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Optimization of grid-connected voltage support technology and intelligent control strategies for new energy stations based on deep learning

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Abstract

To explore the optimization method of grid-connected voltage support technology in new energy stations, this study first analyzes and discusses this technology. Second, this study describes the deep learning model architecture and feature selection in detail and determines the framework used for the optimization model proposed here. Lastly, the development of optimization and control strategies is investigated, and the optimized model's effectiveness is verified through experiments. The results reveal that the optimized model's accuracy, precision, recall, and F1 score are higher than those of the comparison model in the performance comparison experiment, reaching the highest values of 0.890, 0.888, 0.878, and 0.883, respectively. This reflects that the optimized model shows high performance on small datasets, and its performance benefits become more pronounced as the data volume increases. This feature is particularly significant because, in practical applications, power systems often need to process large amounts of data to achieve efficient voltage support. In simulation experiments, the optimized model demonstrates excellent performance in terms of response time, stability, robustness, and energy consumption. Moreover, this model effectively addresses various data challenges and uncertainties encountered in grid-connected voltage support technology for power systems, thereby providing robust support for stable and efficient voltage regulation. In light of the findings, this study offers substantial insights for advancing research in the realms of power systems and new energy technologies. The exploration into the application of deep learning and intelligent control strategies within power systems reveals significant potential for transforming grid optimization practices. This study accentuates how data-driven methodologies can revolutionize energy management, paving the way for smarter and more efficient energy systems. By enhancing both the responsiveness and operational efficiency of power grids, the study contributes to the acceleration of digital transformation within the energy sector, fostering innovation and laying a robust foundation for future advancements in energy informatics.

Keywords: Deep learning, New energy station, Grid-connected voltage support, Power system stability

Introduction

With the growing global demand for sustainable energy, the rapid development of new energy stations, such as solar and wind power stations, has become an integral part of the power system (Wang et al. 2022a). However, these new energy generation methods' intermittency and instability pose new challenges to the stable operation of the grid, especially in terms of voltage support. Grid-connected voltage support technology is one of the vital technologies to ensure the stability and reliability of power systems (Amir, et al. 2024; Al-Saadi et al. 2023; Liu et al. 2022). Traditional voltage support methods are often unable to flexibly cope with the volatility of new energy generation, resulting in increased risks to grid stability. Traditional voltage support mechanisms predominantly hinge on static compensation devices and regulation strategies such as static VAR compensators and synchronous condensers. However, these methods exhibit notable limitations. Conventional equipment typically operates with a response time measured in seconds, a timeframe that starkly contrasts with the millisecond-level fluctuations often encountered in new energy generation. The fixed compensation approach, while historically reliable, fails to adapt dynamically to real-time variations in load and power generation, struggling to keep pace with the rapid and unpredictable nature of new energy sources. The challenges posed by new energy generation are considerable, given its inherent intermittency and instability. For instance, wind power stations experience substantial output fluctuations due to shifting wind speeds, with the National Renewable Energy Laboratory noting that wind power output can vary by over 50% within minutes. Similarly, solar power generation faces significant variability influenced by the cycle of day and night as well as weather conditions. The disparity in photovoltaic output between sunny and cloudy days can be dramatic, with output levels potentially differing several times or exhibiting swift changes within brief intervals.

In previous studies, Shekhar et al. found that the traditional proportional-integral–differential control had problems with reaction lag and insufficient adjustment accuracy when handling voltage fluctuations, which made it difficult to maintain power grid stability when large-scale new energy was incorporated (Shekhar et al. 2023). Hu et al. pointed out through simulation analysis that the existing voltage regulators could not quickly adapt to the rapidly changing load, which was particularly unfavorable for the stations that relied on wind and solar power generation (Hu et al. 2022). Alam et al. showed that although flexible alternating current (AC) transmission system technology achieved some results in improving voltage stability, it still faced challenges regarding cost and energy efficiency (Alam et al. 2022). Abualigah et al. presented the Convolutional Neural Network (CNN) application in power grid state prediction, which accurately predicted the voltage variation trend in various scenarios (Abualigah et al. 2022). Yin and He utilized Long Short-Term Memory (LSTM) to effectively predict the output power and grid load of wind power stations, offering data support for the dynamic regulation of voltage support (Yin and He 2023). Behara and Saha employed reinforcement learning algorithms to optimize the grid-connection strategy of distributed generation, effectively reducing voltage fluctuations and losses, and improving the overall stability of the power grid (Behara and Saha 2022). Rehman et al. explored the adaptive control strategy based on deep learning (DL) and found that it showed better adaptability and accuracy than traditional methods in adjusting voltage support parameters of new energy grid connection (Rehman et al. 2022). Wu and Liu adopted deep reinforcement learning (DRL) to optimize the power grid's voltage support strategy in real-time and proved the effectiveness and efficiency of this method in dealing with complex scenarios caused by new energy grid connections (Wu and Liu 2022).

The current utilization of DL primarily concentrates on predicting grid states and optimizing distributed generation grid-connected voltage support strategies. However, research regarding the specific operations and strategy adjustments for grid-connected voltage support in new energy stations remains relatively limited. In this study, techniques such as DRL are employed to achieve real-time optimization of voltage support strategies and automatically adjust control parameters in response to dynamic changes in power grid operations. This approach enhances the robustness and flexibility of the power grid. Furthermore, through comprehensive analysis and discussion, this study not only addresses present challenges but also offers theoretical and technical foundations for future research on grid-connected voltage support technology in new energy stations. Consequently, this study contributes to the advancement of this field.

Model optimization based on integration of DL and control strategy

This section delves into the intricacies of grid-connected voltage support technology, offering a comprehensive analysis of its current application landscape and the technical challenges encountered in new energy stations. The discussion extends to the architecture and feature selection of DL models, explaining how these models can enhance prediction accuracy and adaptability through sophisticated DL techniques. Attention then shifts to the development and refinement of optimization and control strategies, illustrating the fusion of advanced DL methodologies with traditional control approaches to achieve intelligent optimization of grid-connected voltage support. By integrating these cutting-edge technologies and methodologies, this section aspires to provide both a theoretical foundation and practical insights aimed at augmenting the voltage support capabilities of new energy stations.

Grid-connected voltage support technology

Grid-connected voltage support technology is a key technology in the power system, which is mainly used to maintain the stability and reliability of the voltage in the power grid, especially in the case of large-scale grid connection of new energy. With the wide application of new energy such as wind energy and solar energy, its instability and intermittency have brought new challenges to the power grid's voltage stability (Hossain et al. 2023; Wang et al. 2022b; Li et al. 2023; Slama and Mahmoud 2023).

