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RESEARCH ARTICLE

Application of Spectrum State Prediction Method Based on CNN-LSTM Network in Communication Interference

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ABSTRACT The continuous development of communication technology and various deep learning models has led to the invention and application of many anti-interference technologies in the field of communication countermeasures. The existing communication interference models have defects such as low anti-interference rate and low accuracy in communication spectrum prediction. To solve these problems, this study attempts to construct a Convolutional Neural Networks Long Short Term Memory (CNN-LSTM) and apply it to the communication jamming system for spectrum state prediction. Firstly, the framework of the communication interference system using the USRP RIO radio platform software was designed, and based on it, the communication interference channel was optimized using reinforcement learning Q-learning algorithm. Next, to further predict the signal spectrum state during the communication process, neural networks are utilized to construct a communication spectrum state prediction model. According to the optimization effect of communication interference channel and network spectrum prediction effect tested, the communication model under the Q-learning algorithm can achieve a 100% effective interference probability in fixed communication strategies. The Convolutional Neural Networks-1 Long-Short Term Memory-2 model has a prediction accuracy of 95.2% and can accurately predict changes in the communication spectrum. In summary, the Convolutional Neural Networks-1 Long-Short Term Memory-2 network constructed by this paper can provide new solutions and achieve good results for communication spectrum prediction.

INDEX TERMS Convolutional neural networks, long-term and short-term memory network, communication interference, spectrum, state prediction.

I. INTRODUCTION

With the rapid development of information technology in modern society, significant research results have been achieved in the field of wireless communication. As the carrier of information transmission, electromagnetic spectrum has an important role in the field of wireless communication [1]. To ensure that information can be transmitted wirelessly without interference and damage from the external environment, many communication countermeasure technologies have been gradually developed. With the continuous development of wireless communication technology, the communication interference problem has become more and more complex and serious [2]. Predicting the state of communication interference is one of the keys to solve the communication interference problem. The traditional prediction methods are usually based on the statistical characteristics of the signal, such as time domain, frequency domain and code domain. However, this method suffers from low prediction accuracy and poor generalization ability. Therefore, it is of great theoretical significance and application value to study the spectrum state prediction method based on deep learning [3]. Currently, a number of scholars have conducted a series of studies on the communication interference problem. Wang et al. focused on the wireless communication spectrum state prediction problem and proposed a spectrum prediction model based on deep neural networks. The scholars first conducted an in-depth analysis and processing of historical

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spectrum occupancy data, and then used a deep neural network for spectrum prediction. Experimental results show that the proposed prediction model possesses a high prediction accuracy [4]. Li et al. proposed a prediction model based on long- and short-term memory recurrent neural networks, and the study mainly used long- and short-term memory recurrent neural networks to predict historical spectrum data, with particular attention to the time-series characteristics of spectrum states. The experimental results show that the prediction accuracy of the adopted model is significantly improved and its prediction performance is better than that of the traditional neural network model in the complex changing spectrum environment [5].

Accurate spectrum state prediction and interference analysis have significant relevance and importance in communication systems, which are mainly reflected in the following aspects. First, spectrum resources are optimized. Accurate spectrum state prediction and interference analysis can help the communication system effectively utilize the available spectrum resources. By predicting spectrum usage and analyzing interference sources, the system can make resource deployment and spectrum allocation according to actual demand, thus maximizing the utilization efficiency of spectrum resources. This is essential to meet the growing demand for communications, provide higher data transmission rates and support more user connections. Second, interference suppression and communication quality enhancement. Accurate spectrum state prediction and interference analysis can help the system reduce the impact of interference on communication signals and improve communication quality and reliability. By timely identifying and analyzing the interference sources, the system can take corresponding suppression measures, such as selecting appropriate interference cancellation algorithms, adjusting transmission parameters or changing the channel, etc., so as to reduce the interference noise in the communication and improve the signal quality and transmission performance. Third, prediction performance optimization and network planning. Accurate spectrum state prediction and interference analysis are important for network planning and performance optimization. By accurately predicting the spectrum state and interference, the system can reasonably plan the network topology, optimize resource allocation and spectrum allocation strategy, so as to improve the capacity, coverage and performance of the network. This helps to meet users' demand for high-speed, high-quality communications and provide a better network service experience. Despite continuous optimization of the communication interference equipment and increased transmission of communication information, a significant amount of information is still subject to disruption during transmission. This leads to fluctuations in its spectrum data, making it difficult to read. The continuous development of deep learning makes all kinds of neural networks and reinforcement learning algorithms are gradually applied to the field of wireless communication. To improve the jamming system's ability to resist interference during communication, we utilize the Q-learning reinforcement algorithm to study the communication interference channel and design a communication interference system framework using USRP RIO radio platform software. In addition, the paper also utilizes neural networks to construct a communication spectrum state prediction model, aiming to optimize the current spectrum prediction techniques and provide accurate spectrum prediction for the implementation of accurate interference in communication jamming systems.

