ISSN-L 2664-9969; E-ISSN 2706-5448

UDC 004.89
DOI: 10.15587/2706-5448.2025.329154

Yevhen Kholiavka,
Yuliia Parfenenko

INTELLIGENT ENERGY CONSUMPTION FORECASTING AND MICROGRID STATE ASSESSMENT USING MACHINE LEARNING AND FUZZY LOGIC

The object of research is the processes of generation, consumption and storage of electricity in microgrids with renewable energy sources. They are characterized by the certain parameters and together determine the state of the energy microgrid. The task of assessing the state of the microgrid, which is relevant for maintaining its stable operation, can be solved using machine learning methods.

Time series of data, which are created as a result of monitoring energy microgrids and contain indicators of their operation, were used as input dataset. Since microgrids operate in variable conditions, the ability of energy microgrids to meet the demand for electricity is characterized by uncertainty, and to assess the state of microgrids, there is a need for adaptive methods that can process inaccurate and incomplete data. Traditional methods of statistical analysis and deterministic algorithms do not provide sufficient accuracy in forecasting, which creates risks of incorrect management of energy resources. To solve this problem, this study uses a combination of machine learning and fuzzy logic, which allows not only to forecast the load, but also to adaptively assess the state of energy assets in real time.

The essence of the obtained results is to create models for the information technology of assessing the state of microgrids, which integrates BiLSTM for forecasting electricity consumption and a fuzzy logic system for determining the state of the microgrid. The use of a neural network approach allows to take into account time dependencies in electricity consumption, while fuzzy logic classifies the state of the microgrid based on the battery charge level, current solar energy generation and forecasted load. The features of the obtained results are the integration of several approaches, which provides expansion of analytical capabilities and the formation of a comprehensive assessment of the energy balance in conditions of uncertainty and variability of input data.

The obtained results confirm the effectiveness of the proposed approach and its practical applicability in the tasks of monitoring and controlling microgrids. Experimental tests on real data showed that the BiLSTM model provides a mean absolute error (MAE) of load forecasting at the level of 18.15 W, a root mean square error (RMSE) of 20.74 W, and a mean absolute percentage error (MAPE) of 5.0%. The fuzzy logic-based assessment system classified the state of the microgrid with an accuracy of 93.2%, which indicates its ability to interpret situations with potential energy deficit. The developed models allow for timely detection of unstable operating modes, formation of solutions for load balancing, reduction of the load on batteries, and prevention of energy losses.

Keywords: *time series, microgrids, load forecasting, state estimation, machine learning, BiLSTM, fuzzy logic.*

Received: 20.02.2025
Received in revised form: 06.04.2025
Accepted: 26.04.2025
Published: 10.05.2025

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How to cite
Kholiavka, Y., Parfenenko, Y. (2025). Intelligent energy consumption forecasting and microgrid state assessment using machine learning and fuzzy logic. Technology Audit and Production Reserves, 3 (2 (83)), 20–26. https://doi.org/10.15587/2706-5448.2025.329154

1. Introduction

Microgrids are key components of modern energy infrastructure, contributing to increased reliability of electricity supply, integration of renewable energy sources (RES) and development of the concept of decentralized generation [1, 2]. In the context of increasing RES share in the energy balance, the need for tools capable of ensuring stable operation of such systems is increasing. In particular, it is important for distributed energy system operators to have means of early detection of disturbances in the functioning of energy facilities, forecasting peak loads and making decisions under conditions of uncertainty. This opens the way to the development of applied information technologies that allow reducing operating costs, increasing energy efficiency and guaranteeing uninterrupted electricity supply in critical infrastructures. The practical need is to develop tools that are capable not only of recording current changes, but also of forecasting instability in the operation of the microgrid in advance. This allows for a prompt response to situations of power shortage in the context of a growing RES share.

The widespread implementation of microgrids allows for more efficient use of local energy resources, reduction of losses during electricity transmission and increase of energy sustainability of regions. However, the functioning of microgrids is accompanied by a number of challenges, including instability of RES generation, unpredictable load changes and the need to ensure their reliable operation in different operating modes [1]. That is why there is a need to create methods for automated assessment of the state of microgrids, which allow to ensure their stability and effective management.

