A Deep Learning-Based Microgrid Energy Management Method Under the Internet of Things Architecture

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ABSTRACT

Given that the current microgrid incorporates highly connected distributed energy sources, the conventional model control methods do not suffice to support complex and ever-changing operating scenarios. This paper proposes a deep learning-based energy optimization method for microgrid energy management in the new power system scenarios. This article constructs a microgrid cloud edge collaboration architecture, which collects interactive network status data through terminal devices and network edge sides. A microgrid energy management model is constructed based on Bi-LSTM attention in the network cloud. And the model is sunk to provide real-time and efficient comprehensive load and power generation prediction output optimal scheduling decisions at the edge of the network, achieving collaborative control of microgrid light load storage. The simulation based on the actual available microgrid data shows that the proposed Bi-LSTM attention energy management model can achieve rapid analysis and optimize decision-making within 7.3 seconds for complex microgrid operation scenarios.

KEYWORDS

Attention Mechanism, Bidirectional LSTM, Energy Management, Internet of Things, Microgrid

INTRODUCTION

A microgrid utilizes and consumes renewable energy, interacts with the large grid, and can improve the utilization level of renewable energy, creating economic and environmental benefits while ensuring the safety and stability of the large grid (Dashtdar et al., 2022; Muchande & Thale, 2022). However, as the installed capacity of distributed power sources continues to expand, the uncertainty of their output could impact the large power grid.

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Microgrids need to manage various power generation and consumption equipment to meet the requirements for stability, cost-effectiveness, and safety so as to reduce the adverse impacts of renewable energy on the stability of the system and the economy (Zhang et al., 2022; Alvarez et al., 2023). Energy management of microgrids plays a vital role in ensuring economic operation, and its research has, therefore, become a matter of necessity and great urgency.

Currently, microgrids rely mainly on classical optimization methods, planning-based methods, Heuristic algorithms, etc. for energy management, which require precise mathematical model construction. In actual microgrids, however, wind and solar energy exhibit a high degree of randomness, which makes the traditional methods ill-suited for the actual situation (Ben Mansour et al., 2022; Nara, 2022; Zhang et al., 2020). At the same time, management of energy storage is so complex that it is difficult to use accurate data models and numerical calculation methods.

The emerging Internet of Things (IoT) has played an important role in the situational awareness of microgrids, which are gradually developing toward intelligent, information-based, and diversified new power systems (Altaf et al., 2022; Kandari et al., 2021). IoT devices are distributed at different power-equipment locations in the microgrid, achieving reliable network-state perception, providing complete data support for energy-scheduling optimization, and ensuring reliable monitoring, detection, and operation-optimization control of energy equipment (Tabassum et al., 2022; Savoli & Bhatt, 2022).

The traditional mathematical-modeling method faces challenges in extracting extensive and diverse microgrid-state data. In contrast, deep learning, with its complex neural network modules, excels at associating and extracting valuable information. Consequently, it offers a new and effective solution for navigating the complexities of microgrid energy-management scenarios.

Based on a multilayer network structure model, deep learning continuously trains and learns the power-grid dataset, constructs a complete and reliable energy-management model, and achieves effective assessment of network status and optimization of decision-making (Yang et al., 2022; Arul et al., 2021). Deep learning has allowed scholars to conduct energy-optimization research. Fang et al. (2021) combine reinforcement learning and deep-learning networks to design a deep Q-network model to achieve microgrid energy management and market-trading platforms, supporting stable operation. Parfenenko et al. (2023) adopt multilayer convolutional channels to optimize and improve the long-term and short-term memory network, improve the resource allocation of microgrids, and ensure energy-regulation security. Suresh et al. (2020) build an automatic encoder architecture based on the LSTM model and introduce an ant-colony algorithm to achieve global optimization, supporting the analysis of energy-optimization management in microgrids. Nahid et al. (2023) integrate a convolutional neural network (CNN) model and LSTM network model to achieve short-term output prediction for microgrid wind power. They focus on the application of deep learning in microgrid energy management, including the building of reliable energy-management models, optimization of decision-making, and integration with various deep-learning techniques to enhance performance.

However, most of the above methods are centralized decision-making management, and the analysis and calculation center is far from the terminal equipment, making real-time and rapid optimization scheduling analysis difficult to attain (Pu et al., 2021); at the same time, the presence of a great deal of redundancy in massive data requires energy-management models to discriminate and eliminate the redundant data to ensure the completeness of the model and achieve correct analysis of microgrid energy. For the redundant and abundant microgrid data, deep-learning models excel in capturing long-term dependencies and nonlinear relationships within time-series data. They can more precisely model the inherent complex dynamic characteristics of microgrid systems, enhancing the understanding of the relationships among energy generation, storage, and consumption. This deep learning–based approach is expected to better adapt to the complexity of microgrid systems, providing assistance in improving energy-utilization efficiency and system stability.

The paper presents a novel energy-management method for microgrids based on a Bi-LSTM-Attention model within an Internet of Things architecture. It develops a cloud–edge collaborative architecture for microgrid energy management, leveraging IoT technology. This structure facilitates efficient and real-time energy-optimization management by supporting data at the terminal, model construction in the cloud, and decision-making analysis at the edge. It enhances the Bi-LSTM network model with an attention mechanism. This approach optimizes the performance of energy-scheduling decisions by weighting different data features, thus capturing crucial data characteristics and avoiding the impact of erroneous data on analysis results.

The main innovative points are as follows:

1) Building a cloud–edge collaborative architecture for microgrid energy management based on Internet of Things technology, supporting data at the terminal, building models in the cloud, and conducting edge decision analysis to achieve efficient and real-time energy optimization management;
2) Introducing the attention module to optimize the Bi-LSTM network model, assigning weights to the information feature differences of different data, obtaining important data information features, avoiding the impact of incorrect data on analysis results, optimizing energy-dispatch decision-making performance, and achieving correct situation analysis and accurate unit output of the power grid.

