Robust Fault Diagnosis for Gas Turbine Rotor via Transfer Reinforcement Learning

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***Abstract*—As the central component of a significant power machine, the gas turbine's fault diagnosis accuracy is critical to the equipment's safety in service. However, the fault detection of the gas engine rotor system still faces challenges due to the difficulty of acquiring sensitive features and the lack of labeled data. To address these issues, we propose an improved DQN-based Transfer Reinforcement Learning method (Transfer-DQN) for robust gas turbine rotor fault diagnosis. The proposed method takes the collected one-dimensional raw vibration signal as input, with the fault sample set and fault category serving as the model environment and action. It uses a multi-scale one-dimensional wide convolutional neural network (M-WDCNN) with ϵ-greedy strategy for Q-network fitting and decision making. Additionally, to consider the computational efficiency and differences between fault classes, Transfer-DQN uses multiple fault sample data as the source domain and a single fault class as the target domain, while performing the source-to-target domain transfer learning based on generative adversarial. Extensive experiments on the bearing dataset of Western Reserve University and our gas turbine test bench demonstrate the superiority of Transfer-DQN, achieving accuracies of 98.95% and 96.91%, respectively. Compared with baseline approaches, our method breaks through the previous upper limit of 95% to meet the need for robust and efficient fault diagnosis.**

***Index Terms*—deep reinforcement learning, fault diagnosis, transfer learning, Gas turbine rotor**

I. INTRODUCTION

Gas turbines are efficient power machinery that convert thermal energy into kinetic energy, providing high safety, stability, and thermal efficiency. They have found extensive application in various fields, including public transportation, power generation, and military [1], [2]. Despite technological advancements in mechanical technologies, the problem of gas turbine rotor fault diagnosis has not been adequately addressed [3]. Rotor damage is a common occurrence that significantly impacts gas turbine operations due to its complex structure, harsh operating environment, rapid speed change, and uneven force. Traditional fault diagnosis methods, which are either model-based [4], [5] or hardware-based [6], [7], have several limitations. The former requires a lot of computational resources to meet the computational demands of rotor nonlinear signals, while the latter is too dependent on sensors and can be costly. Additionally, fault diagnosis for complex electromechanical systems is challenging due to unclear mechanisms and difficulties in modeling, necessitating the development of efficient data-driven methods to compensate for the lack of experience. However, data-driven model building is still a challenging task, owing to the difficulty in collecting fault samples and labeling them accurately.

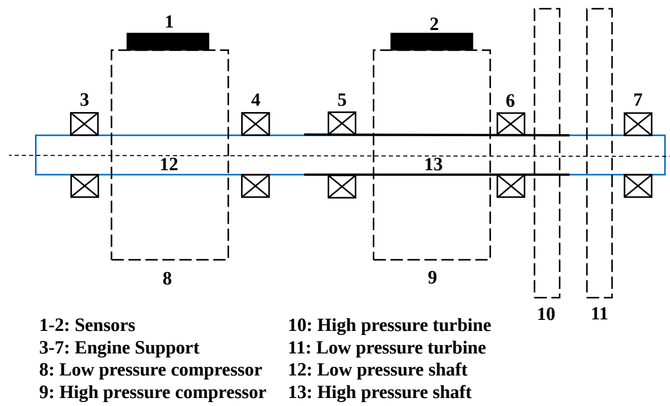

Fig. 1. The principle of the gas turbine.

To address the aforementioned problems, this paper proposes a data-driven technique for diagnosing gas turbine rotor faults. This technique serves as an additional line of defense to prevent equipment damage caused by rotor faults and is based on open-source rotor fault handling data. The proposed method employs reinforcement learning to address the issue of insufficient samples in reality. The data is collected from two sensors, as illustrated in Figure 1, which are configured on the test gas turbine to extract rotor vibration signals in real-time from the low-pressure and high-pressure compressors forming the rotor system. The front-side and rear measurement points of the two sensors respectively provide four indicators, including oscillating signal, airflow excitation, rotor bending, and rotor unbalance degree [8]. Since the sensor data within the gas turbine can be influenced by factors such as machine type, their validity will be analyzed based on sample differences.

