10.63550/ICEIP.2026.52.34.045

Self-Organizing System for Management Decision-Making in Energy Systems

Isamidin Siddikov[1][a], Noilaxon Yakubova[1][b] Sadikova Feruzaxon[1][c] and Gulchexra Alimova[1][d]
[1] *Department of Information Processing and Control Systems, Faculty of Electronics and Automation, Tashkent State Technical University named after Islam Karimov, Tashkent, Uzbekistan*
isamiddin54@gmail.com, noila.yakubova@gmail.ru, feruzakhon94@mail, rualimova250479@gmail.com,

Keywords: Self-organizing systems, intelligent control, machine learning, neuro-fuzzy networks, energy systems optimization, artificial intelligence, big data analytics, uncertainty management.

Abstract: The paper investigates the development of a self-organizing control system for managing the operational modes of power system facilities, grounded in the application of intelligent technologies. The approach integrates advanced data analytics techniques and artificial intelligence algorithms to enhance system adaptability and efficiency. A hybrid machine learning methodology is proposed, combining classification and regression models for the analysis of the operational state of technological units. This enables more accurate forecasting and facilitates the optimal distribution of energy flows within the system. To address the challenges associated with forecasting and optimizing the operating regimes of energy facilities, the study advocates the use of big data analytics in conjunction with artificial intelligence techniques. In particular, the implementation of neuro-fuzzy systems is emphasized, allowing for greater flexibility in decision-making processes under conditions of uncertainty, incomplete information, and dynamic load variations. The proposed framework contributes to improving the resilience, energy efficiency, and overall reliability of modern energy systems.

1 INTRODUCTION

Modern trends in the development of power systems—such as the widespread integration of distributed energy resources (DERs), including solar and wind power, and the growing demand for electricity—have necessitated the digitalization of energy infrastructures (Vorob'ev, Vorob'eva, Makarov, Svirkov, Sysoev, Artem'ev, Belyaev, Fedosova, Bogatyreva, 2019). This transformation increasingly relies on artificial intelligence (AI) technologies that enhance system adaptability in response to dynamic operational conditions. In light of these challenges, there is a heightened demand for intelligent systems capable of not only real-time energy flow management but also highly accurate forecasting of future consumption and generation trends (Marzband, Amjady, Savaghebi, 2023; Utkarsh, Feng, Zhang, Li, 2022; Nasiri, Bahrami, 2021; Siddikov, Alimova, Rustamova, Usanov, 2025; Lazareva, Porubaj, 2024).

This growing reliance on information and intelligent technologies in energy generation management is closely linked to advancements in machine learning methods, which provide autonomous learning capabilities based on historical data. These capabilities allow intelligent systems to accurately forecast energy consumption patterns and support effective, data-driven decision-making for power system operation. The hybrid use of AI and machine learning techniques in energy management offers substantial benefits, including reduced energy losses, enhanced reliability, and increased resilience of energy infrastructure—largely due to the improved precision in load forecasting and control optimization. At present, most energy management systems rely on mathematical modeling approaches grounded in deterministic and probabilistic methods

[a] https://orcid.org/0000-0002-6983-6709
[b] https://orcid.org/0009-0002-2343-2650
[c] https://orcid.org/0009-0007-4013-2939
[d] https://orcid.org/0000-0002-4889-9372

(Martins, da Silva, 2020; Chen, Wang, Liu, 2023). These models require precise input data and are constrained by the operational limitations of power equipment. However, the continuous nature of processes in electric power systems, coupled with the discrete nature of state assessments—often without considering system structure—leads to control delays and information loss, necessitating the frequent recalibration of the underlying mathematical models.