MICROGRID ENERGY-MANAGEMENT ARCHITECTURE

Current microgrid operation scenarios are complex and variable, with high real-time data interaction, which makes it difficult for the traditional cloud-centralized computing mode of microgrid energy management to respond efficiently and accurately (Cao et al., 2022; Azeroual et al., 2021).

Edge-computing mode syncs some functions of cloud computing to the edge of the network, realizes data processing and analysis at the data-source end, and can effectively match the friendly interaction and efficient response requirements of microgrid energy management and control (Karthik & Kavithamani, 2021; Munir et al., 2021; Verbeek & Overbeek, 2022).

This paper builds a cloud–edge collaborative microgrid energy management architecture based on edge computing and cloud computing, as shown in Fig. 1.

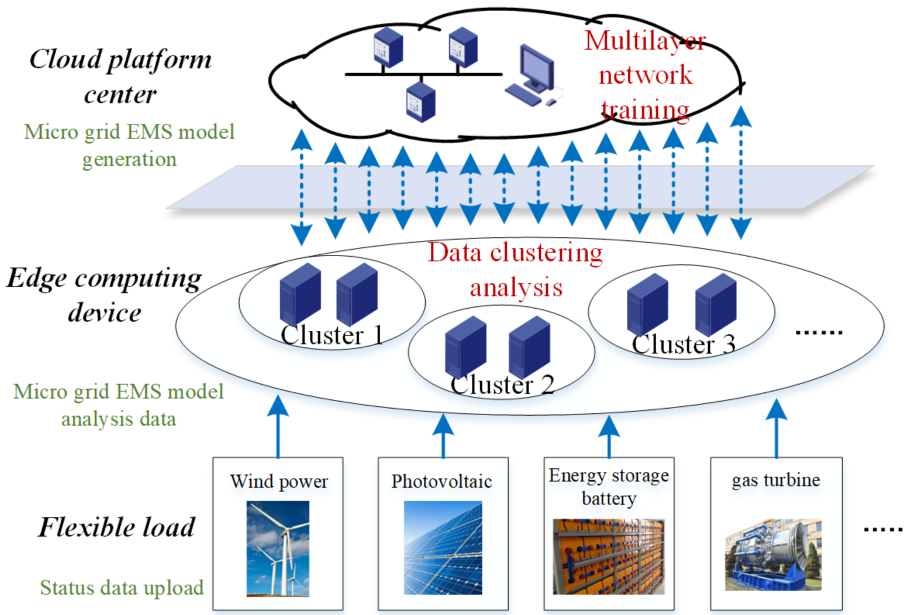
Figure 1 shows the microgrid energy management architecture for cloud–edge collaboration.

The network cloud serves as the brain of the energy-management architecture, receiving system datasets uploaded by the network edge layer. Based on a multilayer network model structure, the network cloud learns and trains the operational status and data information of the microgrid system, establishes a complete energy-management model, and then syncs the model to the network edge to achieve real-time response to terminal data (Ngassam et al., 2022; Taouche et al., 2022).

The edge side of the network serves as the central hub for the energy-management architecture. It plays a crucial role in facilitating data interaction and conducting model analysis. The network edge layer serves as the data-interaction hub between the network cloud and the terminal side, which can summon the terminal side network status dataset and also upload the necessary home-interaction data for building the model to the network cloud (Lv et al., 2022; Wang et al., 2020). At the same time, the network edge layer adopts the data-analysis model of cloud computing center syncing. By amalgamating terminal interaction data at the network's edge, the architecture provides energy-interaction management for microgrids. This approach attains situational awareness of the network status in proximity to terminals, enabling swift analysis of and decisive judgment about energy transfers.

The microgrid terminal equipment is equipped with various IoT sensing devices, which can achieve high situational awareness of the source, load, storage devices, and network status in the microgrid. The sensing data are uploaded to the cloud and edge sides of the network to achieve learning and monitoring of data-analysis models. Meanwhile, the proximity of the network edge data-analysis model to terminal devices enables the achievement of real-time and efficient demand response and load control.

Figure 1. The schematic diagram of hierarchical energy management architecture for microgrids



MICROGRID ENERGY MANAGEMENT SYSTEM MODEL

To better fit the actual operation of the power grid, this article considers the mathematical model construction and completes the construction of microgrid energy management scenarios (Yang & Wang, 2020).

Microgrid Energy Model

As a common DE source in microgrids, the power of wind turbine (WT) models presents uncertainty. The power model P_w and cost model C_w are as follows:

$$P_w = \begin{cases} 0 & v < v_{\min} \\ P_N \dfrac{v - v_{\min}}{v_{\max} - v_{\min}} & v_{\min} \le v < v_N \\ P_N & v_N \le v \le v_{\max} \\ 0 & v > v_{\max} \end{cases} \tag{1}$$

$$C_w = P_w k_w \tag{2}$$

where $v_{\min}$ is the cut-in wind speed of the fan, $v_{\max}$ is the cut-out wind speed, v_N is the rated wind speed of the fan, P_N is the rated power of the fan, and k_w is the operation and maintenance coefficient of the fan.

The photovoltaic (PV) power model P_p and cost model C_p are as follows:

$$P_p = P_{st} \frac{G_u}{G_{st}} [1 + k(T_u - T_{st})] \tag{3}$$

$$C_p = P_p k_p \tag{4}$$

where P_{st} is the standard rated power of the PV cell, G_{st} is the light intensity under standard state, T_{st} is the ambient temperature under standard state, T_u is the ambient temperature of the PV cell, G_u is the light intensity under ambient temperature T_u, and k_p is the PV operation and maintenance coefficient.

