Eng Int Syst (2026) 1: 5–16

Engineering
Intelligent Systems

Intelligent Decision-Making System for Power Grid Dispatching Based on Generative AI

Yu Liu[1,a]*, Weihua He[1,b], Jianfei Zhu[1,c], Ran Yang[1,d] and Xinrui Yang[1,e]

State Grid Shanxi Electric Power Company Xinzhou Power Supply Company, Xinzhou 030021, Shanxi, China

With thecurrentintelligent decision-making system for the power grid (PG), it is difficult for dispatching mechanisms to automatically update theirdecision logic according to the changing PG status and external environment, and to predict new risks in advance and make adaptive adjustments. In this study, an intelligent decision-making system is constructed for PG dispatching to improve itsintelligence and risk response capabilities. This studycollected historical load, grid status and meteorological conditions data, sampled them in 5-minute units, and constructed a data set. The CGAN (Conditional Generative Adversarial Network) was used to take grid status, historical load data, meteorological conditions, etc., as conditional inputs, and generates different risk scenario data through adversarial training. CNN (Convolutional Neural Network) wasused to extract local features, which werethen input into Bi-LSTM (Bidirectional Long Short-Term Memory Network) for sequence modeling and grid risk identification. The identified risk category and current grid status are used as input, and DQN (Deep Q-Network) uses experience replay and ε-greedy strategy to make scheduling decisions. The results show that the average risk identification accuracy rate in various risk scenarios reached 98.1%, and the average identification precision rate reached 97.8%. Compared with the average response time of 7.4s for traditional systems, the average response time of this system was 1.2s. In various risk scenarios, the average supply and demand balance rates of this system and traditional systems were 0.97 and 0.93 respectively. Therefore, the intelligent decision-making system proposed in this paper can cope with the changing grid status and external environment, accurately identify risks and respond quickly, showing its broad potential in smart grid applications.

Keywords: Power Grid Dispatching, Intelligent Decision-making System, Generative Artificial Intelligence, Conditional Generative Adversarial Networks, Risk Identification

1. INTRODUCTION

As the global demand for energy increases, power systems [1–2] are becoming increasingly complex. Traditional PG dispatch systems face challenges such asrapid demand fluctuations, renewable energy integration, and PG [3–4] security. The intermittent nature of renewable energy sources necessitates improved operational efficiency and raises risks such as equipment failure and load variability. Consequently, it has become critical to enhancethe adaptability and intelligence of PG dispatch decision-making systemsin order to achievepower system reform.

Generative AI can dynamically generate various risk scenarios and improve the risk identification capability of the PG. Combining convolutional neural networks and Bi-LSTM can make full use of historical data and time series characteristics to improve sensitivity to changes in PG status. Deep reinforcement learning can be used for real-time dispatch decisions to improve the dispatch efficiency and flexibility of the PG. This study not only offersa new intelligent decision-making framework for PG dispatching, but also provides a theoretical basis for subsequent research, promoting the intelligent transformation of power systems, and has important practical application value and social significance.

This paper proposes an intelligent decision-making method for PG dispatching that integrates CGAN, CNN-Bi-LSTM and DQN models. Aiming at the complex

*Address for correspondence:Yu Liu, State Grid Shanxi Electric Power Company Xinzhou Power Supply Company, Xinzhou 030021, Shanxi, China, Email: [a]gzyouxiang20241@126.com, [b]2832633413@qq.com, [c]18435164021@163.com, [d]1417188779@qq.com, [e]120945249@qq.com

operating environment and diversified risk scenarios of the PG, it achievesefficient and intelligent management of PG dispatching. Through the data collection and preprocessing stage, the present studyobtains the data set of PG status, loads data and meteorological conditions, and constructs training data containing various risk scenarios. The CGAN model is used to generate PG status data such as voltage and current under various risk scenarios. The CGAN model generates simulated PG data based on the input risk condition labels through adversarial learning, making the generated data close to the real scenario. The CNN-Bi-LSTM model is used to extract features and identify risks of the generated PG data. The CNN componentis used to extract local spatial features, whileBi-LSTM is used to capture risk sequence features. Based on the risk identification results, the DQN model inputs the current state of the PG and risk category information into the decision network, and balances exploration and utilization through experience replay and ε-greedy strategy, thereby realizing intelligent scheduling decisions. This studyuses CGAN to expand the diversity of PG data sets, so that the model can be trained in the absence of complete data and can simulate various risk scenarios. The CNN-Bi-LSTM model combines local feature extraction and sequence modeling capabilities to achieve highly-accurate risk identification, and realizes real-time linkage between risk identification and intelligent scheduling through DQN. The CGAN used in this paper can accurately generate data for various risk scenarios. Combined with CNN and Bi-LSTM, it can accurately identify multiple risks, with a higher recognition accuracy than CNN-LSTM, Bi-LSTM, Transformer, and TCN (Temporal Convolutional Network). Compared with traditional systems, the proposed system has more advantages in terms of response time and supply-demand balance rate, and has greaterstability whendealing with different risk scenarios.

2. RELATED WORK

Research on PG dispatch decision-making systems has gained significant attention due to complex power demand and renewable energy integration. Many researchers are focused on enhancing the intelligence of PG dispatch to adapt to the evolving market environment. Zhang et al.'s research [5] introduced a data-driven prediction model that analyzes historical loads and equipment status to improveaccuracy and real-time performance. Hussain Shahbaz [6] applied genetic algorithms to develop a new PG dispatch model that balances economy and safety under various constraints. Traditional systems [7–8], reliant on empirical rules, struggle to adapt to rapid changes. To address this, Mo Qiu [9] proposed a dynamic dispatching strategy that leverages real-time monitoring and forecasting data to improve responsiveness, effectively managing load fluctuations and intermittent renewable generation. Zhao Xiwu [10] examined grid dispatch challenges in competitive markets, proposing a model based on market demand and price signals for optimal resource allocation. Additionally, multi-objective optimization [11] in grid dispatching addresses economy, environmental impact, and system stability by balancing objectives through weights and constraints. Overall, research in PG dispatch is moving toward intelligence, real-time adaptability, and multi-objective optimization, integrating advanced algorithms to enhance power system safety and economy.