Meanwhile, combining gas turbine rotor vibration data with appropriate machine learning tools can help identify different fault categories, make necessary corrections, and significantly reduce the wear and tear of gas turbines. However, labeling mechanical faults is a challenging task that requires significant resources to support large-scale computation. Additionally, gas turbine rotor vibrations are continuous data, while some faults manifest as discrete samples in the vibration spectrum, making it difficult for traditional machine learning algorithms to accurately capture sensitive features and make fast decisions. In contrast, reinforcement learning-based methods, such as the Monte Carlo method [9] and DQN [10], can learn from the environment and obtain optimal policies without manual intervention.

This paper proposes an improved DQN-based transfer reinforcement learning method (Transfer-DQN) for robust gas turbine rotor fault diagnosis. The model takes the collected one-dimensional raw vibration signals as input and uses the DQN deep reinforcement learning method to capture fault features from the environment without the need for rigorous data labeling procedures. Combined with the transfer learning strategy used in this paper, Transfer-DQN can further improve computational efficiency while reducing the possibility of falling into local optima due to convergence limitations. Compared to other conventional machine learning methods, our approach shows robust performance even under conditions of data scarcity or noisy sensor data reading. The main contributions of this paper are summarized as follows.

- We propose an improved DQN-based transfer reinforcement learning method (Transfer-DQN) (Section III) using M-WDCNN with an ϵ-greedy strategy for Q-network fitting and decision making, while using the temporal difference error (TD-error) to give priority to experience playback for fast convergence.
- An efficient generative adversarial-based transfer learning strategy (Section III) is proposed to improve detection efficiency by feature transfer from source to target domains.
- Extensive experiments (Section IV) are constructed to evaluate the performance of Transfer-DQN under the condition of labeled data scarcity.

II. Related Works

In recent years, there has been a growing interest in utilizing artificial intelligence models, specifically machine learning algorithms and intelligent control techniques, for diagnosing mechanical equipment failures. This section provides a brief overview of the work conducted by researchers in the field of industrial fault diagnosis, with a focus on power machinery [11]–[13]..

Traditional methods for fault diagnosis rely on hardware sensing and manual judgment [14]. By adding sensors to different components of the prototype, researchers can capture information on different parts, such as vibration, pressure, and temperature, and analyze the wear and tear of the target based on experience [15]–[17]. However, these approaches require a deep theoretical foundation and significant human resources, which may result in large differences between quality inspectors [18], [19].

With the rise of artificial intelligence, data-driven methods based on machine learning have provided new ways for industrial fault diagnosis [20]–[23]. Among these methods, the concept of deep learning based on neural networks has garnered significant attention in the field of mechanical fault diagnosis. For example, Feng et al. [21] proposed the fault description based attribute transfer method, which introduced the idea of zero-shot learning into the industry field to address the zero-sample fault diagnosis task. Jiang et al. [22] used a stacked multi-stage denoising auto-encoder for wind turbine gearbox fault diagnosis, while Chai et al. [23] proposed a new method called the fine-grained adversarial network-based domain adaptation (FANDA) to address the cross-domain industrial fault diagnosis problem.

Applying deep learning methods to mechanical fault diagnosis has yielded significant results [24], [25]. Compared with methods based on manual discrimination or model-based algorithms, data-driven algorithms greatly save computational resources while maintaining fault diagnosis accuracy. However, most of these methods are supervised learning, and the learning method of mapping directly to fault types through classifiers is static [18]. Therefore, it is difficult to make effective decisions for dynamically changing core components, such as gas turbine rotor fault diagnosis, leading to a decrease in accuracy.

