

Autonomous Decision-Making and Control Algorithm for Live Working Robots Based on Artificial Intelligence

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The current autonomous operation of live working robots in high-voltage power environments faces problems such as inadequate decision-making precision, poor adaptability, and slow response. This is mainly because the existing algorithms lack the flexibility to deal with complex dynamic environments. To solve this problem, this paper proposes an autonomous decision-making and control algorithm that combines deep learning with classical control strategies to improve the robot's operating ability and execution efficiency in high-voltage environments. First, a Deep Convolutional Neural Network (DCNN) is used to extract the spatial features of the environment; this is used together with Long Short-Term Memory (LSTM) to model time series data to capture the dynamic change information of the environment. Then, Deep Q-Network (DQN) is applied for decision optimization, enabling the robot to autonomously adjust its operating strategy in a complex environment. Secondly, at the control level, the robot evaluates the operating risk through a neural network, and achieves precise motion control based on PID (Proportional Integral Derivative) control and fuzzy control strategies to improve the stability and safety of the operation. The experimental results show that the task success rate of this method in the live working environment reaches 90%. When facing complex environmental changes, the execution time is reduced by about 30%, and the response time is shorter than that of the traditional algorithm. The research results verify the effectiveness of the proposed method in improving the autonomous working ability and efficiency of the live working robot.

Keywords: Autonomous Decision-making; Control Algorithm; Deep Q-Network; Reinforcement Learning; Live Working Robot

1. INTRODUCTION

As the scale of the power system continues to expand, the complexity of high-voltage transmission networks and power equipment is increasing, and the maintenance and fault repair of the power system has become more important and complex. Although the traditional manual live working method can ensure the stable operation of power facilities to a certain extent, due to the high risk of the working environment, workers face the risk of electric shock and

environmental uncertainty during operation, and accidents occur frequently and may even cause serious personal injury [1–2]. Therefore, automated operation has gradually become an important development direction of the power industry. As they are a type of technical equipment that can inspect, maintain, and detect high-voltage power facilities under real-time conditions, live working robots have gradually become an indispensable tool in high-risk power environments [3–4]. Research on live working robots has shown that they not only effectively reduce the risks of manual operation, but also significantly improve operational efficiency and safety [5–6]. However, current live working robots face many technical challenges, one of the most prominent of which is the

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lack of autonomous decision-making and control capabilities [7–8]. When robots face complex live environments, they often cannot make appropriate decisions quickly due to their poor adaptability to environmental changes, resulting in response delays and low task completion during operations [9–10]. Existing decision-making and control algorithms [11] have limited effects on improving the performance and efficiency of robots in dynamic environments. Many algorithms do not fully consider the real-time perceived environmental information, and the behavior of robots in complex operating environments is not precise enough to achieve global optimization [12–13]. Existing technologies also face great challenges in terms of balancing safety and efficiency. Currently, control strategies often sacrifice efficiency for safety assurance, or ignore the dynamic changes in the environment in order to obtain high efficiency, and lack flexible adjustment mechanisms [14–15].

Increasingly, live working robots are being used in distribution networks, especially for the inspection and maintenance of power equipment [16–17]. In response to this demand, Ikeuchi et al. proposed an intelligent perception method based on scenario semantics. This method successfully achieved multi-angle and multi-position point cloud data collection and target recognition by integrating laser radar with equipment semantics, effectively solving problems such as strong light interference, noise points, and data collection disconnection, and significantly improving the positioning accuracy and operation reliability of live working robots in distribution networks [18]. In addition, breakthroughs have been made in the design of autonomous navigation systems for live working robots on distribution lines [19–20]. Zhao et al. achieved precise target recognition through the Larger Scale ‘You Only Look Once’ Version 4 (LS-YOLOv4) algorithm, combined with the Node Control Optimal Rapidly Exploring Random Trees (NC-RRT*) method for robot motion planning and obstacle avoidance, and optimized the grasping point detection using the Lightweight-based Convolutional Neural Network (L-CNN) method. The experimental results showed that the system performed well in target recognition and grasping tasks, and motion planning achieved good results in regard to both efficiency and accuracy [21]. At the same time, Chen et al. proposed a smart distribution live working robot system based on a stereo camera that combined visual perception with a virtual simulation environment. The robot performed well in precise positioning, path planning, and obstacle avoidance in the distribution network. The experimental results showed that the system could efficiently complete the single-phase power line access task, requiring an operation time of only 10 minutes [22]. Although these studies have made significant progress in terms of intelligent perception, motion planning, and precise positioning, these methods have certain shortcomings regarding the robots’ adaptability to complex environments, real-time decision-making, and multi-task execution capabilities [23–24].

With the development of artificial intelligence (AI) technology, the application of autonomous decision-making and control algorithms in the field of robotics has gradually become a research focus [25–26]. Maroto-Gomez et al. systematically reviewed the development of decision-making

systems and control architectures for automated and social robots over the past three decades, explored new methods based on biologically inspired models and machine learning, and analyzed the challenges and future directions of these systems in practical applications. They proposed current issues in action selection software architecture and revealed the potential and direction of future robot system development [27]. In addition, Shu et al. also made breakthroughs in the field of autonomous driving by constructing a framework based on transfer deep reinforcement learning and studied the decision transfer of driving tasks in unsignaled intersection environments [28]. Experiments showed that transfer rules could enable decision strategies for similar tasks so as to achieve a high success rate, reduce time consumption, and support online real-time decision-making, providing an effective framework for real-time decision strategies for autonomous vehicles [29–30]. At the same time, Kherroubi et al. proposed a fully automatic highway-ramp-merging solution based on off-ramp roadside units and artificial neural networks. The TD3 (Twin Delayed Deep Deterministic policy gradient algorithm) agent was trained through deep reinforcement learning to achieve a “safe” and “cooperative” driving strategy. This strategy outperformed traditional methods and could effectively cope with the challenges brought by human-driven vehicles and sensor limitations [31–32]. Although these studies have demonstrated a variety of advanced decision-making and control methods, their adaptability and real-time response capabilities in the face of complex and changing working environments remain unresolved issues.

In response to the challenges associated with autonomous decision-making and control of high-voltage power by live working robots, this paper proposes an autonomous decision-making and control algorithm that integrates deep learning and reinforcement learning. Essentially, this method is applied to perceive and extract environmental information features through DCNN, and uses deep reinforcement learning to optimize the decision-making process so that the robot can perform tasks autonomously in complex working environments. Through multi-sensor fusion technology, various types of information in the real-time working environment are collected, such as power facility status data, real-time changes in the surrounding environment, etc. DCNN is used to obtain effective spatial features from sensor information, and LSTM is used to describe time series data to detect dynamic changes that may occur during operations. Based on the DQN algorithm, reinforcement learning is used to maximize the robot’s behavior so that it has the ability to make real-time decisions under different working conditions, and the ability to change working methods according to changing conditions and task requirements. For the design of the control strategy, a combination of PID (Proportional Integral Derivative) control and fuzzy control is adopted to ensure that the robot’s actions are both precise and adaptive to uncertainties in complex environments. Through this method, the robot not only achieves efficient and safe operation in high-voltage live environments; it also adjusts the control strategy in real-time during the task execution to ensure the quality and safety of task completion.