Generative algorithms are increasingly being utilized in PG systems to address power demand fluctuations and renewable energy uncertainties. Generative adversarial networks [12] and conditional GANs [13] generate simulated data that help decision makers identify potential risks. CGANs specifically create power load data under varying meteorological conditions, allowing for analysis of weather impacts on PG operations and enhancing dispatch flexibility and response speed. By integrating generative models [14] with historical PG operation data, diverse scenario data are generated to simulate the volatility of renewable energy, providing valuable support for dispatch decisions. These risk scenario datasets enable better evaluation of PG operating status under uncertainty and optimize dispatch strategies. The adoption of generative algorithms [15] facilitates the analysis of complex scenarios, effectively identifying potential risks. Research by Siniosoglou[16] demonstrates that combining generative algorithms with deep learning enhances the PG system's ability to detect patterns in historical data, improving risk identification and early warning accuracy. Overall, the study of generative algorithms in PG systems offers new insights for dispatch decisions and supports the intelligence, flexibility, and efficiency of PG operations.

Risk perception and identification in PG dispatching are vital for safe power system operation. The opening of the power market [17] and the growth of renewable energy have increased the complexity of risk management. Researchers are improvingrisk identification methods using advanced data analysis and machine learning, such as LSTM [18], which analyze historical load data and weather factors to identify risk patterns and improve short-term load forecasting. Pei Shaoqian [19] used deep learning models to monitor the PG operation status and external environment in real time and achieved dynamic risk perception. This method can not only improve the response speed to emergencies, but also provide strong support for scheduling decisions through risk identification. For complex PG environments, ensemble learning methods [20] combine the advantages of multiple algorithms to improve the accuracy and stability of identification. Some studies have also begun to focus on risk decision-making strategies based on reinforcement learning [21]. Through the interaction between the agent and the environment, the dispatching plan is dynamically adjusted to cope with the changing state of the PG. Although the research on risk perception and identification in PG dispatching hasgradually been paying more attention tointelligence and automation, the aforementionedresearch does not attempt to construct a systematic PG dispatching decision-making system and cannot cope withthe ever-changing PG state environment.

3. METHODS

3.1 Data Collection and Preprocessing

The process of intelligent decision-making for PG dispatching is shown in Figure 1.

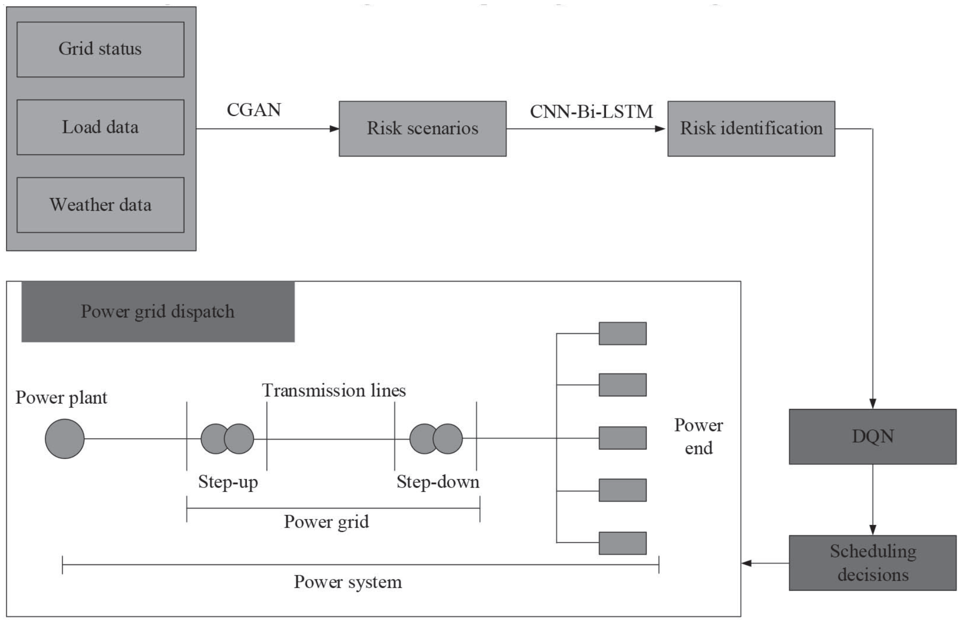

Figure 1 The process of intelligent decision-making in PG dispatching.

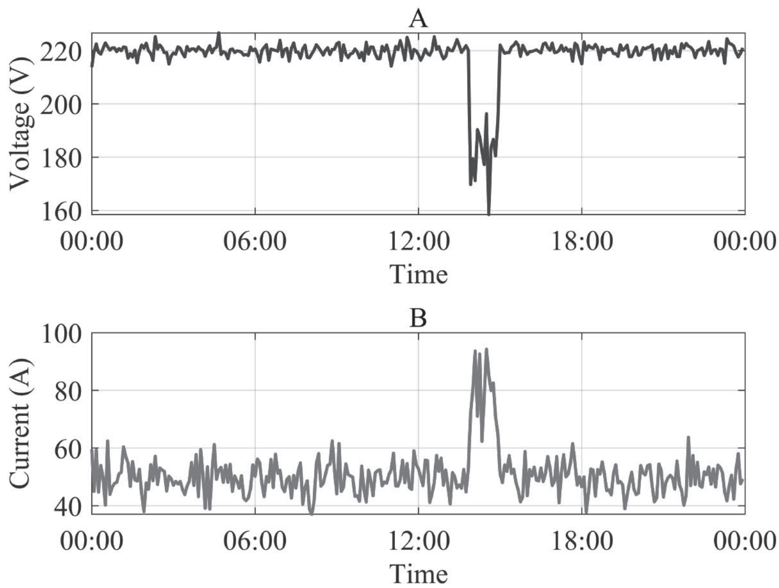

Figure 2 Voltage and current data fluctuations. Figure 2A. Voltage data, Figure 2B. Current data.

CGAN is used to generate data based on PG status, load data, meteorological data, etc., to generate risk scenario data. CNN-Bi-LSTM is used to train risk scenario data to identify possible risks, and DQN is used to optimize dispatching decisions to make appropriate dispatching decisions. The dispatching decision can be applied to the power system to reasonably arrange and control various links such as power generation, transmission and distribution to ensure the reliable supply of electricity.

In the intelligent decision-making of PG dispatching [22–23], the accuracy and comprehensiveness of data are the basis for achieving high-quality risk identification and dispatching decisions. This paper covers the multi-dimensional information of the PG in the data collection stage: historical PG status data, historical load data, meteorological conditions and other data.

The historical status data of the PG comes from the monitoring data collected in real time from each substation and transmission line. The collected content includes information such as grid node voltage, current, power factor, frequency, line load rate, fault records, etc., capturing the operating status of the PG at different times. The data collection period is from January 2019 to December 2019. The PG status data is sampled and updated in 5-minute units to obtain dynamic information of the PG.

The voltage and current data fluctuations of the substation obtained over a certain day are shown in Figure 2.