Deep Reinforcement Learning (DRL), a new breakthrough in artificial intelligence, provides an opportunity for industrial fault diagnosis to overcome the limitation of data scarcity and static detection [26], [27]. Deep Q-Network (DQN), a typical algorithm of DRL, can perform fault feature extraction and optimal decision-making without a strict data labeling procedure [28]. DQN combines the perceptual capability of deep learning and the decision-making capability of reinforcement learning, which has made great achievements in industrial fault diagnosis in recent years. Ding et al. [29] constructed an end-to-end fault diagnosis architecture using DQN to autonomously mine the relationship between raw vibration signals and failure modes. Wang et al. [30] proposed a new fault diagnosis method based on time-frequency representation and deep reinforcement learning (DRL) to learn the optimal classification policy automatically. Dai et al. [31] used DRL methods and the reciprocal of smoothness index to select a frequency band with the highest signal-to-noise ratio and then performed envelope demodulation for fault diagnosis.

However, most current DRL algorithms use time-frequency images as input and randomly sample them during experience replay memory caching, which may lead to the loss of weak information on fault-sensitive features [24], [31]. In addition, the convergence limitation of DQN makes complex gas turbine rotor fault diagnosis challenging. Therefore, this study aims to improve feature acquisition and DQN and explore the effect of feature transfer and other means on the algorithm's performance improvement.

III. PROPOSED METHODOLOGY

In this section, we will discuss our construction of an enhanced transfer deep learning method (Transfer-DQN) based on the DQN algorithm for the purpose of robust gas turbine rotor fault diagnosis. First, we will examine the problem formulation for fault diagnosis. Next, we will provide details on the design of Transfer-DQN, including the framework structure we adopted to ensure target specificity. Finally, we will illustrate the transfer learning process we employed to optimize the model.

A. Problem Formulation

Assuming that pure target data without any noise interference has been collected at the testbed, we formulate the fault diagnosis problem as an optimal selection task for the action space after fault mapping. The state space S_t comprises training set samples, while the action space A_t consists of fault types, as illustrated in Figure 2. Additionally, we examine the performance and convergence effect of Transfer-DQN optimization under the condition of feature transfer learning.

B. Transfer-DQN

The quality of the rotor system has a direct impact on the operating performance of a gas turbine. To achieve robust gas turbine rotor fault diagnosis, we propose Transfer-DQN, which overcomes the convergence limitations through feature transfer and improves the diagnostic performance of the model through DQN improvements, such as M-WDCNN.

DQN is a combination of neural networks, Q-learning, and experience replay mechanisms, which can solve larger and more complex problems. Unlike traditional algorithms that store states, DQN analyzes states and actions through neural networks. It then selects the action with the maximum value based on the principle of Q-learning to filter the optimal policy. This approach avoids the dimensional disaster, value function approximation, and representation problems of high-dimensional state input and low-dimensional action output of traditional DRL methods. However, the traditional DQN algorithm has limitations when it comes to fault diagnosis of gas turbine rotor systems.

Firstly, the research target input is a vibration signal based on time series, and the traditional DQN network can lose sensitive features easily. Although small fixed convolutional kernels can effectively dissect the deep semantics, they can also ignore fluctuating noise and other signals at the fault point that lead to errors. Secondly, the DQN algorithm is prone to fall into local optima due to convergence limitations and has a high time cost.

To address these issues, we propose M-WDCNN for feature extraction of pre-processed 1D working original vibration signals. We then utilize ϵ-greedy strategy for Q-network fitting, which reduces the probability of effective sensitive fault information loss during the conversion of 1D vibration signals to 2D images. Additionally, the agent uses TD-error to prioritize the experience pool for empirical playback and filter the optimal strategy through continuous interaction with the environment. The framework of Transfer-DQN is shown in Figure 2.

