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Stability Analysis and Optimization of Power System in New Energy Grid Connection Control

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In response to the challenges that the volatility and uncertainty of new energy pose to the stability of the power system, this study applied the Long Short-Term Memory (LSTM) algorithm to establish a prediction model for new energy generation. By combining historical data and meteorological information, the stability of the system was analyzed in depth. The LSTM model adopted a multi-layer stacked structure, with the input layer receiving multidimensional features from the SDWPF (Spatial Dynamic Wind Power Forecasting) dataset and using 128 hidden units to capture dynamic features in the time series. This study combined Adam optimizer to improve training efficiency and introduced the Dropout mechanism to reduce the risk of overfitting. Based on the prediction results of LSTM, this study designed dynamic scheduling and energy storage system optimization strategies to improve the stability of the power system. The dynamic dispatch strategy adjusted the power generation of the generator sets in real-time to match the load demand, and the energy storage system smooths wind power fluctuations by means of charge and discharge management, thereby maintaining the stability of the grid frequency and voltage. Experimental data show that the LSTM model performs well in terms of prediction, with a mean square error as low as 0.0021 and a mean absolute error of 0.037. When the wind speed fluctuates at low speeds, the dispatch strategy stabilizes within 5 seconds; when the fluctuation is high, the adjustment time and error increase. The energy storage system responds well to low fluctuations; but although it responds quickly to high fluctuations, it has reduced stability, highlighting the advantages and disadvantages of each strategy under different conditions.

Keywords: new energy stability, LSTM algorithm, power system dispatch, energy storage system optimization, load management

1. INTRODUCTION

Given the global pursuit of sustainable development, renewable energy [1–2] has become a core component of energy strategies of various countries. Renewable energy such as wind and solar energy has become increasingly prominent in the power supply system due to its rich resources and environmental friendliness [3–4]. According to the International Renewable Energy Organization, by 2030, the total installed capacity of global renewable energy power generation is expected to reach about 8,000 GW, of which the contribution of wind and solar energy will continue to grow. However, the instability and unpredictability of renewable energy have a significant impact on the stability of the power system [5]. Standardizing the access of renewable energy to the power grid and ensuring stable power supply have become important issues that need to be addressed as a matter of urgency in the field of power engineering.

The stable operation of traditional power grids depends on the precise balance between power generation and power consumption, and load forecasting and power generation planning play a key role in this process [6–7]. The connection of new energy to the grid makes the fluctuation of power

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generation more significantly affected by natural conditions, breaking the original balance of power supply and demand, thereby threatening the stability of the power system. In the face of this change, traditional control methods have become incapable of coping with it. Existing stability analysis tools cannot deal effectively with the nonlinear and dynamic characteristics of new energy, resulting in reduced prediction accuracy and lack of real-time dynamic prediction capabilities.

To cope with the above challenges, data-driven methods, especially machine learning [8–9] and deep learning [10–11], have begun to receive widespread attention. Among them, the LSTM network [12–13], with its powerful memory and nonlinear data processing capabilities, has shown great potential in solving power system dynamic prediction problems. This study uses the LSTM algorithm to address the shortcomings of traditional power system stability analysis when dealing with nonlinear and dynamic characteristics, as well as its lack of real-time prediction capabilities. By building a new energy power generation prediction model based on LSTM and integrating historical power generation data and meteorological data, the study attempts to improve the accuracy and timeliness of prediction. Based on the prediction results, the impact of new energy on the stability of the power system can be analyzed in depth, corresponding stability evaluation indicators can be proposed, and the system's performance under the fluctuation conditions of new energy can be evaluated. In addition, this study also designs a power system dispatching scheme based on the prediction results and formulates a dynamic dispatching and load adjustment strategy to improve the stability and security of the power system under the condition of high proportion of new energy access. This article provides theoretical support for the efficient use of new energy, and contributes to promoting the transformation and upgrading of the power system and building a stable, efficient and sustainable power grid.

2. RELATED WORK

Power system stability analysis is a fundamental topic in power engineering, encompassing small-disturbance response, transient stability, and dynamic stability. Studies have analyzed system responses to small disturbances using voltage partitioning, verifying the effectiveness of related mathematical models and control strategies [14]. Dual-mode grid-connected control schemes, which switch to asynchronous operation at low speeds, have been proposed to enhance the power generation performance of doubly fed wind turbines. Simulations show that these schemes can reduce rotor current distortion by 55% and improve power control accuracy [15]. Voltage synchronous generator models have also been developed to support stability research; however, simplified assumptions in these models limit their ability to fully capture the complex dynamics of actual power systems [16].

