Journal of Modern Energy Research
Vol. 2, No. 2, Dec 2024, pp. 1-10
ISSN: 3078-3534, DOI: 10.56947/jmer.v2i2.10

Medium-Term Forecasting of Power Consumption by ANN Considering Meteo-Factors

Murodbek Safaraliev[1], Pavel Matrenin[2], Mihail Senyuk[1], Natalia Cheganova[2]
[1]Department of Electrical Engineering, Ural Federal University, Russia
[2]Power Supply Systems Department, Novosibirsk State Technical University, Russia

Article Info

Article history:

Received Sep 3, 2024
Revised Oct 15, 2024
Accepted Nov 17, 2024

Keywords:

Artificial neural network
Medium-term
Forecasting
Meteorological conditions
Power consumption

ABSTRACT

The main task of forecasting power consumption is to analyze objective factors affecting load changes and compute expected schedules of consumption to support energy companies organize the purchase and production of the necessary electricity in the proper volume. However, modern practical requirements for the accuracy of predictive calculations lead to the fact that previously developed methods do not always provide the necessary accuracy of computations. This is because several factors affect the level of power consumption and the accuracy of forecasting, including meteorological, where the growing use of both wind and photovoltaic energy worldwide leads the power systems to become highly dependent on the weather conditions. This study presents the influence of meteorological factors on the medium-term forecast of electricity consumption based on the power system of the Gorno-Badakhshan Autonomous Oblast in the Republic of Tajikistan, where in winter, due to an increase in demand for electricity and a drop in the water level in rivers, to ensure balance, requires additional commissioning of diesel power plants. Thus, it leads to an increase in the costs of electricity production in the region and environmental degradation. To increase the forecasting effectiveness, the authors propose an approach based on the clustering of meteorological conditions, where each cluster has its regression model. The Principal Component Analysis was proposed for aggregating meteorological factors.

Corresponding Author:

Pavel Matrenin
Power Supply Systems Department, Novosibirsk State Technical University
K. Marks Ave, 20, Novosibirsk, Russia
Email: matrenin.2012@corp.nstu.ru

1. INTRODUCTION

In general, the development of the energy sector and the electric power industry largely determines the pace of economic growth of the country. It is expressed not only in increasing the volume of consumed energy but also in diversifying its sources and increasing production efficiency. Compared to other types of energy carriers, electricity is used in all spheres of human activity and is a key driving force for the growth of global energy [1].

Currently, one of the basic principles of operational dispatch management in the electric power industry is to ensure energy balancing for different periods. The medium-term forecasts of electricity consumption volumes are used to form the annual consolidated balances of electricity generation and consumption. Due to the penalties imposed by suppliers when the actual consumption deviates from the previously stated, the large energy consumers are interested in drawing up accurate applications for the planned amount of energy consumption. Therefore, it is important to consider the issues of mathematical modeling of electricity consumption volumes under the conditions of the modern development of the wholesale electricity and capacity market [2]. In turn, electricity producers are interested in forecasts of energy consumption to promptly respond to fluctuations in demand and optimal infrastructure development [3].

The reliability of the constructed forecasts of electricity consumption largely depends on the effectiveness of energy management solutions, the possibility of saving energy resources, and the efficiency of operating modes of the entire power system. Therefore, efficient grid management plays an important role in reducing energy production costs and increasing capacity to meet the growing electricity demand [4].

Most methods of forecasting power consumption are devoted to short-term forecasting (from a few minutes to 24 hours), rather than medium-term forecasting (from several days to several months). As a rule, methods of forecasting power consumption can be divided into two broad categories [5]: statistical methods and machine learning-based methods, although the boundary between them is becoming more and more blurred.

Traditional statistical methods include time series analysis methods [6], Kalman filter method [7], exponential smoothing method [8] and so on. However, the accuracy of traditional forecasting methods may not be high enough in the medium term due to the nonlinear characteristics of power consumption to forecast processes with a high degree of volatility. The latter is especially characteristic of the isolated power systems due to their small size relative to large regional and combined power systems. Forecasting methods based on machine learning include fuzzy logic, classical artificial neural networks (ANN) [9], the support vector machine (SVM) method [10], neural networks with memory [11] and ensemble methods [12]. They can be considered as an unconventional or modern methodology in the tasks of forecasting power consumption. In comparison with traditional methods, the forecasting accuracy of machine learning methods is in many cases significantly higher, but optimization of the parameters of each model is difficult, which affects the effectiveness of forecasting.