Specifically, to process incoming vibration signals from sensors, the Transfer-DQN framework is divided into four stages: preprocessing and dataset partitioning, model building, agent-environment interaction, and network updating. In the first stage, the dataset is split into a training set and a test set. The agent model is then built based on the segmented data. The environment is used to classify the dataset with labels, while the state space S is defined as $S = \{s_0, s_1, s_2, \ldots, s_t, s_{t+1}\}$, consisting of the training set. The action space A is defined as $A = \{a_0, a_1, a_2, \ldots, a_t, a_{t+1}\}$ and represents the fault types, with the actions being trained after mapping the fault types to the action space.

In the second stage, the main network and the target network use M-WDCNN, as illustrated in Figure 3. The environment provides the input state s_t to the agent, which is evaluated by the main network using an ϵ-greedy policy to output the action a_t, according to:

$$a_f = \begin{cases} maxQ_t(a) & p = 1 - \epsilon \\ rand(a) & p = \epsilon \end{cases} \tag{1}$$

where p is the probability of choosing to explore. When $p = 1 - \epsilon$, the action with the highest reward is selected with a probability of $1 - \epsilon$, i.e., the agent uses the exploring information directly. During the agent-environment interaction, the action about the fault type output by M-WDCNN is compared with the fault state s_t in the environment to obtain the reward r_t, after which the next state s_{t+1} can be determined. The importance of the state is judged according to the value function v_s, given by:

$$v(s) = E(G_t | s_t = s) \tag{2}$$

where G_t is the future discount reward that replaces the future cumulative reward, and γ is the discount factor. G_t is calculated as:

$$G_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + ... + \gamma^2 r_{t+n} \tag{3}$$

Each set of experiences $(s_{t+1}, s_t, a_t, r_t, T)$ obtained from the interactions is deposited into the experience replay and randomly selected during model training. To ensure that each class of faults is covered with a small percentage of fault sets, we use TD-error's prioritized experience replay during the training. M-WDCNN acts as the core of both the main network and the target network to output the current Q-value Q_c and the target Q-value Q_{target}:

$$\begin{gathered} Q_c = Q(s_t, a_t, \theta) \\ Q_{target} = r + \gamma \underset{a_{t+1}}{max} Q(s_{t+1}, a_{t+1}, \theta) \end{gathered} \tag{4}$$

Small batch stochastic gradient descent based on the objective function is used for optimization:

$$\mathcal{L}(\theta) = E\left[(Q_{target} - Q(s_t, a_t, \theta))^2\right] \tag{5}$$

After continuous learning, the optimal policy can be obtained and stable fault diagnosis can be achieved in Transfer-DQN eventually.

Notably, we have introduced adversarial-based feature transfer to enhance the overall performance of our agent during construction and training. Given the challenges of limited access to gas turbine fault data and an unbalanced distribution of data, we have explored sample generation and transfer characterization of faults in tests on the testbed. We have employed Domain-Adversarial Neural Networks [32] to identify