The growing integration of renewable energy introduces new challenges for system stability. The impact of photovoltaic (PV) power station grid connections on relay protection has been studied, with proposed improvements addressing access location and capacity considerations [17]. Centralized control in thermal power plants has been analyzed for its effect on system stability, and optimization strategies have been suggested, though overall stability impacts after large-scale renewable integration are often not fully considered [18]. Furthermore, the influence of renewable energy integration on power quality has been examined, along with corresponding mitigation strategies. Nevertheless, these approaches generally lack real-time predictive capability and struggle to adapt to the highly fluctuating nature of renewable generation [19].

Data-driven methods provide a promising alternative for stability analysis. The application of power electronics and novel algorithm-based optimization has been explored to enhance system stability [20]. In time series forecasting, LSTM models are widely used for load prediction due to their ability to capture nonlinear and temporal dependencies. Improvements such as attention mechanisms have been shown to increase prediction accuracy [21], and further parameter optimization using techniques like the Sparrow Search Algorithm demonstrates the potential of LSTM in addressing renewable generation fluctuations [22]. Despite these advances, most research focuses on load forecasting, while applying LSTM directly to stability analysis remains an open area.

Deep learning methods have also been applied to stability control and fault prediction. Strategies combining deep learning with reinforcement learning have effectively improved voltage stability, though challenges such as limited high-quality data and model overfitting remain [23]. Hybrid architectures, including CNN-LSTM models, have shown strong performance in predicting system faults, but their adaptability in complex and dynamic environments requires further validation [24]. Moreover, transient stability assessment approaches based on combinations of support vector machines and CNNs have demonstrated superior performance compared to traditional methods, suggesting that hybrid modeling strategies may overcome the limitations of single-model approaches like LSTM [25].

In summary, research on power system stability is constantly evolving, and both traditional methods and data-driven models face challenges in the context of new energy grid integration. This study combines classic analysis and intelligent prediction models to improve the stability of the power system after the integration of new energy, providing more reliable guarantees of power supply.

3. RESEARCH METHODS

3.1 Data Collection and Preprocessing

The SDWPF dataset [26] contains detailed information on 134 wind turbines, covering the period from January 2020 to December 2021. The core content of this dataset consists of two files: sdwpf_turc_location_ elevation. csv, which records the relative position and altitude of the turbines, reflecting the layout of the wind farm. sdwpf_2001_2112_full.csv collects

Table 1 Dataset Composition.

Category	Data Feature	Data Source	Data Feature Description
Spatial Data	Turbine ID	sdwpf_turb_location _elevation.csv	Unique identifier
	Relative Position (X)		X-coordinate
	Relative Position (Y)		Y-coordinate
	Elevation		Height above sea level
Weather Data	Wind Speed (Wspd)	sdwpf_2001_2112 _full.csv	Wind speed at the turbine top
	Wind Direction (Wdir)		Angle between wind direction and turbine
	Humidity		Relative humidity
	Ambient Temperature (Etmp)		External temperature
	Internal Temperature (Itmp)		Temperature inside the turbine
Power Generation	Power Output (Power)		Record of power generation
Timestamp Information	Timestamp (Tmstamp, UTC+08:00)	Internal time series marking of the dataset	Time information for records

comprehensive weather data, including relative humidity, wind speed, wind direction, and power generation, sourced from the Global Climate Reanalysis Project of ECMWF (European Centre for Medium-Range Weather Forecasts). The timestamp information provides strong support for time series analysis. Table 1 shows the composition of the SDWPF dataset.

In the data preprocessing stage, missing and outlier values were discarded to ensure high-quality inputs required for model training. The study conducted in-depth analysis on the correlation between weather data and power generation, and extracted important features that affect prediction. Subsequently, the data was normalized using standardized methods [27–28] to meet the requirements of the LSTM model. Each feature underwent zero mean and standardization [29–30] processing, which improved the convergence speed of the model and reduced the impact of numerical differences.

To ensure that the model fully learnt and had good generalization ability, the dataset was divided into a training set, a validation set, and a testing set according to time series, with a ratio of 6:1:1. Specifically, data from January 2020 to June 2021 waas used for training to capture the temporal patterns of the system; the data from July to September 2021 was used as the validation set to optimize hyperparameters and prevent overfitting; and the data from October to December 2021 was used to test the actual performance and applicability of the model. This data partitioning method strengthens the reliability of LSTM models in dynamic environments, enabling them to be effectively applied to the stability analysis of power systems.