Medium-term forecasting of electricity consumption is an important category of electrical load forecasting that covers a period up to one year in advance. It is suitable for downtime and maintenance planning, and load switching [13], and has been reflected in a large number of scientific publications that used based on machine learning techniques. Due to the serious impact of climate change on electricity consumption, as well as new trends in smart grids (the use of renewable energy resources, the emergence of consumers, and the general use of energy), medium- and long-term forecasting of the electricity consumption has become an urgent need. Such forecasts are necessary to support plans and decisions in terms of capacity assessment of centralized and decentralized power generation systems, demand response strategies, and operation control [14].

2. STATEMENT OF THE PROBLEM

The forecast of electricity consumption is the core module for making management decisions in electric power systems [15]. The accuracy of forecasts directly affects the effectiveness of management. Medium-term forecasting of electricity consumption is extremely important for energy suppliers and other participants in the production, transmission, distribution, and electricity markets. This helps to make decisions, including those on the purchase and production of utilities of the electric power system. The main role of electric load forecasting in the electric power system is to support energy companies to organize the purchase and production of the required amount of electricity.

One of the approaches to improving the accuracy of forecasts is the use of additional stages of filtering and data preprocessing, including clustering. It allows us to build several individual models instead of a single model for all operating conditions, where each separate model is better adapted to certain meteorological conditions.

Most often, the clustering of meteorological conditions in the tasks of the electric power industry is associated with forecasting the generation of renewable energy sources. For instance, statistical models for predicting solar insolation combined with the k-means clustering algorithm are presented in [16]; clustering of meteorological parameters used to predict the generation of wind power plants is given in [17]. At the same time, for the current conditions, a sample (subset) of the most similar records is formed among all the retrospective data, then a model is trained based on this data.

Clustering can also be used for data filtration. For example, the application of clustering of meteorological parameters to detect outliers is described in [18]. Clustering is also used in the analysis of power consumption, for instance, separating consumers by power consumption profiles [19, 20].

In this paper, clustering is used to divide a dataset of retrospective data into several categories that differ in meteorological conditions. For each cluster, the load forecasting model is developed. Another contribution is the algorithm for choosing the optimal number of previous days, and the meteorological data which are used for clustering. The Principal Component Analysis (PCA) data dimensionality reduction algorithm is applied, which allows us to visually assess how clusters are distributed in the feature space [21]. The PCA algorithm also allows simplifying forecast models by aggregating meteorological data.

3. METHODOLOGY

The proposed approach consists of three main modules such as data selection and their processing, clustering of the meteorological conditions, and forecasting of power consumption. Let us consider each of them.

3.1. Description of the data selection

The isolated power system of the Gorno-Badakhshan Autonomous Oblast (GBAO) of the Republic of Tajikistan is managed by Pamir Energy. It includes eleven hydropower plants (HPPs) with a total capacity of 43.5 MW on its balance sheet and several diesel power plants (DPP) of low capacity. Currently, the isolated GBAO power system is experiencing serious difficulties associated with a steady shortage of electricity in the winter period from November to March, where the main reasons are the following [22-26].

Since the shortage of electricity generated by the HPP is observed during the cold period from November to March inclusive, only data for these five months are considered.

The main hypothesis of this study is the possibility to increase the accuracy of medium-term forecasting of electricity consumption through the use of meteorological data and their clustering.

In addition, the load changes on weekends in the examined power system, thus the number of days of the week is added to the dataset. The numbers of the year, month, and day are also considered features. A complete list of features in the original dataset is the following: year, month, day, day of the week, air temperature, relative humidity, wind speed, and cloud cover. For instance, profiles of consumption changes are given below in Fig.1 and Fig.2.

Power consumption (average daily load capacity) is the target variable.

The dataset contains records for six years (2015-2020) in one-day increments. Thus, the dataset contains 908 rows and 9 columns.

