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Research on the acceptance technology of quality defects of distribution network line project based on reinforcement learning

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ABSTRACT

The electric power industry is an important basic industry of the country, and among all the electric power equipment, the distribution lines are directly facing the end-users, which is an important infrastructure to serve the people's livelihood. In this study, we first transformed the distribution line engineering quality defect acceptance problem into a sequential decision-making problem, and constructed an improved reinforcement learning network model DDQN based on it, and introduced a reward function into the model to improve the intelligent adjustment ability of the intelligent bodies in the model to the data related to the distribution line, so as to improve the detection performance of the DDQN model in the distribution line engineering quality defect acceptance. The results show that the improved DDQN model is highly feasible and effective in the detection of quality defects in distribution line engineering compared with other comparative models. The simulation test of distribution line engineering quality defects found that the accuracy of the DDQN model-based distribution line engineering quality defects acceptance technique in detecting line quality defects is 95%. It is verified that the accurate and reliable distribution network line engineering quality defect acceptance technology based on the improved DDQN model is conducive to guaranteeing the safe and stable operation of the power grid system.

Keywords: DDQN model, sequential decision making, reward function, line fault, distribution network engineering acceptance

1. Introduction

With the development of China's electric power industry, the traditional distribution network line operation and maintenance methods have been difficult to meet the actual needs of the grid facing this serious phenomenon, began to look for new breakthroughs, the operation and maintenance of the

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work is also shifted from artificial to intelligent [1-2]. Intelligent inspection work can be solved due to the transmission line is located in a relatively remote geographical location, complex environment, in the operation process, with the passage of time vulnerable to natural or man-made damage, serious damage and threat to the grid's operational safety and operation and inspection of the personal safety of the staff and other issues [3-6].

Distribution system belongs to a very important part of electric power construction, and distribution network lines as the most common type of power transmission, its safe operation is to support the production of urban and rural residents to live a reliable use of electricity is an important foundation [7-8]. There is a close connection between the distribution network project and the users, which makes the users not only have high requirements on the quality and safety of the distribution network, but also have certain constraints on its economic aspects. Due to the more complex structure of the distribution network, the construction cycle is short, the construction surface is wide, and the construction quality management has high requirements [9-10]. And various defects may occur during the construction of distribution network lines, such as insulation breakdown, tower tilt and other problems, which may lead to serious safety hazards and power outages if these defects are not detected and dealt with in time [11-13]. The different demands of users on the quality, quality and transmission efficiency of electric energy make the supply of electric energy also have obvious differences, which increases the difficulties of distribution network engineering construction to a certain extent [14-16].

In order to ensure the quality of power transmission and reduce the occurrence of power outage and tripping caused by line failure, it is necessary to combine the needs of distribution network construction and the actual situation, and put forward scientific and efficient acceptance technology to improve the safety of distribution network engineering construction and ensure the normal transmission of power [17-20]. In addition, strengthening the management of the quality of distribution engineering construction can also effectively control the cost of engineering construction, reduce the excessive consumption of energy in transmission, and enhance the economic benefits of power enterprises [21-23]. In order to improve the safety and reliability of the distribution network line project, a large number of scholars have studied the acceptance technology of the quality defects of the distribution network project.

Distribution line faults will produce abnormal voltage and current data, through the collection of traveling wave signals at the time of fault generation, the use of double-ended traveling wave ranging technology, associated with the line file distance and tower and other information, to achieve the positioning of distribution line faults, for the distribution network line engineering quality defects acceptance to provide assistance. Literature [24] proposes an improved double-ended traveling wave ranging method based on segmented cable wave speed refinement, which plots the traveling wave ranging function with the time difference of the fault traveling wave and the fault location at both ends of the cable as the variables, so as to carry out high-precision ranging of the fault location of DC distribution network cable lines. Literature [25] used a combination of signal time-frequency method to detect and analyze the traveling wave generated by distribution network faults, using mathematical morphology to extract the time domain features, and smooth wavelet transform to extract the frequency domain features, to obtain a high accuracy rate in distribution network fault location. Literature [26] proposed the variational modal decomposition (VMD) method for the high-frequency components of the traveling wave in response to the phenomenon of modal aliasing that occurs in the wavelet empirical modal decomposition, and significantly optimized the fault location accuracy in distribution networks by constructing a fault distance measurement model with the time difference between the two ends of the line as the input. Literature [27] first determines the initial fault traveling wave arrival time by the VMD method, and subsequently compares it with the actual arrival time on the recorder in order to establish the fault distance difference matrix, and uses the fault branch determination matrix (FBDM) and the transversal indicator Q for fault localization. Literature [28] designed a non-contact electric field sensor to collect power cable fault signals and constructed a fault wave arrival time identification method by combining feedback variational modal decomposition (FVMD) and Wigner-Ville distribution (WVD), which significantly improves the identification performance of the fault wave, and then enhances the accuracy of cable fault detection and localization. However, there is still room for progress in the application of abnormal early warning and rapid fault disposal in distribution lines because the interference of electromagnetic environment around distribution lines will affect the accuracy and stability of defect localization.