The main contributions of this research work are: by combining deep learning and reinforcement learning, a new autonomous decision-making and control framework for live working robots is proposed, which solves the problems of poor environmental adaptability and slow response of traditional decision-making algorithms, and realizes the rapid response of robots to dynamic environments. Combining multi-sensor data fusion and deep neural network feature extraction technology, this method can effectively improve the perceptual accuracy of robots when processing high-dimensional environmental information and provide more accurate information support for subsequent decisions. By applying the DQN algorithm in reinforcement learning, this study gives the robot the ability to make autonomous decisions when performing tasks, enabling it to make real-time adjustments in complex environmental changes to ensure the effective completion of tasks. Finally, the control strategy combining PID and fuzzy control proposed in this paper not only ensures the accuracy and stability of the robot's motion, but also makes the robot sufficiently robust in high-voltage live environments.

2. METHODS

2.1 Environmental Perception and Data Processing

Environmental perception and data processing are key to improving the accuracy and response efficiency of autonomous robot operation decisions in live working. The robot uses a set of sensors to obtain multiple data on the working environment in real time, including electric field strength, temperature, humidity, obstacle location, etc., and uses DCNN for spatial feature extraction. These sensor signals are input into CNN, and the original input is subjected to feature extraction and dimensionality reduction through multiple layers of convolution kernels and pooling layers to form a multi-dimensional spatial understanding of the world. By learning the important features extracted from sensor data, CNN is able to recognize complex patterns in the environment without relying on traditional rules. This approach can effectively reduce the use of manually designed features and enhance the robot's ability to process unstructured data in complex environments.

The temporal transformation of environmental information is crucial for the robot's decision-making. To effectively digitize the dynamic changes in the environment, LSTM is used to learn time series data. The gating mechanism included in LSTM can alleviate the gradient vanishing and explosion problems that occur in RNN in long-time series learning, and maintain long-term memory of past information. The dynamic changes of environmental factors (that is, voltage changes and temperature changes) are modeled through the time dependency of the LSTM network so that the robot can feed back the environmental changes at every moment in real time. This mechanism makes the robot more predictable and flexible when facing uncertain and dynamic environments.

To improve the processing ability of environmental perception information, it is recommended to use data

preprocessing and fusion technology in the environmental perception module. Filtering technology is used to effectively and selectively remove sensor noise, and normalization strategy is used to convert the scale of various sensor data into comparable levels before inputting this information into the neural network. This processing technology can improve data quality, reduce errors caused by signal disturbances, and ensure the accuracy and consistency of data input to the neural network. The sensor data is combined by means of a weighted fusion algorithm to obtain more representative environmental perception data, providing a more reliable basis for subsequent decision-making and control. Figure 1 is a flowchart showing the processing of environmental perception data.

2.2 Time Series Modeling and Dynamic Environmental Adaptation

To determine the time dependency in a complex world, LSTM is used to capture the time series of environmental data. Due to the gating mechanism in LSTM, the gradient vanishing or exploding problem of traditional recurrent neural networks can be avoided while retaining long-term memory, thereby capturing the time-varying characteristics of the environment. In practice, the changing data of the environment is input into the LSTM network in the form of a time series. Through learning, the network obtains the relationship between the previous data and its current state and learns how to predict the future state.

Considering the harsh environmental conditions of the live working robot, an adaptive adjustment mechanism is added to the training of the LSTM model. By recursively readjusting the weights and biases, the model learns to adapt to environmental changes in real time, so that the model can check the relationship between the current state of the environment and the historical input data and predict future changes. In addition to ensuring that the robot completes its work in a known environment, this time series model solution also optimizes the robot's flexibility in a dynamic environment and reduces the decision-making bias caused by environmental adjustments. Figure 2 is a diagram of LSTM time series modeling and environmental data prediction, showing the comparison between the actual environmental data and the LSTM predicted data and the changing trend of the time series.

To further enhance the robot's adaptability to dynamic environments, DQN is applied on the basis of LSTM for reinforcement learning optimization. In the actual operation process, the robot needs to continuously adjust its own operation strategy according to the feedback of the external environment in the continuous decision-making process. Through DQN, the robot obtains reward signals by interacting with the environment and gradually optimizes the decision-making strategy. The application of DQN enables the robot to make more efficient decision adjustments in complex and uncertain environments, thereby improving the robustness and flexibility of the system. DQN updates strategies to maximize long-term returns, solves the challenges of dynamic changes in the environment to traditional decision-making methods,

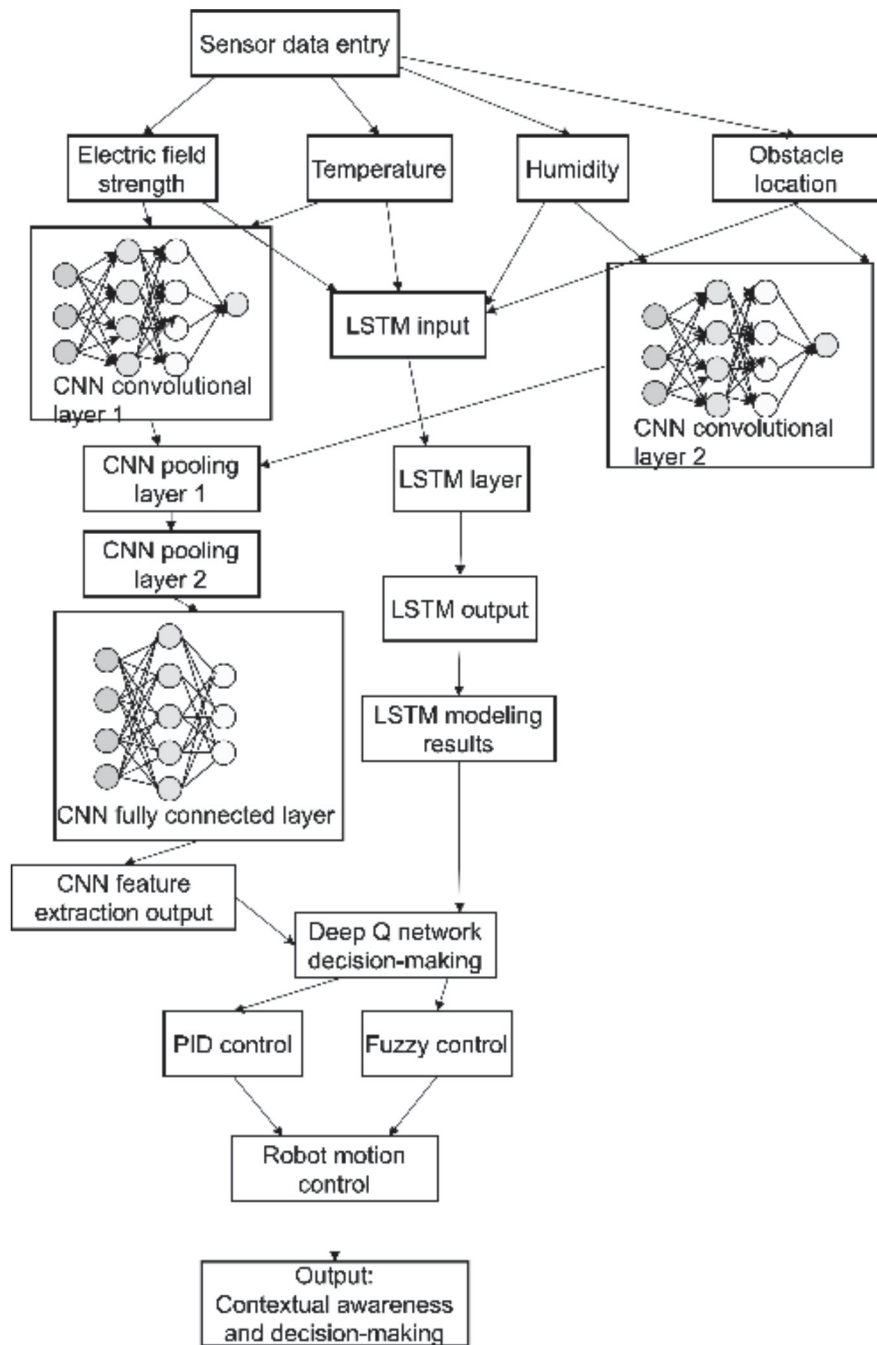


Figure 1 Processing flow of environmental perception data.