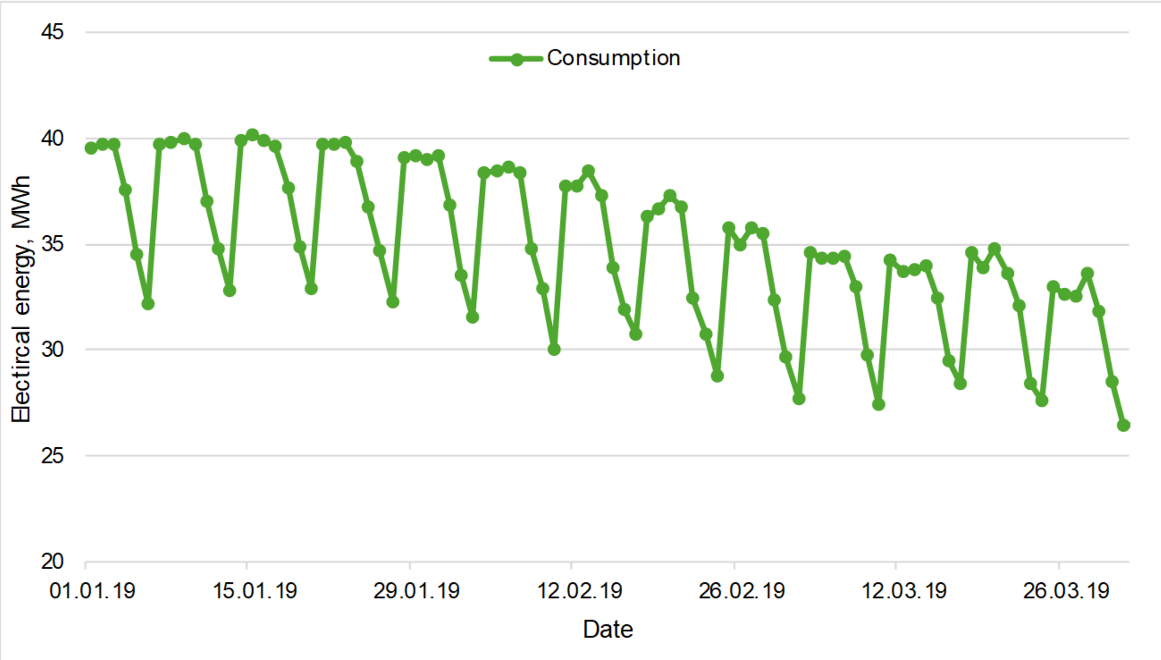

Figure 1. Consumption graph for the period January-March 2019

The correlation coefficients between features and power consumption are shown in Table 1. It can be seen that the greatest dependence is observed between power consumption and the year (0.7) and the day of the week (0.51), for the feature in terms of meteorological conditions – between power consumption and wind speed (0.37). The dependence on meteorological factors such as temperature, humidity, and cloud cover also affects power consumption.

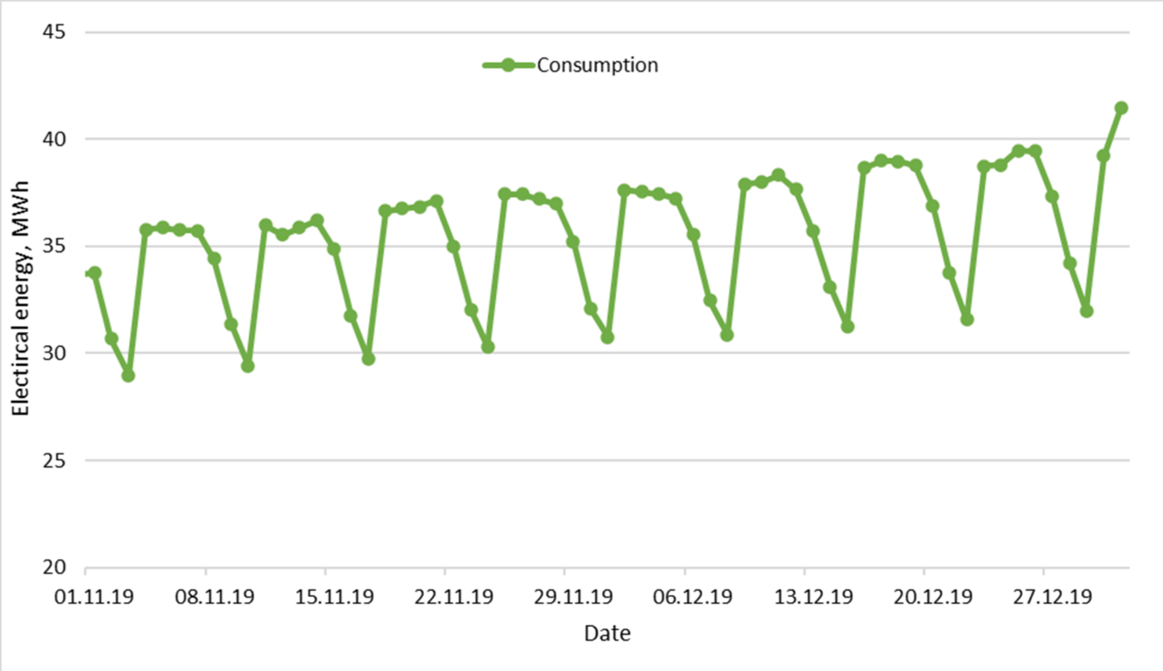

Figure 2. Consumption graph for the period November-December 2019

Table 1. The correlation coefficient between features and power consumption

Feature	Correlation coefficient
Year	0.70
Month	-0.09
Day	0.01
Day of the week	-0.51
Temperature	-0.33
Humidity	0.20
Wind speed	-0.37
Cloud cover	0.01

3.2. Statement of the forecasting problem

A model of medium-term (for a week ahead) forecasting of power consumption of the power system is given as follows:

$$P_i^* = f(W_{i-7},\ W_{i-8}, \dots, W_{i-6-d}) \tag{1}$$

where

P^*_i – predicted power consumption on the i-th day;

f – model; d –number of previous days that used for prediction;

W_i – the vector of values of the used features on the i-th day including P_i.