Moreover, real-world energy control systems are subject to constant internal and external stochastic influences that must be considered when developing effective and adaptive control mechanisms. These challenges underscore the necessity of advancing existing methods through their integration with machine learning and big data analytics to enable accurate, real-time assessments and management of energy systems under uncertainty. To address these issues, the proposed intelligent system incorporates machine learning algorithms and neuro-fuzzy networks, providing the flexibility required to overcome the aforementioned limitations. Historically, thermal load management in the energy sector has relied on automatic control theory and statistical models, such as regression and correlation analysis. While these approaches have proven effective under stable conditions, they suffer from several drawbacks, including high sensitivity to fluctuations, limited adaptability to rapid changes in demand, and poor scalability in processing large datasets (Lee, Kim, 2021; Karthikeyan, Kumar, 2020; Siddikov, Nashvandova, Alimova, 2024; Yakubova, Usmanov, Turakulov, Eshbobaev, 2025).

One promising direction for addressing these limitations lies in the integration of Internet of Things (IoT) technologies and big data analytics. By collecting and analyzing real-time data from multiple distributed sensors, it becomes possible to obtain accurate insights into the operational status of energy assets. This, in turn, improves the system's ability to anticipate and adapt to load fluctuations. Another advanced approach involves the deployment of hybrid models that combine traditional mathematical modeling with machine learning techniques to enhance forecasting and energy distribution optimization. For instance, the integration of recurrent neural networks (RNNs) with time-series analysis has been shown to significantly improve the accuracy of both short-term and long-term demand forecasts, thereby enhancing the responsiveness and quality of system control (Siddikov, Khalmatov, Alimova, Feruzaxon, Usanov, 2024; Alhelou, Shrestha, 2021; Siddikov, Ibragimov, Rustamova, 2024).

Among the most effective solutions for improving the accuracy of forecasting and enhancing the reliability of control decisions is the application of AI techniques, including machine learning, neural networks, and genetic algorithms (Smolyarov, 2024). These technologies allow systems to autonomously adapt to changing demands and external conditions while minimizing human error and optimizing decision-making processes (Wu, Zhao, Han, 2022). The proposed approach to managing the operational modes of energy facilities offers the potential to significantly improve the performance of power system control by enabling more precise forecasting and optimal energy flow distribution (Usmanov, Eshbobaev, Yakubova, 2023; Siddikov, Izmaylova, Miraliyeva, Iskandarov, 2023; Porubay, Siddikov, Madina, 2022).

2 SOLUTION METHOD

In electrical power systems, a stringent balance of active power exists between electricity generation sources and consumers. Besides the active electrical power, it is necessary to include the overall power losses occurring in the electrical network, which result from technical energy dissipation during its transmission (Siddikov, Porubay, Mirjalilov, 2022; Ali, Abbas, Javed, 2023; Guo, Wang, Yang, 2021; Siddikov, Porubay, 2021). The energy balance can be represented in an integral form as follows:

$$\int_0^t P_{ЭС}(t)dt + \int_0^t P_{АИЭ}(t)dt - \int_0^t P_{АКК}(t)dt = \int_0^t P_{П}(t)dt + \int_0^t \sum \Delta P(t)dt$$

where $P_{ЭС}$ – the electrical energy supplied by the sources;

– $P_{АИЭ}$ the power generated by renewable (alternative) energy sources;

– $P_{АКК}$ power of the battery storage system;

– $P_{П}$ power consumed by electrical consumers;

– $\sum \Delta P(t)$ total active power losses in the electrical network. The objective of optimizing the operational modes of the power system is to determine the optimal values of active and reactive power of power system (Vorob'ev, Vorob'eva, Makarov, Svirkov, Sysoev, Artem'ev, Belyaev, Fedosova, Bogatyreva, 2019) units, as well as the voltage and frequency at reference load nodes. Solutions to this optimization problem enable minimization of electrical power losses while ensuring reliable power supply to all consumers at minimal cost. The dynamics of these parameters are described by equations and inequalities (Marzband, Amjady, Savaghebi, 2023; Utkarsh, Feng, Zhang, Li, 2022; Nasiri, Bahrami, 2021; Siddikov, Alimova, Rustamova, Usanov, 2025; Lazareva, Porubaj, 2024; Martins, da Silva, 2020; Chen, Wang, Liu, 2023; Karthikeyan, Kumar, 2020; Siddikov, Nashvandova, Alimova, 2024; Yakubova, Usmanov, Turakulov, Eshbobaev, 2025; Siddikov, Khalmatov, Alimova, Feruzaxon, Usanov, 2024; Alhelou, Shrestha, 2021; Siddikov, Ibragimov, Rustamova, 2024; Smolyarov, 2024; Wu, Zhao, Han, 2022). Variations in these variables have probabilistic and technological characteristics. These and other factors necessitate the enhancement of the optimization algorithm for operational modes based on intelligent technology methods (Lazareva, Porubaj, 2024; Siddikov, Porubay, 2021; Ahmad, Khan, 2022; Hasan, Hasan, 2023; Eshbobaev, Norkobilov, Usmanov, Khamidov, Kodirov, Avezov, 2024; Tang, Zhou, 2021; Siddikov, Umurzakova, 2019; Jinsen Liu, Molin He, Jie Wang, Jie Lu, 2024; Shalaby, Ortiz, Ammar, 2020; Rejabov, Usmonov, Usmanov, Artikov, 2024; Morkowski, 2024; Usmanov, Yakubova, Maksudova, Islomova, Ungbayeva, 2024).