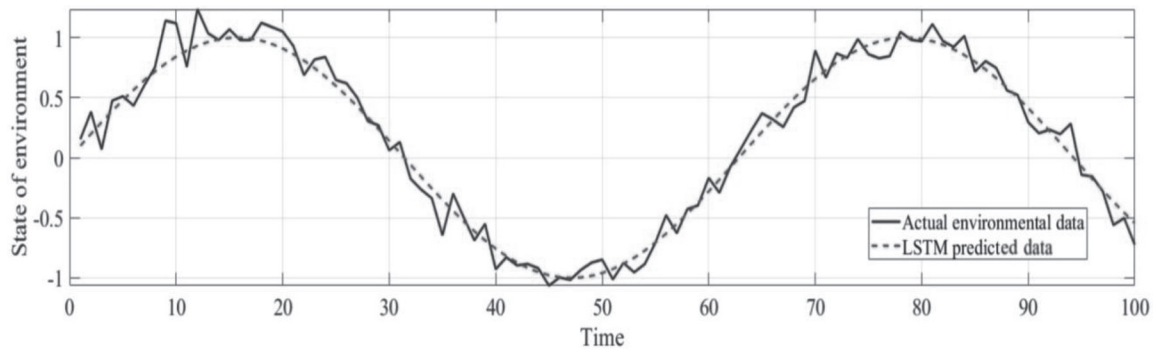


Figure 2 LSTM time series modeling and environmental data prediction diagram.

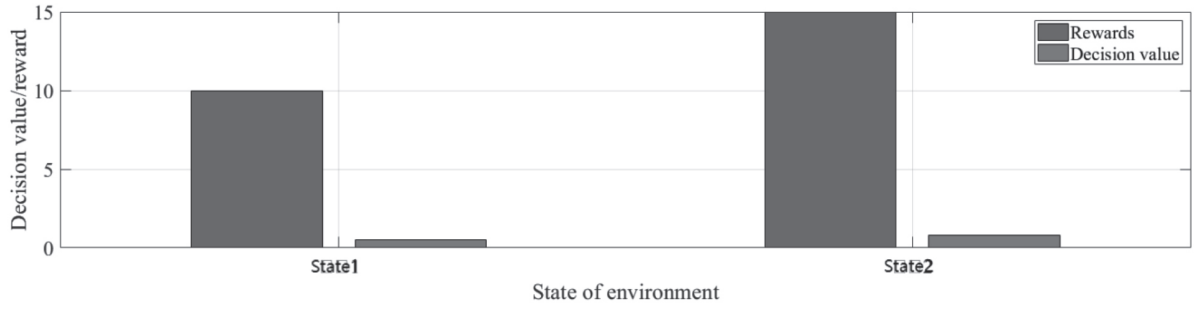


Figure 3 DQN optimization decision and reward diagram.

and ensures that live working robots can autonomously adapt to real-time changing work scenarios. Figure 3 is a DQN optimization decision and reward diagram, which shows how DQN optimizes decision strategies based on environmental feedback through fictitious states and actions. The decision value and reward value in each state are displayed using a bar chart, which indicates how DQN optimizes the operation strategy through reinforcement learning.

For time series modeling and dynamic environment adaptation, the combination of LSTM and DQN enhances the ability to capture environmental changes, and through real-time learning and self-optimization, improves the robot's decision-making efficiency and accuracy in unknown or unexpected environmental conditions.

2.3 Autonomous Decision-making and Reinforcement Learning Optimization

In the autonomous decision-making process of live working robots facing complex, high-pressure, and dynamically changing environments, traditional decision-making methods often find it difficult to adapt to the changing task requirements and environmental conditions. Using reinforcement learning as the core method for decision optimization, and combining DQN to automatically optimize decision strategies, can effectively improve the robot's decision-making accuracy and adaptability. DQN approximates the Q-value function by means of a deep neural network to achieve the optimal strategy. In this method, the robot obtains state information by interacting with the environment and selects actions based on the current strategy, and the environment feeds back corresponding reward or penalty signals. The robot continuously adjusts its decision-making strategy based on these feedback signals, and gradually optimizes its behavior through repeated iterative learning, thereby maximizing long-term returns. In a high-pressure environment, tasks are often high-risk and have high uncertainty, and traditional methods find it difficult to handle such complex decision-making situations. DQN can automatically adjust the operation strategy and select the most appropriate action plan under different environmental conditions by dynamically updating the Q-value, thereby ensuring the stability and safety of the operation. The following is the update formula of the Q-value function:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)) \quad (1)$$

where $Q(s_t, a_t)$ is the Q-value of taking action a_t in the current state s_t ; r_{t+1} is the immediate reward obtained after executing action a_t in state s_t ; γ is the discount factor, which is used to measure the importance of future rewards; $\max_{a'} Q(s_{t+1}, a')$ is the maximum Q-value selected in the next state s_{t+1} , which is used to estimate the maximum reward in the future.

For the optimization of reinforcement learning, two key technologies are used: experience replay and target network. Experience replay breaks the data correlation by storing data such as state, action, and reward during the interaction between the robot and the environment, thereby improving the efficiency and stability of learning. The target network prevents drastic fluctuations in the Q-value function during the learning process by regularly updating the parameters of the target Q-network, thereby improving the convergence and stability of the algorithm. The application of these technologies solves the problems of overfitting and slow convergence that reinforcement learning may face in practical applications, and improves the decision-making efficiency of robots in complex dynamic environments. The following is the experience recycling formula:

$$D = \{(s_1, a_1, r_1, s_2), (s_2, a_2, r_2, s_3), \dots\} \quad (2)$$

where D is the experience replay pool. Each data point (s_t, a_t, r_t, s_{t+1}) contains the current state s_t , the reward r_t received by the selected action a_t , and the next state s_{t+1} transferred to.

Live working robots not only need to perform routine tasks; they are also required to respond to emergencies and unexpected environmental changes in various application scenarios. To make the robot sufficiently adaptable, the reinforcement learning optimization strategy adopts an exploration-exploitation balance mechanism. In the initial training stage, the robot attempts to execute a large number of actions with a high exploration rate, and gradually accumulates experience. As the training continues, the robot gradually relies on the learned high-reward actions to maximize the stability of decision-making. The exploration-exploitation mechanism enables the robot to quickly adjust its strategy and adapt to changing needs when facing a new environment.