Energy-storage equipment consists mainly of batteries, and the mathematical model is as follows:

Charging process:

$$E_{t+1} = E_t - \lambda_1 P_{SOCt} \Delta t \tag{5}$$

Discharge process:

$$E_{t+1} = E_t - \frac{P_{SOCt} \Delta t}{\lambda_2} \tag{6}$$

Battery state of charge (SOC):

$$SOC_{t+1} = \begin{cases} SOC_t + \lambda_1 P_{SOCt} \\ SOC_t + \lambda_2 P_{SOCt} \end{cases} \tag{7}$$

Cost model:

$$C_{SOC} = | P_t e_t k_{SOC} | \tag{8}$$

The mathematical expression for the cost of micro gas turbine power generation is as follows:

$$C_{Mt} = \sum_{t=1}^{24} [r \frac{1}{M_{\min}} \times \frac{P_{Mt}}{\lambda_{Mt}}] \tag{9}$$

$$\lambda_{Mt} = 0.0753(\frac{P_{Mt}}{65})^3 - 0.3095(\frac{P_{Mt}}{65})^2 + 0.4174(\frac{P_{Mt}}{65}) + 0.1068 \tag{10}$$

where C_{Mt} is the fuel cost of the gas turbine at the time t, r is the unit price of natural gas in the microgrid, $M_{\min}$ is the low calorific value of natural gas, P_{Mt} is the output power at the time t, and λ_{Mt} is the power-generation efficiency.

Objective Function of Microgrid Cost

When an energy-management model for microgrids is constructed, in addition to considering the economic costs of microgrid operation, environmental protection should also be considered (Zhang et al., 2021).

Economic Costs

The purpose of microgrid clusters is to minimize the overall operating cost. Therefore, when managing energy on existing microgrid clusters, there is no need to take into account the initial construction cost of the system.

When various types of energy costs in the network are considered, the system's economic objective function is constructed as follows:

$$\min C_1 = \sum_{t=1}^{24}\sum_{i=1}^{N}(C_{wi,t} + C_{pi,t} + C_{SOCi,t} + C_{Mi,t}) \tag{11}$$

where C_1 represents the economic cost of energy management in the microgrid, i represents the number of various power sources in the network, N represents the total number of various power sources, and $C_{wi,t}$, $C_{pi,t}$, $C_{SOCi,t}$, and $C_{Mi,t}$ represent the economic costs of WTs, PVs, SOC, and steam turbines at the time t.

Environmental Protection Costs

Given that gas turbines can produce pollutants such as SO_2 and NO_x during operation, environmental protection measures must be taken to reduce air pollution, and the mathematical model of its environmental protection cost is as follows (Tong & Guo, 2023):

$$\min C_2 = \sum_{t=1}^{24}\sum_{i=1}^{N}(\alpha_i \beta_i P_{Mi,t}) \tag{12}$$

where C_2 is the environmental protection cost of the microgrid, α_i is the pollutant emission coefficient, and β_i is the pollutant treatment cost coefficient.

Comprehensive Cost

Comprehensive cost refers to the sum of the economic and environmental costs of microgrids. This article takes the comprehensive cost of microgrids as the objective function, and its expression is as follows:

$$\min C = \min(aC_1 + bC_2) \tag{13}$$

where C represents the comprehensive cost of the microgrid and a and b represent the economic cost coefficient and environmental cost coefficient, respectively. Since economic and environmental aspects are equally important, both values are 0.5.

Constraints of Microgrid Systems

The power balance constraints of microgrids are expressed as follows:

$$P_{Lt} = P_{wt} + P_{pt} + P_{SOCt} + P_{Mt} \tag{14}$$

As shown in (14), the microgrid system should meet the power balance constraint at any time. P_{Lt} represents the demand load power of the microgrid at t time.

The distributed power output power constraints are expressed as follows:

$$P_{wp,\min} \leq P_{wp} \leq P_{wp,\max} \tag{15}$$

where $P_{wp,\min}$ and $P_{wp,\max}$ are the lower and upper limits of the active wind or PV power at the moment, respectively.

The energy storage battery constraints are expressed as follows:

$$E_{\min,t} \leq E \leq E_{\max,t} \tag{16}$$

$$SOC_{\min,t} \leq SOC_{t} \leq SOC_{\max,t} \tag{17}$$

$$\sum_{t=1}^{24} P_{SOCt}\delta = 0 \tag{18}$$

where $E_{\min,t}$ and $E_{\max,t}$ are the lower and upper limits of the output capacity of the t time battery system and δ is the scheduling time period.

The output of the gas turbine unit is limited by the initial power generation and ramp rate, and the ramp constraints of the unit are as follows:

$$\begin{cases} P_{t-1} - P_{t} \leq v_{m\_down} \times T \\ P_{t} - P_{t-1} \leq v_{m\_up} \times T \end{cases} \tag{19}$$

where v_{m_down} and v_{m_up} are the climbing rate and a scheduling cycle T of 1 hour is set.

The power constraints for interaction between microgrid and main grid are expressed as follows:

$$P_{gird,t}^{\min} \leq P_{gird,t} \leq P_{gird,t}^{\max} \tag{20}$$

ENERGY-MANAGEMENT METHOD BASED ON THE BI-LSTM-ATTENTION MODEL

The cloud of the microgrid network receives the network-status dataset uploaded by terminal devices, constructs a complete energy-management model based on the deep-learning model, and syncs it to the edge of the network to achieve real-time state analysis and energy scheduling.