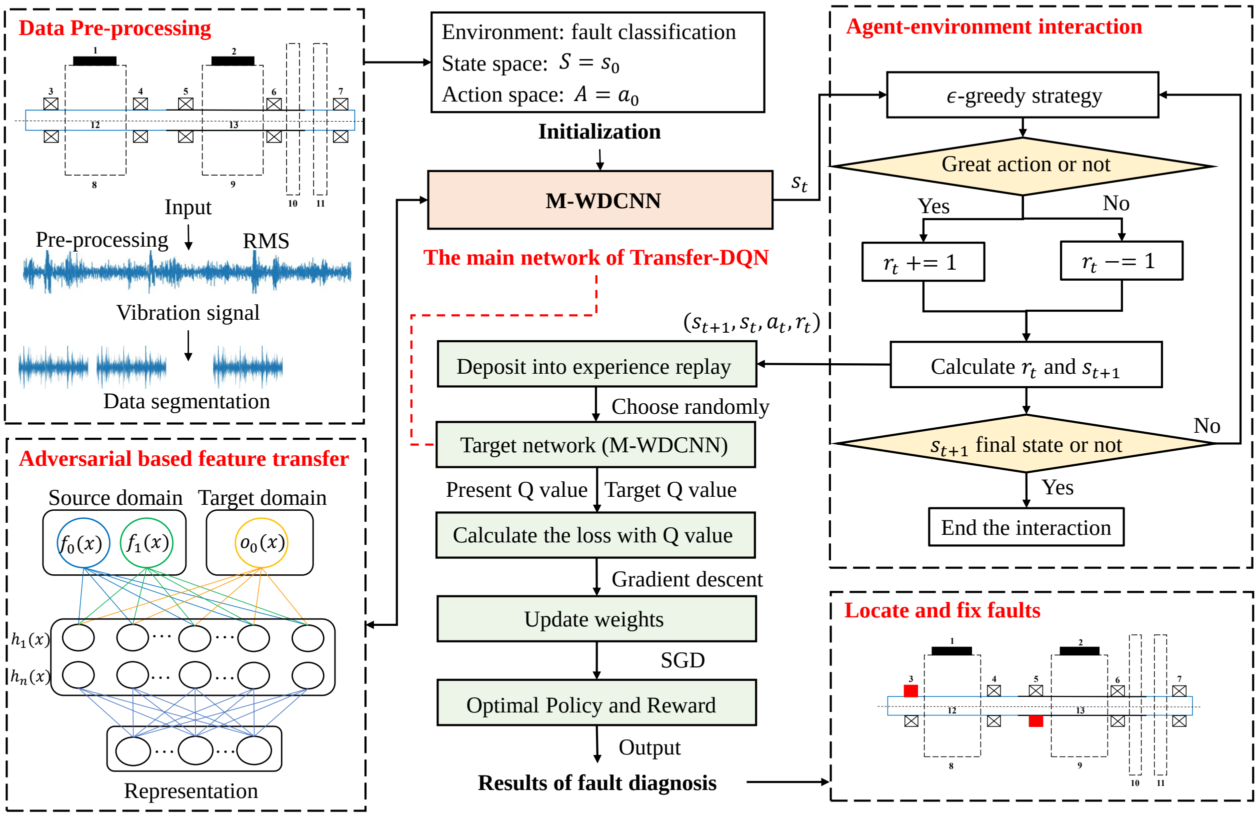

Fig. 2. The framework of the robust fault diagnosis for gas turbine rotor using Transfer-DQN.

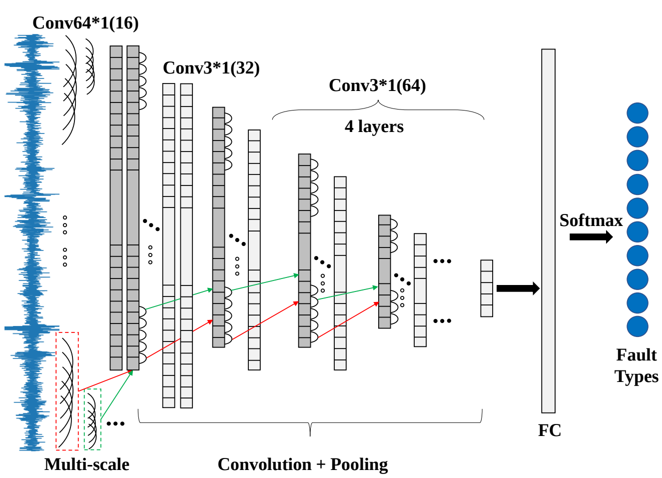

Fig. 3. Architecture of the M-WDCNN model.

transferable representations that can be applied to both source and target domains. The specific structure and transfer process are illustrated in Figure 2.

During the training process of the large-scale dataset in the source domain, the feature extractor of the adversarial network extracts features from both source and target domains and feeds them to the adversarial layer. The adversarial layer of the model distinguishes the feature sources and provides feedback on their differences. If the features exhibit subtle differences, they are deemed transferable and the results are fed back into the training of the M-WDCNN. This strategy mitigates the impact of data scarcity and the limitations of DQN convergence, ultimately improving the accuracy of the model.