The decision-making strategy optimized by reinforcement learning not only enhances the robot's autonomy, but also significantly improves the robot's adaptability in complex environments. Compared with traditional rule-based decision-making strategies, through dynamic learning

Table 1 Hardware configuration table.

Serial number	Component name	Model number	Quantity	Technical Specifications	Remarks
1	High precision sensor	SensorX-1000	4	Accuracy $\pm 0.1\%$, range $-50^\circ \sim 150^\circ$, humidity 0–100% RH	Monitor environment temperature and humidity
2	Voltage sensor	VoltMeter-5000	2	Accuracy $\pm 0.5\%$, range 0–1000kV	Monitor high-voltage line voltage
3	Infrared sensor	IR-Sensor-2000	2	The precision is $\pm 1^\circ\text{C}$ and the response distance is 0.5m–10m	Monitor the environment around the robot
4	Ultrasonic wave sensor	Ultrasonic-3000	2	Accuracy ± 1 cm, measuring range 0.1m–10m	Measure distances and obstacles
5	Servo motor	Servo-Motor-750	6	Torque 15N·m, rotational speed 3000rpm, accuracy $\pm 0.1^\circ$	Actuate the manipulator joints
6	Control system	Control-Unit-4000	1	Support 16 input/ output, response time = 10 ms	Central control system

and adjustment, DQN avoids the limitations of artificially set rules, enabling the robot to respond flexibly when facing uncertain environments and produce the best working results. The successful application of reinforcement learning in task decision-making not only improves the operating efficiency of live working robots, but also improves their safety and stability in complex high-voltage environments, and solves the problems of slow response and imprecise decision-making of traditional algorithms in complex environments.

2.4 Precise Control and Action Execution

To achieve high-precision operation control, neural networks are combined with classical control strategies to optimize the robot's motion path and the accuracy of action execution during the execution process. When performing tasks, the robot needs to evaluate the operation risk in real time, use neural networks to process the dynamic information of the environment, and combine the real-time data in the operation scenario to quantitatively evaluate the robot's risk. By learning the input data, the neural network can predict potential dangers and dynamically adjust the robot's behavior strategy according to environmental changes. This process enables the robot to autonomously make a safety-related judgment in complex environments and adjust the execution strategy in time to reduce potential risks.

To improve the control accuracy, a method combining PID control and fuzzy control is adopted. PID control can maintain the robot's motion state quite accurately by performing proportional, integral and differential operations on the error, so that the robot stays on the desired path every time it performs a task. PID control is accurate and can quickly respond to changes in the surrounding environment when the system is stable. Fuzzy control makes up for the shortcomings of PID control in uncertain situations. Fuzzy control can flexibly adjust control parameters, while adapting to nonlinear and complex systems through fuzzy reasoning mechanisms, and more effectively cope with uncertainty and complexity in reality.

3. EXPERIMENTS

3.1 Experimental Platform and Hardware Configuration

In this research work, a high-voltage live working robot experimental platform is built to verify the feasibility of the proposed algorithm. The hardware implementation of the experimental platform relies on high-precision control systems, actuators, and sensors, which can simulate complex power working environments and provide real-time feedback on changes in various parameters of the working robot. The experimental platform has a series of sensors, including temperature and humidity sensors, voltage sensors, infrared sensors, ultrasonic sensors, etc., to monitor the working status information of the working robot in real-time. The sensor data is transmitted to the central control system through the hardware interface and processed according to the deep learning model and control algorithm. Table 1 presents the hardware configuration.

The platform uses a high-performance embedded computing module as the main processor and is equipped with a GPU acceleration module to achieve the best balance between data processing performance and computing algorithm speed. The embedded module interacts with the robot control system through a real-time data bus to avoid distortion of data transmission due to delays during the entire process. To ensure the stability and responsiveness of the robot under high voltage, a high-voltage power supply simulator equipment is embedded in the experiment to simulate various working conditions under voltage fluctuations. The power supply unit simulates various working conditions that may occur during high-voltage live work by compensating for voltage fluctuations to achieve a perfect level, and tests the robustness of the algorithm under dynamic conditions.

The experimental platform also includes certain actuators and robotic arms driven by servo motors, enabling the robot to have high-precision motion control when performing tasks. The robot is able to respond to changes in the environment by redirecting execution paths and activities in real time. To perform activities accurately, the control system is closely

Table 2 Routine inspection tasks.

Serial number	Voltage (V)	Current (A)	Temperature (°C)	Humidity (%)	Obstacle distance (m)	State of work	Climatic conditions
1	220.5	5.2	30.4	65	2.5	Normal	Sunny day
2	221	5.1	30.6	64	2.6	Normal	Sunny day
3	220.8	5.3	30.7	66	2.4	Normal	Cloudy day
4	221.2	5	30.5	63	2.7	Normal	Cloudy
5	220.7	5.1	30.8	64	2.3	Normal	Thunderstorm

Table 3 Troubleshooting tasks.

Serial number	Voltage (V)	Current (A)	Temperature (°C)	Humidity (%)	Obstacle distance (m)	State of work	Climatic conditions	Power equipment status
1	210	6	32	70	1.8	Failure	Cloudy day	In trouble
2	210.2	6.1	32.1	72	1.9	Failure	A rainy day	In trouble
3	209.5	6.2	32.3	69	2	Troubleshooting	Thunderstorm	In trouble
4	211	6	31.8	68	1.7	Failure	Sunny day	In trouble
5	210.8	6	32	71	1.6	Troubleshooting	Cloudy	In trouble

Table 4 Equipment maintenance tasks.

Serial number	Voltage (V)	Current (A)	Temperature (°C)	Humidity (%)	Obstacle distance (m)	State of work	Climatic conditions	Power equipment status
1	230	4.8	28	60	3	Normal	Sunny day	Normal
2	230.5	4.9	28.2	62	3.1	Normal	Cloudy	Normal
3	229.8	5	28.4	61	3.2	Under maintenance	Strong wind	Normal
4	231	4.7	28.1	63	3	Normal	Sunny day	Normal
5	230.3	4.8	28.3	64	3.1	Normal	Cloudy day	Normal

synchronized with sensor feedback, determines the operation path in real time, and corrects possible deviations during execution through a closed-loop feedback system. The platform can effectively test the real-time reaction and control quality of the algorithm under actual operating conditions.

The efficiency and reliability of the hardware configuration provide a sound basis for the experiment. Through the experimental verification of the platform, the performance of different algorithms in high-voltage power environment can be evaluated, establishing a reliable foundation for subsequent model optimization and algorithm adjustment. At the same time, the design of the experimental platform ensures the testing requirements under various working environment conditions, covering multiple aspects such as environmental changes and task complexity.

3.2 Dataset and Experimental Settings

In this study, a multi-dimensional and multi-scenario dataset is constructed to evaluate the effectiveness of the proposed algorithm. The dataset contains sensor data, task information, and real-time feedback data collected during robot execution in different live working environments. The data is collected from actual live working scenarios and generated through a simulation experimental platform to ensure that it covers a variety of tasks and possible environmental changes.