It can be seen that the voltage is around 220V most of the time, and the current is around 50A most of the time, that is, the state of the substation is stable during the time periods of 00:00-14:00 and 15:00-00:00. However, during the period from 14:00 to 15:00, the voltage data dropped sharply and the

Table 1 Display of meteorological data.

Time	Temperature (°C)	Humidity (%)	Wind speed (m/s)	Rainfall (mm)	Air pressure (hPa)
2019/10/25 4:00	15.5	70	3.5	0	1015
2019/10/25 4:05	15.7	68	3.8	0	1015
2019/10/25 4:10	15.6	69	4	0	1014
2019/10/25 4:15	15.4	72	4.2	0	1014
2019/10/25 4:20	15.3	73	4.5	0	1014
2019/10/25 4:25	15.2	75	4.8	0	1013
2019/10/25 4:30	15	77	5	0	1013
2019/10/25 4:35	14.9	78	5.3	0	1013
2019/10/25 4:40	14.8	80	5.5	0	1012
2019/10/25 4:45	14.7	82	5.8	0	1012
2019/10/25 4:50	14.5	84	6	0	1012
2019/10/25 4:55	14.4	85	6.2	0	1012
2019/10/25 5:00	14.3	86	6.5	1	1011

current rose suddenly, which means that the substation failed during the period from 14:00 to 15:00.

The historical load data is collected through the load database of the PG dispatching department, including power consumption records and historical dispatching data. The collected data includes daily load curves, peak and valley loads, typical power consumption patterns, power consumption distribution, etc. The historical load data is also recorded in 5-minute units to reflect the fluctuation of load in a short period of time.

Through cooperation with the regional meteorological bureau of the PG dispatching area, historical and real-time meteorological data are obtained, including temperature, humidity, wind speed, rainfall, air pressure and other multi-dimensional meteorological data. The changes in meteorological data are recorded in 5-minute units. Table 1 displays the meteorological data over a certain period of time.

In order to ensure the quality and availability of the data, the collected data is preprocessed [24–25]. PG equipment failure or communication interruption may cause PG data to be missing. For a small number of missing values, interpolation is used to fill these, and the mean is used to fill in the missing data. For outliers in the data, the outliers are filtered out through the box plot and the outliers are deleted. For duplicate data records, redundancy is eliminated by deletion.

The timestamps of the PG status data, load data, and meteorological data may be inconsistent when they are collected. By aligning the timestamps, data sampling is performed every 5 minutes to ensure data end alignment. Also,data from different sources can be integrated to build a multi-dimensional data set.

3.2 CGAN Model Construction and Training

CGAN[26-27] is an extended generative adversarial network that generates data that meets specific conditions by introducing conditional variables. CGAN is used to generate risk scenario data related to the current state of the PG, historical load data, meteorological conditions, etc. CGAN [28–29] consists of a generator and a discriminator.

The CGAN model is shown in Figure 3.

The generator accepts random noise z and conditional information c, and the generated sample is:

$$x' = G(z, c) \tag{1}$$

The discriminator accepts samples and conditional information c, and outputs the probability of real samples and generated samples. The loss function of CGAN is based on the form of cross-entropy. The discriminator loss is expressed as:

$$\begin{aligned} L_D = &-\mathbb{E}_{x\sim p_{data}(x)}[\log D(x|c)] \\ &- \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z, c)|c))] \end{aligned} \tag{2}$$

The generator loss is expressed as:

$$L_G = -\mathbb{E}_{z\sim p_z(z)}[\log D(G(z, c)|c)] \tag{3}$$

In the intelligent decision-making system for PG dispatching, CGAN is used to generate risk scenario data related to the PG status, historical load data, meteorological conditions, etc. The generated risk scenarios include load fluctuations, equipment failures, fluctuations on the power generation side, meteorological disasters, transmission network congestion, power market price fluctuations, and frequency fluctuations.

3.3 Feature Extraction and Sequence Modeling

CNN is used to extract local features from the generated risk scenario data, and the features extracted by CNN are input into Bi-LSTM for time series modeling [30]. The cross-entropy loss function is used to evaluate the risk category recognition effect of the model [31]. CNN is used to process the generated risk scenario data, including feature sequences such as voltage, current, temperature, and wind speed, and extract local spatial features in the data.

The CNN-Bi-LSTM model is shown in Figure 4.

The generated risk scenario data is $X \in \mathbb{R}^{T\times N}$, where T represents the time step, and N represents the feature dimension of each time step. The convolution operation is:

$$h_{t,i} = f\left(\sum_{j=0}^{k-1} w_{i,j} \cdot x_{t+j} + b_i\right) \tag{4}$$

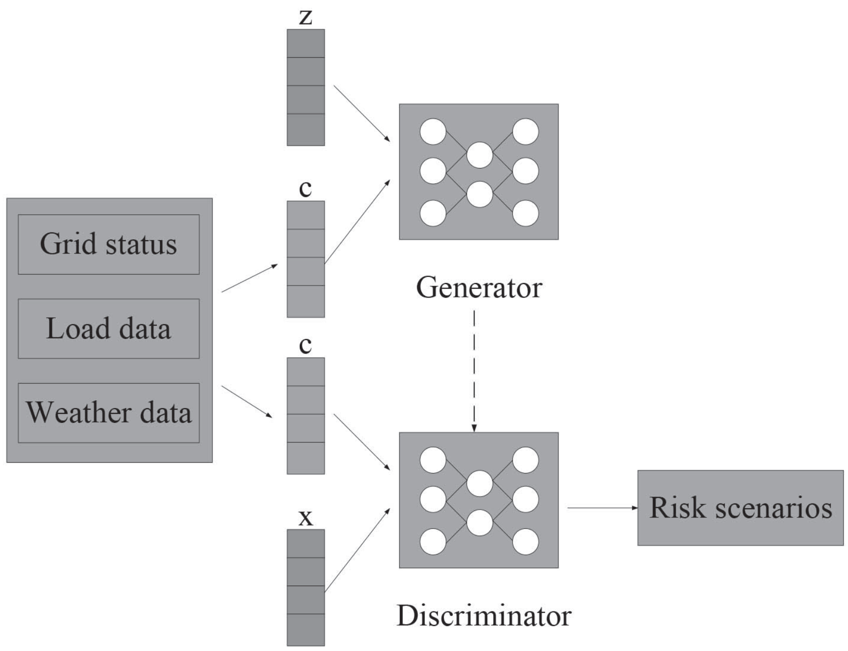

Figure 3 CGAN model.

