framework of this approach, ready-made procedures and blocks of an integrated software system (ISS) are used as the main computing modules (Fig. 1). In other words, the ISS is taken as a basis, developed by specialists in the field of statistical analysis and data processing and containing a wide range of modern mathematical methods, for which a macro program with a user interface is formed, focused on solving specific electric power problems. In the future, such a macro program, in accordance with the built-in set of commands and functions, accesses the corresponding computing modules of the ISS.

A specialized "ANAPRO" software and computing complex has been developed (Fig. 1) [27], where the Statistica Neural Networks (SNN) software package is used as an IPS, representing a modern integrated statistical analysis and data processing system in the Windows environment. The effectiveness of the proposed approach is related both to the ability to work with many models, and to the ability to choose the optimal model corresponding to a qualitative solution of a specific electric power problem.

The object-oriented programming language Visual Basic is used as the main language of the macro program.

Related applied studies by the authors demonstrate the transferability of data-driven analysis and validation approaches to transport and infrastructure engineering tasks, including environmental monitoring and treatment of polluted runoff and wastewater, occupational hygiene assessment, and modeling of building-environment interactions [28]-[35].

5 CONCLUSIONS

The complexity of the functioning of the modern electric power market in Tashkent, the need to form an objective and "transparent" picture of the state of urban electric networks, as well as stricter requirements for the accuracy of power consumption planning determine the expediency of using effective methods of analysis and forecasting of operating parameters and technological characteristics. The analysis and the results of practical research show that the most effective solution to electric power problems in modern conditions is achieved through the use of new information technologies, primarily intelligent data processing methods and artificial neural networks.

It has been established that the use of cluster analysis methods [36] based on self-organizing artificial neural networks, including in combination with factor analysis based on the principal component method (PCM), makes it possible to identify the characteristic features of power consumption, differences in operating modes of electrical networks, as well as normal and abnormal modes.

It is shown that the application of an intelligent approach to system forecasting of operating parameters and technological characteristics provides higher accuracy and stability of forecasts compared with single neural network structures and traditional regression models.

A software and computing complex based on macro applications is proposed, which allows choosing optimal solutions for practical problems of analysis and forecasting in urban electric networks of Tashkent from a set of implemented mathematical and intelligent models.

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