Forecasts of meteorological factors are not used in this work since the system will depend on the accuracy of medium-term forecasts of a weather provider. For forecasting, the data from the previous day is used considering the planning horizon of a week.

The accuracy of the forecast is estimated on a test dataset using mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean squared error (RMSE) as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - P_i^*| \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - P_i^*}{P_i}\right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - P_i^*)^2} \quad (4)$$

where

P – the true value of power consumption;
P^* – predicted value of power consumption;
n – the size of the test set in days.

3.3. Clustering of meteorological conditions

When developing the machine learning models, a choice has to be done: either create a single model that will solve the whole problem or split the task into stages leading to creating separate models for each of them.

Creating a single model allows you to train it to achieve the final goal, while when dividing the task into stages, each model is built to achieve a sub-goal. Then the results of combining such models may not be as high-quality as when training a single model focused on the final result. On the other hand, in planning and management tasks in the electric power industry, the interpretability of machine learning models, the guarantee of their robustness, and the reduction of the risk of unexpected behavior are very important.

In addition, it is necessary to consider the limitations of the dataset, the smaller the dataset, the less reliable the conclusions obtained using complex models are. Splitting the task into parts allows you to apply simpler models at each stage and control them better. Limiting the size of the model can make it more resistant to retraining, more robust, and increase its generalizing ability [27].

The proposed architecture of the forecasting system based on machine learning used in this work is the following:

1) Data preprocessing level;
2) Data clustering level;
3) Prediction level, consisting of m independent neural networks, according to the number of clusters.

3.4. Forecasting of power consumption

The essence of the proposed approach is to divide meteorological conditions into m clusters using unsupervised machine learning (k-means algorithm [30]. Each cluster builds its neural network model. When the system is running, the input data refers to one of the clusters and then the model that was built for this cluster is used to obtain the forecast.

This approach has the following advantages:

- The clustering stage is performed as unsupervised learning, meaning that the risk of fitting to the desired result is excluded;
- The consistency of the clustering result can be checked visually by applying the PCA after clustering and visualizing the resulting clusters using a scatter plot;
- The construction of different models for individual meteorological factors allows for an increase in the accuracy of the forecast since each model is focused on certain operating conditions;
- Individual models may be more compact than a single one, therefore, fewer data can be used for their training and testing, and their work will be more predictable.

4. RESULT AND DISCUSSION

4.1. Data preprocessing

The initial dataset can be written as follows:

$$\{(W_i, P_i)\}, i = 1 \dots n \quad (5)$$

At the preprocessing stage, it is converted into the following form corresponding to the expression:

$$\{(W_{i-7}, W_{i-8}, \dots, W_{i-6-d}, P_i\ )\} \quad (6)$$

The number *d* determines the number of previous days that will be used to build the forecast. With *d* equal to one, the resulting dataset will have 10 columns (9 features and a target variable), with *d* equal to 2–19, etc.

In addition, at the data preprocessing stage, Min-Max normalization is performed so that all feature values are in the range from 0 to 1.

4.2. Clustering

The k-means algorithm is used for clustering since it is a general-purpose algorithm. To check the correctness of clustering and select the most appropriate number of clusters, PCA was used. Clustering is performed by attributes (*Wi-7*, *Wi-8*, ..., *Wi-6-d*). Then PCA is applied to the data with the translation of the dimension of the features into a two-dimensional plane. The points on the plane are then marked with colors according to the cluster labels. The clarity of the boundaries between the resulting clusters shows how well clustering was performed.

The results obtained are shown in Fig.3-7.

Initially, four clusters were used, this number was chosen based on a visual analysis of the PCA results. But then, at the stage of building regression models, it was founded that three clusters give the best result. It can be seen that when the number of days used is less than five, the boundaries between clusters are less clear.