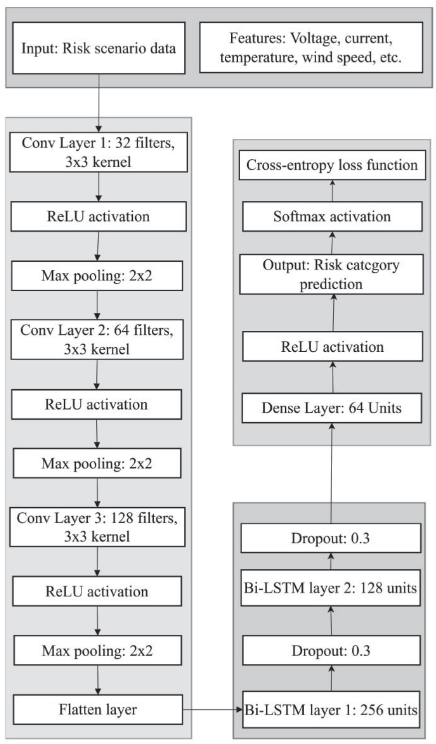

Figure 4 CNN-Bi-LSTM model.

The convolutional features are further downsampled through the pooling layer, and the feature dimension is reduced through the pooling operation. The convolutional and pooled feature maps are used as time series features and input into the Bi-LSTM model for time series modeling. Bi-LSTM captures the forward and backward time dependencies and models risk identification more accurately.

The feature map sequence $H = [h_1, h_2, \ldots, h_T]$ output by CNN is input into Bi-LSTM. Bi-LSTM [32–33] contains both a forward LSTM and a backward LSTM, which calculate the forward hidden state and the backward hidden state respectively. The formula is:

$$\vec{h}_t = LSTM_{forward}(h_t, \vec{h}_{t-1}) \tag{5}$$

$$\overleftarrow{h_t} = LSTM_{backward}(h_t, \overleftarrow{h_{t+1}}) \tag{6}$$

$$H_t = [\vec{h}_t; \vec{h}_t] \tag{7}$$

For each sample, the cross-entropy loss is calculated as:

$$L = -\sum_{c=1}^{C} y_c \log(p_c) \tag{8}$$

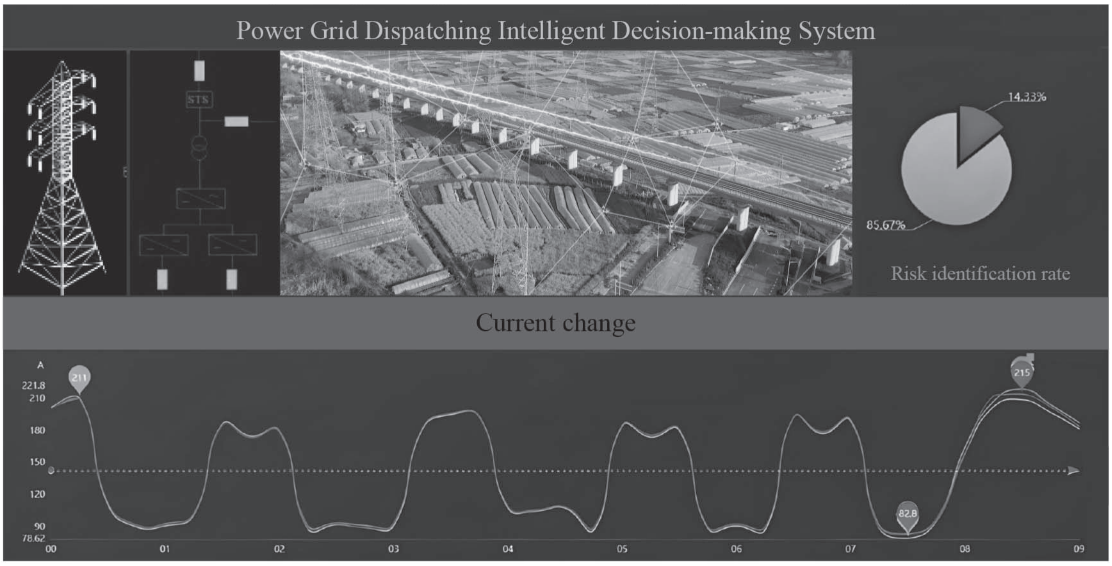

Figure 5 System interface.

Where y_c and p_c are the true label and predicted label of the sample respectively.

3.4 DQN Model Construction and Training

In the PG dispatching intelligent decision-making system, DQN is used as the decision-making core to generate dispatching strategies. The input layer of the DQN [34–35] model receives the status and risk information of the PG. Multiple fully connected layers can be used to construct hidden layers, and complex features can be extracted through nonlinear activation functions. The original state features of the input are mapped into more compact and useful feature representations to improve the decision-making ability of the model. A set of Q values for actions is generated, where each Q value represents the score of a specific scheduling action. Actions include starting and stopping the generators, adjusting the load distribution, etc. By maximizing the Q value, DQN selects the optimal action to perform PG scheduling.

DQN [36–37] introduces an experience replay mechanism in training, storing the historical state-action-reward-next state in the experience pool. The role of experience replay is to evenly cover the state space, so that DQN can more fully generalize to unseen states.

In order to strike a balance between exploring new strategies and using the current best strategy, the ε-greedy strategy is adopted.

DQN updates the Q value through the Bellman equation, the formula is.

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)] \tag{9}$$

An intelligent decision-making system for PG dispatching is constructed by combining CGAN, CNN, Bi-LSTM and DQN modules. The CGAN module is used to receive the PG status and environmental data and generate data for different risk scenarios. CNN is used to extract features from the risk scenario data generated by CGAN to obtain local information that characterizes different risk features. Bi-LSTM is used to capture the time series information in the risk scenario to complete risk identification. DQN is used to receive the risk identification results of Bi-LSTM and the current state of the PG, and output the optimal dispatching strategy.

The interface of the PG dispatching intelligent decision-making system is shown in Figure 5.

In order to effectively analyze and evaluate the effect of risk scenario data generation, the CGAN model is compared with DCGAN (Deep Convolutional Generative Adversarial Network), WGAN (Wasserstein Generative Adversarial Network), and VAE (Variational Autoencoder). MSE (Mean Squared Error) is used to determine the difference between generated data and real data in different scenarios.

The calculation formula of MSE is:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{10}$$

CNN is used to extract features from the generated risk scenario data, and Bi-LSTM is used to identify risks. In order to measure the performance of risk identification, multiple evaluation indicators are set, including accuracy and precision.