For insulator defects in distribution networks, multi-source data fusion can comprehensively utilize information from multiple sensors and data sources to improve the accuracy and reliability of defect detection. Literature [29] investigated the fault localization method for low-resistance grounded distribution networks by secondary reconstruction of the information from multiple data sources in order to roughly determine the scope of the fault and the degree of the power fault, and subsequently introduced Bayesian networks and DS evidence theory to obtain the fusion localization results of the fault. Literature [30] shows that the multi-source heterogeneous data in the distribution network has problems such as storage chaos and insufficient computational performance, adopts Box-Cox transform to solve the data offset problem, and uses PCA algorithm to optimize the process of multi-source data fusion based on the DS inference method in order to achieve the effective fusion and analysis of distributed data. Literature [31] establishes a grid public information model of distribution network that integrates multi-source data, and realizes fast and in-depth distribution network fault analysis by aggregating distributed data from different regions for unified analysis, which effectively improves the efficiency and accuracy of fault diagnosis of distribution network. Literature [32] uses association rules and entropy weight method fuzzy analysis method to fuse and analyze the multi-source data in distribution grid equipment to identify the operating status of distribution grid equipment, and to provide support for the refined operation and maintenance work of distribution grid. Literature [33] based on the fusion analysis of multi-source data in distribution network based on Bayesian network, using probabilistic graph method integrates the multi-source evidence and the complex structure of the distribution system, and establishes the graph structure based on the causal relationship between multiple random variables, which can accurately determine the location of faults in the distribution network. However, due to the complexity and variety of causes of defects in distribution networks, this detection method has large detection errors for certain types of defects.

Although the above methods can effectively identify defects for different inspections, the adaptive breadth and image quality are still insufficient. In this regard, this paper proposes a reinforcement learning-based automatic identification method for distribution network inspection defects, which ensures the effectiveness of inspection defect identification by improving the learning speed and stability.

In this paper, based on the dynamic correlation characteristics of distribution network line data samples, the problem of distribution network line engineering quality defects detection is transformed into a sequential decision-making problem in reinforcement learning, and combined with the fault state-action value Q-function to design a self-reinforcing DDQN model for the target network. The reward function in the model is then used to guide the intelligent body to adjust the input line data parameters in order to improve the accuracy of the reinforcement learning model for the detection of quality defects in distribution network line engineering. Subsequently, the extracted distribution network lines are parameterized, and the processed sample features are input into the improved DDQN model to output the detection results of faulty lines in the distribution network through the processes of initial dynamization processing and state estimation, so as to realize the acceptance technology for the quality defects of the distribution network line engineering. This study tests and analyzes the dataset dependency and line quality defect detection capability of the improved DDQN model to explore the feasibility of the model in distribution network line acceptance. Then the distribution network simulation model is constructed to detect defective lines in the distribution network using the acceptance technique proposed in this paper to verify the application effect of the acceptance technique.

2. Method

2.1. Transformation of Line Quality Defect Acceptance Issues

Reinforcement learning [34] is designed to solve the problem of action strategy selection in sequential decision making, where the action output by the intelligent body influences the state input at the next moment, i.e., the input samples are characterized by dynamic correlation. As for the problem of recognizing the quality defects (i.e., line faults) of distribution network line engineering, the input is the amount of extracted features, and the output recognition results do not change the input sample characteristics, i.e., the input samples are static independent samples. Therefore, in order to use deep reinforcement learning to realize the distribution network line engineering quality defect recognition, the problem needs to be transformed into a sequential decision-making problem, and the key to the transformation lies in the dynamization of the input samples, i.e., to be able to perceive the corresponding environmental changes according to the different actions output by the intelligent body at the current moment, to get the corresponding correlated input state at the next moment, and to get the final recognition results after a series of decision-making sequences.

Thus, in this paper, on the basis of the extracted feature quantity F, the sample dynamization tag - distribution network assumption type tag T_H is added to assume the state type in which this distribution network sample is located. The value of T_H is an integer from 1 to 6, which represents the six quality defect state types of normal, single-phase high-resistance fault, single-phase low-resistance fault, two-phase ground fault, two-phase inter-phase fault and three-phase fault, respectively. This state type label also corresponds to the action output performed by the line engineering quality defect recognition intelligence. The initial state type of the sample is defaulted to normal state, i.e., initial type label $T_{H0} = 1$. Subsequent hypothetical type labels are determined by the action outputs.

After the above dynamization operation, the input state s of the intelligent body can be represented as $s = [F, T_H]$. For the same sample, although its feature quantity F always remains the same, the addition of the dynamization label T_H enables the state s to be updated to the corresponding s' according to the different actions performed by the intelligent body, thus completing the interaction between the intelligent body and the environment.

2.2. Enhanced learning Q-value network design

With the above operation of adding the distribution network hypothesis type label T_H, the transformation of the sequential decision-making problem [35] is realized, and the deep reinforcement learning method can be used to identify the quality defects of the distribution network line works. However, the distribution network data samples exhibit an imbalance, i.e., the number of normal state samples is much larger than the number of fault state samples. This leads to the inability to approximate the true fault state-action value Q function with a small number of labeled fault state training samples when the DDQN discrimination network learning is completed for distribution network operation state matching, thus increasing the probability of omission and misjudgment of the fault state test samples. For this reason, this paper designs a target network self-reinforcing DDQN algorithm for line engineering quality defects identification.