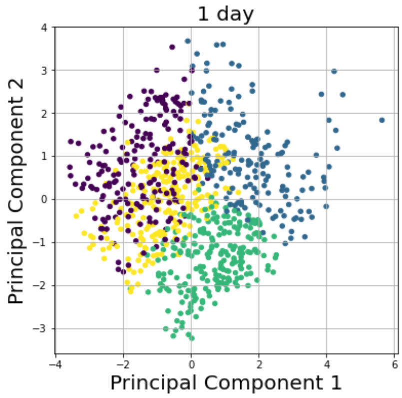

Figure 3. Visualization of four clusters when using data for one day

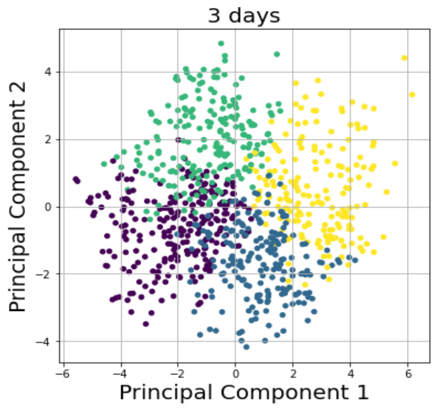

Figure 4. Visualization of four clusters when using data for three days

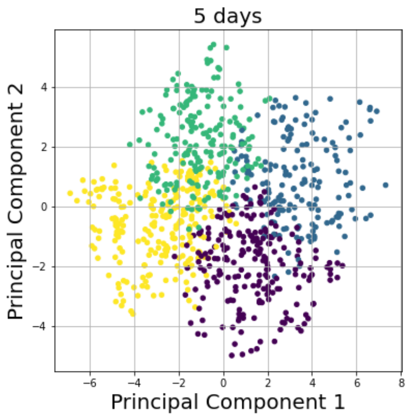

Figure 5. Visualization of four clusters when using data for five days

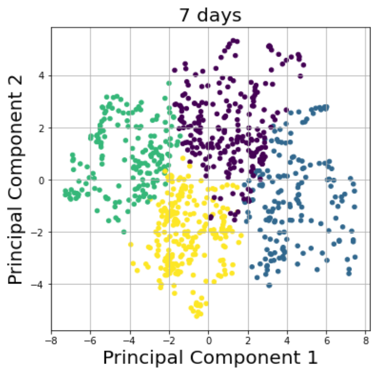

Figure 6. Visualization of four clusters when using data for seven days

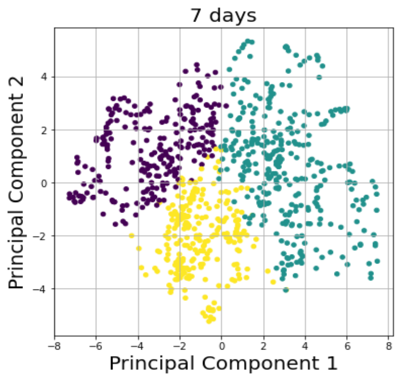

Figure 7. Visualization of four clusters when
using data for seven days

Using more than seven days may lead to the retraining of regression models since there will be too many input features regarding the number of days in the dataset. Thus, in the following stages, daily data for a week and three or four clusters are used.

4.3. Forecasting

Since many heterogeneous factors are used, an artificial neural network (ANN) is chosen as the basic method for constructing a regression model [28-29]. The dataset is not large enough to use more complex architectures such as convolutional or recurrent neural networks. Therefore, a multilayer perceptron of the following type is used:

1) Input layer;
2) Hidden layer of 32 neurons with ReLU activation function;
3) Hidden layer of 16 neurons with ReLU activation function;
4) Hidden layer of 8 neurons with ReLU activation function;
5) Output neuron with a sigmoidal activation function.

The training is performed using the Adam algorithm [31]. The model is implemented using the Python libraries such as Keras and TensorFlow.

The proposed approach is compared with a single ANN model (excluding clusters), an autoregressive (AR) model that does not use meteorological data, and linear regression (LR) that uses meteorological data. The results presented in Table 2 provide the test part of the dataset, where 10% of the newer data and 90% of the older ones were used for training. Let us discuss the conclusions drawn from the obtained results of the model comparison.

The use of clustering by meteorological conditions increases the accuracy for both LR and ANNs. The error reduction was for ANN from 1.023 MW to 0.846 MW (17%), and for LR from 0.774 to 0.586 (24 %). But at the same time, if the number of clusters is more than optimal, there may be a reverse effect since there will be not enough data in each of the clusters to train the model.

The use of meteorological conditions reduces the forecast error, the error difference between the AR model that does not use meteorological parameters and the best model using them such as LR was 0.217 MW (27 %). A significant advantage of LR over ANN models turned out to be somewhat unexpected. This output could be explained by two factors:

1) The use of features obtained using PCA as additional input features made it possible to aggregate meteorological factors in many ways even before the use of regression models;

2) The amount of data is not large enough for the effective use of neural networks, their more efficient operation probably requires data for 10-20 years.