Traditional PG dispatching systems use pre-set rules and control strategies. These rules are based on the experience of experts and accumulated long-term PG operation data, and can handle common PG operations, including load balancing, generator dispatching, fault handling, etc.

The dispatching decision response time is the time interval from the system receiving new status data to generating a dispatching decision. The response time formula is:

$$T_r = T_d - T_i \tag{11}$$

Supply and demand balance error formula:

$$E_b = |P_\mathrm{s} - P_\mathrm{d}| \tag{12}$$

Where E_b is the supply-demand balance error [38–39]; P_s represents the power supply at the current moment; P_d represents the power demand at the current moment.

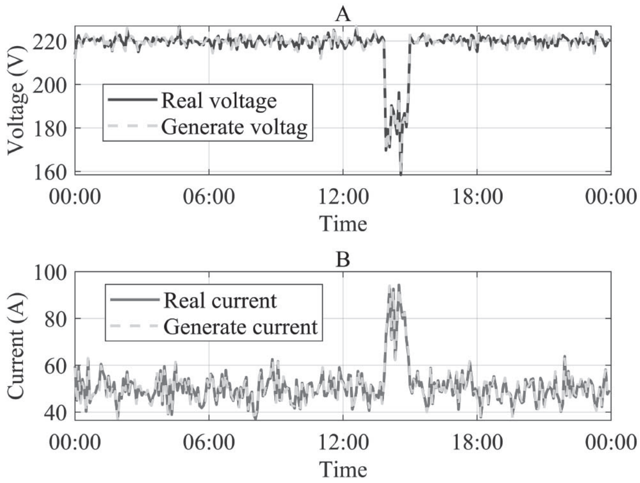

Figure 6 CGAN generated data and real data. Figure 6A. Voltage data generation effect. Figure6B. Current data generation effect.

The supply-demand balance rate can more comprehensively evaluate the system's ability to maintain supply-demand balance over a period of time:

$$B = 1 - \frac{\sum_{t=1}^{T} E_b(t)}{\sum_{t=1}^{T} P_d(t)} \tag{13}$$

This paper compares the number of failures and the failure recovery time of the traditional system and the proposed system in different risk scenarios to evaluate the stability of the system. If the data fluctuations of the failure frequency and failure recovery time of the system are small under different risk scenarios, that is, the performance of the system is less affected by the external environment, this indicates that the system is highly stable.

4. RESULTS

4.1 Effect of Data Generation

This paper uses CGAN for data generation. The generator produces realistic data based on grid status, historical load, meteorological conditions, etc. The discriminator distinguishes between real and generated data. The comparison between the data generated by CGAN and the real voltage and current data is shown in Figure 6.

Combining the data change trends of Figure 6A and Figure 6B, it can be clearly seen that the voltage and current data generated by CGAN are very close to the real data, and the data change trends are consistent. The generator generates realistic voltage and current data to deceive the discriminator, which distinguishes between generated data and real data by learning the characteristics of real data. Through multiple iterations, the generator continuously optimizes its generation ability, making the generated data gradually approach the real data. During the generation process, CGAN inputs conditional information such as grid status, historical loads, and meteorological conditions, so that the generated data meets the physical constraints of the power system while reflecting the changes in the actual operating environment and status, ensuring the authenticity of the data. The generator obtains different voltage and current generation targets through conditional input ateach iteration, simulates the grid behavior under different risk scenarios and load conditions, and makes the generated grid data close to the actual situation. The discriminator continuously compares the real data with the generated data, identifies and optimizes the rationality of the generator output in detail, so that the generated data gradually conforms to the data distribution of the real PG in terms of structure and statistical characteristics. The voltage and current data in the PG have time series characteristics and specific distribution. CGAN captures these characteristics while making the generated data have trend changes and fluctuation characteristics consistent with the real PG data. CGAN can generate grid state data with high fidelity. The results generated by CGAN can match the performance of actual grid data in terms of accuracy and consistency.

In order to more accurately determine the data generation effect of CGAN, CGAN, DCGAN, WGAN, and VAE are compared. The data generation effects of different generation algorithms are shown in Figure 7.

Figure 7 shows the generation effect of voltage data. The average MSE value of voltage data generated by CGAN under different risk scenarios remains at a low level, showing high generation accuracy and stability. In scenarios such as load fluctuations, equipment failures, and meteorological disasters, the MSE value of CGAN does not exceed 0.8 V^2, outperforming DCGAN, WGAN, and VAE. Specifically, for load and frequency fluctuations, CGAN's MSE values are 0.8 V^2 and 0.7 V^2, while DCGAN's MSE reaches 1.8 V^2 and 1.5 V^2, and WGAN and VAE exceed 2.3 V^2. The average MSE values are 0.73 V^2 for CGAN, compared to 1.57 V^2 for DCGAN, 2.06 V^2 for WGAN, and 2.56 V^2 for VAE. CGAN's superior data generation stems from its use of specific conditional inputs, allowing it to effectively capture characteristics of various risk scenarios and enhance the authenticity of the generated data. CGAN's generation discriminant network optimizes the generated data through a dynamic competition mechanism, making the generated data closer to the real data distribution and reducing the difference between the generated data and the real data. The MSE

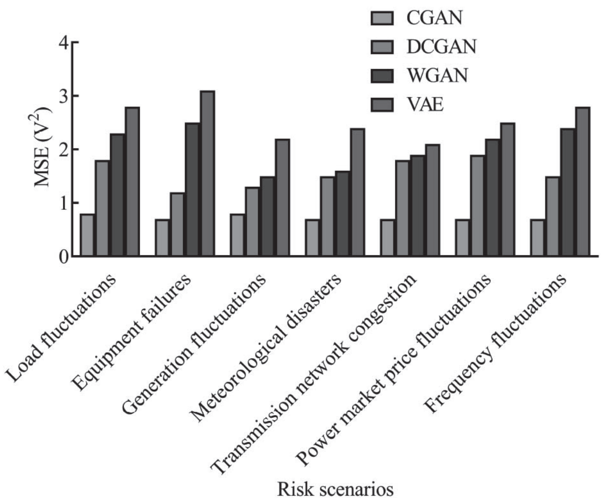

Figure 7 Data generation effects of different generation algorithms.