3.2 LSTM Model Construction

The model architecture in this study was built on a multi-layer LSTM stack, focusing on capturing the dynamic characteristics of the power system across time scales. The model extracts multi-dimensional input features from the SDWPF dataset, including wind speed, wind direction, humidity, and power generation, which map the volatility of renewable energy generation and their potential impact on the stability of the power system. Through deep processing of the LSTM hidden layer, the model is able to identify and learn the temporal correlation patterns between these features. After that, this information is passed to the fully connected layer and further converted into a predicted output of the future power system state.

In the experiment, the number of hidden units was set to 128 to ensure that the model has sufficient complexity while effectively avoiding overfitting. For the selection of optimizer, Adam optimizer [31–32] was adopted mainly because it exhibits strong adaptability and convergence when dealing with non-stationary time series data. The learning rate was set to 0.001, and after debugging, it was proven that this value can maintain stable model updates and accelerate convergence at different training stages.

During the model training process, the batch size was set to 64 to ensure training efficiency while preventing gradient instability caused by too small batches. A dropout mechanism [33–34] can be introduced to randomly discard 20% of neurons to prevent overfitting and improve the generalization ability of the model in practical applications. In order to further improve the generalization performance of the model, an early stopping mechanism was adopted. When the loss on the validation set no longer significantly decreased in consecutive rounds, the training automatically stopped to avoid performance degradation caused by a long training time.

The evaluation of the model wasbased on the MSE loss function [35–36], that can accurately measure the difference between the predicted and actual values of the model, ensuring the accuracy of the prediction. Figure 1 shows the training and validation loss curves, with the orange curve representing the training loss and the blue curve representing the validation loss. As the training progresses, the training loss gradually decreases, while the validation loss also shows a significant decrease in the initial stage.

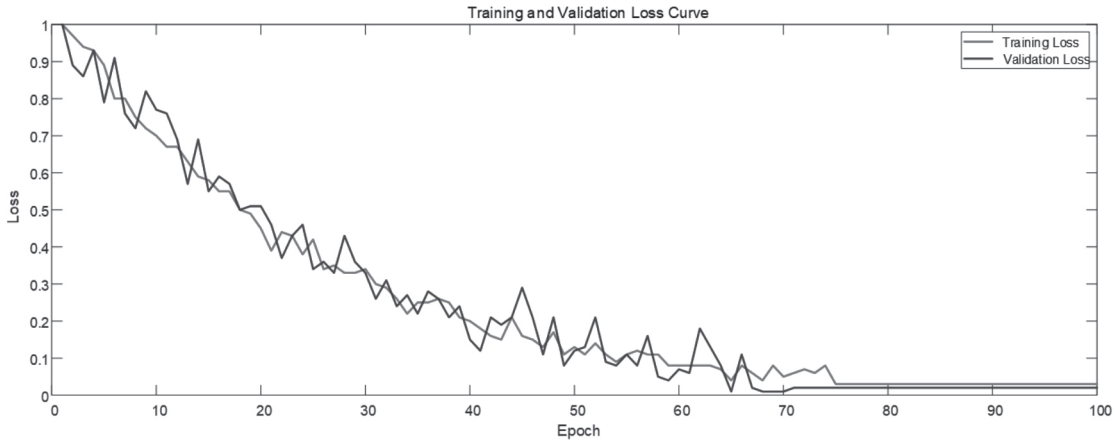

Figure 1 Loss value curve.

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

where y_i is the true value, $\widehat{y_i}$ is the predicted value, and n is the sample size.

4. STABILITY ANALYSIS OF POWER SYSTEM

4.1 System Model Establishment

The aim of this study was to build an accurate wind farm grid-connected system model, using actual operating data as input to ensure the high accuracy of the simulation. The data comprises key information such as wind speed, wind direction, air humidity and power output, which are integrated into the power network simulation environment [37–38]. The simulation environment faithfully reproduces the wind power grid-connected scenario, including core components such as traditional power generation units, transmission systems, power loads and renewable energy power generation components. To cope with the volatility of wind power, the study introduced a wind turbine control strategy based on real data to simulate the impact of wind speed changes on power generation efficiency in real time, and combined it with power generation facilities, transformers and power adjustment equipment to build a highly-integrated simulation platform.