The main contributions of this research are shown as follows:

1. The paper first proposes a Q-learning-based strategy to select the optimal interference channel and constructs a reinforcement learning-driven model of the communication interference system. At the beginning stage, spectrum sensing is implemented through a double threshold energy detection technique to obtain the spectrum state of the communication user. Then, the spectrum state is used as input to determine the interference channel and calculate the reward value by Q-learning algorithm, and then the Q table is updated iteratively. Finally, by analyzing the experimental results, it is confirmed that the strategy has a significantly higher effective interference rate compared to the traditional single-tone interference, multi-tone interference and random interference strategies.

2. In the paper, a CNN-LSTM network-based spectrum state prediction scheme is designed for communication spectrum prediction, and a deep learning-driven communication interference system model is constructed. First, the spectrum energy data of communication users are obtained through spectrum sensing by energy detection techniques. Then, using this spectrum data as input, a CNN-LSTM network model is trained and the trained model parameters are used to create a CNN-LSTM network prediction model to predict the spectrum data on a time-period-by-time basis. These predictions are used to select interference channels and implement interference. Finally, the analysis of experimental results shows that the scheme can effectively predict the spectrum state and apply it to the selection of interference channels to achieve effective interference.

II. RELATED WORK

To apply reinforcement learning technology to the field of wireless communication, strengthen wireless communication signals, and optimize systems to make better decisions, many experts have conducted a series of studies [6]. Ding et al. conducted research on spectrum sharing satellite systems and proposed a spectrum prediction model that integrates Convolutional Neural Networks-Bi Long Short-Term Memory (CNN-BiLSTM). They preprocessed the historical spectral occupancy data of the geostationary orbit and then used the CNN-BiLSTM neural network model for prediction. The prediction model used has good prediction performance, the prediction accuracy is higher than the traditional convolutional neural model and short-term memory model, and the average error value is also far lower than the two traditional models [7]. Since cognitive radio plays an important role in realizing the spectral efficiency of wireless communication networks, Bhowmik and Malathi proposed a hybrid prediction model to assist cognitive radio in better sensing spectral efficiency. The constructed hybrid prediction model is composed of an actor critical neural network optimized by Krill Herd Whale and a hidden Markov network. This model has better throughput performance, with a maximum sensing time of only 650 seconds [8]. To improve spectral efficiency in cellular networks, Silva et al. optimized for two duplex modes: full duplex and dynamic time division duplex. The purpose is to demonstrate that both full duplex and dynamic time division duplex models can improve spectral efficiency by increasing the capacity of cellular networks. Experiments have shown that the optimized two duplex models can suppress cross link interference while improving the capacity and user throughput of cellular networks [9]. For improving the spectrum acquisition rate of large-scale wireless networks and alleviate channel interference issues, Ren et al. utilized a cooperative spectrum acquisition model to mitigate interference channels and improve spectral efficiency. In response to the problem that existing indicators cannot meet the requirements of performance testing, researchers have also proposed two new indicators: spectrum access level and user participation level, which are used as model performance testing indicators. The results indicated that the cooperative spectrum acquisition model can have good performance in spectrum access level and user participation level, while also improving the spectrum acquisition efficiency of wireless network systems [10]. To achieve efficient management of satellite spectrum resources, Li et al. proposed a market driven technology to improve spectral efficiency. This technology aims to provide an incentive scheme for agents to participate in the spectrum optimization process, thereby maximizing the benefits between satellite systems and agents and achieving efficient utilization of satellite spectrum. This method can be used to improve the efficiency of satellite spectrum utilization, providing a new approach to reduce the agency costs borne by satellite systems [11].