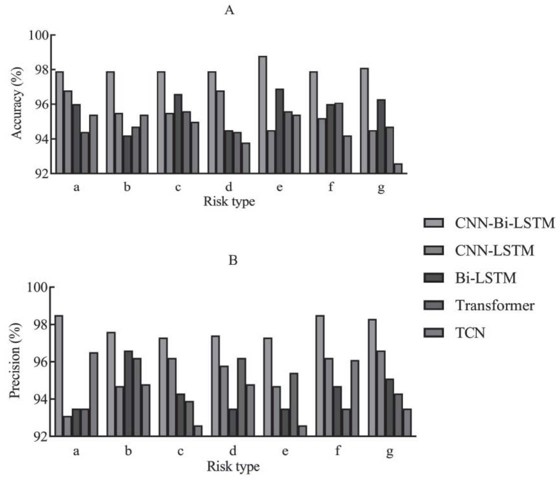

Figure 8 Results of risk identification of different types. Figure 8A. Accuracy results. Figure 8B. Precision results.

values of the data generated by CGAN remain relatively stable in different risk scenarios, indicating that CGAN has high robustness in the data generation process. No matter how the scenario conditions change, CGAN can adaptively adjust the mode of generated data to ensure the reliability of generated data. CGAN can generate stable and accurate data in different PG risk scenarios.

4.2 Results of Risk Identification

The seven risks of load fluctuation, equipment failure, power generation fluctuation, meteorological disaster, transmission network congestion, power market price fluctuation, and frequency fluctuation are labeled a, b, c, d, e, f, and g respectively. In this study, CNN-Bi-LSTM is used for risk identification. The results for different types of risk identification are shown in Figure 8.

The CNN-Bi-LSTM model in Figure 8A performs better than other models when dealing withvarious risk types. The accuracy of the risk types of load fluctuation, equipment failure, power generation fluctuation, meteorological disaster, and power market price fluctuation is 97.9%, and the accuracy of transmission network congestion and frequency fluctuation is 98.8% and 98.1% respectively. CNN-Bi-LSTM has obvious superiority and stability in identifying various risks. CNN-Bi-LSTM makes full use of CNN's ability to extract local features and combines it with Bi-LSTM's bidirectional sequence modeling capabilities to effectively capture the spatiotemporal characteristics of data and improve the recognition accuracy of complex risk patterns. Although CNN-LSTM and Bi-LSTM have higher recognition accuracy in some scenarios, their overall performance is not as stable as CNN-Bi-LSTM. Although the Transformer and TCN models performed well under certain types of risks, their recognition accuracy declined in complex environments involving meteorological disasters and frequency fluctuations. The average recognition accuracy of CNN-Bi-LSTM, CNN-LSTM, Bi-LSTM, Transformer, and TCN were 98.1%, 95.5%, 95.8%, 95.1%, and 94.5%, respectively. Figure 8B shows the risk recognition precision of different recognition models. The average recognition precision of CNN-Bi-LSTM, CNN-LSTM, Bi-LSTM, Transformer, and TCN were 97.8%, 95.3%, 94.5%, 94.7%, and 94.4%, respectively. Similarly, CNN-Bi-LSTM has the highest recognition precision in terms of all risks. By combining CNN and Bi-LSTM, the proposed systemcan accurately identify various risks.

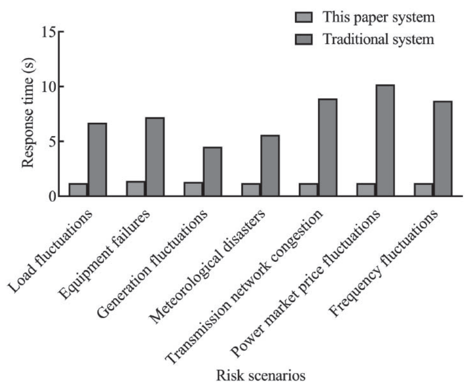

Figure 9 Response time of dispatching decision.

4.3 Dispatch Decision Performance

In this study, DQN was adopted to make PG dispatch decisions, and the performance of the proposed system was compared with that of the traditional system. The response time comparison results of the dispatch decision are shown in Figure 9.

The proposed system has a better response time than traditional systems whendealing with various grid risk scenarios. The response time of the proposed system in scenarios involving load fluctuation, equipment failure, generation side fluctuation, meteorological disaster, transmission network congestion, power market price fluctuation and frequency fluctuation is between 1.2 and 1.4 seconds. The response time of the traditional system is significantly longer, far exceeding the response time of the system in this paper. The average response time of the system in this paper and the traditional system is 1.2s and 7.4s respectively. The system in this paper uses CGAN and CNN-Bi-LSTM to identify grid risks, and combines DQN for real-time scheduling decisions. According to the historical data, real-time status and external environmental conditions of the PG, risk scenarios are generated to predict potential risks in advance, and then the local features of the data are extracted using convolutional neural networks. Bi-LSTM is used for time series modeling to identify specific risk types in a short time. The DQN algorithm can dynamically generate the optimal dispatching plan and respond to different grid status changes in a timely manner. The system proposed in this paper has a higher degree of automation, can adapt to the rapid changes in grid status, and greatly reducesthe response time.

Traditional systems rely on preset rules and control strategies and cannot quickly adapt to complex and dynamic changes in the grid environment. In scenarios where there is transmission network congestion or power market price fluctuation, traditional systems need to rely on manual decisions by dispatchers or the response of semi-automated rules, resulting in time lags. For the complex economic dispatch problem of power market price fluctuations, the preset strategy of the traditional system lags behind the changes in market prices, resulting in a response time of up to 10.2 seconds. In the case of transmission network congestion and frequency fluctuations, due to the complexity of the network and high real-time requirements, the response time of the traditional system is significantly longer than that of the proposed system. The proposed system shows extremely high response efficiency in dealing with various types of PG risks, and demonstrates extremely short response time in multiple risk scenarios.

The supply-demand balance rate indicatesthe balance between power supply and demand over a period of time, and the value range of the supply-demand balance rate is 0–1. A supply-demand balance rate of 1 means that during a certain period, power supply is completely equal to power demand. A supply-demand balance rate of 0 means that during a period of time, power supply is completely unable to meet power demand. The supply-demand balance rate results of the proposed system and the traditional system are shown in Figure 10.

The proposed system achieves a better supply and demand balance rate than the traditional system, with averages of 0.97 and 0.93, respectively. For load fluctuations, the proposed system maintains a balance rate of 0.96, compared to 0.93 for the traditional system, demonstrating superior responsiveness. It employs DQN to formulate dispatch strategies, minimizing supply and demand errors. In cases of equipment failures and generation fluctuations, the proposed system's balance rate is 0.97 versus 0.95 for the traditional system. Utilizing CGAN to generate risk scenarios and Bi-LSTM for timing information, the proposed system can make real-time adjustments. In scenarios involving meteorological disasters ortransmission network congestion, the proposed system achieves a balance rate of 0.98, compared to 0.96 and 0.92 for the traditional system, with a notable difference in network congestion scenarios. The proposed system identifies congestion issues more quickly, allowing for dynamic strategy adjustments. For market price and frequency fluctuations, the proposed system maintains a balance rate of 0.97, significantly outperforming the traditional system's 0.91. This higher balance rate is due to the proposed system's intelligent decision-making and efficient real-time data processing, enabling proactive risk prediction and flexible responses.