The output of solar power generation is directly tied to sunshine conditions, exhibiting pronounced periodic fluctuations between day and night. Moreover, intermittent factors such as clouds, shadows, and varying weather conditions—ranging from sunny spells to overcast skies—can induce dramatic short-term variations in photovoltaic (PV) output. Optimal sunshine can substantially lower the voltage level within the power grid, whereas sudden reductions in sunlight, triggered by rapidly advancing dark clouds, can precipitate sharp voltage drops and frequent voltage fluctuations (Ashok Babu et al. 2024). Such shifts have the potential to overload equipment or cause damage, subsequently driving up maintenance and operational costs. Wind power generation, conversely, is influenced by the erratic nature of wind speed and direction. The inherent randomness and unpredictability of wind conditions can drastically alter power generation efficiency. For instance, rapid increases in wind speed can lead to excessive power production and consequent voltage surges, while sharp decreases can cause insufficient voltage, thereby compromising power quality and the safe operation of grid infrastructure. Biomass power generation, though generally stable, faces its own challenges. The stability of biomass energy can be undermined by disruptions in the supply chain, such as difficulties in raw material procurement and transportation, leading to fluctuations in power output. When combined with other volatile energy sources, such as wind or solar, the stability of biomass energy can be further compromised, particularly during dramatic load changes within the power grid. Ocean energy sources, including tidal and wave energy, introduce additional complexities. The periodic and localized nature of ocean conditions and tidal movements can lead to significant voltage distribution changes within the grid. In regions experiencing substantial tidal fluctuations, the alternating peaks and valleys of power demand can exacerbate voltage instability, posing challenges for maintaining grid stability.

The implementation method of grid-connected voltage support is exhibited in Table 1:

To improve the response speed and precision of grid-connected voltage support technology, DL technology is introduced into the voltage regulation process. DL models, such as CNN and LSTM, can predict the state changes of the power grid and new energy generation, and provide data support for voltage regulation (Albogamy et al. 2022). By analyzing historical and real-time data, these models learn the operating patterns of the grid, which enables them to predict voltage trends and automatically adjust voltage support measures. Leveraging the DL model, the system can predict changes in grid status and new energy generation in real-time, thus adjusting voltage support strategies more accurately. This method can improve the speed and accuracy of voltage regulation and optimize the effect of voltage support according to the real-time data of the power grid, reduce energy consumption, and enhance the power grid's overall stability (Shirzadi et al. 2022; Hafeez et al. 2023; Alrifaey et al. 2022; Dehnavi et al. 2023).

The DL-based intelligent control strategy is utilized to dynamically adjust voltage support parameters. This strategy combines real-time data analysis and automated control technology to automatically adjust reactive power output and other relevant parameters based on immediate changes in the grid. This not only enhances the stability of the power grid but also improves the operation economy and energy efficiency (Alturas et al. 2020). For instance, an intelligent control system can monitor the voltage level of

Table 1 The implementation of grid-connected voltage support

Method	Description
Static devices	It encompasses capacitors and reactors, which can adjust reactive power to hedge against voltage changes. These devices respond quickly and are suitable for rapid voltage regulation
Dynamic devices	For example, synchronous generators and static reactive compensators can dynamically adjust reactive power output according to the grid's needs to adapt to more complex voltage regulation demands
Advanced devices	Flexible AC transmission system devices, such as static synchronous compensators and unified power flow controllers, offer more precise and flexible reactive power regulation capabilities to adapt to rapidly changing grid conditions

the grid and the output of new energy generation in real-time, and automatically adjust reactive power according to the predicted results to minimize voltage fluctuations.

Through the above content, it can be found the importance of grid-connected voltage support technology in maintaining the stability of the power system. With the continuous increase of new energy, combined with DL and intelligent control strategy, this technology can adapt to the dynamic variations of the power grid more efficiently and accurately to ensure the power system's stable operation (Ahmad et al. 2022; Fellner et al. 2022; Al-Ja'Afreh et al. 2023).

DL model architecture and feature selection

DL model architecture and feature selection are the core parts of grid-connected voltage support technology optimization. Through carefully designed model architecture and appropriate feature selection, the model's prediction accuracy and response efficiency can be improved, thus more effectively supporting the stability of power grid voltage (Mostafa et al. 2022; Zheng et al. 2023).

In the choice of model, CNN is suitable for processing spatial data, while LSTM is good at dealing with time series data. Considering that the power grid data contains both temporal characteristics (such as voltage and current changes) and spatial distribution characteristics (such as voltage measurement points at different locations), this study selects a hybrid model integrating CNN and LSTM, namely the CNN-LSTM model. Through the sliding of convolutional kernels across data, CNNs exhibit the capacity to autonomously discern and extract pivotal local patterns and features, such as the intricate correlations among voltage measurement points distributed across various locations. This capability is further enhanced by CNN's use of parameter sharing and sparse connections, which considerably diminishes model complexity, thus streamlining training processes on extensive datasets and mitigating the risk of overfitting. LSTM networks are engineered to manage and predict long-range dependencies within time series data. Their distinctive gating mechanisms enable the retention and application of historical information over extended distances, making them adept at capturing the dynamic evolution of grid data—such as fluctuations in voltage and current over time. LSTMs also adeptly address the issue of gradient vanishing, which enhances the stability and precision of learning across prolonged time spans. This attribute is crucial for managing the long-term dependencies and periodic fluctuations inherent in power grid operations. Given these attributes, the choice of CNN and LSTM models in this study, as opposed to alternative DL architectures, underscores their superior suitability for addressing the complexities of grid data analysis and forecasting.