Modern microgrids operate in conditions of high load dynamics, variable generation from RES and limited capabilities of energy storage. This leads to an increase in the risk of energy deficit, microgrid overloads or system failures. Existing monitoring tools are mostly focused on fixing current parameters without taking into account their dynamics. In addition, most approaches to assessing the operational state of energy facilities do not provide for forecasting changes, which can lead to delays in decision-making and a decrease in the reliability of supply. Therefore, the problem lies in the lack of integrated methods capable of combining forecasting and assessing the state of the microgrid, taking into account external influences and consumption characteristics. In recent years, there has been an active development of approaches to assessing the operational state of energy facilities, taking into account their dynamics and operating conditions. In particular, the study [3] considers a method for forecasting the state of microgrids based on deep recurrent networks taking into account time series. Another study [4] proposes the use of ensemble machine learning models to assess equipment degradation under unstable load conditions. The proposed approaches allow for high-accuracy forecasting of system failures and timely application of preventive maintenance measures. However, the work [4] does not take into account the dynamic change in the characteristics of microgrid elements in the long term, which limits its suitability for adaptive assessment of the state in conditions of environmental changes. The study [3] lacks mechanisms for taking into account external influences, in particular weather or emergency factors, which reduces the effectiveness of the model in real operating conditions.

Assessment of the state of energy objects of a microgrid is one of the key aspects of managing distributed energy systems, as it allows not only to monitor the current state of the microgrid, but also to timely identify the risks of peak loads, generation instability and potential equipment failures [5, 6]. At the same time, the paper [5] does not consider the mechanisms of generalization of scenarios taking into account multifactor uncertainty, which limits the application of the obtained results for the formal assessment of the energy state of microgrids. In the publication [6], the main attention is focused on long-term forecasting of natural factors, however, there is no coordination of the obtained forecasts with the criteria for the operability of energy components, which makes it difficult to directly use the model for tasks of diagnosing the state of microgrids. Today, there is significant progress in the development of methods for analyzing the state of microgrids, but a number of unresolved problems remain. One of them is to increase the resilience of microgrids to external influences, including extreme weather conditions and emergencies. To solve this problem, the study [7] proposed quantitative metrics for assessing the resilience of microgrids to wind storms, which allow forecasting potential damage and developing adaptation strategies. At the same time, the study [8] emphasizes the need to create methods for adaptive management of microgrids that can ensure their resilience in real time. In recent years, information technologies based on the concept of the Internet of Things (IoT) have been actively spreading, playing an important role in remote monitoring, telemetric data collection and energy resource management in microgrids. Such solutions allow integrating sensors, storage devices and renewable energy sources into a single digital ecosystem, which is the basis for the formation of modern DSS [9, 10]. The IoT implementation makes it possible to provide continuous analysis of the functional state of equipment and timely detect risks or system failures. However, IoT technologies are mainly focused on capturing current states, without the ability to predict future loads or change the energy balance.

The issue of long-term planning for the RES integration in a microgrid is also relevant, which is considered in the study [11]. The proposed model of energy system development allows for optimizing the use of local resources, but it does not take into account the assessment of the state of equipment in real time, which is critically important for maintaining the reliability of microgrids. Additionally, the problem of fault diagnosis and forecasting of potential failures requires attention, since traditional control methods do not provide sufficient flexibility. The study [12] proposed methods for determining the location of damage in DC microgrids, but their application is limited in complex distributed systems with a large number of energy assets. In addition, the analysis of the state of the microgrid is impossible without taking into account the degradation of battery systems, which affects the stability of energy supply. Study [13] considers methods for forecasting battery degradation in microgrids with renewable energy sources, but the proposed approach does not take into account a comprehensive assessment of the entire energy system and its flexibility to change.

Modern microgrids operate in conditions of high consumption dynamics, variable generation and limited resource of storage systems. This creates additional challenges for their stable operation. In such conditions, the need to create tools that allow assessing the functional state of the system in real time is especially relevant. It is also important to have tools for forecasting the main energy parameters. Such an approach is critical for maintaining uninterrupted energy supply, early detection of energy deficit and making informed decisions under conditions of uncertainty, which is especially important for microgrids with a high-RES share.

Practical application involves the creation and development of mathematical models for information technology for analyzing the state of energy facilities in microgrids. This will ensure timely detection of malfunctions, increase the efficiency of energy resource management and reduce operating costs. The implementation of such an approach will ensure stable and safe operation of microgrids, increase their adaptability to changes in the external environment and contribute to more efficient use of renewable energy sources. The focus of research is the problem of ensuring stable and reliable operation of microgrids by timely detection of potential energy supply shortages based on forecasts of generation, consumption and storage charge level.

The aim of research is to develop a model for predictive assessment of the state of the energy microgrid taking into account the results of forecasting electricity consumption and generation. The use of such a model ensures timely detection of shortages and overloads, as well as increasing the microgrid's resilience to the impact of environmental changes.

To achieve the aim, the following research objectives were defined:

– to build a power consumption forecasting model based on BiLSTM (Bidirectional Long Short-Term Memory);

– to develop a microgrid state assessment module based on fuzzy logic;

– to form a set of fuzzy classification rules taking into account SoC (State of Charge), generation and load parameters;

– to conduct experimental testing of models on a real data set;

– to assess the accuracy and adaptability of the proposed models using the MAE, RMSE, MAPE metrics.