4.4 System Stability Analysis

In order to test the stability of the system, the number of system failures and failure recovery time under different risk scenarios are determined and analyzed. The results of the system stability analysis are shown in Table 2.

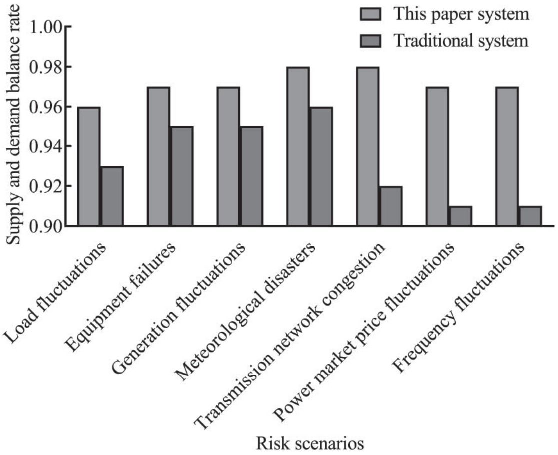

Figure 10 Supply and demand balance rate.

Table 2 System stability.

Risk scenarios	This paper system		Traditional system	
	Number of system failures	Failure recovery time (s)	Number of system failures	Failure recovery time (s)
Load fluctuations	2	29	4	65
Equipment failures	2	34	5	125
Generation fluctuations	2	26	3	76
Meteorological disasters	2	30	8	234
Transmission network congestion	1	32	5	296
Power market price fluctuations	1	29	6	78
Frequency fluctuations	2	29	4	64

Table 2 shows the number of system failures and fault recovery times under different risk scenarios. From the comparative results, it can be concluded that the proposed system has fewer failures and shorter fault recovery time than the traditional system. In the proposed system, the number of failures is mostly 2, and only 1 in the scenario of transmission network congestion and power market price fluctuation. However, the number of failures in traditional systems varies greatly depending on the scenario. The number of failures due tometeorological disasters is 8, and the number of failures in power generation fluctuation scenarios is 3. The failure recovery time of the proposed system fluctuates less, with the shortest recovery time being 26s and the longest recovery time being 34s. The shortest recovery time of the traditional system is 64s and the longest recovery time is 296s. These results demonstrate that the proposed system can effectively improve the stability of the system by generating a variety of complex risk data, identifying and making appropriate scheduling decisions.

5. CONCLUSIONS

In this study, a PG dispatching intelligent decision-making system is constructed based on CGAN, CNN-Bi-LSTM and DQN, achieving remarkable results in generating high-quality risk data and realizing high-precision risk identification in multiple types of PG risk scenarios, which significantly improves the intelligence level of PG dispatching and system reliability. This studyuses CGAN to generate realistic risk scenario data, combines the CNN-Bi-LSTM model to achieve multi-dimensional risk feature extraction and sequence modeling, and optimizes the scheduling decision of DQN to ensure PG security and load balance. The proposed system can cope with complex PG risk scenarios, providesan accurate basis for decision-making, and demonstrates its potential value in smart grid systems. However, the system may still experience performance degradation when the data volume is large or the scenario is highly specific, and the requirements for real-time computing and model computing are high, which limits the real-time deployment capability in ultra-large-scale PGs. Future research couldexplore various ways to improve themodel efficiency and adaptive capabilities, and further combine distributed computing technology to optimize real-time scheduling performance and adapt to a wider range of application scenarios.

FUNDING

State Grid Shanxi Electric Power Company Xinzhou Power Supply Company2024 Technology Project “Application Research of Generative AI Technology in Power Grid Dispatching” (P24SYG002).