The construction of the dataset is based on the collaborative work of sensors and robot execution systems. Through high-precision sensors, multiple data including voltage, current,

temperature, humidity, obstacle distance, etc., are collected. These data reflect the dynamic changes of the environment during live working in real time. Through the precise positioning and data collection of sensors, the environmental changes during the operation process and the status of the robot under different conditions can be fully captured. All sensor data are preprocessed, which includes denoising, normalization and standardization, to ensure the data quality and effectiveness of model training. The scale of the dataset includes real-time data for thousands of robot operations to ensure coverage of multiple environmental states and operating situations.

To verify the performance of the algorithm in different environments, the experiment sets up a variety of live working tasks including, but not limited to, routine inspections, troubleshooting, equipment maintenance, etc. Each task is tested under different environmental conditions, including the working status of power equipment, various climate changes, and different voltage load conditions. In the experimental setting, the robot automatically performs actions according to the task requirements, monitors and feeds back the changes in the environment in real time, and makes autonomous decisions through the proposed algorithm. The success or failure of each operation task, as well as the real-time feedback information during the execution process, such as task completion time, success rate, response time, etc., are included in the experimental evaluation indicators. The data in Tables 2 to 5 covers a variety of environmental conditions, including different voltage loads, currents, temperatures, humidity, obstacle distances, climates, and equipment working

Table 5 High-voltage equipment maintenance tasks.

Serial number	Voltage (V)	Current (A)	Temperature (°C)	Humidity (%)	Obstacle distance (m)	State of work	Climatic conditions	Power equipment status
1	300	8	35	75	2	Under maintenance	Thunderstorm	Equipment shutdown
2	305	7.8	35.2	74	2.1	Under maintenance	Thunderstorm	Equipment shutdown
3	302.5	7.9	35.3	73	2.2	Under maintenance	Cloudy	Equipment shutdown
4	301.5	8.1	35.5	76	2	Under maintenance	Sunny day	Equipment shutdown
5	300.8	8	35.4	78	1.9	Under maintenance	Strong wind	Equipment shutdown

conditions. The conditions of various tasks are changed according to the experimental settings to test the performance of robot operations in different environments.

To ensure the comparability and scientificity of the experiment, several benchmark algorithms are compared. The performance of each algorithm is quantitatively measured by factors such as execution time, response time, and task success rate. In each experimental task, the dataset is used not only to train the reinforcement learning model, but also to verify the robustness and adaptability of the algorithm in real-time complex dynamic environments. The performance of the method under different tasks is fully tested, and its superiority in complex environments is verified.

3.3 Evaluation Indicators and Experimental Objectives

In this study, different quantitative indicators are used to comprehensively evaluate the performance of the proposed algorithm when applied to live working robots in experimental measurements. To verify the effectiveness and mobility of the algorithm, the main indicators—task completion rate, execution time, and response time—are selected, and the superiority of the algorithm is measured by comparing it with the benchmark algorithm.

During the execution of each task, the robot operates according to the real-time perception and decision results, completes the planned tasks within the specified time, and achieves the predetermined goals. The calculation of the task success rate depends on whether all planned tasks can be implemented correctly during the operation without serious errors or accidents. According to this indicator evaluation, the decision accuracy and operation efficiency of the algorithm in different environmental scenarios can be understood. To prevent the deviation caused by the randomness of the results of a single task, the experimental setting repeatedly simulates the same task in different environments to determine the consistency and reliability of the results. The following is the formula for the task success rate. In Formula (3), $N_{success}$ is the number of successfully completed tasks, and N_{total} is the total number of tasks executed in the experiment.

$$S_{task} = \frac{N_{success}}{N_{total}} \times 100\% \quad (3)$$

Execution time is another important evaluation measurement that indicates the efficiency of the robot in completing the task. The execution time includes the total time required for the robot to complete the task from the start of the task to its completion. In the live working environment, the execution time of the task is directly related to the robot's operating efficiency and system response speed. Reducing the execution time can not only improve the efficiency of the robot's operation, but also reduce the external environmental risks that may be encountered during the operation. The experiment compares the execution time of the traditional algorithm with that of the proposed method for the same task to evaluate the performance of the algorithm in improving the efficiency of task execution. Formula (4) is the execution time ($T_{execution}$) to calculate the total time required from the start to the completion of the task. Assuming that the task start time is t_{start} and the completion time is t_{end} , the execution time is:

$$T_{execution} = t_{end} - t_{start} \quad (4)$$

In addition, the execution time can also be divided into multiple stages, such as task planning time, execution stage time, etc. Task execution includes multiple steps i :

$$T_{execution} = \sum_{i=1}^n T_{step_i} \quad (5)$$

where T_{step_i} is the execution time of the i -th step, and n is the total number of steps.

As an indicator of the robot's ability to adapt to environmental changes, response time refers to the time it takes for the robot to make decisions and take actions based on changes in the external environment. In live working situations, the dynamic changes in the environment place high demands on the robot's operating tasks. A rapid and accurate response to environmental change is required to ensure the stability and safety of the operation. The experiment tests the robot's reaction time to environmental changes so as to evaluate the flexibility and effectiveness of the algorithm in dealing with environmental complexity and uncertainty. Compared with traditional algorithms, the reaction time of the proposed algorithm in complex environments is significantly shortened, verifying its superiority in dynamic environment flexibility.

To further comprehensively study the performance of the algorithm on working robots, the experimental objectives also

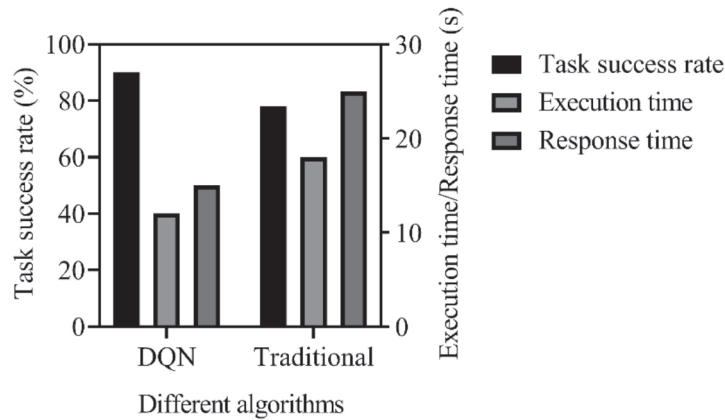


Figure 4 Comparison of different indicators between DQN and traditional control algorithms.

include risk analysis, control accuracy and stability analysis. In terms of control accuracy and stability, the robot's path, posture, and execution error are monitored in real-time, and the accuracy and stability of the robot under different control modes under live high-voltage working conditions are studied. By integrating PID control and fuzzy control technology, the actual operation accuracy of the robot under actual working conditions is verified, and the superiority of this method in terms of stability and accuracy of control task execution is also verified.

4. RESULTS

4.1 Task Success Rate and Execution Time

To ensure the reliability and integrity of the test results, this study conducts a variety of repeated task tests in different test environments for tasks of varying complexity, from routine testing to emergency repairs. The execution process required by each task is rigorously tested to ensure that the robot can perform tasks repeatedly and efficiently, avoiding safety risks or system crashes. In the experiment, the robot can make decisions automatically according to the recommended algorithm, and DQN dynamically adjusts its state during use, making real-time decisions based on environmental conditions and task requirements, and representing the success rate of the task by comparing the set goals with the actual completion.