2. Materials and Methods

The object of research is the processes of electricity generation, consumption and storage in microgrids with RES, which are characterized by parameter variability and uncertainty. They are displayed in the form of time series formed in the process of monitoring the operation of energy facilities. These data reflect changes in the parameters of electricity generation, consumption and storage, including the charge level of battery systems, the output power of solar panels, voltage, current and temperature characteristics of energy assets. The research is aimed at developing methods for analyzing these data, which allow to increase the accuracy of forecasting the operational state of the microgrid, timely detect possible equipment failures and assess the energy balance of the system.

The hypothesis of research is that the use of BiLSTM [14] for the analysis of time dependencies and fuzzy logic for assessing the operational state makes it possible to anticipate future energy deficit and identify potential equipment failures compared to traditional methods of statistical analysis. Confirmation of the hypothesis is based on a comparison of the MAE, RMSE and MAPE metrics. It is expected that the combination of

 ISSN-L 2664-9969; E-ISSN 2706-5448

these methods will ensure adaptability to changes in the system and reduce the number of incorrect decisions. The problem that the research solves is the need to build such a forecasting and assessment system that can provide early detection of energy deficit and unstable operating modes of microgrids without the need for continuous real-time monitoring.

The research includes the analysis and preparation of an input data set, which is formed on the basis of collected microgrid performance indicators received during monitoring from sensor systems and energy flow controllers. Data on solar energy generation, battery status, electricity consumption and network equipment operating parameters are used. Machine learning and fuzzy logic methods are used to process this data. In particular, electricity consumption forecasting is performed using the BiLSTM neural network, which allows taking into account time dependencies in load changes. The choice of the BiLSTM model is due to its ability to analyze both direct and inverse time dependencies, which is critically important in tasks where parameter changes depend on the context of previous and subsequent states. This allows the model to better detect complex patterns in energy consumption.

In the developed fuzzy system, the input variables are: forecasted load, current solar energy generation, and battery charge level (SoC). Three membership functions (low, medium, high) with a triangular shape are used for each variable. The output variable – the assessment of the microgrid state – is also described by three functions: "stable", "risk of instability", "shortage". The center of gravity defuzzification method is used to interpret the output. The rule base consists of expert statements of the "if–then" type.

The implementation of the forecasting software module was carried out in Python using the pandas, numpy, matplotlib, scikit-learn, keras, and tensorflow libraries. In particular, MinMaxScaler was used for data normalization, the Sequential, Bidirectional, LSTM, Dense modules from keras were used for model building, and the MAE, RMSE, and MAPE calculation functions from sklearn.metrics were used to assess the accuracy of forecasting. Model training and testing were performed on a personal computer with an AMD Ryzen 5 PRO 5650U processor, 16 GB of RAM, without a hardware graphics accelerator (GPU). Despite the lack of a separate GPU, computational experiments were successfully implemented due to the optimization of the BiLSTM neural network and the use of a compact dataset.

The dataset formed based on monitoring data from a microgrid of a private house with renewable energy sources was used. Information was collected automatically through a monitoring system that periodically read indicators from sensor devices, inverters, and energy flow controllers. The obtained data was presented as a time series containing meteorological parameters, solar generation characteristics, battery charge level, voltage parameters and energy balance of the microgrid. The input data is presented as a multidimensional time series

$$X_t = \left[x_{(t-1)}, x_{(t-2)}, \dots, x_{(t-n)} \right], \tag{1}$$

where X_t – the vector of microgrid parameters at time t, containing the values of microgrid indicators (Table 1).

The target variable is the forecasted value of electricity consumption

$$Y_t = pLoad_t. \tag{2}$$

To ensure the correct operation of the neural network, all input parameters were normalized using Min-Max normalization

$$X_{scaled} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{3}$$

where $X_{\max}$, $X_{\min}$ – the minimum and maximum values of the corresponding parameter. After normalization, the data is passed to a bidirectional LSTM.