The CNN-LSTM model's structure is presented in Fig. 1:

Figure 1 illustrates the intricate flow of data through a complex neural network architecture. At the outset, the input layer assimilates raw data, which may encompass time series or other multi-dimensional data necessitating feature extraction. This data is then subjected to processing within the CNN layer, where the convolution operation methodically extracts local features. The convolutional kernel scans across the data, unveiling essential spatial features. Subsequently, the activation layer applies a nonlinear activation function to the convolutional output, imbuing the model with enhanced expressive power by performing a nonlinear transformation. This step enriches the model's ability

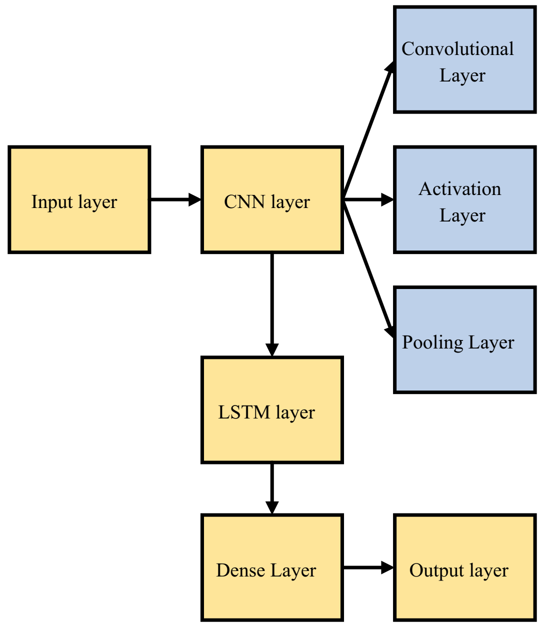

Fig. 1 The structure of the CNN-LSTM model

to capture intricate patterns and interactions within the data. Furthermore, the pooling layer executes a downsampling operation on the convolutional output, which reduces the dimensionality of the data while preserving critical features and bolstering the model's translation invariance. This reduction process ensures that the model focuses on the most pertinent information, effectively minimizing redundancy. In parallel, the LSTM network layer addresses the temporal dependencies and long-range relationships inherent in sequential data. This layer's unique capability to retain historical information makes it highly effective for prediction tasks requiring consideration of past data impacts. The fully connected layer then amalgamates high-level features through a nonlinear combination, achieved by multiplying the LSTM output with weight matrices. This step further refines the integration and extraction of information from the data. Ultimately, the output layer generates the final prediction results, utilizing either linear or nonlinear functions for output transformation. The nature of the output—whether for classification, regression, or other tasks—is determined by the specific requirements of the application at hand.

The model structure exhibits remarkable prowess in feature extraction, with the CNN layer adeptly capturing spatial features and the LSTM layer skillfully handling the temporal aspects of sequence data. This configuration excels in managing intricate datasets brimming with dense spatio-temporal information. By harnessing the strengths of both CNN and LSTM, the model adeptly grasps the spatial and temporal nuances within the data, facilitating precise predictions in complex scenarios. This hybrid architecture finds extensive application in various domains. In time series prediction, it adeptly forecasts power loads and stock prices. Within natural language processing, it effectively performs sentiment analysis and text classification. In computer vision, it shines in tasks such as video classification and action recognition. The synergy of CNN and LSTM structures enables the comprehensive capture and efficient utilization of spatio-temporal features, thereby enhancing the model's predictive capabilities and broadening its application scope. By integrating these technologies, the model not only captures the intricate spatial and temporal patterns but also leverages them for superior predictive performance. This dual-layered approach ensures that the model remains robust across diverse applications, adeptly navigating the complexities inherent in varied datasets. The fusion of CNN's spatial acuity with LSTM's temporal depth creates a versatile and potent tool for addressing multifaceted prediction tasks, ultimately driving advancements in fields ranging from energy management to financial forecasting.

Before training DL models, data preprocessing and feature engineering are essential steps. Initially, the data is cleaned to remove outliers and missing values. Subsequently, feature engineering is carried out to extract the most influential features for voltage support prediction. Common characteristics include voltage, current, frequency, load level, and weather conditions (influence on solar and wind output) of the grid. Feature importance is assessed using correlation analysis and machine learning methods to determine which features are most useful for model predictions. Meanwhile, to reduce overfitting and improve the model's generalization ability, dimensionality reduction techniques such as principal component analysis are adopted in this study to simplify the model input and retain the most critical information. Utilizing selected features and architectures, the model is trained on a large amount of historical grid data. Cross-validation and regularization techniques, such as L2 regularization, are employed to optimize model parameters and prevent overfitting. Moreover, appropriate loss functions and optimization algorithms are used to ensure the stability and efficiency of model training. Lastly, the model's F1 score, accuracy, precision, and recall are evaluated on the verification set to verify its validity. Furthermore, the model is tested in real-time through actual power grid operation data to ensure its performance in practical applications. Combined with the above content, this study aims to offer a more efficient and accurate intelligent control strategy for grid-connected voltage support, to ensure the stable operation and efficient management of the power system.

Optimization and control strategy development

To realize grid-connected voltage support more effectively, this study designs a set of voltage support optimization strategies by using DL and integrates it with an intelligent control system to adjust and optimize system parameters and achieve the best performance. Despite the formidable data processing and predictive capabilities of DL models, several challenges and limitations persist. Grid data can often be incomplete or missing due to sensor failures, significantly affecting the training and performance of these models. Additionally, sensor data might be plagued with noise or false readings, necessitating meticulous pre-processing to ensure model accuracy. The computational resource demands of DL models are substantial, especially with intricate architectures, potentially leading to decision delays. However, the power grid control system mandates real-time responses to maintain system stability, and in real-time or edge environments, the available computing power might fall short of supporting complex models. Moreover, DL models are frequently perceived as "black boxes" with opaque decision-making processes. This lack of transparency poses particular challenges in power grid control, where it is crucial for system operators and engineers to comprehend the model's decision logic. High transparency and interpretability of control decisions are essential to quickly diagnose and address issues under abnormal conditions. The need for clarity in decision-making processes underscores the importance of developing methods to elucidate the inner workings of these models in power grid applications.

The voltage support optimization strategy designed by DL is outlined in Table 2:

The trained DL model is embedded into the power system's control frame. This step requires that the output of the model can directly interact with the control system of the grid. For example, the model's prediction results can directly trigger the adjustment action of capacitors, voltage regulators, and other devices. A real-time feedback system is constructed that allows control strategies to be adjusted based on actual grid conditions and model predictions. This dynamic adjustment mechanism ensures that voltage support measures can quickly respond to changes in the state of the grid. In the integration process, the safety and reliability of the system can be ensured. The control system is rigorously tested, encompassing its ability to cope with extreme situations and potential failures. Ultimately, the parameters are adjusted and optimized to obtain the best performance, as listed in Table 3:

The optimized system architecture is displayed in Fig. 2:

The layered architecture depicted in Fig. 2 illustrates a multifaceted approach to power system management, beginning with the data collection and preprocessing layer. Here, a diverse array of relevant power system data is gathered from multiple sources, including sensor readings and historical operation logs. This data undergoes a rigorous preprocessing phase involving cleaning, normalization, and feature extraction, ensuring data quality and consistency. Subsequently, the DL model training and optimization layer utilizes the refined data to train the DL models. This phase is crucial for accurately capturing the intricate characteristics and patterns within the power system. Model performance and adaptability are further enhanced through meticulous parameter tuning and

Table 2 Optimization strategy

Strategy	Application
Goal determination	Within wind power stations, voltage fluctuations frequently arise due to the inherent variability in output power caused by shifts in wind speed. By predicting the effects of these wind speed changes on voltage with high accuracy, the settings for reactive power compensation equipment can be adjusted in real time to maintain grid voltage stability. Similarly, in photovoltaic power stations, rapid voltage changes often result from fluctuations in sunshine conditions, such as cloud cover. Predicting these sunshine trends allows for preemptive adjustments in the energy storage system's charging and discharging strategy, mitigating voltage fluctuations
Model implementing	In the power grids of large cities, the spatial distribution of load demand exhibits distinct characteristics. The CNN layer excels at identifying the voltage characteristics across different areas, while the LSTM layer forecasts load demand trends within these areas, thereby optimizing the power dispatching plan. In regional power grids, the combined use of CNN and LSTM models enables real-time monitoring and prediction of grid states, offering critical decision support for grid operators to ensure efficient and safe power system operations
Feature engineering	By analyzing weather forecast data (such as temperature and wind speed) alongside historical load data, feature engineering identifies the factors with the most significant impact on voltage fluctuations. This optimization of voltage control strategies enhances the power grid's reliability. In regions with pronounced seasonal load changes, feature engineering pinpoints key influencing factors, enabling more accurate load change predictions, formulation of proactive load management strategies, and prevention of voltage instability

Table 3 Adjustment strategies

Dimension	Application
Parameter adjustment	In wind power stations where wind speed varies dramatically, real-time adjustments to reactive power output stabilize grid voltage, mitigating the impact of wind fluctuations on the power grid. Meanwhile, urban distribution networks dynamically adjust capacitor states based on real-time load data, optimizing power factors and enhancing transmission efficiency
Performance evaluation	Large regional power grids employ performance evaluation indicators to monitor grid stability, ensuring rapid response and voltage stability during peak load periods. In industrial parks, performance evaluations uncover potential energy-saving opportunities, leading to optimized operation strategies for electrical equipment and reduced overall energy consumption
Iterative optimization	Smart grids continuously refine control algorithms and parameters through iterative optimization, enhancing the grid's adaptability to seasonal changes and fluctuating loads. Regional dispatching centers leverage iterative optimization strategies to improve dispatch algorithm accuracy, reducing power loss and allocation errors

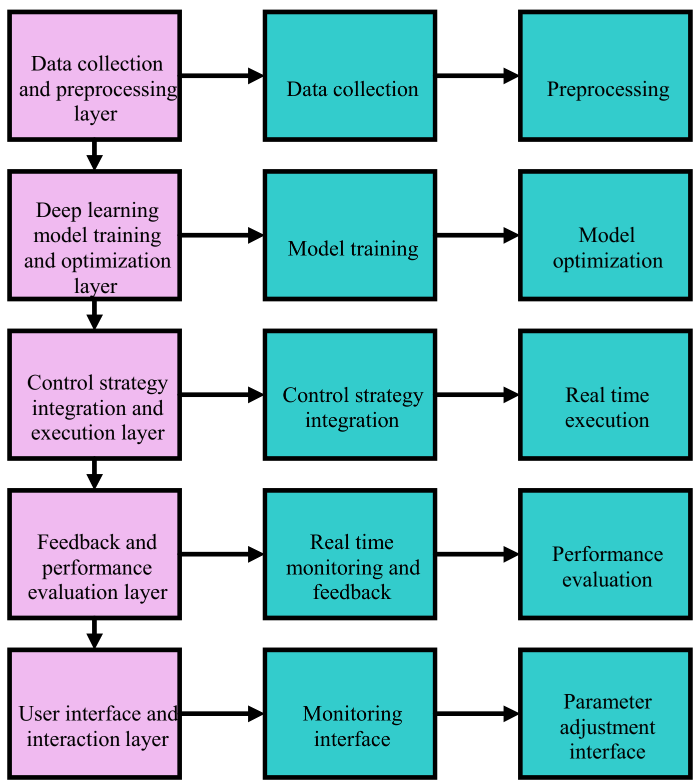

Fig. 2 Optimized system architecture

structural adjustments. Moving forward, the control strategy integration and execution layer melds the optimized DL models with traditional control strategies, culminating in a comprehensive control strategy. This hybrid approach is implemented within the actual power system, facilitating real-time responsiveness and adjustments. The feedback and performance evaluation layer then takes center stage, continuously monitoring the power system's operational status. Feedback data is meticulously analyzed to assess the effectiveness of the model and control strategy across various performance indicators, including response time, stability, and energy consumption. Finally, the user interface and interaction layer offers a user-friendly platform for operators, providing intuitive visualizations of the system's status and performance metrics. Operators can dynamically adjust model parameters and control strategies based on real-time monitoring and evaluation outcomes, ensuring the system remains adaptive to evolving requirements.

Data preprocessing begins with normalization, applying Eq. (1):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

In Eq. (1), x' represents the normalized data, x denotes the original data, and x_{max} and x_{min} are the maximum and minimum values of the dataset, respectively. This normalized data serves as the foundation for model training. In the training phase, the model's performance is evaluated using the mean squared error (MSE) as the loss function, defined by Eq. (2):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{2}$$

In Eq. (2), n signifies the number of samples, y_i denotes the true value, and $\widehat{y}_i$ refers to the predicted value. To optimize the model, the gradient descent algorithm is employed, updating model parameters using Eq. (3):

$$\theta_{t+1} = \theta_t - \eta p_\theta J(\theta_t) \tag{3}$$

Here, θ_t and θ_{t+1} denote the model parameters, $p_\theta J(\theta_t)$ represents the gradient of the loss function with respect to the model parameters, and η stands for the learning rate.

Through this system architecture, the DL-based grid-connected voltage support optimization and intelligent control strategy can achieve voltage stability more efficiently and accurately, while furnishing enough flexibility and scalability to adapt to the changing and evolving needs of the power system.