In response to the power instability caused by the generation of renewable energy, a power balance control function was added, which can simulate the changes in system frequency and voltage when wind power fluctuates. It not only indicates the direct impact of wind power on frequency, but also considers voltage fluctuations under different loads. By integrating multiple grid-connected control strategies, such as frequency response and reactive power compensation, the model can flexibly adapt to system operation under different wind power penetration rates. All simulation results are compared and verified with past data to ensure that the model can accurately capture the dynamic characteristics of the power system and provide a reliable basis for subsequent stability assessment and optimization.

4.2 Stability Index Evaluation

To determine the impact of renewable energy grid connection on the stability of the power system, quantitative indicators need to be established. To assess the frequency stability, the degree of deviation between the actual frequency of the system and the preset standard frequency is measured. The frequency deviation (Δf) is represented by the following formula:

$$\Delta f(t) = f(t) - f_{\text{nominal}} \tag{2}$$

where $f(t)$ represents the actual frequency of the system at time t, while f_{nominal} is the set normal frequency.

Voltage stability focuses on the voltage changes of the power system after disturbance, and the evaluation of voltage stability also depends on monitoring the difference between the bus voltage ($\mathrm{V_{bus}}$) and the set voltage value (V_{nominal}). The voltage deviation (ΔV) is expressed as:

$$\Delta V(t) = V_{\text{bus}}(t) - V_{\text{nominal}} \tag{3}$$

To analyze the stability of voltage, the voltage change rate (R_{v}) is used as an indicator, and its calculation formula is:

$$R_v = \frac{\Delta V}{\Delta t} \tag{4}$$

To obtain a comprehensive understanding of the stability of the power system, the study adopted a variety of dynamic response analysis methods. Specifically, the simulation model was used to perform time domain analysis to intuitively observe the dynamic change trends of frequency and voltage. This analysis process involved the calculation of frequency response function and voltage response function, which are expressed as:

$$H(f) = \frac{F_{\text{out}}(f)}{F_{\text{in}}(f)} \tag{5}$$

$$G(f) = \frac{V_{\text{out}}(f)}{V_{\text{in}}(f)} \tag{6}$$

$F_{\text{out}}(f)$ and $F_{\text{in}}(f)$ represent the frequency domain representations of output frequency and input frequency respectively, while $V_{\text{out}}(f)$ and $V_{\text{in}}(f)$ represent the frequency domain representations of output voltage and input voltage.

5. OPTIMIZE STRATEGY DESIGN

5.1 Dynamic Scheduling Strategy Based on LSTM

The wind power prediction capability of LSTM increases the accuracy of the dynamic dispatch of the power system. Through real-time analysis of wind power trends, the dispatch system can adjust the output power of the generator sets to cope with fluctuating load demands. These forecast data become an important basis for the system to predict possible future power shortages, thereby planning power generation plans in advance. When wind power output decreases, the system can quickly start the backup generator to compensate for the power supply gap and prevent power supply shortages. However, when wind power resources are abundant, the system reduces the output of traditional units, reduces the burden on the power grid, and ensures that the frequency remains stable within a safe threshold. This dispatch strategy not only covers the power adjustment of the generator set, but also extends to the flexible management level of the load. In the face of peak loads, the system issues warnings in advance and optimizes the allocation of power generation resources; during low load periods, intelligent regulation is used to reduce the energy consumption of part-load equipment and maintain a balance between supply and demand. This intelligent adaptive scheduling mechanism significantly improves the response speed and stability of the system, and effectively reduces the risk of frequency fluctuations. The control logic behind it can be summarized by the following formula:

$$P_{\text{load}}(t) = P_{\text{wind}}(t) + P_{\text{thermal}}(t) \tag{7}$$

where $P_{\text{load}}(t)$ represents load demand, $P_{\text{wind}}(t)$ is the predicted wind power generation, and $P_{\text{thermal}}(t)$ is the output power of conventional generators. By predicting future wind power trends, the system adjusts $P_{\text{thermal}}(t)$ to ensure that load demand is met.