Table 1

Input data set

Variable	Value
Date	Date and time of measurement of microgrid parameters
vpv1	Voltage on the first solar panel (V)
vpv2	Voltage on the second solar panel (V)
vBat	Voltage on the battery (V)
ppv1	Power generated by the first solar panel (W)
ppv2	Power generated by the second solar panel (W)
pCharge	Battery charging power (W)
pDisCharge	Battery discharging power (W)
vacr	Line voltage on phase R (V)
vact	Combined voltage/frequency (Vac/Fac)
vepsr	Input voltage to the house (phase R) (V)
vepss	Input voltage to the house (phase S) (V)
vepst	Input voltage to the house (phase T) (V)
pLoad	Power consumed by the house (W)
ePv1All	Total energy generated by the first panel (kWh)
ePv2All	Total energy generated by the second panel (kWh)
pToGrid	Power exported to the external grid (W)
pToUser	Power imported from the grid (W)
eInvDay	Daily energy input of the inverter (kWh)

BiLSTM – a modification of the standard LSTM (Long Short-Term Memory), which uses bidirectional learning. The standard LSTM operates on the basis of three information management gates [13]:

– Forget Gate

$$f_t = \sigma\left(W_f \cdot \left[h_{(t-1)}, x_t \right] + b_f \right). \tag{4}$$

– Input Gate:

$$i_t = \sigma\left(W_i \cdot \left[h_{(t-1)}, x_t \right] + b_i \right); \tag{5}$$

$$\tilde{C}_t = \tanh\left(W_c \cdot \left[h_{t-1}, x_t \right] + b_c \right). \tag{6}$$

– Cell state update

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t. \tag{7}$$

– Output Gate:

$$o_t = \sigma\left(W_o \cdot \left[h_{(t-1)}, x_t \right] + b_o \right); \tag{8}$$

$$h_t = o_t \cdot \tanh(C_t). \tag{9}$$

Unlike the standard LSTM, BiLSTM consists of two data streams [10]:

– Forward propagation

$$h_t^{forward} = LSTM_{forward}(x_t, \cdot h_{t-1}^{forward}). \tag{10}$$

– Backward propagation

$$h_t^{backward} = LSTM_{backward}(x_t, \cdot h_{t+1}^{backward}). \tag{11}$$

– Joint output

$$h_t = [h_t^{forward}, h_t^{backward}]. \tag{12}$$

The fuzzy logic module that performs the assessment of the operational state of the microgrid was implemented based on the classical Mamdani fuzzy logic. All rules, membership functions and logical constructs are formulated and coded without using any artificial intelligence or automatic generation methods. The system is built as a set of formalized rules based on the technical analysis of the microgrid operation and expert experience.

The assessment is based on three input parameters:

– $\{SoC\}$ – battery charge level (%),
– $\{\hat{P}_{load}\}$ – forecasted electricity consumption (W),
– $\{P_{solar}\}$ – current solar energy generation (W).

For each input variable, three triangular membership functions are specified, which overlap and ensure smooth transitions between linguistic levels, for SoC:

– *Low* – triangular function with a peak of 20%, stretched from 0% to 40%.
– *Medium* – triangular function with a peak of 50%, range 30–70%.
– *High* – peak value of 100%, stretched from 60%.

Such functions were not formed automatically. They were specified manually according to the technical understanding of the physical processes in the microgrid.

The input variables of the fuzzy inference system are described as term sets:

$$\{SoC\} - \{\text{Low, Medium, High}\},$$

$$\{\hat{P}_{load}\} - \{\text{Low, Medium, High}\},$$

$$\{P_{solar}\} - \{\text{Low, Medium, High}\}. \tag{13}$$

Output variable

$$\{\text{Status}\} = \{\text{Deficit, Warning, Stable}\}.$$

Each term in these sets is a qualitative characteristic of the state of the variable, and is given by a membership function

$$\mu_A(x): X \to [0,1], \tag{14}$$

where X – domain of definition, $\mu_A(x)$ – term membership function.

To determine the state of the microgrid, a base of fuzzy rules of the IF–THEN type was formed:

$$\textit{IF } \{SoC\} \textit{ is Low AND } \{\hat{P}_{load}\} \textit{ is High AND } \{\hat{P}_{solar}\} \textit{ is Low THEN } \{Status\} = \text{"}\textit{Deficit}\text{"},$$

$$\textit{IF } \{SoC\} \textit{ is Medium AND } \{\hat{P}_{load}\} \textit{ is Medium AND } \{\hat{P}_{solar}\} \textit{ is Medium THEN } \{Status\} = \text{"}\textit{Warning}\text{"},$$

$$\textit{IF } \{SoC\} \textit{ is High AND } \{\hat{P}_{load}\} \textit{ is Low AND } \{\hat{P}_{solar}\} \textit{ is High THEN } \{Status\} = \text{"}\textit{Stable}\text{"}.$$

A total of 9 basic rules were defined, covering typical scenarios of microgrid operation. Defuzzification is performed using the centroid method – a classical method that calculates the center of the area under the output membership function.