IV. Experiments

The development and experimental process of Transfer-DQN consists of three parts: data preparation, implementation details, and experiments to test the robustness of Transfer-DQN, as well as comparison with the baselines.

A. Data Description

To verify the validity and accuracy of this method, experiments are conducted using a benchmark bearing dataset from Case Western Reserve University, as well as practical testing data.

The CWRU bearing dataset is collected from a testbed consisting of a 2 hp motor, a torque sensor/translator, a power tester, and an electronic controller. The test bench has a sampling frequency of 12 kHz and a load of 0 hp, and includes four types of samples: normal samples, outer ring damage samples, inner ring damage samples, and rolling element damage samples. These samples are described in Table I. The labels 0-3 indicate inner ring failure (IR) data, 4-6 indicate outer ring failure (OR) data, and 7-9 indicate rolling body failure (B) data. The data are also used as a training set to support training.

The gas turbine used in the practical testing data has a rotor system consisting of a low-pressure rotor with a maximum speed of 9600 r/min and a high-pressure rotor with a maximum speed of 5900 r/min. Acceleration sensors are mounted on the low-pressure and high-pressure compressors on the outer side of the engine box, which are used as the front and rear measurement points to collect the engine's vibration signals. The commissioning test time for each gas turbine is 2 hours, and the sampling frequency is 6000Hz. The practical testing data is used to provide additional validation of the model. Figure 1 shows the principle of the gas turbine in the testbed.

B. Implementation Details

In this study, the 1D vibration data samples are divided into training and data sets based on a 70% vs. 30% ratio. The data samples constitute the state set, and the fault types are the action set.

To preprocess the 1D oscillation data, we remove singular values and noise and calculate their root mean square (RMS) values. An abnormal condition is considered to have occurred if the filtered signal's RMS value at the front and backside points exceeds the high-pressure speed or vibration exceedance value. The sensor provides the vibration, airflow excitation, rotor bending, and rotor unbalance at the front and rear side points, respectively.

Transfer-DQN's main network and target network use a novel multiscale one-dimensional wide convolutional neural network (M-WDCNN). The network's convolutional structure consists of six layers, with each layer connected to 2×1 pooling operations after convolution. The first layer of convolution includes 16 64×1 convolutional kernels, the second layer includes 32 3×1 convolutional kernels, and the other four layers include 64 convolutional kernels of size 3×1. Additionally, the hyperparameters of Transfer-DQN are optimized and updated after training, with a discount factor of $\gamma = 0.8$, learning rate of $\eta = 0.01$, and a greedy strategy of $\epsilon_0 = 0.8$, and $\epsilon_{min} = 0.01$ for empirical replay.

TABLE I
THE DESCRIPTION OF THE CWRU DATASET

Number	Type	Training Samples	Test Samples
0	Normal(N)	560	240
1	IR007(R)	560	240
2	IR014(R)	560	240
3	IR021(R)	560	240
4	OR007(R)	560	240
5	OR014(R)	560	240
6	OR021(R)	560	240
7	B007(B)	560	240
8	B014(B)	560	240
9	B021(B)	560	240

C. Results

To evaluate the effectiveness of Transfer-DQN for fault diagnosis, experiments were conducted on the CRWU dataset.

TABLE II
THE ACCURACY AT DIFFERENT ITERATIONS IN THE BENCHMARK BEARING DATASET FROM CASE WESTERN RESERVE UNIVERSITY (CWEU) AND THE GAS TURBINE TEST BENCH (GTTB).