The DDQN algorithm uses a function approximator, i.e., a neural network, to estimate the value function $Q(s,a)$, while taking the state value s and action value a as inputs and outputting the corresponding long-term return expectations. This neural network structure has three data flow paths, which are state data path, action data path, and common data path.

The specific network structure used for the fault parameter identification model is as follows. The input of the state path contains only the current state information s_t of dimension N_s, and the action a_t of dimension 1 is used as the input value of the action path. The common path receives the sum of the outputs of the state and action paths and outputs the long-term reward expectation corresponding to the current state and action pair (s_t, a_t). The three paths are similar in structure. There are two hidden layers between the inputs and outputs of each path. Each of these two hidden layers has $N_{1s}, N_{1a}, N_{2s}, N_{2a}$ neurons, and both are immediately followed by a corrected linear unit layer (ReLU). The output layer of the common path is an all-connected layer where one of the units outputs a Q-valued scalar. All three paths have their own distinct roles. The state path obtains the mapping between states and rewards from the raw data. The action path combines the current action with the reward and represents the functional relationship between them. The public path combines the functionality of the first two approaches and further extracts the relationship between state, action, and reward through a neural network. Deep Q networks outperform basic reinforcement learning algorithms because they are deep enough to explore the environment directly without additional redundancy and are able to establish a mapping between the current raw environmental data, the action behavior, and the final expected reward.

2.3. Acceptance model of quality defects in distribution line engineering

2.3.1. Parameterization of quality defects. The distribution system is simulated as a model whose parameter set contains two subsets α, β. Subset α includes the parameters of the normal lines of the power system. In this study, these parameters are considered to be accurate and valid. Subset β contains fault parameters that indicate whether or not a quality defect in the line has occurred and where the defect has occurred. The domain of β is a $N+1$ -dimensional vector $\beta_i \in (\beta_0, \beta_1, \beta_2, \dots, \beta_{N-1}, \beta_N)$, where N is the number of fault types to be identified, β_0 represents the normal condition, and the others represent fault types 1 through N.

The signals ω_{ref} collected from the field dataset during line faults are used as inputs to the parameter identification process. The objective function ϖ, also known as the reward function, describes the difference between ω_{ref} and the actual simulation output ω. This is shown below:

$$\varpi = \sum_{i=1}^{k} \left| \omega_{ref} - \omega \right| \tag{1}$$

where k denotes the number of steps in the fault recognition process. By adjusting the value of parameter β, the recognition method minimizes the value of the objective function ϖ and brings the fault parameters progressively and intelligently closer to the real situation.

2.3.2. Fault parameter identification methods. The intelligences in the reinforcement learning network must intelligently adjust the fault parameters during the dynamic simulation to make the model closer to the actual situation. Therefore, a reward function [36] is designed to guide the intelligent body:

$$r(\varpi) = \begin{cases} 10 \varpi \le 0.6 \\ -20 \varpi > 0.6 \end{cases} \tag{2}$$

where ϖ is the reward evaluation index calculated using a sliding window of fixed duration. Depending on the size of ϖ thereby deciding whether to give the intelligent body a reward or a punishment. The specific calculation of ϖ is shown in the following equation:

$$\varpi = \frac{\sum_{i=1}^{5} \left| Pe_i - Pe_{ref} \right|}{WL} \tag{3}$$

where WL is the length of the sliding window.

The intelligent body first initializes the weights of the Q and Q' networks as well as other training hyperparameters. The observable measurements $\left(V, Pe, Pe_{ref}, \varpi\right)$ in the distribution network are collected by the intelligent body as state quantities s_t. Based on the state s_t, the intelligent body selects the action a_t that modifies the fault parameters β to interact with the environment. The selection of actions is based on the E-greedy strategy. After a time step, the intelligent body receives a reward r_t given by the reward function and can simultaneously observe the next state s_t'. The experience vector consisting of (s_t, a_t, r_t, s_t') is stored in the fault experience playback buffer pool D for later updating Q the parameters of the network. The output y_i of the Q network is used to evaluate the results of the actions a_t performed in the s_t state. A larger value y_i indicates that the values of the fault parameters represented by the actions of the intelligent body in that step are closer to the actual fault situation. When the amount of data in the fault experience replay buffer pool is greater than M, the intelligent body removes fault data of size M from the buffer pool and uses stochastic gradient descent to update the network parameters θ and θ. Parameters θ and θ of the modeled network imply a relationship between some observable measurements of the power system and the fault parameters in the fault identification model. If s_t' is a termination state, a new round will be initiated, the environment will be randomly initialized, and the intelligences repeat the above steps.