5.2 Energy Storage System Optimization

In regard to accessing renewable energy in the grid, the energy storage system can adjust the balance of power supply and demand. Through intelligent management, the energy storage system can store excess power during the low power demand period and release it during the peak period or when renewable energy generation is insufficient, thereby alleviating the power fluctuations caused by the grid connection to renewable energy. With its powerful time series analysis ability, the LSTM model accurately predicts the power generation trend of renewable energy such as wind power, provides forecast information for the power dispatching system, and guides the charging and discharging strategy of the energy storage system. When wind power resources are sufficient, the energy storage system absorbs excess power; when wind power resources are scarce, the energy storage system releases stored power to smoothly regulate the power output. In order to improve the overall efficiency of the energy storage system, this paper proposes an optimization model for energy storage. The model comprehensively considers factors such as energy storage capacity, charging and discharging efficiency, and energy loss in order to achieve optimal performance under different load demands. By dynamically adjusting the charging and discharging behavior of energy storage equipment, the grid frequency and voltage can be maintained stable even when wind power fluctuates greatly, thereby reducing the system operation cost. The relevant mathematical expressions are:

$$E(t+1) = E(t) + \eta_{\text{charge}} P_{\text{charge}}(t) - \frac{P_{\text{discharge}}(t)}{\eta_{\text{discharge}}} \tag{8}$$

where $E(t)$ represents the remaining power of the energy storage system, η_{charge} and $\eta_{\text{discharge}}$ represent the charging and discharging efficiency, and $P_{\text{charge}}(t)$ and $P_{\text{discharge}}(t)$ represent the charging and discharging power, respectively.

The goal of optimizing energy storage systems is to minimize frequency and voltage deviations caused by power fluctuations, with the objective function being:

$$\min \sum_{t} (\Delta f(t)^2 + \Delta V(t)^2) \tag{9}$$

where ΔV is the voltage deviation. By optimizing the charging and discharging strategies of the energy storage system, it is ensured that the grid frequency and voltage remain stable during large fluctuations in wind power, thereby improving the system's economical and operational efficiency.

6. EXPERIMENT AND RESULTS ANALYSIS

6.1 Experimental Setup

To verify the application effectiveness of the LSTM prediction method and its optimization effect in the actual power system, a power system simulation scenario based on Simulink was constructed. The scenario simulates the complex operating environment after the grid connection of renewable energy, including multiple key elements such as wind farms, traditional generators, transmission networks, and loads. The data set was obtained from a real wind farm, and records in detail the geographical location, altitude, ambient temperature, wind speed, wind direction, and power generation of wind turbines. The output of wind power is calculated by means of a dynamic control algorithm combined with Betz's law, turbine diameter, and air density. The traditional generator model simulates the dynamic characteristics of thermal and nuclear power generation, and adjusts the output power through a PID (Proportional Integral Derivative) controller. The transmission network model is based on power flow analysis, taking into account line resistance and reactance, adopts a DC (Direct Current) [38] power flow model, and adds node voltage constraints and power balance conditions. The load model is constructed based on actual needs, combined with historical data and meteorological information, using a multivariate linear regression method. During the simulation process, the

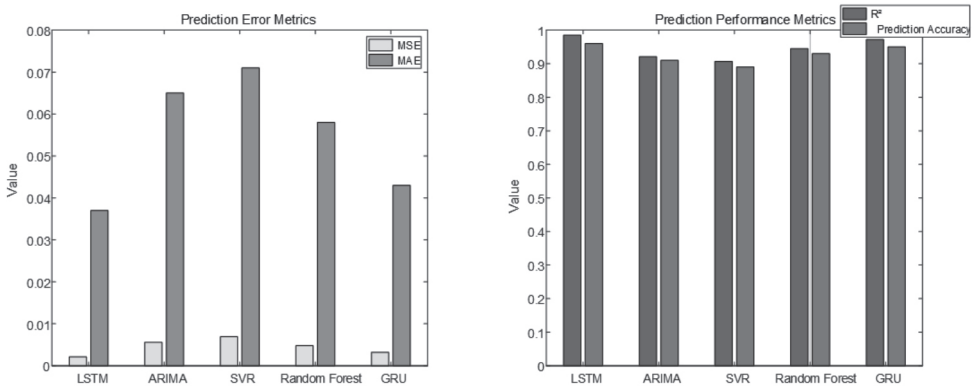

Figure 2 Prediction performance evaluation.

LSTM model was used to predict the power output of the wind farm under various meteorological conditions. Its input is historical power and meteorological data, and its output is the predicted wind power value for a period of time in the future.

6.2 Comparison of Prediction Performance between LSTM Model and Other Algorithms

This study compared the performance of LSTM model with four algorithms, namely ARIMA (AutoRegressive Integrated Moving Average), SVR (Support Vector Regression), Random Forest Regression, and GRU (Gated Recurrent Unit), in wind power prediction. All models are trained and tested on the same dataset to ensure accuracy in comparison. Comprehensive evaluation can be conducted using indicators such as MSE, MAE, coefficient of determination (R^2), and prediction accuracy. Among them, MSE highlights the impact of large errors, MAE reflects the degree of deviation in model predictions, and R^2 approaching 1 indicates that the model can effectively explain the variability of data.