Unlike traditional algorithms, DQN enhances decision-making based on reinforcement learning, enabling the robot to adjust its approach quickly according to environmental changes, thereby reducing the number of failures or accidents caused by decision-making errors. Through the spatial features learned by DCNN and the time series data of LSTM, the robot can identify possible risks in complex environments and make corresponding adjustments, greatly improving the success rate of operations.

As can be seen from Figure 4, the experimental results show that the success rate of DQN in different tasks is higher than that of traditional algorithms on average. In common test environments, the task success rate of DQN is 90%, which is about 12% higher than that of traditional methods, mainly due to its flexibility and decision-making accuracy in dynamic

environments. Especially when faced with complex power equipment failures or emergencies, robots can avoid errors through real-time decision-making and ensure the correct execution of tasks. By applying a combination of various deep learning and traditional control methods, the improvement in the success rate not only proves the efficiency of the method in complex environments, but also verifies its feasibility in practical applications. DQN performs better in task success rate, reaching 90%, while the traditional algorithm is 78%. The execution time of DQN is 12 seconds, while the traditional algorithm takes 18 seconds. The response time of DQN is 15 seconds, while the traditional algorithm takes 25 seconds.

In further analysis, the improvement of task success rate is also closely related to the stability and safety of the robot during execution. The robot uses a neural network to evaluate the risks in the environment in real-time and adjusts according to the control strategy to ensure that no accidents occur during the operation. Combining the optimization strategy of PID control and fuzzy control, the robot's execution action is precise, further enhancing the consistency of task success.

In the analysis of execution time, attention is paid to the time efficiency required by live working robots to perform various tasks. In the experiment, the calculation of execution time includes the entire process from the robot receiving the operation instruction to the completion of the task, covering multiple links such as environmental perception, decision making, and action execution.

To ensure precise measurement of execution time, standardized task scenarios are used in the experimental setting, including routine inspections, equipment maintenance, and troubleshooting. The execution process of each task is recorded in detail, especially the time consumed by the robot to complete the task under various environmental changes and different task complexities. The experiment compares the algorithm in this paper with the traditional benchmark control algorithm to evaluate its time efficiency when executing different tasks under various environmental conditions. The algorithm in this paper optimizes decisions through DQN, allowing the robot to make faster and more accurate decisions in a dynamic environment, thereby shortening the task-execution time.

A comparison of the experimental results shows that the proposed algorithm has a significant advantage in terms of execution time. Given the same task and environmental

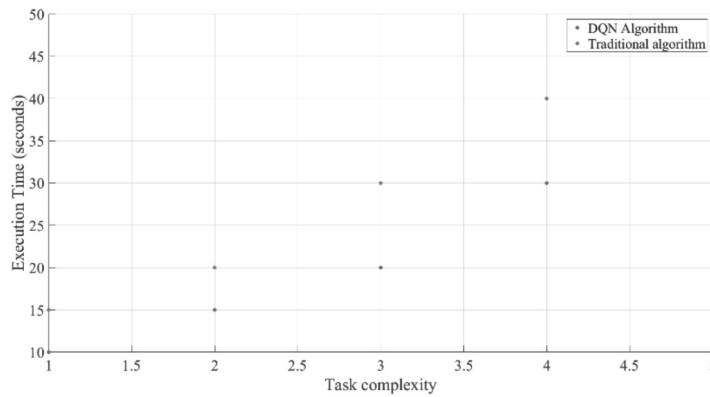


Figure 5 Relationship between execution time and task complexity.

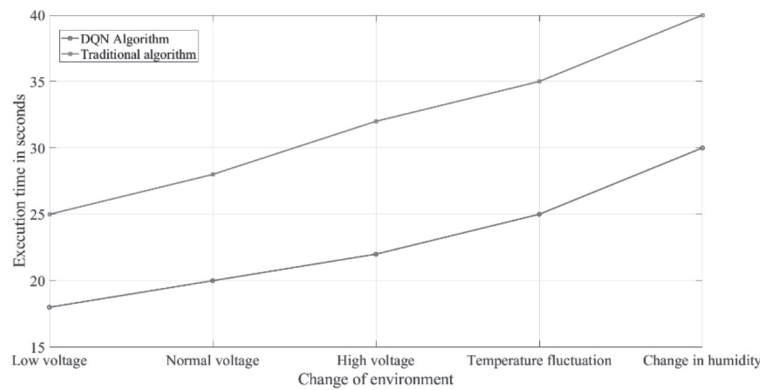


Figure 6 Change of execution time under environmental changes.

conditions, the execution time of the traditional algorithm is generally longer. Especially when facing complex tasks and environmental uncertainties, the response time and decision delay increase the overall execution time. Conversely, DQN optimizes the decision-making process of the robot in a dynamic environment through the combination of deep learning and reinforcement learning, so that the robot can adjust the task strategy in real time when facing environmental changes, reduce invalid operations and waiting time, and thus significantly reduce the total time of task execution. Figure 5 shows the relationship between execution time and task complexity. As the complexity of the task increases, the execution time of the DQN algorithm increases from 10 seconds to 40 seconds, while the execution time of the traditional algorithm increases from 15 seconds to 50 seconds. This indicates that although the execution time of both algorithms increases when the task complexity increases, the DQN algorithm always requires less execution time. This phenomenon can be attributed to the advantages of the DQN algorithm in task decision optimization, which can quickly adjust strategies and thus reduce unnecessary operations and waiting time.

In complex environments, especially in tasks such as emergency repairs or maintenance of power equipment, environmental uncertainty requires robots to have higher adaptability and faster response speed. Experimental results show that the execution time of the DQN algorithm under different environmental conditions is about 30% less than that of traditional algorithms. For example, under low-voltage

conditions, the execution time of the DQN algorithm is 18 seconds, while that of the traditional algorithm is 25 seconds. The gap under other environmental conditions is also obvious. This reduced execution time is not only due to decision optimization, but also due to the high efficiency of DCNN and LSTM in environmental perception and data processing. By extracting spatial features through CNN and combining LSTM modeling time series data, the robot can predict and adjust the operation strategy in advance when the environment changes, avoiding slow response to emergencies and decision errors. Figure 6 is a curve chart showing the change of execution time under various environmental changes.

To further improve the execution efficiency, the control strategy combines PID control and fuzzy control methods to reduce the redundancy of operations and unnecessary adjustments through precise action execution. PID control ensures the accuracy of the robot's execution path by correcting errors in real time. Fuzzy control effectively copes with uncertainties in complex environments and optimizes the robot's motion control, enabling it to speed up its response while maintaining high precision, thereby shortening the time required to execute the entire task.

Comprehensive analysis shows that the algorithm significantly reduces the task execution time by optimizing the decision-making process, improving environmental adaptability, and reducing action redundancy. This not only improves the robot's operating efficiency in high-voltage power environments, but also guarantees better operating safety and response speed. Compared with traditional

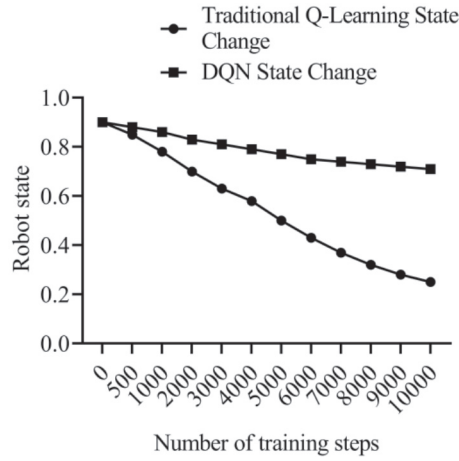


Figure 7 The decision-making state transfer process of the robot under different environmental conditions.

methods, the significant reduction in execution time of the proposed method verifies its application potential in high-voltage power environments and provides effective technical support for the efficient execution of future robot autonomous operation tasks.