Comparative analysis of model performance and simulation experiment results

This section embarks on an intricate performance analysis juxtaposed with simulation results will be meticulously examined. Initially, the evaluation hinges on comparing the optimization model's performance metrics—accuracy, precision, recall, and F1 score—against a benchmark model. Delving deeper, a suite of simulation experiments contrasts the models' efficacy across dimensions such as response time, stability, robustness, and energy consumption. These evaluations aim to provide a holistic assessment of the optimization model's practical application, substantiating its value and feasibility within real-world power systems. Through these rigorous analyses, the section endeavors to underscore the model's operational merit and applicability.

Analysis of performance comparison results

This study draws upon an open dataset curated by the United States. Energy Information Administration (EIA), renowned for its extensive and freely accessible data, available through Excel plugins and various analytical tools. This dataset encompasses a rich collection of time series data related to electricity, forming a robust foundation for experimental analysis. The dataset includes hourly operational metrics for balancing authority areas, detailing power supply and demand on an hourly basis. These metrics reflect the dynamic load conditions and supply scenarios of the power system across different temporal intervals. Analysis of these data provides valuable insights into load characteristics and voltage fluctuations, facilitating the optimization of model design and validation through practical, real-time data. Additionally, the dataset features monthly generation statistics, categorized by fuel type, sector, and state. It offers detailed insights into monthly power generation across various fuel sources—such as coal, natural gas, and renewables—as well as different sectors like commercial, industrial, and residential, with state-by-state breakdowns. This granularity aids in evaluating the contributions of diverse fuel types and sectors to power production and assessing the influence of geographic variables on electricity supply. Such comprehensive data enable a thorough assessment of grid voltage support technologies' performance under varying conditions.

The experimental environment is shown in Table 4:

To ensure the accuracy of the experiment, the parameters of the model are set uniformly. The learning rate, regularization coefficient, and batch size are set to 0.01, 0.001, and 64; the number of iterations and hidden layer elements are 50 and 100; the activation function is ReLU, and the optimizer is Adam. The comparison models are Graph Neural Network (GNN) and Attention Mechanism Model (AMM). Power systems naturally form a graph structure, consisting of nodes (such as power stations and substations) and edges (such as power lines). GNN can directly process this graph-structured data and is suitable for analyzing spatial dependencies and topological relationships in power grids, providing in-depth insights into voltage support technologies. Grid-connected voltage support technology involves the prediction of voltage changes, which is a typical time series problem. Models based on attention mechanisms, such as Transformer, can efficiently process time series data and improve prediction accuracy by focusing on key parts of historical data. Both GNN and AMM have been hot topics in the DL field in recent years, and they have shown superior performance in several areas. Choosing these two models can help evaluate the potential and effectiveness of grid-connected voltage support technology when adopting the latest DL technology. The indicators for experimental comparison comprise accuracy, precision, F1 score, and recall. The accuracy rate offers a swift snapshot of a model's overall performance, reflecting the proportion of correct predictions made. As a widely adopted metric, accuracy is

Table 4 The experimental environment

Equipment type	Parameter configuration
Processor	Inter(R) Xeon(R) CPU E5-2620 v4 @ 2.10 GHz
Graphics card	NVIDIA Titan Xp 12 GB
Memory	128 GB
Operating system	Ubuntu 16.04 LTS
Programming language	Python 3.6

straightforward and intuitive, facilitating easy comprehension and interpretation. This measure indicates the model's effectiveness in minimizing false alarms, which is crucial in specific scenarios like fault detection. In power systems, the emphasis lies more on precisely identifying voltage points requiring support (positive samples) rather than those that do not (negative samples), underscoring accuracy as a pivotal metric. Recall quantifies the proportion of actual positive samples correctly identified by the model. A low false negative rate is essential in scenarios such as fault prediction and power grid maintenance, where high recall ensures that more instances needing voltage support are detected, thereby bolstering system stability. The F1 score, a harmonic mean of precision and recall, serves to balance these two metrics and is particularly valuable in contexts where there is class imbalance. In the realm of power system optimization, relying solely on precision or recall may not provide a complete picture of model performance. The F1 score integrates both aspects, offering a more comprehensive evaluation of the model's effectiveness and ensuring a nuanced assessment of its overall capabilities.

The performance comparison results are depicted in Fig. 3:

Figure 3 denotes that the optimized model has an accuracy of 0.870, 0.880, and 0.890 when the data volume is 1000, 2000, and 3000, respectively. This series of results reveals that with the increase in data volume, the optimized model accuracy is also steadily improved, showing good learning ability and robustness. This performance improvement is due to the optimized model's innovation in algorithm design, allowing it to more efficiently handle complex problems in grid-connected voltage support. The GNN demonstrates an accuracy of 0.852 with 1000 data volumes, which increases to 0.865 with 2000 data volumes. These results suggest that GNN exhibits superior performance in handling grid graph structure data, albeit with a growth rate slightly lower than that of the optimized model. Conversely, the AMM achieves an accuracy of 0.840 with 1000 data volumes, indicating a disadvantage particularly evident in smaller datasets. Regarding precision, the optimized model's precision is 0.862, 0.875, and 0.888 when the data volume is 1000, 2000, and 3000, respectively. This indicates a consistent enhancement in precision as the data volume increases for the optimized model, demonstrating commendable learning capability and robustness. This performance improvement is attributed to the innovative algorithm design of the optimized model, enabling it to effectively tackle intricate challenges in grid-connected voltage support. In contrast, the GNN demonstrates a precision of 0.843 at 1000 data volumes, while the AMM exhibits a precision of 0.831 under identical data volume conditions. These data illustrate that on smaller datasets, GNN and AMM perform slightly worse than the optimized model, especially the AMM. This may indicate that although GNN and AMM have their unique advantages when dealing with specific problems, they are slightly less accurate in capturing and optimizing grid-connected voltage support in the scenario of this study. In terms of recall, the optimized model achieves a recall of 0.855, 0.869, and 0.878 for data volumes of 1000, 2000, and 3000, respectively, demonstrating a steady increase in recall with increasing data volume. This indicates that the optimized model can more comprehensively identify relevant data when facing complicated grid-connected voltage support issues, thereby effectively supporting the stable operation of the power system. In contrast, the recall growth of GNN and AMM is slower across diverse data volumes, especially performing slightly inferior to the optimized model on small datasets. This