Table 2. Results of forecast models using meteorological data (test set)

Model	Number	Cluster of clusters number	MAE, MW	MAE, MW	RMSE, MW
ANN	**-**	**-**	**1.023**	**7.48**	**1.27**
ANN	4	1	0.653	4.73	0.81
ANN	4	2	0.779	8.16	0.97
ANN	4	3	1.495	9.60	1.68
ANN	4	4	0.905	8.81	1.34
ANN	**4**	**Weighted average**	**0.939**	**7.70**	**1.19**
ANN		1	1.067	7.15	1.40
ANN	3	2	0.734	6.13	0.92
ANN	3	3	0.776	6.90	1.00
ANN	**3**	**Weighted average**	**0.846**	**6.67**	**1.09**
LR	**-**	**-**	**0.774**	**5.82**	**0.99**
LR	3	1	0.604	5.03	1.04
LR	3	2	0.751	4.86	0.73
LR	3	3	0.397	3.52	0.56
LR	**3**	**Weighted average**	**0.586**	**4.53**	**0.77**

AR	**-**	**-**	**0.803**	**6.11**	**0.96**

The average forecast error (MAE) on the test part of the dataset was 0.59 MW, the RMSE was 0.77 MW, and the average percentage error (MAPE) was 4.5%. Compared with the autoregression model without clustering and taking into account meteorological factors (MAE 0.80 MW, RMSE 0.96 MW, MAPE 6.11%), it can, according to preliminary estimates, lead to an average decrease in the generation capacity of DPP by 0.2 MW or 5 MWh per day.

It should be emphasized that the result obtained makes it possible to create a reliable and very simple model based on machine learning, and, at the same time, with minimal use of complex and poorly controlled machine learning methods.

The final model is presented as follows:

1. At the stage of creating a forecast system, the following is performed:

1.1. Clustering data by the k-means algorithm into three clusters;

1.2. Applying the PCA for the formation of the two most significant features aggregating meteorological parameters;

1.3. Creating a linear regression model for each cluster.

2. At the stage of operation, the following is performed:

2.1. Determining which cluster holding the current meteorological observations during the previous week;

2.2. Using PCA to obtain aggregated features;

2.3. Using the trained linear regression model to obtain a forecast of electricity consumption.

Figure 8 shows a comparison between the true and the forecast load plot for one fragment of the test set.

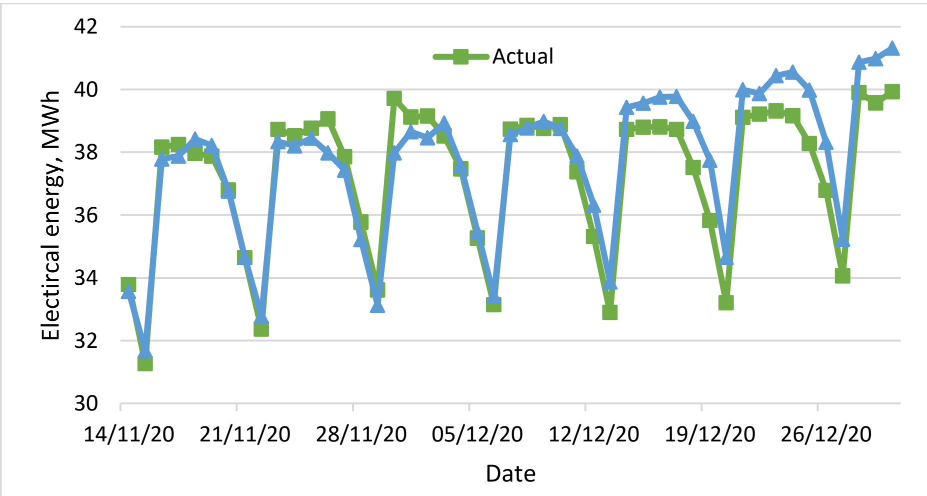

Figure 8. Comparison of true and forecast consumption schedules of the electrical energy

5. CONCLUSION

The investigation of the problem of medium-term forecasting of electricity consumption of the Gorno-Badakhshan Autonomous Oblast of the Republic of Tajikistan was performed for the cold season when there is a shortage of electricity generated by HPPs.

The study uses daily data for the 2015-2020 years (November-March). To increase the accuracy of forecasting power consumption, meteorological factors and clustering of conditions were used in this work. Only retrospective data were used to exclude dependence on meteorological forecasts. At the stage of data preprocessing, the PCA was applied, which allows for checking the correctness of clustering and aggregating meteorological parameters. Further clustering allows to make several simpler and more accurate models instead of one model that considers all possible operating conditions of the power system. Due to clustering and the PCA, it was possible to obtain higher accuracy using linear models than using a single neural network model. The decrease in MAE due to clustering was 0.19 MW (MAE decreased by 24%). The use of meteorological conditions allowed to reduce the forecast error by 0.22 MW (27%).