4.2 Autonomous Decision-making and Environmental Adaptability

The robot's autonomous decision-making in high-voltage power environments relies on the strategy optimization of deep reinforcement learning in order to adapt to complex and dynamic working scenarios. This paper uses DQN to construct an autonomous decision-making framework, and optimizes the operation strategy using the state-action value function based on the environmental information provided by the perception system. DQN alleviates the instability caused by dynamic changes in the environment during reinforcement learning through experience replay and target network mechanisms, so that the robot converges to the optimal strategy in the high-dimensional decision space. During the training process, the Huber loss function is used:

$$L(\theta) = \mathbb{E}_{(s,a,r,s') \sim D} \times \begin{cases} \frac{1}{2}(y - Q(s, a; \theta))^2, & |y - Q(s, a; \theta)| < \delta \\ \delta(|y - Q(s, a; \theta)| - \frac{1}{2}\delta), & \text{otherwise} \end{cases} \quad (6)$$

The policy gradient is adjusted to improve the training stability and suppress the influence of outliers. To address the problem of environmental adaptability, the robot combines the Long Short-Term Memory (LSTM) network to model time series data and predict the dynamic changes of the working environment. The LSTM structure can capture historical state information and optimize long-term dependency problems by means of a gating mechanism. During the training process, the time series prediction error is used:

$$E_t = \frac{1}{T} \sum_{t=1}^T (\hat{s}_t - s_t)^2 \quad (7)$$

The model's ability to adapt to environmental changes is evaluated, and the long-term memory capacity is optimized by adjusting the Forget Gate parameters of LSTM. During the experiment, the robot is trained under different power scenarios, including fluctuations in electric field intensity and operations where the robotic arm is space-constrained. By predicting the environmental state and optimizing the decision strategy, the decision error is reduced to less than 5% under conditions of large environmental changes.

During the decision execution process, the double Q-learning strategy is adopted to reduce decision bias. The decision network and the target network calculate the action value respectively, and take the smaller value to update the Q-value. The calculation formula is:

$$Q(s, a) = r + \gamma Q(s', \arg \max_{a'} Q(s', a'; \theta)); \quad (8)$$

By means of the double Q-value update mechanism, the over-estimation problem in the strategy learning process is reduced, and the robot's adaptability to environmental changes is improved. Figure 7 shows the decision state transition process of the robot under different environmental conditions, where the horizontal axis represents the number of training steps and the vertical axis represents the change trend of the robot state. The data shows that under the traditional Q learning method, the robot state value fluctuates greatly with the increase of training steps, and the state convergence speed is slow. When the training reaches 5000 steps, the state value drops to 0.50, while the DQN method remains at around 0.77 at the same number of steps, with a more stable convergence trend. After further training to 10,000 steps, the state value of traditional Q learning drops to 0.25, while DQN remains at 0.71, indicating that DQN converges faster and has stronger strategy stability when encountering complex environmental changes.

In the robot decision-making process, the uncertainty of the working environment is reflected in the ambiguity of the target state and the disturbance effect during the execution of an action. To further optimize the decision stability, a state evaluation module based on the self-attention mechanism is applied. This module calculates the correlation between environmental states and optimizes the state representation

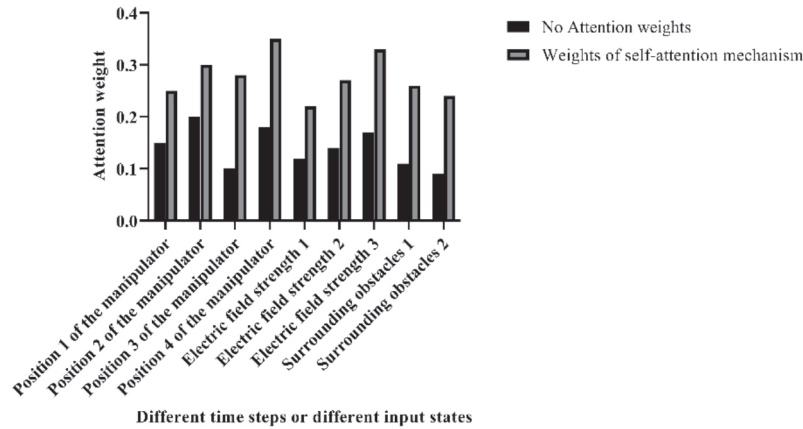


Figure 8 Attention weight distribution during robot operation.

to improve the robot's perception of sudden environmental changes. The self-attention mechanism calculates the state vector representation by weighted summation:

$$H = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V \quad (9)$$

where Q , K , and V represent state query, key value, and numerical vector, respectively, and d_k is the vector dimension. This mechanism strengthens the representation ability of environmental states, enabling the robot to more accurately identify changes in the operating scenario during the decision-making process.

Figure 8 shows the distribution of the robot's attention under different operating states. The horizontal axis represents the different environmental states of the robot's position, electric field strength, and surrounding obstacles, and the vertical axis represents the attention weight. The data shows that the robot without the self-attention mechanism has a more dispersed weight distribution on the key states. For example, the attention in the "robot position 4" state is only 0.18, while after adding the self-attention mechanism, the weight of this state rises to 0.35, indicating that the model pays more attention to the key operating state and improves the perception of important environmental variables. The weights of other states such as "electric field strength 3" and "surrounding obstacles 1" increase to 0.33 and 0.26 respectively after using the attention mechanism, reflecting that the robot can more accurately identify key state information in a high-risk environment. Hence, the self-attention mechanism optimizes the state feature extraction capability, enables the robot to make precise decisions in complex environments, and improves the stability of autonomous operations.

4.3 Safety and Risk Assessment

In this paper, a safety assessment technology combined with neural networks is proposed so as to measure potential risks in real-time operations, and take corresponding control measures to ensure smooth operation and avoid accidents. The risk assessment process involves multi-dimensional safety considerations, namely electrical hazards, physical contact,

environmental changes, etc., and enhances the decision-making process based on these assessment results.

The key to risk assessment is to monitor potential risk factors in real time by conducting a thorough examination of the robot's surrounding environment and neural network models. The robot uses a sensor network to obtain environmental information such as voltage, current, temperature, obstacle location, and operation trajectory, and processes data through models such as convolutional neural networks (CNNs) and LSTM to extract key information and predict possible risks. Neural networks can assess risks based on historical data and estimate their impact, and then adjust operating strategies to avoid high-risk areas. Combining PID control and fuzzy control methods, the robot can adjust the motion state in real time to ensure stability and precision. When power fluctuations occur or obstacles appear, the PID controller responds in time, while fuzzy control provides flexible decision-making in uncertain environments to ensure safe operation and reduce accidents.