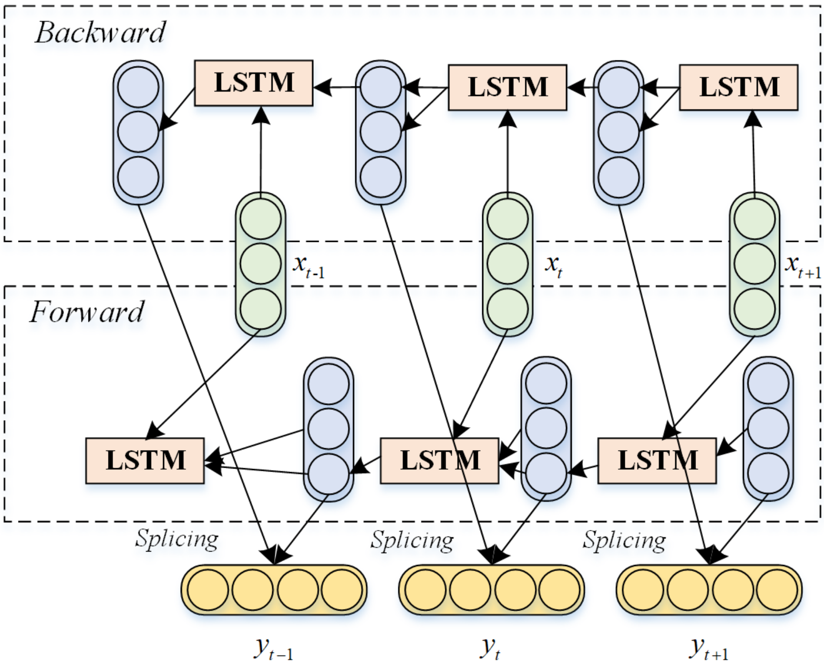
The microgrid network data has obvious temporal attributes, and such data features can be mined by the recurrent neural network (RNN) model to optimize network energy allocation and scheduling.

Bi-LSTM Network Model

As a type of RNN network, LSTM can achieve effective information mining. The conventional LSTM models, however, often ignore the global information of historical load data during training, and previous data are left untreated due to the long time series of data samples.

To tackle the aforementioned issues, the Bi-LSTM network connects a forward LSTM and a reverse LSTM. This design enables the model to learn from the entire data sequence in both directions, conducting bidirectional analysis and training on sample load data. This approach proves effective in extracting more comprehensive information from the sample data.

Figure 2. Bi-LSTM network structure



Used by the previous model, given the microgrid operation scenario, the input sequence of the data-analysis model $X = [x_1, x_2, \cdots, x_n]$ is the data sequence collected by the energy-management structure.

The forward implicit output state sequence is obtained through the forward LSTM:

$$\vec{h}_t = \overrightarrow{LSTM}(x_t, \vec{h}_{t-1}) \tag{21}$$

After passing through the reverse LSTM, the reverse implicit output state sequence is obtained:

$$\overleftarrow{h}_t = \overleftarrow{LSTM}(x_t, \overleftarrow{h}_{t-1}) \tag{22}$$

The outputs of each hidden state are then merged bit by bit, namely:

$$h_t = \kappa_t \vec{h}_t + \varepsilon_t \overleftarrow{h}_t + s_t \tag{23}$$

where κ_t is the weight matrix of the forward output at t time; the weight matrix ε_t for reverse output at t time; and the bias parameter s_t for the time t.

Attention Mechanism

The mechanism needs to allocate different weights based on the importance of waveforms at different times, so hidden layer units are added to the neural network u_d, which is expressed as follows:

$$u_d = \tanh(G_u H_d + e_u) \tag{24}$$

The parameter matrix G_u is initialized using a uniformly distributed random method, with the output vector H_d of the previous layer as input and obtained u_d through the activation function, and e_u is the weight offset of the hidden layer unit.

Input the transposed dot product results with the weight matrix G_a into the softmax activation function f_{softmax} for normalization processing to obtain the attention vector a_d:

$$a_d = f_{\mathrm{softmax}}(u_d^T, G_a) \tag{25}$$

Connect a fully connected layer with the same dimension and classification number in the data analysis network, and use the softmax classification network to generate a one-dimensional vector y of the class probability distribution of the interval $(0,1)$ as the final output of the neural network, which is expressed as follows:

$$y = f_{\mathrm{softmax}}(G_y H_d + e_y) \tag{26}$$

where G_y is the weight of the fully connected layer and e_y is the weight offset of the fully connected layer.

The overall structure of the Bi-LSTM neural network with attention mechanism (Bi-LSTM-Attention) is shown in Fig. 3. With its training data coming from the edge or terminal side of the microgrid network, the input layer learns and constructs a neural network. The Bi-LSTM layer extracts the features of each segment of the microgrid network state, and the attention mechanism layer assigns weights to construct a complete and reliable energy-scheduling model.

In Fig. 3, $X = [x_1, x_2, \cdots, x_n]$ represents the sample data sequence of the microgrid and St_f and St_b represent the cell state.