In the future, it is planned to develop a model for a more accurate assessment of the reduction in fossil fuel consumption by increasing the accuracy of load forecasting. And to explore the possibility of using energy storage devices to increase the flexibility of managing the electric power system.

ACKNOWLEDGEMENTS

The reported study was supported by the Russian Science Foundation, research project No. 23-79-01024.

REFERENCES

[1] International Renewable Energy Agency (IRENA). Global energy transformation. A roadmap to 2050. (2018). https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2018/Apr/IRENA_Report_GET_2018.pdf
[2] Hattab, M., Ma'itah, M., Sweidan, T., Rifai, M., Momani M. (2017). Medium Term Load Forecasting for Jordan Electric Power System Using Particle Swarm Optimization Algorithm Based on Least Square Regression Methods. J. of Power and Energy Engineering, 5, 75-96. https://doi.org/10.4236/jpee.2017.52005
[3] Proposal for a Regulation of the European Parliament and of the Council on the Internal Market for Electricity. European Commission. (2017). https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52016PC0861R(01)&from=EN
[4] Nti, I.K., Teimeh, M., Nyarko-Boateng, O., et al. (2020). Electricity load forecasting: a systematic review. J. of Electrical Systems and Inf. Technol. 7, 13. https://doi.org/10.1186/s43067-020-00021-8
[5] Nti, I.K., Teimeh, M., Nyarko-Boateng, O., Adekoya, A.F. (2020). Electricity load forecasting: A systematic review. Journal of Electrical Systems and Information Technology, 7(1), 1-19. ttps://doi.org/10.1186/s43067-020-00021-8
[6] Espinoza, M., Joye, C., Belmans, R., De B. (2005). Short-term load forecasting, profile identification, and customer segmentation: a methodology based on periodic time series. Moor. IEEE Transactions on Power Systems, 20(3), 1622-1630. https://doi.org/10.1109/TPWRS.2005.852123
[7] Sharma, S., Majumdar, A., Elvira, V., Chouzenoux, É. (2020). Blind kalman filtering for short-term power load forecasting. IEEE Transactions on Power Systems, 35(6), 4916-4919. https://doi.org/10.1109/TPWRS.2020.3018623
[8] Arora, S., Taylor, J.W. (2013). Short-term forecasting of anomalous load using rule-based triple seasonal methods. IEEE Transactions on Power Systems, 28(3), 3235-3242. https://doi.org/10.1109/TPWRS.2013.2252929
[9] Saidmurodov, B., & Odinaev, I. (2023). Current Transformer Saturation Detection Bases On Artificial Neural Networks. Journal of Modern Energy Research, 1(1), 7-16. https://doi.org/10.56947/jmer.v1i1.2
[10] Chen, B.-J. Chang, M.-W., Lin, Ch.-J. (2004). Load forecasting using support vector machines: a study on EUNITE competition 2001. IEEE Transactions on Power Systems, 19(4), 1821-1830. https://doi.org/10.1109/TPWRS.2004.835679
[11] Rafi, S.H. Nahid-Al-Masood, Deeba, S.R., Hossain, E. (2021). A short-term power load forecasting method using integrated CNN and LSTM network. IEEE Access, 9, 32436-32448. https://doi.org/10.1109/ACCESS.2021.3060654
[12] Sergeev, N.N., Matrenin, P.V. (2022). Enhancing Efficiency of Ensemble Machine Learning Models for Short-Term Load Forecasting through Feature Selection. IEEE 23rd International Conference of Young Professionals in Electron Devices and Materials (EDM): proc., Altai, 30 June 2022 - 04 July 2022. – Altai: IEEE, 368-371. https://doi.org/10.1109/EDM55285.2022.9855022
[13] Abu-Shikhah, N., Elkarmi, F., Aloquili, O. (2011). Medium-Term Electric Load Forecasting Using Multivariable Linear and Non-Linear Regression. Smart Grid and Ren. Energy, 2, 126-135. https://doi.org/10.4236/sgre.2011.22015
[14] Shirzadi, N., Nizami, A., Khazen, M., Nik-Bakht, M. (2021). Medium-Term Regional Electricity Load Forecasting through Machine Learning and Deep Learning. Designs 5, 27. https://doi.org/10.3390/designs5020027