During the risk assessment experiment, the robot simulated multiple operating tasks in high-voltage power environments and records the safety data of the completed tasks in real-time. The experimental results show that the safety assessment method based on deep learning models and control strategies greatly reduces the accident rate during the operation. When compared with traditional methods, the operation safety of the proposed method has been significantly improved. In particular, when complex situations such as electrical failures and equipment abnormalities occur, the robot can detect potential dangers in time and respond effectively. Through the prediction of the operating environment by neural networks and the real-time assessment of risks, the robot's emergency response capability in complex dynamic environments is significantly improved, and the success rate of tasks is significantly improved. Figure 9 is an electrical risk assessment diagram. The voltage fluctuation range is approximately between 100V and 110V, and the current fluctuation range is between 50A and 55A. These fluctuations reflect the instability of the power system and may cause equipment failures or electrical safety problems. The fluctuations of voltage and current are large, with standard deviations of approximately 3.1 and 1.4, respectively, indicating that the system is prone to fluctuations.

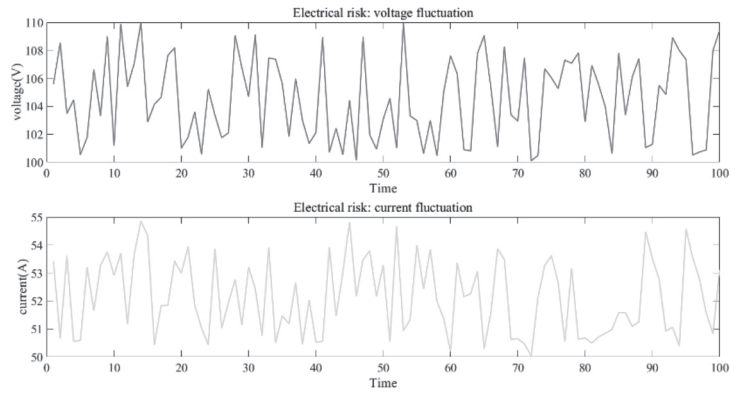


Figure 9 Electrical risk assessment diagram.

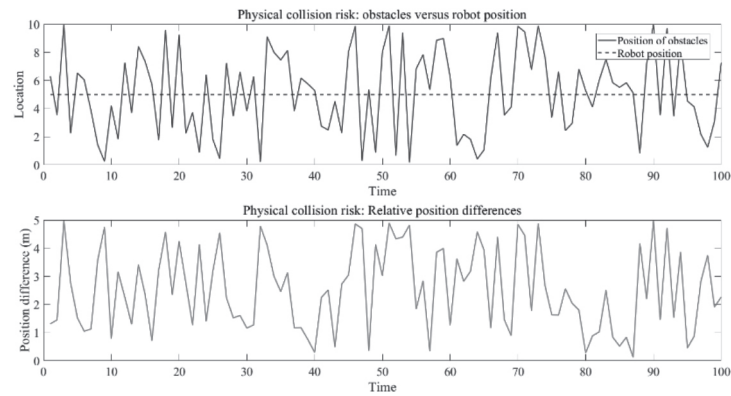


Figure 10 Physical collision risk assessment.

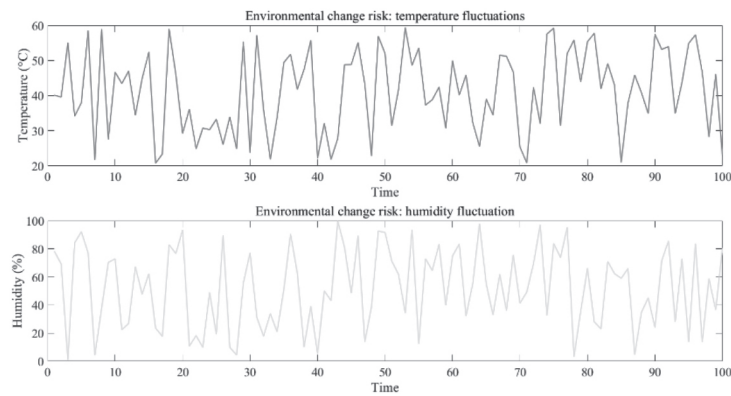


Figure 11 Environmental change risk assessment diagram.

Figure 10 depicts a physical collision risk assessment, showing the changes in the position of the obstacle and the robot, as well as the relative position difference between them, to help determine whether the robot faces the risk of collision. The change in the obstacle position is between 0 and 10 meters, while the robot position remains at 5 meters. The relative position difference between the robot and the obstacle can reach up to 5 meters, indicating a high risk of collision, especially when the obstacle appears unexpectedly.

Figure 11 is an environmental change risk assessment diagram, which shows the changes in ambient temperature and humidity, as well as their degree of fluctuation. Drastic changes in the environment may affect the operational stability of the robot. The temperature fluctuates between 20°C and 60°C, and the humidity fluctuates between 0% and 100%,

indicating that the instability of the environment affects the robot’s operational stability, especially when the humidity changes dramatically, which may affect the reliability of electronic components.

Figure 12 is a comprehensive risk assessment diagram. The comprehensive risk score generated by the neural network model reflects the impact of electrical risk, physical collision, environmental change, and other factors on the overall risk. The comprehensive risk score fluctuates between 0 and 100, with the maximum value close to 100, showing the impact of the superposition effect of electrical fluctuations, physical collisions, and environmental changes on the overall risk.

Furthermore, in the safety analysis, the robot’s emergency plan was tested. When facing voltage fluctuations or environmental obstacles, the robot adjusts the operation

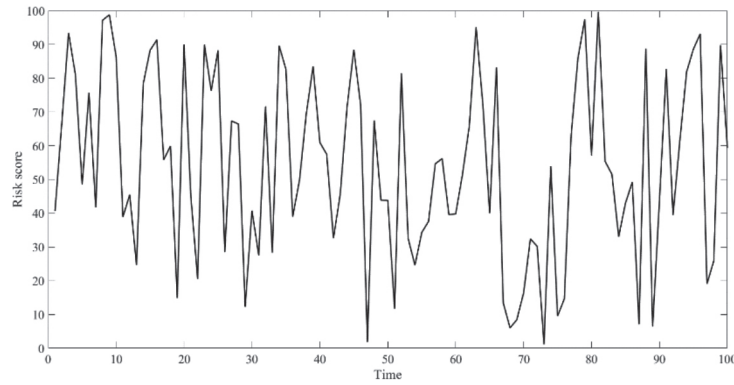


Figure 12 Comprehensive risk assessment diagram.

strategy through a real-time decision-making algorithm and chooses a safer operation method to avoid accidents caused by improper decision-making. Combined with the decision-making method optimized by DQN, the robot can make the best response strategy when facing a variety of emergencies to ensure safety and stability during the operation process.

5. CONCLUSIONS

In this paper, an autonomous decision-making and control algorithm was proposed for live working robots that combines deep learning and classical control strategies, aiming to solve the problems of poor adaptability and the slow response of existing algorithms in complex and high-voltage power environments. Through DCNN and LSTM for environmental perception and data processing, combined with DQN to optimize the decision-making process, the robot can adjust the operation strategy in real-time to achieve efficient and safe live working tasks. Experimental results show that the algorithm significantly improves the task success rate and execution efficiency, can quickly respond to changes in dynamic environments, and reduce execution time and response delays. Despite this, the current method still lacks adaptability to certain extreme environments. Future research can further optimize the robustness and efficiency of the model and improve the performance of the algorithm in complex scenarios. In addition, combining more sensor data with multi-task learning can provide a broader development space for improving the robot's autonomous decision-making ability.

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