REFERENCES

1. Shu Yinbiao, Chen Guoping, He Jingbo, Zhang Fang. “Research on the framework of building a new power system with

renewable energy as the main body". China Engineering Science 23.6 (2021): 61–69.
2. Zhang Zhigang, and Kang Chongqing. "Challenges and prospects of building a new power system under the goal of carbon neutrality". Proceedings of the CSEE 42.8 (2022): 2806–2819.
3. Xu Huifang, Zhang Zhonghao, Tan Yuanpeng, Han Fujia. "Entity recognition technology for power grid dispatching". Electric Power Construction 42.10 (2021): 71–77.
4. Yang Junwei, Du Lulu, Liu Xia, Sun Fei, Huang Kai, Chai Tao, et al. "Smart microgrid dispatching method considering demand-side management strategy under high wind power penetration". Smart Power 49.3 (2021): 32–39.
5. Zhang Jun, Zhang Zhongdan, Wang Zhou, Peng Jing, Wang Tao. "Two-layer robust optimization dispatch of microgrid based on data-driven". Electric Drive 52.1 (2022): 68–75.
6. Hussain, Shahbaz. "Implementation and comparison of particle swarm optimization and genetic algorithm techniques in combined economic emission dispatch of an independent power plant". Energies 12.11 (2019): 2037–2037.
7. Zhou, Mike, Jianfeng Yan, and Xiaoxin Zhou. "Real-time online analysis of power grid". CSEE Journal of Power and Energy Systems 6.1 (2020): 236–238.
8. Li, Qingming, Xi Zhang, Jianbo Guo, Xiwen Shan, Zuowei Wang, Zhen Li, et al. "Integrating reinforcement learning and optimal power dispatch to enhance power grid resilience". IEEE Transactions on Circuits and Systems II: Express Briefs 69.3 (2021): 1402–1406.
9. Mo Qiu, Deng Jiaxin, and Liu Fang. "Microgrid Dynamic Dispatch Model". Journal of Engineering Thermophysics 41.2 (2020): 293–298.
10. Zhao Xiwu. "Research on the Application of Modern Grid Dispatch Operation Mode in Power System". Water Resources and Electric Power Technology and Application 6.22 (2024): 64–66.
11. Zhang, Huifeng, Dong Yue, Chunxia Dou, Gerhard P. Hancke. "PBI based multi-objective optimization via deep reinforcement elite learning strategy for micro-grid dispatch with frequency dynamics". IEEE Transactions on Power Systems 38.1 (2022): 488–498.
12. Fekri, Mohammad Navid, Ananda Mohon Ghosh, and Katarina Grolinger. "Generating energy data for machine learning with recurrent generative adversarial networks". Energies 13.1 (2019): 130–130.
13. Wang, Peng, Fengqi Si, Wei Fan, Zhuang Shao, Shaojun Ren. "Data Enhancement for Data-Driven Modeling in Power Plants Based on a Conditional Variational-Adversarial Generative Network". Industrial & Engineering Chemistry Research 60.24 (2021): 8829–8843.
14. Vega-Marquez, Belen, Cristina Rubio-Escudero, and Isabel Nepomuceno-Chamorro. "Generation of synthetic data with conditional generative adversarial networks". Logic Journal of the IGPL 30.2 (2022): 252–262.
15. Yuan, Ran, Bo Wang, Yeqi Sun, Xuanning Song, Junzo Watada. "Conditional style-based generative adversarial networks for renewable scenario generation". IEEE Transactions on Power Systems 38.2 (2022): 1281–1296.
16. Siniosoglou, Ilias, Panagiotis Radoglou-Grammatikis, Georgios Efstathopoulos, Panagiotis Fouliras, Panagiotis Sarigiannidis. "A unified deep learning anomaly detection and classification approach for smart grid environments". IEEE Transactions on Network and Service Management 18.2 (2021): 1137–1151.
17. Wen Yunfeng, Yang Weifeng, Wang Ronghua, Xu Weiting, Ye Xi, Li Ting, et al. "Review and Prospects of Building 100% Renewable Energy Power System". Proceedings of the CSEE 40.6 (2020): 1843–1856.
18. Son, Namrye, Seunghak Yang, and Jeongseung Na. "Deep neural network and long short-term memory for electric power load forecasting". Applied Sciences 10.18 (2020): 6489–6489.
19. Pei, Shaoqian. "Multi-step ahead short-term load forecasting using hybrid feature selection and improved long short-term memory network". Energies 13.16 (2020): 4121–4121.
20. Cui Shuyin, and Wang Xinjie. "Short-term photovoltaic power prediction based on ensemble learning based on feature engineering". Science Technology and Engineering 22.2 (2022): 532–539.
21. Hosseini, Mohammad Mehdi, and Masood Parvania. "Resilient operation of distribution grids using deep reinforcement learning". IEEE Transactions on Industrial Informatics 18.3 (2021): 2100–2109.
22. Qiao Ji, Wang Xinying, Min Rui, Bai Shuhua, Yao Dong, Pu Tianjiao, et al. "A preliminary study on the knowledge graph framework and key technologies for power grid dispatching fault handling". Proceedings of the CSEE 40.18 (2020): 5837–5849.
23. Efiong, J. E., Akinwale, A., Akinyemi, B. O., Olajubu, E., &Aderounmu, S. (2024). CyberGrid: an IEC61850 protocol-based substation automation virtual cyber range for cybersecurity research in the smart grid. Cyber-Physical Systems, 11(1), 47–66.
24. Jin Xincheng, and Yang Xiuyuan. "Data preprocessing method based on distorted data denoising and its application in wind power forecasting". Power Generation Technology 41.4 (2020): 447–451.
25. Ru, H., Lin, Y., Xu, C., & Chen, T. (2025). Dynamic event-triggered control of multiple electric vehicles in smart grids. Cyber-Physical Systems, 1–16.
26. Luo, Jia, Jinying Huang, and Hongmei Li. "A case study of conditional deep convolutional generative adversarial networks in machine fault diagnosis". Journal of Intelligent Manufacturing 32.2 (2021): 407–425.
27. Abu-Srhan, Alaa, Mohammad AM Abushariah, and Omar S. Al-Kadi. "The effect of loss function on conditional generative adversarial networks". Journal of King Saud University-Computer and Information Sciences 34.9 (2022): 6977–6988.
28. Wang, Jinrui, Baokun Han, and Yuwei Shen. "Data augment method for machine fault diagnosis using conditional generative adversarial networks". Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 234.12 (2020): 2719–2727.
29. Ding, Xin, Yongwei Wang, Zuheng Xu, William J. Welch, Z. Jane Wang. "Continuous conditional generative adversarial networks: Novel empirical losses and label input mechanisms". IEEE Transactions on Pattern Analysis and Machine Intelligence 45.7 (2022): 8143–8158.
30. Tao, Dong. "Road image enhancement and real-time vehicle detection at night based on convolutionalneural network". Engineering Intelligent Systems 32.2(2024): 175–184.
31. Professor Oliver Tamine, Professor Jochen Baier. "Advancing sustainable mobility infrastructure and environment throughautomated low threshold analyzation of road and cycling path surfaces". Engineering IntelligentSystems 32.1(2024): 9–17.
32. Suebsombut, Paweena, Aicha Sekhari, PradornSureephong, Abdelhak Belhi, Abdelaziz Bouras. "Field data forecasting using LSTM and Bi-LSTM approaches". Applied Sciences 11.24 (2021): 11820–11820.
33. Le, Tuong, Minh Thanh Vo, Bay Vo, Eenjun Hwang, Seungmin Rho, Sung Wook Baik, et al. "Improving electric energy consumption prediction using CNN and Bi-LSTM". Applied Sciences 9.20 (2019): 4237–4237.

34. Iqbal, Amjad, Mau-Luen Tham, and Yoong Choon Chang. "Convolutional neural network-based deep Q-network (CNN-DQN) resource management in cloud radio access network". China Communications 19.10 (2022): 129–142.
35. Kumar, Naresh, P. Pramod Kumar, Ch. Sandeep, V. Thirupathi, S Shwetha. "A study on deep Q-learning and single stream Q-network architecture". International Journal of Advanced Science and Technology 28.20 (2019): 586–592.
36. Quek, Yang Thee, Li Ling Koh, Ngiap Tiam Koh, Wai Ann Tso, Wai Lok Woo. "Deep Q-network implementation for simulated autonomous vehicle control". IET Intelligent Transport Systems 15.7 (2021): 875–885.
37. Zhou, Shicheng, Jingju Liu, Dongdong Hou, Xiaofeng Zhong and Yue Zhang. "Autonomous penetration testing based on improved deep q-network". Applied Sciences 11.19 (2021): 8823–8823.
38. Liu Junlei, Liu Xinmiao, Lu Xun, Zhang Donghui, Xu Yunxia. "Analysis methods and countermeasures for supply and demand balance of high-proportion new energy systems". High Voltage Technology 49.7 (2023): 2711–2724.
39. Chao Xiji, Wei Xin, Hailun Ye, Yanming Ye. "Power supply and demand balance problems and solutions in non-stop operation". Engineering Technology and Management 7.24 (2024): 232–234.