A crucial performance metric for energy facilities is maintaining balance between energy production and consumption. Considering active power losses at system load nodes:

$$\Delta P_{\Sigma} = \Delta P_{НАГР} + \Delta P_{РЕАЛ} + \Delta P_{РАЗ},$$

where ΔP_{Σ} - total active power loss in power systems; $\Delta P_{НАГР}$ – active power losses at nodal loads; $\Delta P_{РЕАЛ}$ - normalized values of active power losses, without power discharge; $\Delta P_{РАЗ}$ - active power losses in electrical transmission lines.

The goal is to minimize active power losses of electrical energy at the system nodes:

$$W = \sum_{i=1}^{k} W_i = \sum_{i=1}^{k} \left[\begin{array}{l} \dfrac{\left(\sqrt{P_i(U)^2 + Q_i(U)^2}\right) \cdot R_{Эi}}{U_i^2} \cdot \left(\dfrac{1}{\left(1 + \dfrac{\Delta U_{\%i}}{100}\right)^2} - 1 \right) + \\ + \Delta P_{xx(i)} \cdot \left(\dfrac{U_i}{U_{уст(i)}} \right)^2 + \Delta P_{раз(i)} \cdot L_i \cdot k_{Uppa(i)} \end{array} \right] \to \min,$$

where W - active power losses at nodes of the electrical network ();

$R_Э, L$ - active and inductive resistance transmission lines;

$\Delta U_{\%}$ - voltage variation in electrical networks;

$\Delta P_{xx(i)}$ - power loss during no-load operation;

$\Delta T_{ф(i)}$ - duration of EPS operation during energy transmission;

$\Delta P_{раз(i)}$ - specific power losses during battery discharge;

$k_{Uppa(i)}$ - coefficient of power loss during discharge.

The constraints are boundary conditions (Porubay, Siddikov, Madina, 2022):

$$\begin{cases} \left|P_{вн(i)} + P_{внеш(i)}\right\rangle 0; \\ \left|Q_{вн(i)} + Q_{внеш(i)}\right\rangle 0; \\ \quad i = 1,...,k; \end{cases}$$

where $P_{вн(i)}, P_{внеш(i)}, Q_{вн(i)}, Q_{внеш(i)}$ - internal and external values of active and reactive power respectively (Lazareva, Porubaj, 2024).

To solve forecasting and energy consumption optimization tasks, a fuzzy neural network was chosen, which (Siddikov, Porubay, 2021) significantly enhances the adaptive properties of the neural network.

The mathematical forecasting model is formulated as (Ahmad, Khan, 2022):

$$X_{k+1} = \Phi(k) X_k + \xi_ф,$$

where $\Phi(k)$ is a load variation curve, $\xi_ф$ is the stochastic components. Then, the control conclusions can be represented as (Tang, Zhou, 2021):

$$R^k : если (t-1) есть X_1^k, x(t-r) есть X_r^k,$$

$$то\ y(t) = a_0^k + r\sum_{l=1}^{r} a_0^k y(t-1), k = \overline{1,k},$$

where R^k - set of control rules for operation; $x(t) = (x_1(t),...,x_m(t))$ – input variables; $y(t)$ - output variables; X_1^k, X_r^k, Y^k - domains of input and output variables; a_0^k - mapping of output signals to weighted input influence (Rejabov, Usmonov, Usmanov, Artikov, 2024).