The fuzzy inference system is formalized as a 7-element structure

$$F = \{X, Y, \{A_i\}_{i=1}^{n}, \{B\}, R, \mu_{A_i}, \mu_B, method\_defuzzification\}, \tag{15}$$

where $X = (x_1, x_2, ..., x_n)$ – vector of input variables ({SoC}, {Load}, {Gen}), $Y = y$ – output variable ({Status}), $\{A_i\}$ – sets of terms for input variables, $\{B\}$ – term set for output: {Deficit, Warning, Stable}, R – base of fuzzy rules (products), μ_{A_i}, μ_B – membership functions for input/output terms, defuzzification method: centroid method.

The entire system is implemented as a rule logic in Python using the scikit-fuzzy library. All rules, membership functions, and threshold values were proposed analytically, based on the practice of microgrid management and expert ideas about normal and critical operating modes.

Thus, the research is aimed at developing forecasting and classification models that will become components of the information technology for assessing the state of the microgrid, which allows improving the accuracy of forecasting equipment failures, optimizing energy resource management, and increasing the stability of energy supply. The combination of the BiLSTM forecasting model with a fuzzy logic system allows, on the one hand, to obtain accurate forecasting of load changes, and on the other hand, to adaptively interpret forecast data in complex conditions. This provides a more flexible response of the system to the risks of instability in real time.

3. Results and Discussion

The integration of the predictive model into the microgrid state assessment system allows taking into account future load changes and assessing possible risks of power supply instability in advance. To implement this approach, a bidirectional recurrent neural network BiLSTM was used, which showed high efficiency in the tasks of time series forecasting and determining electricity consumption patterns. The choice of this model is justified by studies [14, 15], which proved that BiLSTM has a better ability to recognize complex patterns in data than classical LSTM or statistical analysis methods. Predictive modeling allowed not only to obtain future values of electricity consumption, but also to improve the efficiency of fuzzy logic by expanding the set of parameters taken into account when assessing the state of the microgrid [16–18].

Since load forecasting is performed using the BiLSTM machine learning model [14], the results obtained allow not only to assess the current state of the microgrid, but also to make a forecast for future periods. This makes it possible to ensure stable operation of the microgrid by early identification of possible energy deficit. However, forecasting electricity consumption alone is not sufficient for a comprehensive assessment of the state of the microgrid, as additional factors such as the battery charge level and renewable energy generation must be taken into account. In this context, the use of fuzzy logic is a key stage of the analysis, which allows taking into account uncertainty in the data and providing a comprehensive assessment of the operation of the power system.

Using fuzzy logic, a state assessment model was built that integrates not only the forecasted electricity consumption data, but also the actual battery charge level and generation from solar panels. This allows for a more accurate assessment of the overall energy balance of the microgrid and to form decisions regarding its stability. The assessment is based on an analysis of the interaction of three main parameters: the SoC battery charge level, forecasted electricity consumption $\hat{P}_{load}$, and current solar energy generation P_{solar}. The presence of these parameters in the fuzzy logic system allows interpreting the state of the microgrid under conditions of uncertainty, which is critically important for its effective functioning.

The assessment of the microgrid state is carried out using fuzzy membership functions, which allow for flexible classification of the level of each parameter into three levels: low, medium and high. This provides a smooth transition between possible network states and eliminates sudden changes in the assessment, which can lead to instability of management decisions.

Since the obtained results are presented in the form of fuzzy variables, the method of defuzzification of the center of gravity (Centroid Defuzzification) was used to determine the final state of the microgrid.

The determined value shows the general state of the microgrid, which can be interpreted as "stable" (Stable), "risk of instability" (Warning) or "electricity deficit" (Deficit). Accordingly, if the obtained value $S_{network}$ is greater than 0.7, then the network is considered stable, if it is in the range from 0.3 to 0.7 – there is a risk of instability, and if the value is less than 0.3, then there is an electricity deficit in the microgrid.

The novelty of the proposed model lies in the use of the forecasted value of electricity consumption calculated using the BiLSTM neural network, combined with an adaptive assessment of the state of the microgrid based on fuzzy logic. This approach allows not only to increase the accuracy of the assessment of the energy state of the microgrid, but also to ensure timely detection of potential risks of electricity shortages. This contributes to more effective microgrid management, allowing timely measures to be taken to optimize energy consumption, reduce the load on the batteries and improve the stability of the system.

To quantitatively assess the accuracy of electricity consumption forecasting, classical metrics were used: mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE).

To implement the forecast model, a bidirectional recurrent neural network BiLSTM, built using the Keras library, was used. The model architecture included an input layer with 24 features (measured microgrid parameters), one BiLSTM hidden layer with 50 neurons, and an output dense layer with linear activation for power consumption forecasting. Training was performed using the MSE loss function, Adam optimizer, and normalized input data (scaling using MinMaxScaler). The forecasting time horizon was 3 days, and the batch size (batch_size) was 24. The model showed the following results:
- *MAE* (Mean Absolute Error): 18.15,
- *RMSE* (Root Mean Squared Error): 20.74,
- *MAPE* (Mean Absolute Percentage Error): 5.00%.