2.3.3. Model realization process. According to the above analysis, combined with the line fault parameterization method and Q network module, the design obtains the improved DDQN-based distribution network line engineering quality defect acceptance model in this paper, and the model implementation process is shown in Fig. 1. Input normalized samples to be detected, initial dynamic processing of static detection samples provided by the environment, the introduction of the initial state type label $T_{H0} = 1$, to obtain the sample state $s = [F, T_{H0}]$. Subsequently, based on the target Q-network obtained in the training process, according to the current state s, calculate the action values corresponding to all possible actions in the action space A_1, $Q\left(s, A_1 \mid \theta_{1_1\, target}\right)$. Based on the time-varying $\varepsilon-$ greedy strategy, select the action a_1 and execute it. Calculate the next state s' and update state s to $s = s'$. Repeat the above steps using the updated state s. When the judgment is terminated, the hypothesis type label T_H' of state s' is output, which is the acceptance result of the quality defects of the distribution network line project output by the model, and this sample acceptance is finished.

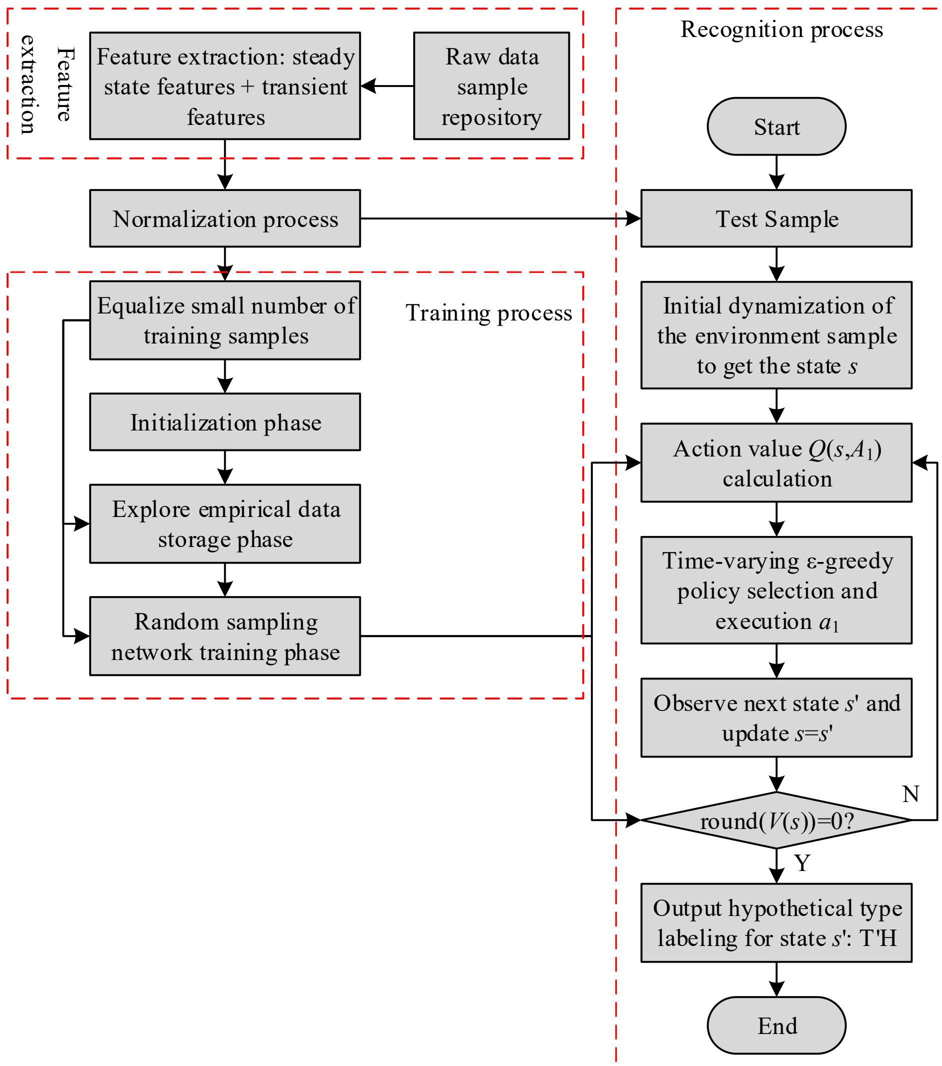


Fig. 1. Acceptance model of distribution circuit quality defects

3. Results and discussion

3.1. Model Testing and Evaluation

3.1.1. Experimental environment:

1) Hardware environment. This paper is based on deep reinforcement learning design of distribution network line engineering quality defect detection model, deep reinforcement learning model training and inference computational volume is large, so the choice of computing platform equipped with a graphics processor (GPU) [37]. The CPUs are two Intel(R) Xeon(R) CPU E5-2620 v4 @ 2.10GHz with 16 physical cores and 32 threads. The memory is 256GB DDR3 1600Hz. the graphics card composition is four TITAN Xp with 12GB of video memory per GPU. The hard disks are 128GB SSD disks and 4TB 7200 RPM mechanical disks.

2) Software environment. The software environment used for the experiments in this paper is Ubuntu 16.06LTS, and the Python version is Python 3.5.2. The implementation of the reinforcement learning model in this paper is based on the Pytorch framework, and the version is Pytorch 1.0.1. As for the development environment, the Pycharm of the Jetbrains series is used. In addition, the dataset used is based on the simulation data generated from the logical principles of relay protection in the distribution network, and the process is generated strictly according to the principles of relay

protection.