During the model training process, the ARIMA model is set to autoregressive term 2, differencing term 1, and moving average term 1. The penalty parameter of the SVR model is 10, and the width of the loss function is set to 0.1. The number of trees in random forest regression is 100, the number of hidden layer units in GRU model is 64, the learning rate is set to 0.001, and the batch size is 32. These parameters have been optimized for each model's characteristics to ensure an improvement in its predictive performance.

After completing the model training, performance evaluation was conducted using the test set to calculate MSE, MAE, R^2, and prediction accuracy. The results are shown in Figure 2. The MSE of the LSTM model is 0.0021, and the MAE is 0.037, both of which are the lowest values, demonstrating excellent performance in wind power prediction. In contrast, the MSE of ARIMA and SVR are 0.0056 and 0.0069, respectively, while the MAE is 0.065 and 0.071, indicating their limitations in dealing with wind power fluctuations. Although random forest regression and GRU have shown some predictive ability in certain situations, their error levels are still lower than LSTM. In terms of coefficient of determination (R^2) and prediction accuracy, the R^2 of LSTM is close to 1 (0.985), and the prediction accuracy reaches 0.96, indicating that the model can effectively capture changes in wind power. Conversely, the R^2 values of ARIMA and SVR are 0.921 and 0.907, respectively, with prediction accuracies of only 0.91 and 0.89, indicating their shortcomings in model fitting and accuracy. Although random forest regression performs well under certain specific conditions (R^2 of 0.945, prediction accuracy of 0.93), overall, the performance of LSTM is clearly superior to that of other algorithms.

6.3 Stability Assessment of Power System

A comprehensive analysis of frequency and voltage changes is conducted to evaluate the stability of the power system. Frequency deviation is an important evaluation indicator, and by monitoring the deviation of the system frequency relative to the rated value, it can quantify the system's response capability when faced with disruptions. Time monitoring equipment is responsible for collecting frequency data, which is smoothed and filtered to identify the characteristics and trends of the system under dynamic conditions. At the same time, by recording the fluctuation of bus voltage, in-depth analysis of voltage changes can be carried out, involving the measurement of instantaneous values and spectral analysis, to explore the contribution of different frequency components to system stability.

In the experiment, various wind speed fluctuation scenarios were designed to simulate the impact of wind power on the power system under different meteorological conditions. Scenario 1 sets the wind speed to rapidly increase from 3 m/s to 8 m/s within 10 minutes, and then rapidly decrease back to 3 m/s, in order to examine the system's ability to respond to such rapid fluctuations. Scenario 2 maintains a wind speed of 4 m/s for 30 minutes to evaluate the performance of the system under stable breeze conditions. In scenario 3, the wind speed is set to repeatedly change between 5 m/s and 6 m/s every 15 minutes to determine the impact of small changes in wind speed. Finally, in scenario 4, the wind speed remains at 6 m/s, while the wind direction periodically changes within 30 minutes, shifting from 30 degrees northeast to 30 degrees northwest, and then back to 30 degrees northeast. This change affects the efficiency of the power generation turbine, resulting