The results obtained are comparable or better than those in previous studies: in particular, in [19] the hybrid PSO-LSTM-AE model showed $MAE \approx 22.5$ and $MAPE \approx 6.4\%$. In our work, the BiLSTM model achieved $MAE = 18.15$ and $MAPE = 5.0\%$, which indicates increased accuracy under similar input data conditions. This indicates high accuracy of the model in forecasting daily load fluctuations. Peak discrepancies mainly occur in the evening hours, which is due to uneven consumption and changes in RES generation.

After forecasting pLoad, the results were transferred to the fuzzy logic block. Three input parameters were used: vBat, ppv1+ppv2 (generation), forecasted_pLoad. Triangular membership functions (Low, Medium, High) were defined for each parameter, and in total the system had 9 expert rules. The evaluation was performed manually according to the rule

$$Available\_Power = \{SoC_{scaled}\} \times \{C_{bat}\} + \{P_{solar}\}, \tag{16}$$

where $\{C_{bat}\}$ – system capacity in Wh. All calculations were performed with a sampling frequency of 1 hour.

The classification was as follows:
- *Stable* – when the available power exceeds the demand by 20%;
- *Warning* – when the power is just enough for the needs;
- *Deficit* – when the forecast exceeds the available resources.

To assess the accuracy of the classification of the microgrid state, the Accuracy metric was used

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} = 93.2\%, \tag{17}$$

where *TP* – the system correctly warned about the unstable mode; *TN* – the system correctly recognized the state as normal; *FP* – false alarm; *FN* – the system did not detect a critical state (the most dangerous case).

The reference values were formed based on the energy balance: if the forecasted load exceeded the generation and battery condition – a deficit was recorded.

The obtained results (Fig. 1) of the analysis of electricity consumption forecasting allow to assess the effectiveness of the applied methodology and draw conclusions about the current state of the microgrid. Visualization of the obtained data demonstrates that the constructed fuzzy logic system is capable of analyzing the forecasted load and determining the level of microgrid stability. The presented results contain historical and forecasted data on the consumed power, as well as a classification of the state of the microgrid based on fuzzy logic. This approach allows assessing the situation in real time, which allows to quickly make decisions on the optimal distribution of energy resources and prevent potential problems associated with a shortage of electricity.

Date	pLoad	predicted_pLoad	network_status
2023-10-19 00:00:00	383.583333	382.432220	Stable
2023-10-19 01:00:00	444.500000	440.763184	Stable
2023-10-19 02:00:00	371.666667	365.183655	Stable
2023-10-19 03:00:00	223.833333	216.182129	Stable
2023-10-19 04:00:00	114.750000	105.033829	Stable
2023-10-19 05:00:00	257.583333	244.201202	Stable
2023-10-19 06:00:00	399.333333	369.163330	Stable
2023-10-19 07:00:00	407.666667	373.473022	Stable
2023-10-19 08:00:00	402.384615	382.229279	Stable
2023-10-19 09:00:00	322.666667	290.590637	Stable
2023-10-19 10:00:00	328.333333	305.426086	Stable
2023-10-19 11:00:00	363.166667	335.469421	Stable
2023-10-19 12:00:00	301.916667	292.914001	Stable
2023-10-19 13:00:00	796.416667	768.281921	Stable
2023-10-19 14:00:00	786.416667	801.030273	Stable
2023-10-19 15:00:00	375.500000	352.390717	Stable
2023-10-19 16:00:00	339.083333	307.083466	Stable
2023-10-19 17:00:00	398.750000	363.552612	Stable
2023-10-19 18:00:00	515.166667	499.807861	Warning
2023-10-19 19:00:00	589.666667	574.066528	Deficit
2023-10-19 20:00:00	573.083333	563.654968	Deficit
2023-10-19 21:00:00	516.583333	502.481659	Warning
2023-10-19 22:00:00	341.083333	322.107971	Stable
2023-10-19 23:00:00	174.333333	163.663834	Stable

Fig. 1. Results of microgrid state forecasting

Analyzing the graph (Fig. 2), which displays the forecasted and actual electricity consumption, it can be seen that the developed fuzzy logic model provides a high level of accuracy in assessing the state of the microgrid. The blue line represents the actual load, while the points of different colors correspond to the forecasted values and the determined state of the microgrid. Green indicates a stable state of the system, orange signals the need for monitoring due to a decrease in available power, and red indicates periods of electricity shortage. Detailed analysis shows that during peak loads, in particular in the evening hours, there is a significant increase in consumption, which can lead to an excess of available power. Identifying such periods allows for timely load balancing, energy redistribution and taking appropriate measures to maintain the stability of the microgrid.