3.1.2. Model dependency testing on datasets. In this paper, the performance of the designed distribution line engineering quality defect detection model will be comprehensively evaluated from several aspects. In order to more objectively and comprehensively assess the comprehensive performance of the distribution line engineering quality defect detection method designed in this paper, the artificial neural network-based distribution line engineering quality defect detection method (FDNN) and the supervised learning-based adaptive distribution line engineering quality defect detection method (AFD-SL) are used as the comparison methods in this experiment. The FDNN method uses an artificial neural network to design a line engineering quality defect identification model, using the protection system state 0-1 values as inputs and all possible fault conditions as outputs to realize the distribution network line engineering quality defect detection. This method has a similar origin to the distribution line engineering quality defect acceptance technology designed in this paper, so it is appropriate to use this method as a comparison method. In this paper, Accuracy, Precision, Recall, and F1 Score are comprehensively used as evaluation indexes, and their mathematical representations are shown below:

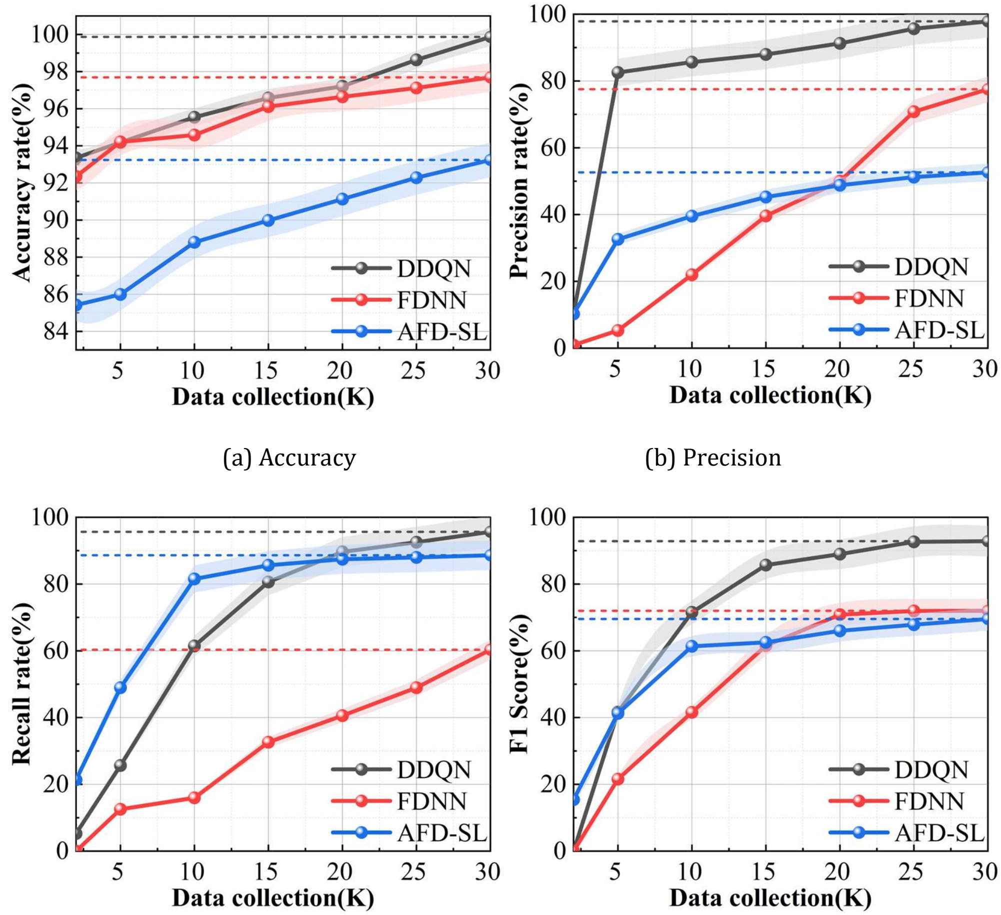
$$P=\frac{TP}{TP+FP} \tag{4}$$

$$R=\frac{TP}{TP+FN} \tag{5}$$

$$F1=\frac{2TP}{2TP+FP+FN} \tag{6}$$

Where TP denotes the number of positive classes judged as positive, FP denotes the number of negative classes judged as positive, TN denotes the number of negative classes judged as negative, and FN denotes the number of positive classes judged as negative.The F1 value is the reconciled mean of precision and recall, and the F1 value is higher only when both precision and recall are higher.

Training sets containing 2k, 5k, 10k, 15k, 20k, 25k, and 30k samples are used in this comparison experiment. The analysis results of the model detection performance evaluation indexes are shown in Fig. 2, (a)-(d) represent the analysis results of accuracy, precision, recall and F1 value, respectively. With the increase of the number of training sets, the evaluation indexes of each method are improved, and the AFD-SL model has the largest improvement (9.15%), which shows that AFD-SL utilizes the dataset more efficiently than the other two models. When the number of training sets increases to 30k, the four evaluation indexes of the DDQN model (99.87% and 97.85% for accuracy and precision, respectively, and 95.63% and 92.84% for recall and F1 value, respectively) are significantly higher than those of the other two, which indicates that when the amount of labeled data is sufficient, the improved DDQN model has a very good performance of defect detection in the quality of the distribution line engineering. When the dataset is small (2k), although the FDNN model has a high accuracy (93.35%), the other three indicators are close to 0. This is due to the phenomenon caused by the imbalance of positive and negative samples in the test set, which accounts for more than 92% of the total number of samples in the test set, and therefore, for the FDNN that has not been adequately trained, it is easy to judge the samples as negative classes (i.e., there is no line engineering quality defects). In addition, the AFD-SL model has better performance when the dataset is very small, thanks to the fact that the AFD-SL model is trained without labels. Because of the special way supervised learning utilizes the data, AFD-SL has better performance in the case of very few samples. Comprehensively comparing the precision and recall of each model, it can be found that the recall of the improved DQNN model is much better than that of FDNN and AFD-SL, indicating that the improved DQNN model proposed in this paper has a high recognition rate for distribution lines with faults and quality defects, and can be applied as an acceptance technique.