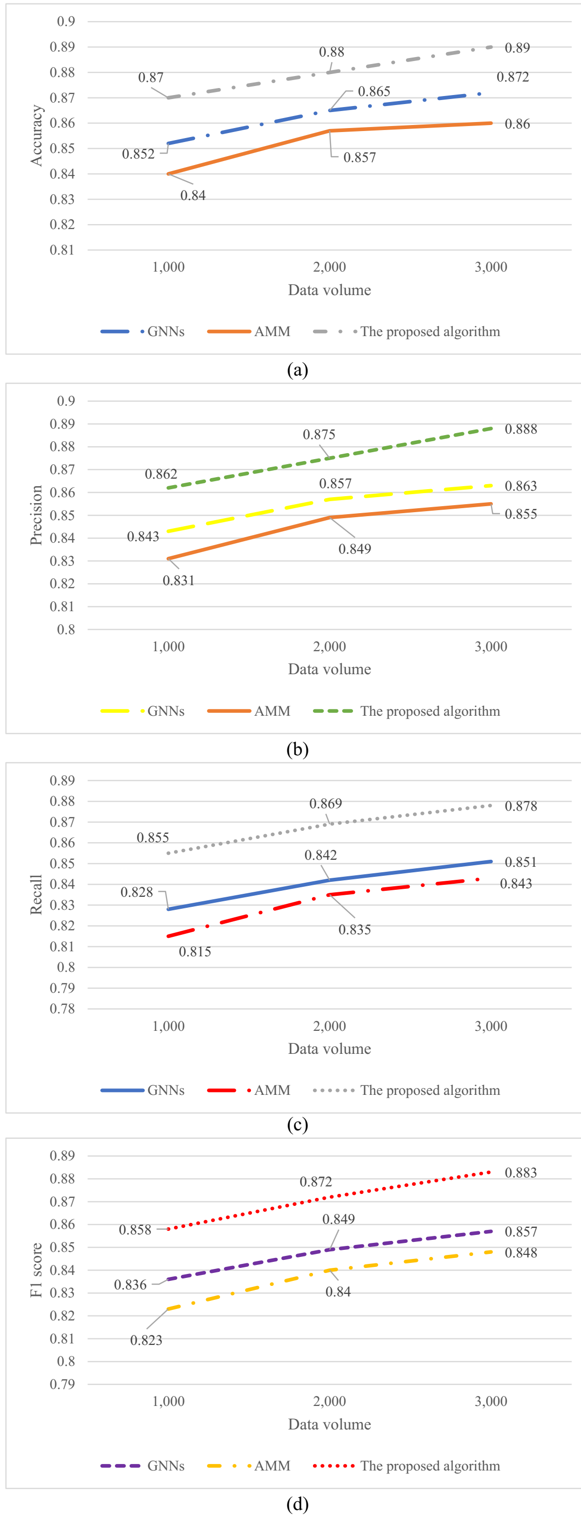

Fig. 3 Performance comparison results **a** Accuracy; **b** Precision; **c** Recall; **d** F1 score

reflects the advantage of the optimized model in algorithm design, resulting in better performance in capturing key information and reducing the omission of important data. Considering the F1 score, the optimized model attains F1 scores of 0.858, 0.872, and 0.883 for data volumes of 1000, 2000, and 3000, respectively. These results underscore that as the data volume increases, the F1 score of the optimized model also steadily improves, demonstrating good learning ability and robustness. The F1 score is the harmonic mean of precision and recall, which comprehensively evaluates the model's performance in accurately identifying and fully capturing target categories. The optimized model's high F1 score suggests its ability to balance these two aspects, making it particularly suitable for handling complex issues in grid-connected voltage support. Compared to other models, GNN reaches an F1 score of 0.836 when the data volume is 1000. This suggests that GNN also performs well in handling grid graph structure data, but slightly lags behind the optimized model in balancing precision and recall. The AMM attains an F1 score of 0.823 at the same data volume, exhibiting a disadvantage on smaller datasets, possibly because its model structure struggles to fully exploit its potential with small sample data.

Comparative results of simulation experiments

Simulation experiments selected are conducted to further verify the optimized model's effectiveness, and the comparative indicators include stability, response time, energy consumption, and robustness. The experimental training dataset spans historical records from the past 5 years, with the validation and test sets comprised of data from the most recent year. Stability, a crucial attribute, signifies a system's capacity to uphold consistent performance and reliable operation over extended periods. High stability ensures that the optimization model preserves its predictive accuracy and control capabilities across long-term and expansive applications, thereby safeguarding the continuity and dependability of the power system. Response time measures the duration required for a system to generate an output following input reception. An optimization model capable of swift data processing and decision-making aligns more effectively with the real-time control demands of the power system, thereby enhancing the overall system performance. Energy consumption represents the aggregate electrical energy used for system operations. In the context of power systems, minimizing energy consumption not only lowers operational costs but also supports energy conservation and emission reduction goals, aligning with sustainable development objectives. Robustness refers to a system's ability to sustain performance and stability amid various uncertainties and disturbances. A robust model exhibits superior adaptability, maintaining high performance across diverse scenarios and conditions, thereby bolstering the system's reliability and practical applicability.

The experimental results are suggested in Fig. 4:

Figure 4 depicts that in the stability comparison, the optimized model exhibits a noise resistance capability of 82.0%, which is higher than GNN's 78.2% and AMM's 76.5%. This indicates that the optimized model can more effectively maintain the accuracy and stability of predictions in the presence of noise and uncertainty in the data. It is crucial for grid-connected voltage support technology as real-world grid data often comes with noise and fluctuations. Regarding training convergence speed, the optimized