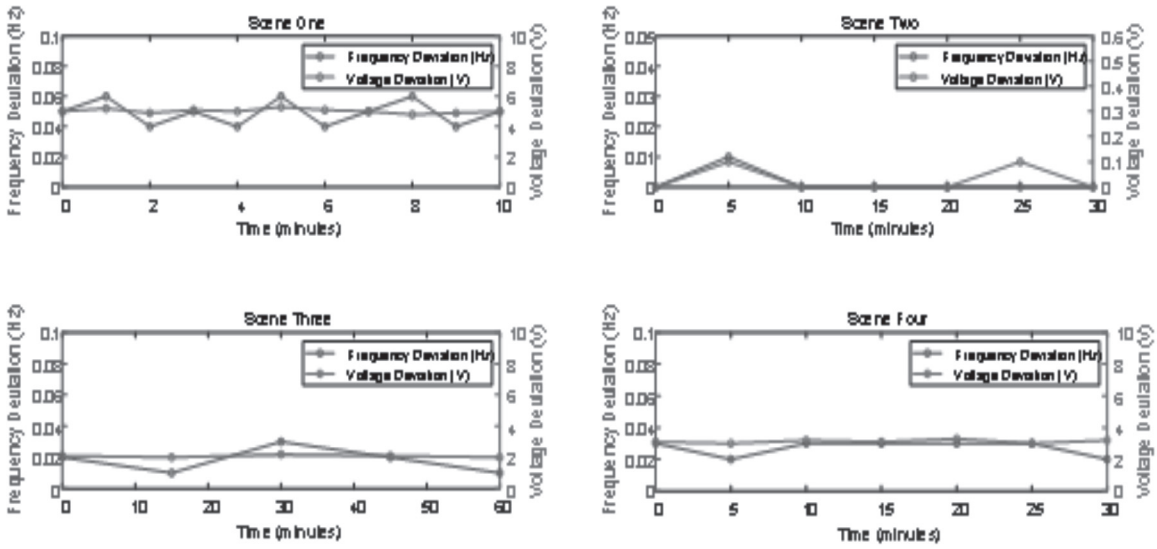

Figure 3 The impact of different scenarios on power system stability.

in power fluctuations. These experimental settings facilitate an in-depth analysis of the dynamic response of power systems under different wind conditions and help to optimize control strategies.

The experimental results presented in Figure 3 show the changes according to different scenarios. The X-axis represents time (minutes), the Y-axis (left side) displays system frequency deviation (Hertz, Hz), and the Y-axis (right side) indicates voltage deviation (volts, V). In scenario one, the frequency deviation range is between 0.04 Hz and 0.06 Hz, while the voltage deviation is between 4.8 V and 5.3 V. On the other hand, the frequency and voltage deviation of scenario two are almost zero, indicating good stability of the system under this condition. Wind speed fluctuations in scenario three result in a frequency deviation of 0.01 Hz to 0.03 Hz and a voltage deviation range of 2.0 V to 2.2 V, reflecting the system's high sensitivity to small changes. Although the wind speed in scenario four is fixed at 6 m/s, the change in wind direction causes a frequency deviation between 0.02 Hz and 0.03 Hz, and a voltage deviation between 3.0 V and 3.3 V, which also affects the power generation efficiency. By examining the experimental results obtained for various scenarios, the response capability and stability performance of the power system under different meteorological conditions can be clearly understood. Future research should further optimize the control strategy to ensure the reliability and stability of the power system.

6.4 Comparative Analysis of Optimization Strategies

The aim of the comparative analysis of optimization strategies is to evaluate the effectiveness of strategies in different scenarios and determine when specific solutions should be prioritized to ensure the stability of the power system. The experimental setup includes multiple scenarios, simulating low, medium, and high wind speed fluctuations and load changes. For each wind speed fluctuation scenario, the wind power prediction data generated by the LSTM model can be used to implement dynamic scheduling and optimization strategies for energy storage systems. The dynamic scheduling strategy aims to address the instability of power supply caused by wind speed fluctuations by adjusting the output of conventional power sources in real time. The optimization strategy of the energy storage system analyzes the regulatory role of energy storage equipment between power supply and demand, and determines its effectiveness under various fluctuating conditions. During the implementation process, frequency deviation, voltage deviation, and system response time can be monitored for subsequent comparative analysis. At the same time, the time required for the power system to recover to a stable state can be recorded, and the recovery ability of each strategy under different fluctuation conditions can be evaluated. The experimental objective is to ascertain which of the optimization strategies can more effectively maintain the stability of the power system under different wind speed fluctuation conditions, providing guidance for practical operation so as to quickly respond to power supply instability problems in various scenarios.

Table 2 shows the experimental results of the dynamic scheduling strategy. Under low wind speed fluctuations, the average deviation between frequency and voltage is small, with a response time of 5 seconds and a stabilization time of only 5 seconds. This indicates that the strategy can quickly adjust and maintain system stability. However, with the increase of wind speed fluctuations, especially under high fluctuation conditions, both frequency and voltage deviations have increased; the response time has been shortened to 3 seconds; and the stabilization time has reached 10 seconds.

Table 3 lists the performance of the energy storage system strategy under different wind speed fluctuations. When the wind speed fluctuates at low speed, the energy storage system responds quickly, taking only 3 seconds, and the stabilization time is also 3 seconds, which indicates highly efficient performance. Although its average frequency and voltage deviations are slightly higher than the dynamic dispatch strategy, they are still at an acceptable level. When there are large fluctuations in wind speed, the power system faces large frequency and voltage deviations. The response time of

Table 2 Dynamic Scheduling Strategy.