An important stage in forming the fuzzy neural network is its training process. Training the neural network is generally considered as a multi-extremal optimization problem.

The quality of the network training is evaluated by a function describing the sum of squared differences between the actual and expected output signal values (Usmanov, Yakubova, Maksudova, Islomova, Ungbayeva, 2024):

$$E(w)=\frac{1}{2}\sum_{j=1}^{p}\sum_{m=1}^{M}\left(y_m^{(j)}-e_m^{(j)}\right)^2,$$

where m - number of output neurons in the network;

j - number of training samples input to the network;

$y_m^{(j)}$ - output of the neural network;

$e_m^{(j)}$ - required output signal value;

$E(w)$- objective (loss) function of the neural network.

Using this approach, the predicted value of energy consumption is formed as:

$$y(x)=F(y_1(x),y_2(x),...,y_n(x)),$$

where $y_i(x)$ — data obtained at discrete time moments;

F — function defining the resulting forecast.

In general, the proposed neural network has a three-level structure. The input to the neurons of the first level is the training sample vector, and the output provides the predicted energy consumption values. The input vector of the second level is the output variable vector of the first level, but the number of neurons is reduced and trained similarly.

The neurons of the third level can be described in aggregated form:

$$y_3(x)=f_3^B\left(w_3^B f_3^A\left(w_2^A f_2^A\left(w_1^A f_1^A(w_1,x)\right)\right)\right),$$

where

$F_1^A=\left[f_{11}^A f_{12}^A ... f_{1n_1}^A\right]^T$, $F_2^A=\left[f_{21}^A f_{22}^A ... f_{2n_2}^A\right]^T$ — activation functions of the internal layers of the neural networks;

$F_1^B=\left[f_{11}^B f_{12}^B ... f_{1n_1}^B\right]^T$, $F_2^B=\left[f_{21}^B f_{22}^B ... f_{2n_2}^B\right]^T$ — activation functions of the output layers of the neural networks;

f^3 — activation function of the third layer of the third-level neural network;

f^{3^B} — activation function of the output neuron of the neural network

w — synaptic weights of the layers of the neural networks.

Such a representation of the neural network structure facilitates the refinement of energy consumption forecasts at every level of the hierarchy, which significantly enhances the neural network architecture and leads to a reduction in the number of tunable synaptic connections.

3 RESULTS

To evaluate the feasibility of the proposed approach, a comparison was carried out between two well-known methods: the Least Squares Method and the Backpropagation Error Method. The analysis revealed that using the Least Squares Method to solve the forecasting problem resulted in an average error of 2.5%, with a training time of 9.1 seconds. In contrast, the application of the proposed approach resulted in a lower average training error of 2.1%, and a shorter training time of 8.5 seconds. The study also proposes a synthesis methodology for managing the operational modes of power system facilities.

4 CONCLUSIONS

An algorithm for tuning a fuzzy neural network has been developed, distinguished by its capability to utilize data obtained from implementing multi-alternative training procedures for the neural network model. An analysis was conducted to assess the effectiveness of the fuzzy control model under various operational conditions of the local energy system. Additionally, a software package was developed for the intelligent management of energy supply modes. This package is based on a fuzzy neural network for forecasting energy consumption levels and a fuzzy control model. The solution is distinguished by its ability to integrate with automated dispatch control systems of energy supply organizations and has been tested under real-world operating conditions.

REFERENCES

Vorob'ev, N.I., Vorob'eva, L.V., Makarov, O.V., Svirkov, S.A., Sysoev, N.N., Artem'ev, E.V., Belyaev, M.A., Fedosova ,A.V., Bogatyreva, N.V., 2019. Kommentarij k Federal'nomu zakonu ot 26 marta 2003 g. № 35-FZ "Ob elektroenergetike". Special'no dlya sistemy GARANT.