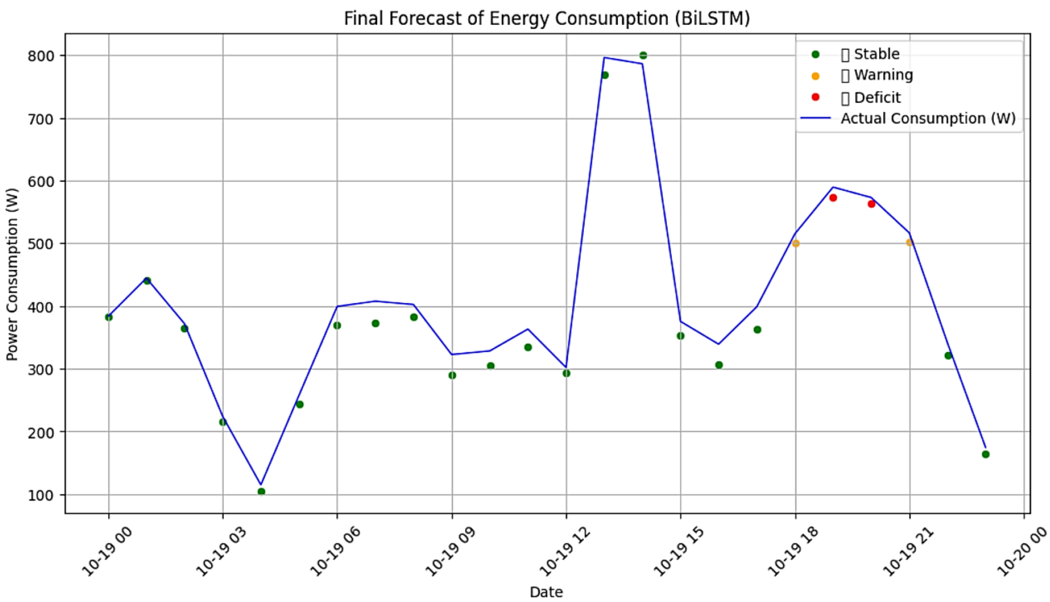

Fig. 2. Forecasted and actual electricity consumption data with microgrid state assessment

Based on the developed models, a decision support system was built that provides automated assessment of the microgrid state based on the integration of machine learning and fuzzy logic. For a better understanding of the automated assessment process, a UML diagram was used (Fig. 3), which demonstrates the interaction between the user, the forecasting system, the database and the model repository. The UML diagram demonstrates the logic of the interaction of the components underlying the proposed model. Full-fledged software implementation of information technology is planned as the next stage of further research.

As a research result, mathematical models were developed that form the basis for building an information technology for assessing the state of the microgrid. Key components of this technology were implemented, in particular, a BiLSTM-based forecasting model and a fuzzy logic state assessment module, which provide a consistent analysis of the load and energy balance.

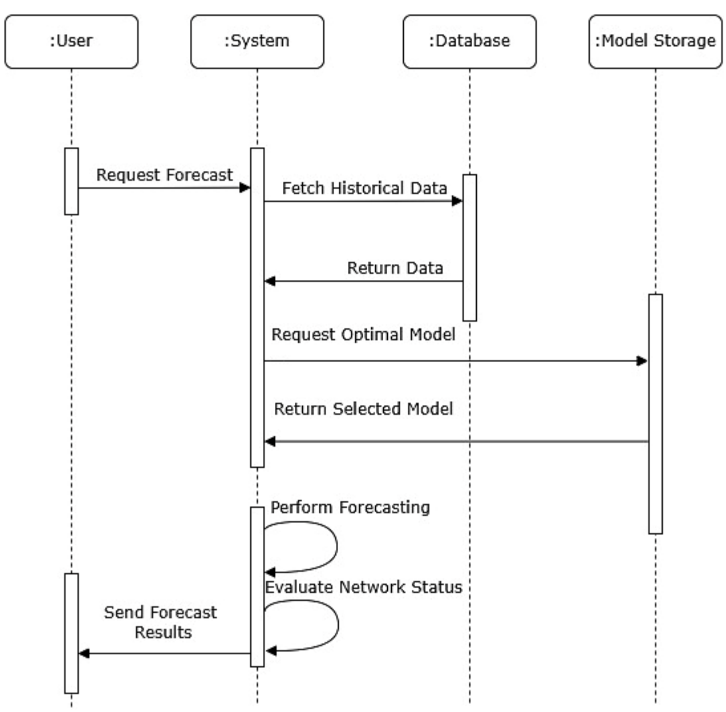

Fig. 3. UML diagram of microgrid state assessment

The assessment process involved several consecutive stages. After receiving a request for analysis, historical data on consumption, generation, and battery charge level were transferred to the forecasting module. The BiLSTM model performed time series analysis and calculated a forecast of electricity consumption based on multifactor input parameters.