Wind Speed Fluctuation	Average Frequency Deviation (Hz)	Maximum Frequency Deviation (Hz)	Average Voltage Deviation (V)	Maximum Voltage Deviation (V)	Response Time (s)	Stabilization Time (s)
Low Fluctuation	0.01	0.03	0.5	1	5	5
Medium Fluctuation	0.03	0.05	0.8	1.5	4	8
High Fluctuation	0.05	0.08	1.2	2	3	10

Table 3 Energy Storage System Strategy.

Wind Speed Fluctuation	Average Frequency Deviation (Hz)	Maximum Frequency Deviation (Hz)	Average Voltage Deviation (V)	Maximum Voltage Deviation (V)	Response Time (s)	Stabilization Time (s)
Low Fluctuation	0.02	0.04	0.6	1.2	3	3
Medium Fluctuation	0.02	0.06	0.7	1.4	2	5
High Fluctuation	0.03	0.07	1	1.8	2	8

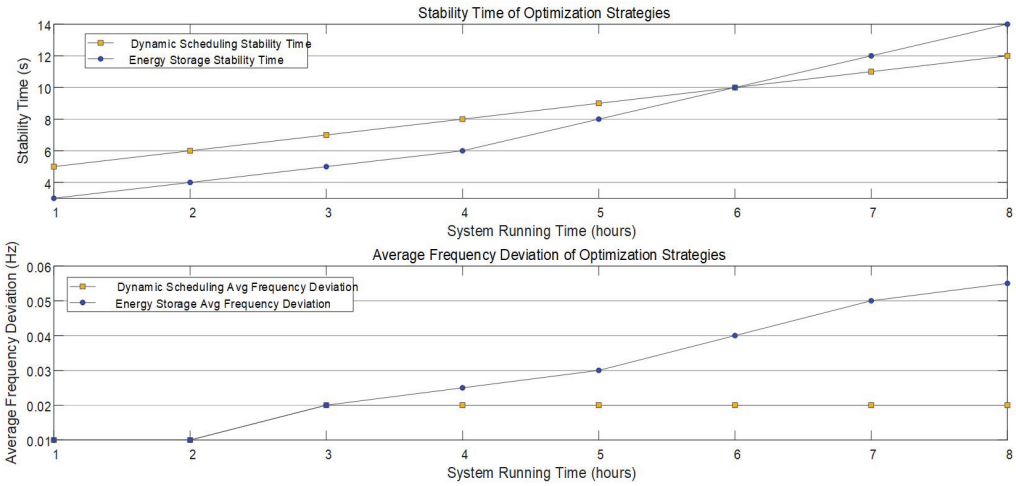

Figure 4 The impact of different running times.

the energy storage system is shortened to 2 seconds, but the stabilization time is extended to 8 seconds, showing strong adaptability. However, it should be noted that the stabilization time and deviation of the energy storage system can gradually increase in long-term operations, and it is necessary to balance sustainability and long-term benefits in practical applications.

To compare the effects of dynamic scheduling and energy storage system strategies in maintaining the stability of the power system, the study focuses on the stabilization time and average frequency deviation. This article sets multiple operating times from 1 hour to 8 hours, combined with low, medium, and high wind speed fluctuation scenarios, and uses the wind power prediction data generated by the LSTM model to implement corresponding strategies, recording the system's stable time during each operating time period. In addition, energy storage systems ensure stability in fluctuating situations by absorbing excess electricity and releasing stored energy when there is an imbalance between power supply and demand.

Figure 4 shows the comparison of the stabilization time and average frequency deviation of the dynamic scheduling and energy storage system strategies during different hours of operation. The Figure 4a shows that the stabilization time of the dynamic scheduling strategy increases with the increase of operating hours. Although the stabilization time of the energy storage system increases, it is generally lower than the dynamic scheduling. The Figure 4b shows that the average frequency deviation of the dynamic dispatch strategy has remained at 0.02 Hz for a long time, while the frequency deviation of the energy storage system has increased after a long period of operation, indicating that there is a high risk of frequency fluctuations in its long-term operation.

7. CONCLUSIONS

This study systematically analyzed the impact of renewable energy grid-connected control on power system stability,

covering aspects such as power volatility, frequency constancy, and voltage stability. In response to the challenges of renewable energy grid-connected control of power system stability, a predictive control optimization strategy based on the LSTM model is proposed. This strategy predicts the future state of the power system and dynamically adjusts the control parameters to improve system stability. Experimental simulation results verify the effectiveness of this method in improving power system stability. Future research could focus on expanding the scope of the data set to cover more meteorological conditions and power load conditions. At the same time, a variety of optimization strategies can be explored to develop customized control methods based on the characteristics of different types of renewable energy.

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