	Iterations	1	25	50	75	100
CWEU	**ACC-DQN(%)**	51.81	89.61	94.82	95.13	96.67
	ACC-Ours(%)	61.94	90.82	97.69	98.31	98.58
GTTB	**ACC-DQN(%)**	48.83	74.98	90.48	92.03	92.31
	ACC-Ours(%)	69.70	90.47	96.62	98.97	99.23

TABLE III
THE VARIATION OF REWARD VALUES FOR DIFFERENT TRAINING BATCHES IN FIVE TESTS.

Training batches	25	50	75	100	125	150	300
Reward values-1	-2	379	431	447	451	453	453
Reward values-2	-10	354	429	448	454	454	454
Reward values-3	-8	361	424	438	449	455	456
Reward values-4	0	385	430	452	457	458	458
Reward values-5	-15	338	418	432	445	450	452

The model training was performed for 300 iterations, with an empirical pool capacity of 4500 and a minimum batch size of 32. Table II shows the accuracy of our approach under different numbers of iterations between Transfer-DQN and DQN. From the table, it can be observed that the accuracy of Transfer-DQN starts to equalize after 50 iterations and finally reaches 98.95%, while DQN stabilizes around 125 iterations. Moreover, we tested the reward values separately for the training batches to enable better optimization and tuning. Table III displays the variation of reward values for different training batches. It was found that the reward value converges from an initial negative value to $450 \sim 460$ at around 150 training batches as the training batches are increased.

Additionally, a fault detection experiment for the gas turbine rotor system was conducted on the testbed of our lab. The empirical pool capacity for this experiment was set to 5000, and the minimum batch size was set to 32. Figure 4 shows the accuracy of Transfer-DQN on the two experimental environments with the data, achieving 98.95% and 96.91%, respectively.

To provide a more objective evaluation, comparative experiments were conducted to explore the effectiveness of Transfer-DQN in terms of fault diagnosis performance and computational overhead. In this experiment, cutting-edge methods for gas turbine rotor system fault diagnosis were introduced as baselines, including modified auto-encoders based (e.g., SDAE [33], DWAE [34]), CNN based (e.g., ST-CNN [35], MS-DCNN [36]), DBN based (e.g., DBNs+CD-k [37], HDN-DBN [38]), GAN based (e.g., DCGAN [39], WDMAN [40]), and RL based methods (e.g., double Q-learning [41], DQN [29]). The fault diagnosis accuracy results of the different methods are presented in Table IV. Good results were obtained for all five types of algorithms involved in the experiments. The

TABLE IV
COMPARISON WITH BASELINES.

Method	**Average accuracy(%)**	**Runtime(s)**	**Accuracy on CWEU(%)**	**Accuracy on GTTB(%)**
SDAE [33]	89.945 ± 0.639	NA	93.849 ± 0.897	86.041 ± 0.273
DWAE [34]	90.260 ± 0.474	NA	94.498 ± 0.287	86.052 ± 0.238
ST-CNN [35]	85.273 ± 0.568	NA	92.832 ± 0.783	77.714 ± 0.898
MS-DCNN [36]	87.051 ± 0.009	NA	94.849 ± 0.198	79.253 ± 0.298
DBNs+CD-k [37]	86.438 ± 0.490	NA	90.783 ± 0.428	82.093 ± 0.239
HDN-DBN [38]	94.744 ± 0.868	NA	96.868 ± 0.283	92.620 ± 0.930
DCGAN [39]	90.562 ± 0.206	NA	94.897 ± 0.787	86.227 ± 0.347
WDMAN [40]	92.095 ± 0.417	NA	95.987 ± 0.283	88.203 ± 0.685
double Q-learning [41]	92.429 ± 0.172	447.5	95.783 ± 0.389	89.075 ± 0.284
DQN [29]	94.491 ± 0.261	468.3	96.672 ± 0.298	92.310 ± 0.437
Transfer-DQN(Ours)	98.953 ± 0.042	429.7	98.583 ± 0.189	99.323 ± 0.008