Marzband, A. B., Amjady, M., Savaghebi, M., 2023. Integration of renewable energy forecasting and demand response using fuzzy neural networks. IEEE Transactions on Sustainable Energy. *Piscataway, NJ,* USA. 14(1), 123–134.

Utkarsh, L., Feng, H., Zhang, W., Li, 2022. Fuzzy neural network for short-term load forecasting in smart grids. Electric Power Systems Research. Amsterdam, Netherlands. 210, 107979.

Nasiri, M., Bahrami, S., 2021. Fuzzy-based energy management systems with neural network controllers. Applied Energy. Oxford, UK. 282, 116117.

Siddikov, I., Alimova, G., Rustamova, M., Usanov, M., 2025. Digital adaptive control with pulse width modulation of signals. *International Journal of Electrical and Computer Engineering,* 15(1), 252–261.

Lazareva, M.V., Porubaj, O.V., 2024. algoritmizaciya resheniya zadachi upravleniya rezhimami regional'noj elektroenergeticheskoj sistemy. Universum: tekhnicheskie nauki : elektron. nauchn. zhurn. 12(129).

Martins, J. P., da Silva, A. P., 2020. Optimization of energy systems using fuzzy logic and neural networks. Renewable and Sustainable Energy Reviews. Amsterdam, Netherlands. 129, 109909.

Chen, Y., Wang, H., Liu, X., 2023. Hybrid fuzzy neural network for wind power forecasting. IEEE Transactions on Industrial Informatics. Piscataway, NJ, USA. 19(3), 2007–2017.

Lee, K. R., Kim, S. H., 2021. Fuzzy neural network based energy consumption prediction in smart buildings. Energy and Buildings. Amsterdam, Netherlands. 249, 111208.

Karthikeyan, P. S., Kumar, M., 2020. Fuzzy-neural approach to optimize load forecasting and energy management. *International Journal of Electrical Power & Energy Systems. Amsterdam, Netherlands.* 123, 106256.

Siddikov, I., Nashvandova, G., Alimova, G., 2024. Neural network optimizer of proportional-integral-differential controller parameters. *International Journal of Electrical and Computer Engineering*, 14(3), 2533–2540.

Yakubova, N., Usmanov, K., Turakulov, Z., Eshbobaev, J., 2025. Application of Quantum Computing Algorithms in the Synthesis of Control Systems for Dynamic Objects. Engineering Proceedings, 87(1), 68.

Siddikov, I., Khalmatov, D., Alimova, G., Feruzaxon, S., Usanov, M., 2024. Investigation of auto-oscillational regimes of the system by dynamic nonlinearities. *International Journal of Electrical and Computer Engineering,* 14(1), 230–238.

Alhelou, M. A., Shrestha, S. R., 2021. Energy consumption prediction using fuzzy neural networks and deep learning techniques. Sustainable Energy Technologies and Assessments. Amsterdam, Netherlands. 48, 101665.

Siddikov, I., Ibragimov, B., Rustamova, M., 2024. Synthesis of an adaptive digital system for modal control of a dynamic plant. Proceedings of SPIE – The International Society for Optical Engineering, 13217, 1321714.

Smolyarov, M.V., 2024. Pravovye aspekty algoritmizacii: targetirovannaya reklama, obrabotka personal'nyh dannyh. "PRAVO.by" № 5/2024.

Wu, D., Zhao, Y., Han, J., 2022. Multi-level fuzzy neural network for power system load forecasting. IEEE Access. Piscataway, NJ, USA. 10, 69535–69544.

Usmanov, K., Eshbobaev, J., Yakubova, N., 2023. Modeling and Optimization of the Ammonium Solution Extraction Process. Engineering Proceedings, 56(1), 198.

Siddikov, I., Izmaylova, R., Miraliyeva, A., Iskandarov, Z., 2023. Decomposition method of synthesis of autonomous control system of multidimensional dynamic object. E3S Web of Conferences, 460, 04016.