Next, the forecast results were transferred to the fuzzy logic module, where, together with the current values of battery charge and solar energy generation, an assessment of the overall energy state was carried out. For this, three inputs with triangular membership functions were used, describing the levels "low", "medium" and "high". The system classified the microgrid state as stable, potentially unstable, or deficient using a set of fuzzy "if–then" rules. The final value was calculated using the center-of-gravity defuzzification method.

Comparison of forecasted and actual values confirmed sufficient accuracy and stability of the model, as well as its ability to detect critical deviations in the energy balance. Visualization of the results showed that the model correctly responds to peak loads and periods of reduced generation.

The conducted research allowed to form a practical basis for further design of a fully functional information technology for assessing the state of microgrids. A promising direction is to expand the set of input parameters by forecasting weather conditions and changes in consumer activity, as well as improving the system of fuzzy rules to increase sensitivity to non-standard operating modes.

The results obtained create a basis for further expansion of the system functionality. In particular, it is promising to supplement the model with an economic evaluation block taking into account the cost of storing and selling electricity to the grid. This will allow implementing adaptive logic for choosing the operating mode: accumulating or selling excess energy. Other possible directions are automatic generation of fuzzy rules using tutored learning methods, as well as integration of weather forecasting to improve the accuracy of the generation model.

The experiments were partially complicated by limitations associated with the martial law conditions in Ukraine, in particular, the inability to conduct continuous testing on a physical object for a long time. This limited the possibility of large-scale testing on third-party microgrids.

ISSN-L 2664-9969; E-ISSN 2706-5448

The limitations of research are the use of only one type of microgrid (a private household), the absence of external weather variables in the forecast, and the use of fuzzy logic with fixed membership functions, without automatic adaptation.

Further research should be aimed at eliminating the identified limitations, adapting models to changing external conditions, and integrating additional influencing factors, including weather. Special attention should be paid to improving network status assessment algorithms and developing automated decision-making support mechanisms.

4. Conclusions

The article solves the problem of assessing the state of a microgrid under conditions of variable energy balance using technology that integrates machine learning and fuzzy logic. For this purpose, appropriate models, methods and software tools have been developed, which are combined into a comprehensive system for analyzing the operational state of energy assets. The proposed approach automates the assessment of the level of stability of a microgrid based on the forecasted electricity consumption, battery charge level and solar energy generation.

The features of the obtained results are the combination of time series forecasting methods and fuzzy logic, which provides the possibility of assessing the operational state of microgrids in future periods of time, which is important for maintaining their stable functioning.

The obtained results confirm the effectiveness of using fuzzy logic for analyzing the state of a microgrid. Forecasting electricity consumption using BiLSTM is only the input stage of the assessment, which provides the necessary data for the fuzzy model. The use of fuzzy membership functions allows classifying the state of the microgrid into three categories: "Stable", "Warning" and "Deficit". This approach minimizes the impact of uncertainty on the analysis results and ensures the adaptability of the network assessment.

The interpretation of the results shows that the BiLSTM model demonstrates high efficiency in forecasting short-term changes in electricity consumption even without specialized hardware. The fuzzy logic system adequately responds to typical microgrid operating modes and allows for early detection of potential deficit risks. The peak forecast error occurs in the evening hours, which is due to high consumption with reduced generation.

The practical application of the developed models allows increasing the reliability of microgrids, reducing the risks of energy deficit and improving energy resource management. The combination of BiLSTM and fuzzy logic provides accurate load forecasting and effective processing of uncertainty, which allows microgrid operators to make more informed decisions. Comparison with traditional approaches showed that the combination of machine learning and fuzzy logic is a promising direction for increasing the resilience of microgrids.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, including financial, personal, authorship or other, which could affect the study and its results presented in this paper.

Financing

The research was conducted at the expense of state budget research funding "Intelligent information technology for proactive management of energy infrastructure under conditions of risks and uncertainty", state registration number 0123U101852, which is being carried out at Sumy State University.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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Yevhen Kholiavka, *PhD Student, Department of Information Technology, Sumy State University, Sumy, Ukraine, ORCID: https://orcid.org/0000-0002-9841-7909*

✉***Yuliia Parfenenko,*** *PhD, Department of Information Technology, Sumy State University, Sumy, Ukraine, ORCID: https://orcid.org/0000-0003-4377-5132*

✉*Corresponding author*