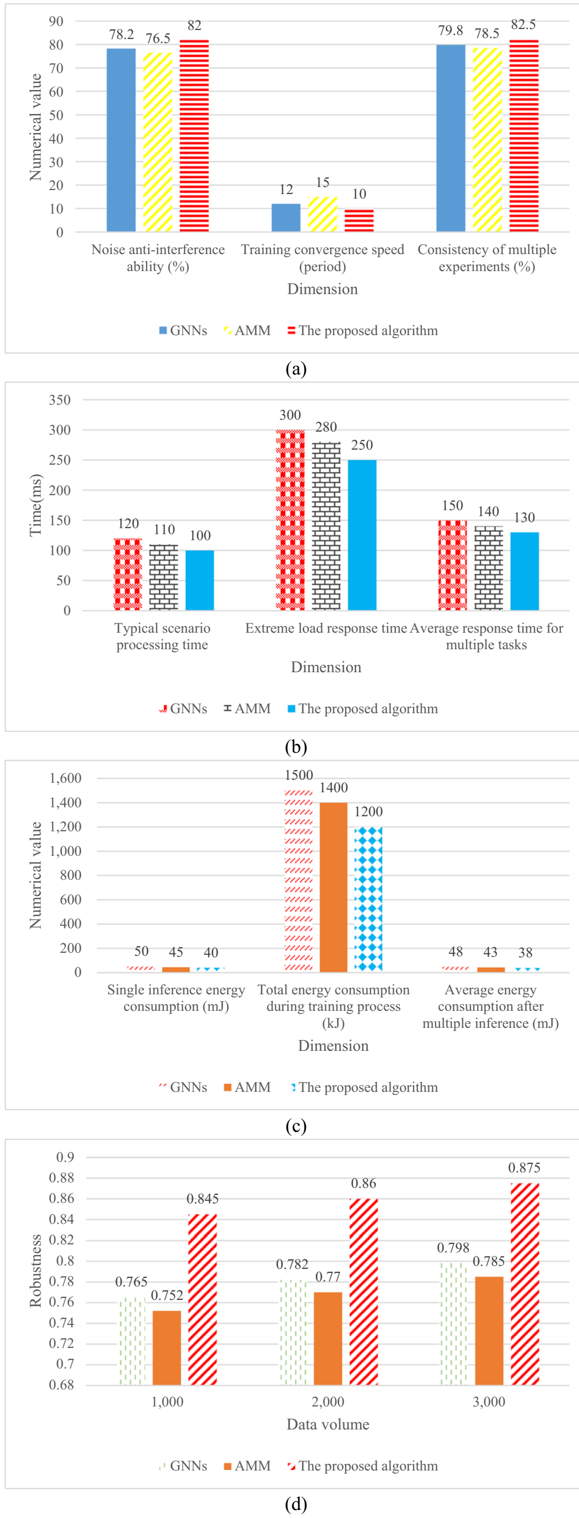

Fig. 4 Analysis of simulation experiment results **a** Stability; **b**: Response time; **c** Energy consumption; **d** Robustness

model converges on average in only 10 epochs, while GNN and AMM require 12 and 15 epochs. This rapid convergence suggests that the optimized model is more efficient in learning and adapting to new data, achieving stable performance in a shorter time, which is essential for responding quickly to grid changes and real-time optimization of grid-connected voltage support strategies. Lastly, in terms of consistency across multiple experiments, the optimized model demonstrates a consistency of 82.5%, while GNN's consistency is 79.8%. This reveals that the optimized model can maintain high performance stability across diverse datasets and multiple experiments, ensuring its reliability and predictive accuracy in practical applications. In comparison of response time, under typical scenarios, the optimized model and GNN exhibit a response time of 100 and 120 ms. This discrepancy underscores the optimized model's ability to swiftly address common voltage support scenarios, a crucial aspect for ensuring the real-time performance and stability of power systems. In scenarios necessitating extreme load responses, the optimized model achieves a response time of 250 ms, notably enhancing efficiency compared to GNN's 300 ms. This rapid responsiveness empowers the proposed model to sustain stable performance when confronted with sudden large-scale data or high-pressure situations, thereby mitigating potential risks. In terms of multitask average response time, the optimized model's and GNN's time are 130 and 150 ms. This signifies that the optimized model can maintain high efficiency even when handling multiple tasks simultaneously, which is particularly crucial for scenarios in power systems that require multiple operations and calculations simultaneously.

In the comparison of energy consumption, regarding single-inference energy consumption, the optimized model's consumption is 40 millijoules, lower than GNN's 50 millijoules. This suggests that the proposed model is more efficient in analyzing individual data points, resulting in more energy-efficient utilization and helping to reduce overall operating costs. Considering total energy consumption during training, the optimized model's consumption is 1200 kilojoules, compared to AMM's 1400 kilojoules, exhibiting higher energy efficiency of the proposed model. This is particularly important as it indicates that the optimized model has higher overall energy efficiency when learning and adapting to new data, aiding in maintaining lower energy consumption in large-scale data processing. In the aspect of average energy consumption for multiple inferences, the optimized model's consumption is 38 millijoules, remarkably lower than GNN's 48 millijoules. This reflects the optimized model's ability to maintain lower energy consumption levels during long-term operation, which is especially crucial for grid-connected voltage support systems requiring continuous long-term operation. The optimization model demonstrates markedly lower energy consumption during both inference and training phases, indicating that its deployment on a large scale could substantially curtail power usage. This reduction in energy demand not only alleviates operational expenses for data centers and servers but also translates into significant savings for power companies, thereby enhancing overall economic efficiency. By minimizing energy consumption, the optimization model aligns with sustainable development objectives and diminishes the carbon footprint, a vital consideration for entities striving to mitigate their environmental impact and embrace greener operational practices. Enhanced energy efficiency enables the system to operate longer within the same energy budget or to sustain equivalent performance levels with reduced energy expenditure. Such efficiency is indispensable for grid voltage support systems that require uninterrupted, long-term operation, ensuring consistent and stable support throughout their operational lifespan.

In the comparison of robustness, the optimized model's robustness at data volumes of 1000, 2000, and 3000 are 0.845, 0.860, and 0.875, respectively. This demonstrates that the proposed model can effectively handle data of various scales and maintain high performance stability when facing various challenges and changes. Particularly, as the data volume rises, the proposed model's robustness also shows a gradually increasing trend, indicating its design has good scalability and adaptability. In contrast, GNN's robustness at a data volume of 1000 is 0.765, while AMM's is 0.752. These data suggest that although GNN and AMM also have some robustness, their performance stability is slightly inferior to the optimized model when dealing with smaller datasets. This gap further widens with increasing data volume.

Conclusion

In this study, the optimized model has higher precision, faster response time, lower energy consumption, and better robustness when dealing with grid-connected voltage support problems. These characteristics enable it to effectively deal with various intricate scenarios and challenges in the power system and facilitate the stability and efficiency of the power grid. These findings highlight the optimized model's potential application value in new energy grid-connected voltage support and provide strong technical support for the stable operation of power systems.