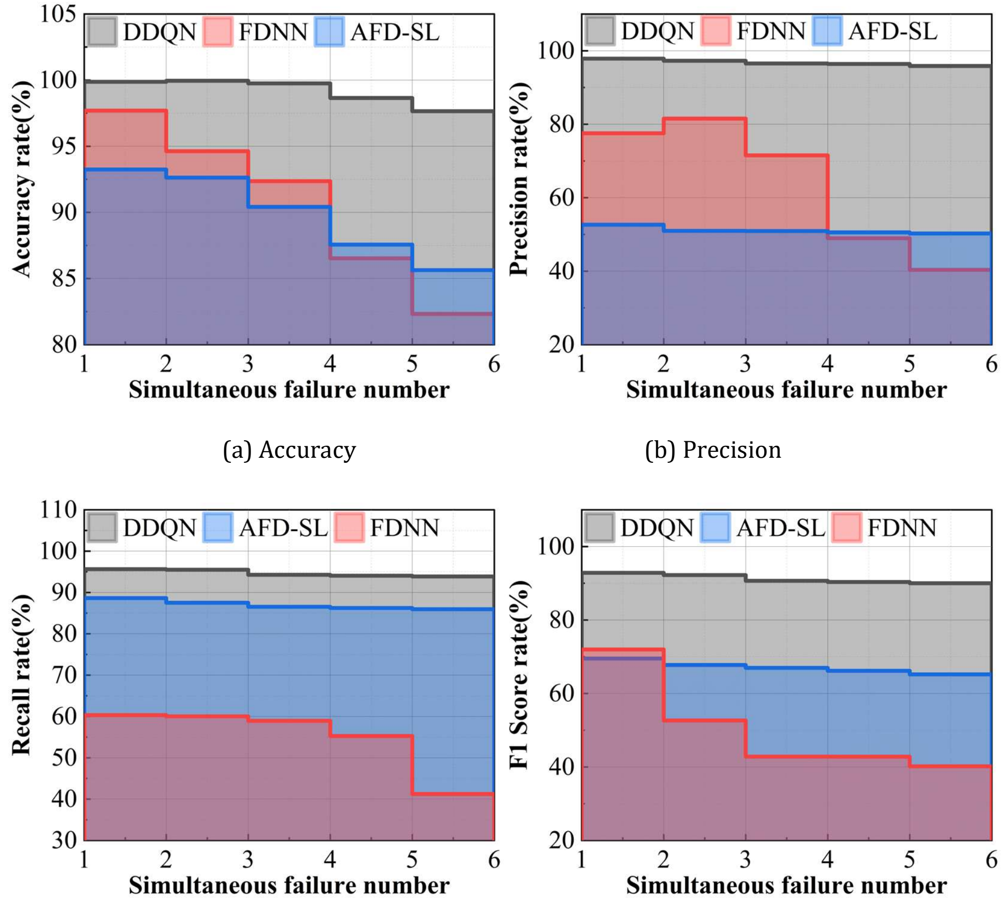


(a) Accuracy (b) Precision

(c) Recall (d) F1 Score

Fig. 2. The impact of training concentration on the evaluation index

3.1.3. Testing of model quality defect detection capabilities. Multi-defect detection of distribution line engineering quality refers to the process of defect detection of distribution line engineering quality performed by the model when multiple lines in the grid fail at the same time. The model training set contains only one fault with a total of 20k samples. The test sets with the number of simultaneous faults of 1, 2, 3, 4, 5, and 6 are used to evaluate the model's multi-distribution line engineering quality defect detection capability, and each test set contains 5k samples, respectively. The results of the influence of the number of multiple faults on the evaluation indexes of the model distribution line engineering quality defect detection correctness are shown in Fig. 3, with (a)-(d) representing the accuracy rate, precision rate, recall rate and F1 value, respectively. With the upward adjustment of the number of simultaneous faults, the accuracy rate of the DDQN model can be maintained above 97.26%, which proves that the model can well solve the problem of multi-distribution network line engineering quality defect detection. The accuracy rate of AFD_RL is lower (48.19%) when the number of quality defective lines is found to be 6 at the same time, which is due to the fact that AFD_RL is a supervised learning model, and the model is easy to make decisions many times, so it is easy to judge more positive classes than the actual ones, i.e., the model is easy to judge more than one line with no faults as quality defective lines. For FDNN, with the upward adjustment of the number of simultaneous faults, the decline rate of its four evaluation indexes (17.56%, 66.92%, 40.83%, and 70.79%) are more serious, which indicates that FDNN can not solve the problem of detecting the quality defects of multi-distribution line engineering well.