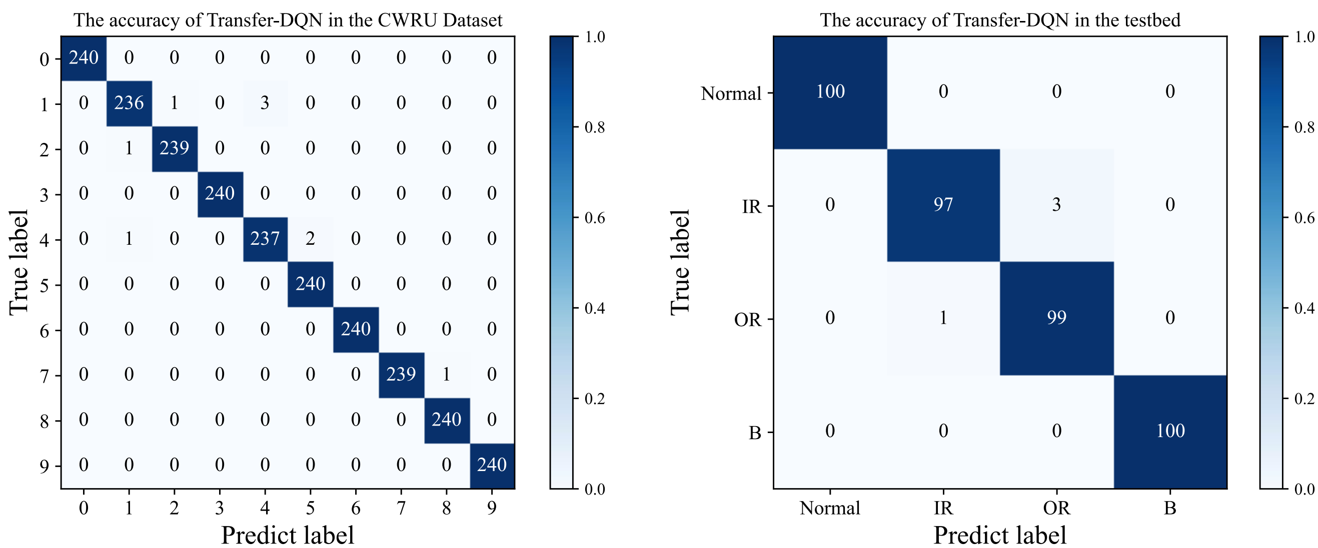

Fig. 4. The accuracy of Transfer-DQN on the two experimental environments, including the benchmark bearing dataset from Case Western Reserve University (CWEU) and our gas turbine test bench (GTTB).

results show that our method achieved nearly 4% improvement compared to DQN and almost 10% improvement on average compared to DBN-based methods.

Regarding computational overhead, we compared the CPU computing time consumption results of the RL-based baselines and the Transfer-DQN training proposed in this paper, as shown in Table IV. This experiment aimed to roughly evaluate the effect of transfer learning on efficiency improvement for reinforcement learning. The average time consumption of this method was 429.7s, which is nearly 4% less compared to the RL-based methods. Although more time is consumed due to the multi-scale strategy used in feature extraction, a balance of accuracy and time cost was achieved.

V. Conclusion

In this paper, we propose a transfer reinforcement learning approach, called Transfer-DQN, to achieve fault diagnosis for gas turbine rotor system. It utilizes a novel multiscale one-dimensional wide-convolutional neural network (M-WDCNN) with an ϵ-greedy strategy for Q-network fitting and decision making. To overcome the limitations of DQN and alleviate the effects of data scarcity, we propose an adversarial-based domain feature transfer method. Compared with other methods, our model is able to extract sensitive features more comprehensively and quickly. Extensive experiments demonstrate the superiority of Transfer-DQN in terms of diagnostic accuracy and time overhead, reaching 98.9% accuracy in the CWRU dataset and 96.91% in the practical testing data of testbad in reality. In future work, we plan to further explore the balance between accuracy and time cost for gas turbine rotor fault diagnosis to achieve even better optimization.

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