Porubay, O., Siddikov, I., Madina, K., 2022. Algorithm for optimizing the mode of electric power systems by active power. 2022 International Conference on Information Science and Communications

Usmanov, K. I., Yakubova, N. S., Urmanova, V. T., Abdurasulova, G. E., 2023. Synthesis of a control system for the process of diesel fuel hydropuring with the Adar method. In E3S Web of Conferences (Vol. 458, p. 01025).

Siddikov, I., Porubay, O., Mirjalilov, O., 2022. An algorithm for optimizing short-term modes of electric power systems, taking into account the conditions of the nature of the probability of the information flow of data. Journal of Physics: Conference Series, 2373(8), 082014.

Ali, Z., Abbas, H., Javed, M., 2023. Energy consumption forecasting in smart grids using hybrid fuzzy-neural models. Energy Reports. Amsterdam, Netherlands. 9, 2051–2061.

Guo, L., Wang, M., Yang, F., 2021. Adaptive fuzzy neural network for demand-side management in smart grids. IEEE Transactions on Smart Grid. Piscataway, NJ, USA. 12(5), 4321–4330.

Siddikov, I., Porubay, O., 2021. Neural network model of decision making in electric power facilities under conditions of uncertainty. E3S Web of Conferences, 304, 01001.

Lazareva, M.V., Porubaj, O.V., 2024. Algoritmizaciya resheniya zadachi upravleniya rezhimami regional'noj elektroenergeticheskoj sistemy. Universum: tekhnicheskie nauki : elektron. nauchn. zhurn.12(129).

Siddikov, I., Porubay, O., 2021. Neural network model of decision making in electric power facilities under conditions of uncertainty. In O. Tursunov (Ed.), Proceedings of the 2nd International Conference on Energetics, Civil and Agricultural Engineering (ICECAE 2021) (Vol. 304, Article 01001). E3S Web of Conferences.

Ahmad, F., Khan, A. A., 2022. Fuzzy logic and neural network-based hybrid system for energy demand forecasting. Energy Reports. Amsterdam, Netherlands. 8, 1345–1354.

Hasan, M. R., Hasan, M. K., 2023. Hybrid fuzzy neural approach to optimize renewable energy integration in smart grids. Renewable Energy. Amsterdam, Netherlands. 200, 427–439.

Eshbobaev, J., Norkobilov, A., Usmanov, K., Khamidov, B., Kodirov, O., Avezov, T., 2024. Control of Wastewater Treatment Processes Using a Fuzzy Logic Approach. Engineering Proceedings, 67(1), 39.

Tang, H., Zhou, Y., 2021. Fuzzy neural network-based load forecasting for smart grid operation. Journal of Cleaner Production. Amsterdam, Netherlands. 320, 128821.

Siddikov, I. X., Umurzakova, D. M., 2019. Neuro-fuzzy adaptive control system for discrete dynamic objects. International Conference on Information Science and Communications Technologies: Applications, Trends and Opportunities (ICISCT 2019), 9012027.

Jinsen Liu, Molin He, Jie Wang, Jie Lu, 2024. Distribution network planning using fuzzy optimization. EAI Endorsed Transactions on Energy Web. Guizhou, China. Article 10598.

Shalaby, M.A.W., Ortiz ,N.R., Ammar, H.H., 2020. Neuro-fuzzy approach for energy consumption and profit operation forecasting. Biotechnology School. Cairo, Egypt. Conference Paper.

Rejabov, S., Usmonov, B., Usmanov, K., Artikov, A., 2024. Experimental Comparison of Open Sun and Indirect Convection Solar Drying Methods for Apricots in Uzbekistan. Engineering Proceedings, 67(1), 26.

Morkowski, J., 2024. Forecasting accuracy of neural networks with fuzzy sets in the currency market. Scientific *Journal of Bielsko-Biala School of Finance and Law.* Bielsko-Biala, Poland. 28(1), Article 3.

Usmanov, K. I., Yakubova, N. S., Maksudova, A. I., Islomova, F. K., Ungbayeva, D. U., 2024. «Synthesis of dynamic object control systems based on quantum calculation methods». E3S Web Conf., 549, 08012.