Energy-Management Methods for Microgrids

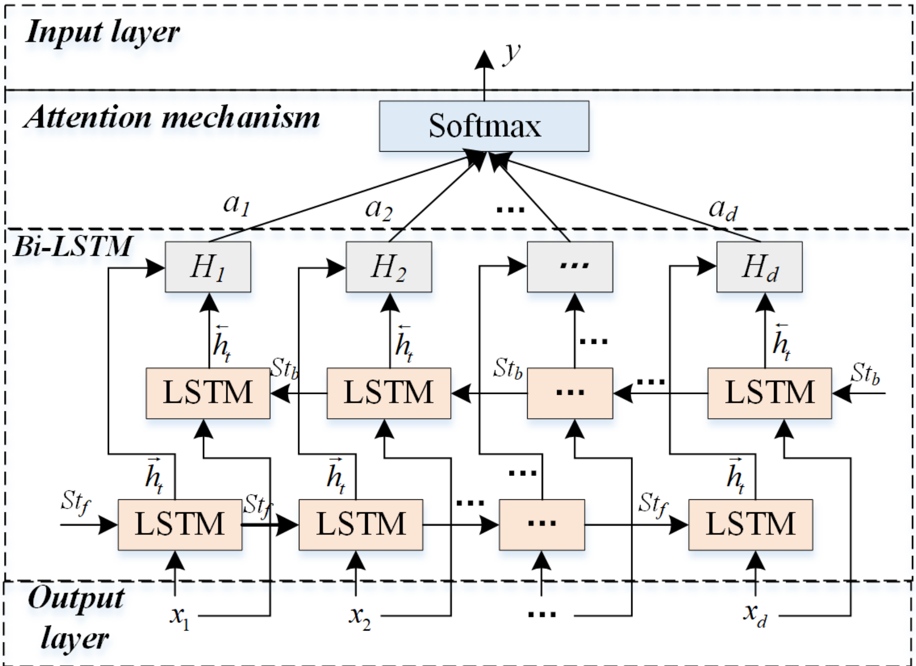
The microgrid energy scheduling model based on a deep Bi-LSTM neural network is trained with massive historical data to construct a mapping relationship between the microgrid-operation scenarios and the scheduling-decision results. The mature data-analysis model is synced to the edge of the network to achieve energy-optimization analysis, and the corresponding scheduling-decision results are mapped in real-time response to terminal uploaded data.

The Bi-LSTM-Attention energy-management model and the detailed decision-making process are shown in Fig. 4.

As can be seen from Fig. 4, the deep-learning model for the optimization scheduling of microgrids is composed of a Bi-LSTM-Attention neural network. The input of the overall model is the monitoring data of the microgrid terminal equipment; the output of the overall model is the scheduling-decision result.

The Bi-LSTM-Attention energy-management model is deployed to the network edge, enhancing its proximity to terminal power equipment. The accumulation of historical input and output data facilitates the continuous and rapid refinement of the deep-learning model. This capability enables effective handling of historical scheduling-decision outcomes, leading to a continuous improvement in the accuracy and efficiency of microgrid-optimization scheduling.

Figure 3. Structure of Bi-LSTM-attention neural network



This article uses the Adam optimization algorithm to train the Bi-LSTM-Attention energy-management model. The mean square error (MSE) is selected as the loss function. The expression of MSE and the weight update formula of the Adam algorithm are as follows:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2 \tag{27}$$

$$\sigma_{t+1} = \sigma_t - \frac{\delta}{\sqrt{\hat{q}_t + \varepsilon}}\hat{p}_t \tag{28}$$

$$\hat{q}_t = \frac{\gamma_2 q_{t-1} + (1-\gamma_2)\nabla^2\sigma}{1-\gamma_2} \tag{29}$$

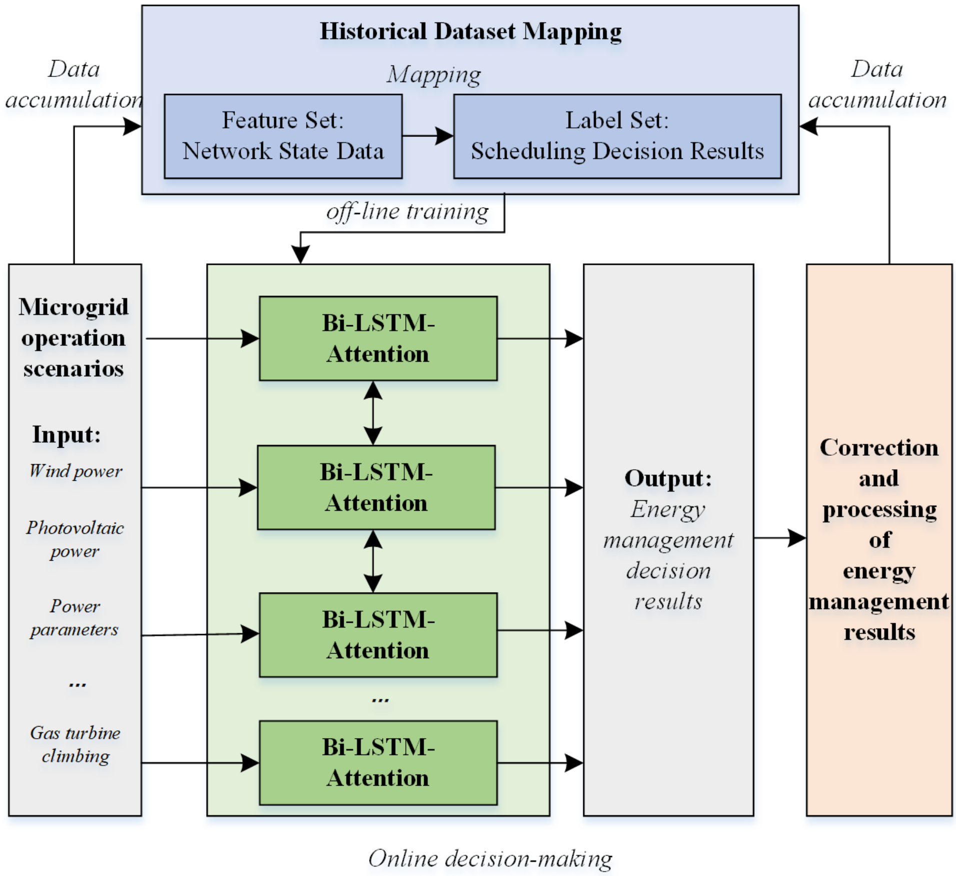
$$\hat{p}_t = \frac{\gamma_1 p_{t-1} + (1-\gamma_1)\nabla\sigma}{1-\gamma_1} \tag{30}$$

where y_t is the actual value of the microgrid and $\hat{y}_t$ is the predicted value of the model, σ_t is the weight parameter of the network to be updated, δ is the learning rate, ε is the smoothing parameter, $\hat{q}_t$ and $\hat{p}_t$ are the first-order moment mean and second-order moment mean of the gradient, respectively, and γ_1 and γ_2 are the attenuation factor.