(a) Accuracy (b) Precision

(c) Recall (d) F1 Score

Fig. 3. The impact of the failure quantity on the evaluation index

3.2. Distribution network line project quality defects identification analysis

3.2.1. Distribution network modeling. In China, 66kv and below distribution network system adopts small current grounding method, this paper selects 10kv small current system as the research object. In MATLAB, we build a small current system with four branch circuits to simulate the acceptance scene of the quality defects of the distribution network line project, and the positive sequence parameters of the small current grounding system model are R_1=0.1326Ω / km , $X_1 = 0.9524 mH / km$, $B_1 = 0.01254 \mu F / km$, and the zero sequence parameters are $R_0 = 0.3652\Omega$ / km, $X_0 = 4.6325 mH / km$, $B_0 = 0.00748 \mu F / km$. The lengths of the four lines are 10km, 8km, 7km, and 4km, and the active loads are 1.52MW, 1.69MW, 3.54MW, and 7.48MW, respectively. The arcing coil is overcompensated with 10% compensation L=24.856 H. The initial phase angles of the faults are set to be 0°, 30°, 60°, 90°, and the grounding resistances are 0 Ω, 50 Ω, 200 Ω, and 400 Ω, and the points of faults are from the beginning of the line to the end of the line, and the interval between the adjacent faults is 1 km, and the degree of compensation of the arcing coil is 0% and 10%, which are simulated by ULINKMATLAB/SIM. SIM simulation.

3.2.2. Effectiveness of line quality defect detection. The experiment uses Python language, under the 7.3.2 pycharm201 version and Anaconda3 development environment, to build the reinforcement learning model, usually the model learning rate takes the value of [0.01,0.001,0.0001], in this paper, the reinforcement learning network learning rate is set to 0.001. Set the maximum number of iterations to 1000 times, when the error rate is lower than the the set value, the training stops. The extracted 956 sets of data are divided into two groups, and 100 sets of data are selected at equal intervals as test samples, and the remaining data are used as training samples. The value of the mean squared error loss function of the reinforcement learning network usually decreases with the training of the network, and the training stops when the value of the training species mean squared error loss function reaches the set value of 0.001. The results of the training error analysis of the reinforcement learning network are shown in Figure 4, which shows that the reinforcement learning network model with the combination of the Sigmoid activation function and the mean squared error loss function reaches the set value when it is trained for the 78th time, and the training ends.

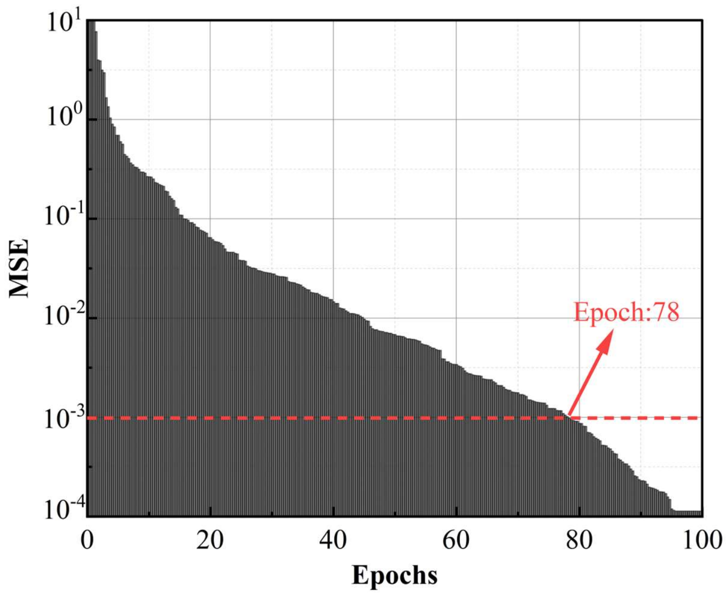


Fig. 4. Strengthening learning network training error

The 100 groups of test samples will be input into the network to test the effect of improved DDQN model distribution network line engineering quality defect detection, and after the reinforcement learning network acceptance test, the output of the distribution network line engineering quality defect acceptance results are shown in Table 1. Through the output of the DDQN model test, it can be seen that the output value of the reinforcement learning model of the faulty line is greater than that of the non-faulty line, so the line corresponding to the node with the largest output value of the DDQN model is the acceptance result of the quality defects of the distribution network line project. For example, the fault code “1000” indicates that there is a quality defect at the initial end of the distribution line, and the nodes with the largest output values in the output results of the line L1 model are all at the initial location of the line (0.7662-0.9895).