The optimization model exhibits substantial applicability across a range of real-world scenarios. In the realm of wind power stations and solar photovoltaic installations, this model plays a crucial role in real-time monitoring and regulation of grid voltage, thus preserving grid stability amidst weather fluctuations or variable loads. Its potential extends to urban smart grid management, where it can optimize power dispatch and enhance efficiency through sophisticated data processing and forecasting techniques. Furthermore, the model holds promise for microgrid management, where it could offer precise control over voltage and frequency in distributed energy systems. Despite notable advancements, the study reveals areas ripe for further exploration. To bolster the model's generalization capabilities, future endeavors should involve validation across a more diverse and representative dataset. This would ensure efficacy across varied power grid environments, encompassing different geographic regions, seasonal variations, and load conditions. Moreover, while the model demonstrates commendable response times and energy efficiency, the dynamic nature of real-world grid operations poses additional challenges. Enhancements in real-time processing and scalability are crucial, potentially involving the development of more efficient algorithms and the adoption of distributed computing strategies. Lastly, the model's performance under various disturbances and anomalies in complex power systems requires attention. To maintain stability in extreme conditions, research should focus on augmenting the model's robustness. Implementing adversarial training techniques or robust optimization methods could fortify the model's resilience against anomalous data and disturbances, ensuring reliable operation under adverse scenarios.

Author contributions
Leiyan Lv: draft manuscript preparation; analysis and interpretation of results; Xuan Fang: data collection; analysis and interpretation of results; Si Zhang: data collection; Xiang Ma: data collection; Yong Liu: writing—review & editing, funding acquisition; All authors reviewed the results and approved the final version of the manuscript.

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Data availability
All data generated or analysed during this study are included in this article.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

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The authors declare that they have no competing interests.

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References

Abualigah L, Zitar RA, Almotairi KH et al (2022) Wind, solar, and photovoltaic renewable energy systems with and without energy storage optimization: a survey of advanced machine learning and deep learning techniques. Energies 15(2):578

Ahmad T, Madonski R, Zhang D et al (2022) Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm. Renew Sustain Energy Rev 160(22):112128

Alam MM, Rahman MH, Ahmed MF et al (2022) Deep learning based optimal energy management for photovoltaic and battery energy storage integrated home micro-grid system. Sci Rep 12(1):15133

Albogamy FR, Paracha MYI, Hafeez G et al (2022) Real-time scheduling for optimal energy optimization in smart grid integrated with renewable energy sources. IEEE Access 10(2):35498–35520

Al-Ja'Afreh MAA, Amjad B, Rowe K et al (2023) Optimal planning and forecasting of active distribution networks using a multi-stage deep learning based technique. Energy Rep 10(11):686–705

Alrifaey M, Lim WH, Ang CK et al (2022) Hybrid deep learning model for fault detection and classification of grid-connected photovoltaic system. IEEE Access 10(1):13852–13869

Al-Saadi M, Al-Greer M, Short M (2023) Reinforcement learning-based intelligent control strategies for optimal power management in advanced power distribution systems: a survey. Energies 16(4):1608

Alturas AM, Elbkosh AO, Imrayed O (2020) Stability analysis of DC-DC buck converters. Acta Electron Malays 4(1):01–06

Amir M, Zaheeruddin, Haque A et al (2024) Intelligent energy management scheme-based coordinated control for reducing peak load in grid-connected photovoltaic-powered electric vehicle charging stations. IET Gener Transm Distrib 18(6):1205–1222

Ashok Babu P, Mazher Iqbal JL, Siva Priyanka S et al (2024) Power control and optimization for power loss reduction using deep learning in microgrid systems. Electr Power Compon Syst 52(2):219–232

Behara RK, Saha AK (2022) artificial intelligence control system applied in smart grid integrated doubly fed induction generator-based wind turbine: a review. Energies 15(17):6488

Dehnavi A, Nithiyananthan K, Arjmandi M et al (2023) Application of machine learning and artificial intelligence in design, optimization, and control of power electronics converters for renewable energy-based technologies. Power Electron Convert Control Renew Energy Appl 5(3):283–300

Fellner D, Strasser TI, Kastner W (2022) Applying deep learning-based concepts for the detection of device misconfigurations in power systems. Sustain Energy Grids Netw 32(5):100851

Hafeez A, Alammari R, Iqbal A (2023) Utilization of EV charging station in demand side management using deep learning method. IEEE Access 11(5):8747–8760

Hossain R, Gautam M, Thapa J et al (2023) Deep reinforcement learning assisted co-optimization of Volt-VAR grid service in distribution networks. Sustain Energy, Grids Netw 35(17):101086

Hu D, Ye Z, Gao Y et al (2022) Multi-agent deep reinforcement learning for voltage control with coordinated active and reactive power optimization. IEEE Trans Smart Grid 13(6):4873–4886

Li Q, Cui Z, Cai Y et al (2023) Renewable-based microgrids' energy management using smart deep learning techniques: realistic digital twin case. Sol Energy 250(33):128–138

Liu Z, Gao Y, Liu B (2022) An artificial intelligence-based electric multiple units using a smart power grid system. Energy Rep 8(1):13376–13388

Mostafa N, Ramadan HSM, Elfarouk O (2022) Renewable energy management in smart grids by using big data analytics and machine learning. Mach Learn Appl 9(3):100363
Rehman A, Ali M, Iqbal S et al (2022) Artificial intelligence-based control and coordination of multiple PV inverters for reactive power/voltage control of power distribution networks. Energies 15(17):6297
Shekhar H, Bhushan Mahato C, Suman SK et al (2023) Demand side control for energy saving in renewable energy resources using deep learning optimization. Electr Power Compon Syst 51(19):2397–2413
Shirzadi N, Nasiri F, El-Bayeh C et al (2022) Optimal dispatching of renewable energy-based urban microgrids using a deep learning approach for electrical load and wind power forecasting. Int J Energy Res 46(3):3173–3188
Slama SB, Mahmoud M (2023) A deep learning model for intelligent home energy management system using renewable energy. Eng Appl Artif Intell 123(17):106388
Wang H, Huang Z, Zhang X et al (2022a) Intelligent power grid monitoring and management strategy using 3D model visual computation with deep learning. Energy Rep 8(2):3636–3648
Wang Y, Mao M, Chang L et al (2022b) Intelligent voltage control method in active distribution networks based on averaged weighted double deep Q-network algorithm. J Modern Power Syst Clean Energy 11(1):132–143
Wu R, Liu S (2022) Deep learning based muti-objective reactive power optimization of distribution network with PV and EVs. Sensors 22(12):4321
Yin L, He X (2023) Artificial emotional deep Q learning for real-time smart voltage control of cyber-physical social power systems. Energy 27(3):127232
Zheng S, Shahzad M, Asif HM et al (2023) Advanced optimizer for maximum power point tracking of photovoltaic systems in smart grid: a roadmap towards clean energy technologies. Renew Energy 206(22):1326–1335

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