SIMULATION EXPERIMENTS

The simulation experiment was run on a high-performance computer, where the hardware running environment is an Intel Core processor, the GPU is NVIDIA GTX 5000, the software running

Figure 4. Bi-LSTM-attention network model and decision flow diagram



environment uses the Python language, and the deep-learning framework is Python. The detailed parameters are shown in Table 1.

Experimental Dataset

For an example analysis of a grid-connected microgrid system, the distributed power sources in the system comprise one WT, one PV, one micro gas turbine, and one battery. For ease of description, WT, PV, DE, and energy storage system (ESS) are used, respectively, while GRID and LOAD are used to represent the superior power grid and load. Fig. 5 shows the predicted values on the dispatch day.

The operating parameters of each distributed power supply are shown in Table 2.

The cost of polluting-gas treatment is shown in Table 3.

Comparative Analysis of Model Convergence

The collected experimental dataset is broken into a training set and a testing set at a ratio of 4:1 to analyze the convergence performance of the energy-management model. Fig. 6 shows the convergence of the Bi-LSTM-Attention energy-management model.

Fig. 6 shows the loss curve of Bi-LSTM-Attention during training. The graph shows that the network converges after approximately 100 iterations and demonstrates good model calculation and

Table 1. Protocol identification experimental parameters

Item	Parameter
CPU	Intel Core i9-13980HX 16GB
GPU	NVIDIA GeForce GTX 5000 16GB
System	Windows 10
Development Tool	PyCharm 2022.2

Figure 5. Predicted daily load, WT, and PV with proposed method

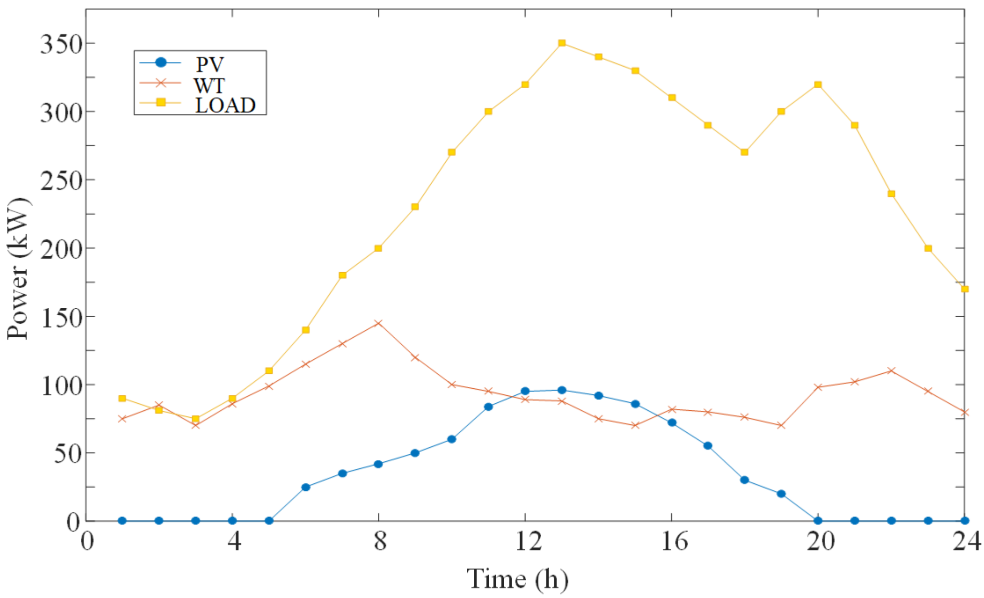


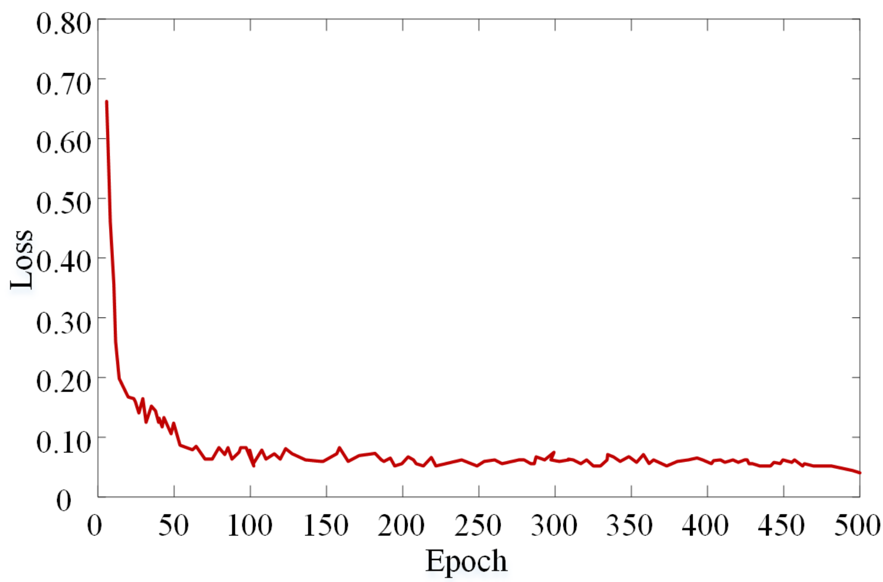
Table 2. Distributed power supply operating parameters

Distributed Generation	Minimum Power Value (kW)	Maximum Power Value (kW)
WT	0	100
PV	0	100
ESS	0	150
DE	-50	50

Table 3. Cost of polluting-gas treatment

Polluting Gas	Emission Coefficient (kg/kW)	Governance Costs (CNY/kg)
CO_x	4.25	0.32
NO_x	3.15	8.495
SO_2	0.38	5.858

Figure 6. Changes in loss function with the increase of epoch



analysis capabilities, indicating that there has been no occurrence of fitting or underfitting during network training.