[15] Hahn, H., Meyer-Nieberg, S., Pickl, S. (2009). Electric load forecasting methods: Tools for decision making. European J. of Operational Research, 199, 902-907. https://doi.org/10.1016/j.ejor.2009.01.062
[16] Kang, C., Sohn, J.-M., Park, J.-Y., Lee, S.-K., Yoon, Y.-T. (2011). Development of algorithm for day ahead PV generation forecasting using data mining method. Proc. of IEEE 54th Inter. Midwest Symposium on Circuits and Systems. https://doi.org/10.1109/MWSCAS.2011.6026333
[17] Wu, W., Peng, M. (2017). A Data Mining Approach Combining K-Means Clustering with Bagging Neural Network for Short-Term Wind Power Forecasting. IEEE Internet of Things J. 4, 979-86. https://doi.org/10.1109/JIOT.2017.2677578
[18] Eroshenko, S.A., Khalyasmaa, A.I., Snegirev, D.A., Dubailova, V.V., Romanov, A.M., Butusov, D.N. (2020). The Impact of Data Filtration on the Accuracy of Multiple Time-Domain Forecasting for Photovoltaic Power Plants Generation. Applied Sciences 10, 8265 https://doi.org/10.3390/app10228265
[19] Panapakidis, I.P., Christoforidis, G.C. (2017). Implementation of modified versions of the K-means algorithm in power load curves profiling. Sustainable Cities and Society 35, 83-93. https://doi.org/10.1016/j.scs.2017.08.002
[20] Viola, L.G. (2018). Clustering electricity usage profiles with K-means. Towards Data Science, https://towardsdatascience.com/clustering-electricity-profiles-with-k-means-42d6d0644d00.
[21] Gorban, A.N., Kegl, B., Wunsch, D.C., Zinovyev, A. (2008). Principal Manifolds for Data Visualization and Dimension Reduction, Springer. https://doi.org/10.1007/978-3-540-73750-6
[22] Manusov, V., Matrenin, P., Nazarov, M., Beryozkina, S., Safaraliev, M., Zicmane, I., & Ghulomzoda, A. (2023). Short-term prediction of the wind speed based on a learning process control algorithm in isolated power systems. Sustainability, 15(2), 1730. https://doi.org/10.3390/su15021730
[23] Dzhuraev, S., Beryozkina, S., Kamolov, M., Safaraliev, M., Zicmane, I., Nazirov, K., & Sultonov, S. (2022). Computation of the zero-wire current under an asymmetric nonlinear load in a distribution network. Energy Reports, 8, 563-573. https://doi.org/10.1016/j.egyr.2022.09.176
[24] Tavarov, S., Matrenin, P., Safaraliev, M., Senyuk, M., Beryozkina, S., & Zicmane, I. (2023). Forecasting of electricity consumption by household consumers using fuzzy logic based on the development plan of the power system of the Republic of Tajikistan. Sustainability, 15(4), 3725. https://doi.org/10.3390/su15043725
[25] Ghulomzoda, A., et al. (2021). A Novel Approach of Synchronization of Microgrid with a Power System of Limited Capacity. Sustainability 13, 13975. https://doi.org/10.3390/su132413975
[26] Odinabekov, M., Sidikov, S., Ghulomzoda, A., & Makhmudov, K. (2023). Accelerated Limitation of Frequency Reduction and Increase in Frequency in Small Power Systems. Journal of Modern Energy Research, 1(1), 17-26. https://doi.org/10.56947/jmer.v1i1.3

[27] Matrenin, P.V., Manusov, V.Z., Khalyasmaa, A.I., Antonenkov, D.V., Eroshenko, S.A., Butusov, D.N. (2020). Improving accuracy and generalization performance of small-size recurrent neural networks applied to short-term load forecasting. Mathematics, 8, 2169. https://doi.org/10.3390/math8122169

[28] Kamalov, F., Zicmane, I., Safaraliev, M., Smail, L., Senyuk, M., & Matrenin, P. (2024). Attention-Based Load Forecasting with Bidirectional Finetuning. *Energies*, *17*(18), 4699. https://doi.org/10.3390/en17184699

[29] Kamalov, F., Sulieman, H., Moussa, S., Avante Reyes, J., & Safaraliev, M. (2024). Powering Electricity Forecasting with Transfer Learning. *Energies*, *17*(3), 626. https://doi.org/10.3390/en17030626

[30] Hartigan, J.A., Wong, M.A. (1979). Algorithm AS 136: A K-Means Clustering Algorithm. J. of the Royal Statistical Society. Series C (Applied Statistics) 28, 100-8. https://doi.org/10.2307/2346830

[31] Kingma, D.P., Ba, J.L. (2014). Adam: A method for stochastic optimization. arXiv.