Table 1. Acceptance results of the quality defects of distribution line road

Number	Fault line	Ground resistance	Fault Angle	Compensation degree (%)	Fault position	Model output				Code
1	L1	0Ω	0°	0	2km	0.8682	0.0126	0.2419	0.137	1000
2	L1	0Ω	30°	10	2km	0.9359	0.1286	0.0065	0.0494	1000
3	L1	50Ω	60°	0	2km	0.9663	0.0509	0.3379	0.1382	1000
4	L1	200Ω	90°	10	2km	0.8341	0.0983	0.1599	0.4726	1000
5	L1	400Ω	0°	0	2km	0.7754	0.2675	0.1833	0.164	1000
6	L1	400Ω	30°	10	2km	0.9895	0.0675	0.1889	0.3467	1000
7	L1	0Ω	30°	0	4km	0.7662	0.0137	0.1706	0.166	1000
......	......	......	......	......	......	......	......	......	......	......
94	L4	400Ω	90°	10	2km	0.3849	0.1079	0.4168	0.9063	0001
95	L4	0Ω	0°	0	4km	0.3784	0.404	0.0987	0.8784	0001
96	L4	50Ω	30°	10	4km	0.2281	0.0968	0.1583	0.8311	0001
97	L4	50Ω	60°	0	4km	-0.0048	0.464	0.1567	0.7913	0001
98	L4	200Ω	90°	10	4km	0.3061	0.3579	0.4042	0.8898	0001
99	L4	200Ω	0°	0	3km	0.3995	0.8225	0.4786	0.3431	0100
100	L4	400Ω	90°	10	4km	0.2334	0.451	0.3745	0.9617	0001

Reinforcement learning model in the distribution network line engineering quality defects in the test, misjudgment data analysis results are shown in Table 2. 100 groups of test data, the 21st, 32nd, 62nd, 85th and 94th groups of data appeared in the misjudgment situation, the model on the distribution network line engineering quality defects detection accuracy is 95%. Among the data with misjudgment of distribution line engineering quality defects, three groups of data (62, 85 and 94) have the actual fault location at the end of the line (0001), and none of the initial phase angles at the time of the fault is zero (90°). It was also found that the difference between the node with the second largest output value and the node with the largest output of the improved DQNN model was less than 0.5 (0.0441-0.4319) in all five sets of misjudged data.

Table 2. Miscalculation in line quality defect test

Number	Fault line	Ground resistance	Fault Angle	Compensation degree (%)	Fault position	Model output				Code
21	L1	0Ω	30°	0	8km	0.7256	0.6815	0.1236	-0.0235	1000
32	L1	400Ω	60°	0	10km	0.7625	0.8549	0.0036	0.0152	0100
62	L2	200Ω	90°	10	6km	0.1254	0.6326	0.1482	0.6954	0001
85	L3	200Ω	90°	10	5km	0.1524	-0.0251	0.3265	0.7584	0001
94	L4	400Ω	90°	10	2km	0.3849	0.1079	0.5168	0.9063	0001

Because in the actual process of acceptance of distribution network line engineering quality defects, there will be errors in the extracted fault data, which is caused by the imperfection of the system that receives the data and the existence of small disturbances in the distribution network system. In order to verify the effectiveness of the reinforcement learning model proposed in this paper for acceptance in the presence of small disturbances, this paper adds random errors within 20‰ of the modal value of the eigenvalues in the extracted eigenvalues to identify the quality defects of distribution network line engineering. Because there are too many test samples, so the paper only lists the samples with wrong identification results and the output values of the reinforcement learning model, and the results of the test error analysis of the DDQN model after adding the random error are shown in Table 3. When random errors are added to the quality defect detection sample of distribution network line engineering, a total of 5 sets of data of the DDQN model are misjudged during the test process, and the accuracy of line selection is 95%, and the fault point of 3 sets of data in these 5 groups of data is located at the end of the line, so the DDQN model proposed in this paper is more likely to misjudge the fault or quality defect at the end of the line when it is applied to the acceptance of quality defects in distribution line engineering.

Table 3. Test the error item after the random error is added

Number	Fault line	Ground resistance	Fault Angle	Compensation degree (%)	Fault position	Model output				Code
25	L1	0Ω	60°	10	8km	0.2635	0.0261	0.0524	0.6875	0001
32	L1	400Ω	60°	0	6km	0.3695	0.0425	0.8754	0.1526	0010
64	L2	200Ω	30°	10	6km	0.0051	0.1524	0.6954	0.6523	0010
79	L3	50Ω	90°	0	5km	0.0625	0.0341	0.6254	0.7052	0001
96	L4	200Ω	30°	0	2km	0.0362	0.1254	0.5142	0.5594	0001

4. Conclusion

This paper proposes the distribution line engineering quality defect acceptance technique based on the improved DDQN model, and tests the validity and reliability of the improved DDQN model, and finds that the recall rate of the improved DQNN model is much better than that of the FDNN and the AFD-SL, and the accuracy of the model is still able to maintain above 97.26% under the situation that the number of faults in the distribution line is constantly increased, which proves that the model can be used as a Acceptance technology of quality defects in distribution line engineering for application. After applying the model in the simulation model of distribution network, it is found that the acceptance technology of distribution line engineering quality defects based on the DDQN model has an accuracy of 95% for the detection of line quality defects, and it can maintain the accuracy of 95% in the case of random error interference of 20‰ or less.

The proposed distribution line engineering quality defect acceptance technology based on the improved reinforcement learning model can effectively detect faulty lines, which is of great significance for the improvement of intelligent distribution line defect acceptance efficiency.

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