To test the neural network's generalization performance, the Bi-LSTM-Attention energy-management model was tested for root mean square error on the test set, and the values of MSE are shown in Fig. 7.

Fig. 7 presents the comparative results between the Bi-LSTM-Attention network and common network models. In comparison to traditional backpropagation networks (BP) and support vector machine (SVM) models, the LSTM deep neural network effectively extracts time-series features from the data, resulting in MSEs of 0.292, 0.219, 0.225, and 0.214 for each output variable, showcasing overall excellent performance. However, when compared to the LSTM network, the Bi-LSTM network, with its ability to bidirectionally learn time-series features, exhibits a slight overall advantage in performance.

Notably, the Bi-LSTM-Attention network achieves the lowest MSE for each output variable, namely, 0.264, 0.202, 0.221, and 0.195. Its superiority is particularly evident in the WT subdataset, where the MSE is only 0.264. This underscores that in wind-power datasets characterized by strong volatility and randomness, the attention mechanism of the Bi-LSTM-Attention network effectively allocates weights, minimizing the overall model error. In the other three subdatasets, the Bi-LSTM-Attention network consistently maintains the lowest MSE, confirming its ability to maintain precision while demonstrating robust generalization performance, thus making it suitable for energy-optimization management in diverse and complex datasets.

Optimization Analysis

The Bi-LSTM-Attention energy-management model optimizes energy scheduling by learning and training microgrid operation status data. The output results of the distributed power supply are shown in Fig. 8.

Fig. 8 reveals that there is a sufficient supply of wind-power resources during the peak hours of power consumption from 23:00 to 6:00, which suggests that priority is given to wind power and superior grid output.

Figure 7. Mean square error performance with different methods

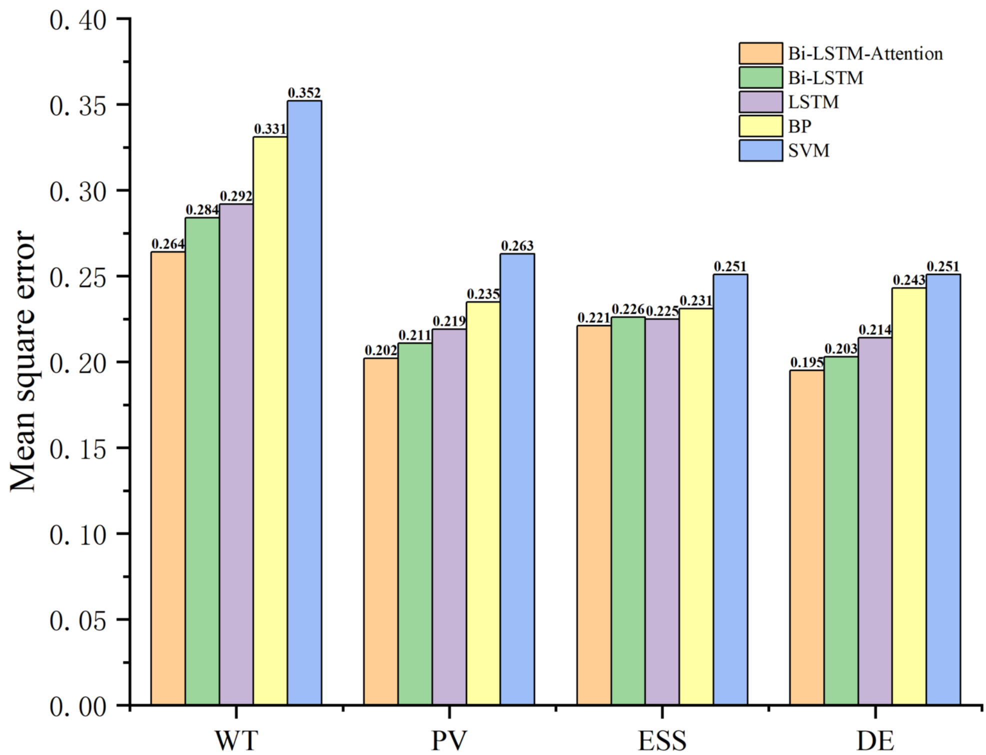
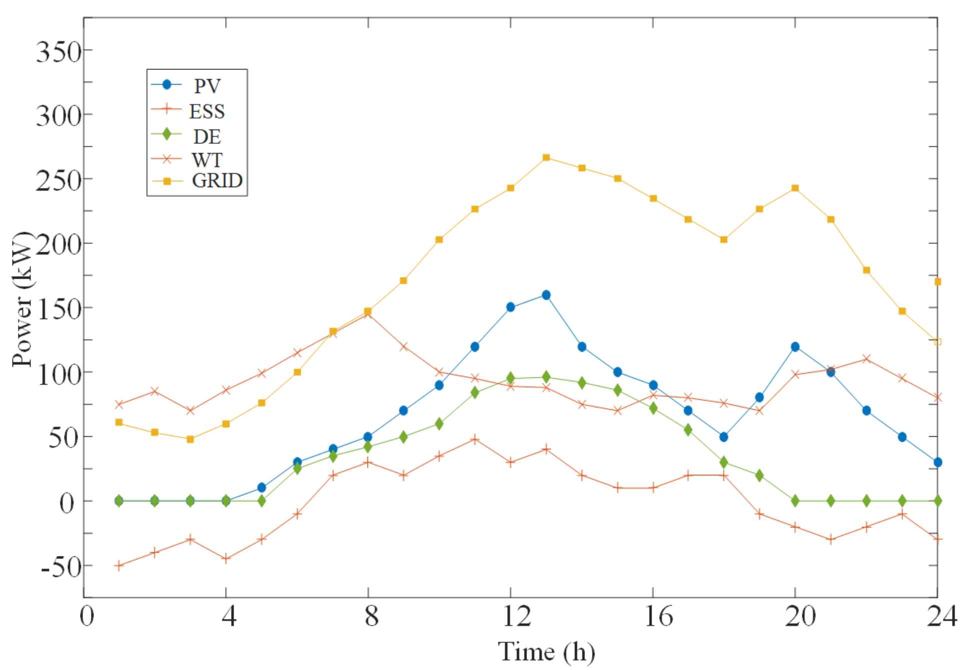


Figure 8. Distributed power output within 24 hours



During the periods from 6:00 to 9:00 and from 13:00 to 19:00, the load demand is greater than the total output of wind, solar, and fuel cells, with environmental pollution costs and system operation costs considered, and there is sufficient sunlight during the 9:00 to 17:00 period. PV power generation is prioritized over gas turbine power generation in scheduling.

During the peak electricity consumption periods from 9:00 to 13:00 and from 19:00 to 23:00, the wind power is fully absorbed and the stability of microgrid operation is improved. PVs, batteries, and gas turbines simultaneously increase output, and PV output takes priority over gas turbines. PVs are operating at close to full capacity. When each distributed power source reaches its operating power limit, it will purchase electricity from the large power grid to meet the grid load demand.

Comparative Analysis of Algorithm Results

To verify the superiority of the energy-management algorithm's performance, this article uses Nahid et al. (2023), Suresh et al. (2020), and Parfenenko et al. (2023) as comparative methods for simulation verification. All energy optimization management methods operate in the same environment.

Parfenenko et al. (2023) adopt the LSTM method to achieve energy optimization and scheduling of microgrids. Suresh et al. (2020) implement output optimization control based on the autoencoder long short-term memory (AE-LSTM) model. Nahid et al. (2023) achieve energy-management optimization and adjustment for microgrids based on the CNN-LSTM network model.

Table 4 shows the optimization-analysis results of different network models for the same microgrid scenario.

Table 4 compares the convergence performance and operating-cost calculation of different neural network models. The Bi-LSTM-Attention model proposed in this article has a fast convergence speed and can effectively calculate and analyze microgrid operation data within 7.28 seconds. The comprehensive cost of network operation is 3.25×10^4 yuan. Compared to the LSTM method, the analysis and calculation time is reduced by 0.95 seconds.

As can be seen from Table 4, Suresh et al. (2020), using the AE-LSTM method, achieve a time of 7.92 seconds in data analysis, although the performance of the AE-LSTM attention model is similar to the proposed method in time, and the comprehensive cost of the AE-LSTM method is 4.59×10^4 yuan, far more than the method presented in this article.

The key driving force behind this lies in the application of the hybrid network model method discussed in this article. This method facilitates situational awareness and energy scheduling for microgrids at the network's edge, enabling efficient and real-time demand response. Consequently, it significantly enhances the speed of decision-making for network energy optimization. The bidirectional LSTM network model integrates historical and global data compared to the LSTM method, achieving data extraction and analysis methods that can quickly obtain information features of network-operation data uploaded by terminal devices. Additionally, the incorporation of the attention module facilitates systematic analysis of information features with varying levels of importance. This helps prevent erroneous data interference with model calculation results, ultimately enhancing the optimization and management capabilities of the energy-management model.

Table 4. Convergence performance of different network models

Method	Convergence Time	Minimum Comprehensive Cost (CNY)
Bi-LSTM-Attention	7.28	3.25×10^4
LSTM	8.51	4.11×10^4
AE-LSTM	7.92	4.59×10^4
CNN-LSTM	9.82	3.71×10^4

CONCLUSION

This article proposes an energy-management method based on the Bi-LSTM-Attention microgrid, which can effectively achieve optimal control of the unit output. A microgrid energy management architecture is constructed based on cloud–edge collaboration mode, by training and learning energy-management models in the network cloud, and syncing complete and mature decision models to the network edge side to achieve real-time and efficient situation judgment and energy-scheduling analysis. The introduction of the attention mechanism into the Bi-LSTM model can deeply extract effective information from network-collected data, avoid erroneous-information interference with scheduling-analysis results, and improve the decision-making analysis ability of the energy-management model. Simulation experiments have shown that the proposed Bi-LSTM-Attention model has good situational analysis and energy-regulation capabilities in practical complex operating scenarios.

Overall, this study presents an innovative approach to microgrid energy management that provides a valuable reference for other researchers seeking to enhance energy-management models in practical applications. The findings are also expected to drive advances in related fields, such as smart energy systems and edge computing, providing useful insights for future research and practical implementation. However, it should be noted that the model of the proposed method is trained offline, and although it can improve energy-regulation ability under most conditions, its regulation ability may be weakened under extreme conditions that occur in real time. The lightweight processing of the network model is also an aspect that needs attention and optimization. Therefore, the next research direction of this paper's authors will focus on the online training of the Bi-LSTM-Attention energy-regulation model and the in-depth discussion of lightweight processing.

AUTHOR NOTE

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