Wang et al. constructed a one-dimensional CNN to identify the line spectrum of noise detection spectrum for the needs of underwater detection. Through training and evaluation, one-dimensional CNN is ensured to have excellent generalization ability. The recognition noise detection based on one-dimensional CNN improves computational speed while ensuring accuracy, and the recognition process is robust and real-time [12]. Chen et al. combined short-time Fourier transform and CNN to construct a new neural network model for spectral sensing, which achieved state-of-the-art detection performance. The research team also analyzed the robustness and generalization ability of the proposed algorithm, indicating that this method outperforms other widely used spectrum sensing methods [13]. Liu et al. believed that one of the key issues in spectrum sensing is the design of test statistics, so they introduced a detection framework based on deep neural networks. To implement a framework based on deep neural networks, the research team used the sample covariance matrix as input to the CNN. A CNN spectrum sensing algorithm based on covariance matrix perception is proposed and analyzed. Its performance has been proven to be closest to the performance of the optimal detector and superior to traditional methods [14]. Huynh The T and others believed that the radar system is faced with disordered access and utilization of electromagnetic spectrum in the environment of sharing spectrum with the radio communication system. The team has developed a new residual attention multi-scale cumulative convolutional network and proposed a high-precision waveform recognition method for intelligent radar systems based on this. Simulation results using this method showed that compared with traditional mechanical learning and state-of-the-art deep learning models, this model can accurately and quickly recognize waveforms in harsh environments and exhibit excellent performance [15].

In summary, there has been an endless stream of research in the field of wireless communication. From communication signals, communication methods, spectrum prediction to channel interference, many experts have applied various deep learning algorithms to the field of wireless communication and achieved certain results [16], [17]. However, how to achieve effective communication interference and effectively predict its spectrum transformation remains a major challenge in the current field of wireless communication [18]. Based on this current situation, this study first optimized the wireless communication system, built a communication interference system model under reinforcement learning, and utilized reinforcement learning algorithms for interference reinforcement. Subsequently, the Convolutional Neural Networks-Long Short Term Memory (CNN-LSTM) was established and used for communication spectrum state prediction, aiming to provide new ideas for achieving effective channel interference and accurate communication spectrum prediction.

III. COMMUNICATION INTERFERENCE SYSTEM BASED ON CNN LSTM NETWORK PREDICTION

To enhance the anti-interference capability of the jamming system during communication confrontations, this paper incorporates the Q-learning reinforcement algorithm to study communication jamming channels. The framework of the communication jamming system is designed using the USRP RIO radio platform software. In addition, the study further utilizes neural networks to construct a communication spectrum state prediction model, aiming to optimize the current spectrum prediction techniques and provide accurate spectrum prediction for the implementation of accurate interference in communication jamming systems.

A. COMMUNICATION INTERFERENCE CHANNEL BASED ON Q-LEARNING ALGORITHM

The communication interference system mainly consists of communication interference equipment, guidance and reconnaissance equipment, command and control equipment, and

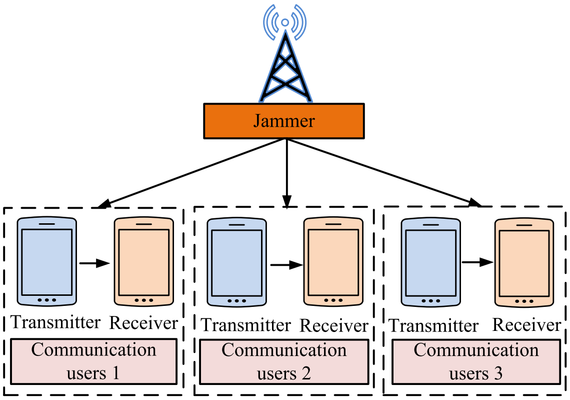

FIGURE 1. Structure of traditional communication interference system.

their supporting devices. As an electronic countermeasure system capable of independently completing communication interference tasks, communication interference systems aim to interfere with the transmission process of information. Figure 1 is a traditional communication interference model.

Fig. 1 shows the general structure of a traditional communication interference system. Traditional communication interference systems generally consist of two parts: the jammer and the communication user [19]. Among them, the communication user part can connect multiple communication user models, and each individual communication user model is composed of a transmitter and a receiver. The jammer achieves communication interference by interfering with the signal transmission process between the transmitter and receiver. Traditional communication interference systems, due to their relatively simple organizational structure, are prone to problems such as poor stability and poor signal interference effects during the signal interference process. To optimize traditional communication anti-interference techniques, the study first designed a communication interference system framework using the USRP RIO radio platform software, and combined reinforcement learning with it to optimize communication interference channels [20].

Reinforcement learning is a machine learning technique that enables agents to learn in an interactive environment through repeated experimentation using feedback values from their own behavior and experience. Although both supervised learning and reinforcement learning use the mapping between input and output, the feedback provided by supervised learning to agents is the correct set of actions to perform tasks; Reinforcement learning, on the other hand, uses rewards and punishments as signals of positive and negative behavior.

Fig. 2 shows the communication interference system model under reinforcement learning. The entire model consists of two parts: communication users and interference systems, where the communication users include transmitters and receivers, with the main function of transmitting and receiving information. The interference system is composed of interference machines, cognitive engines, data processing

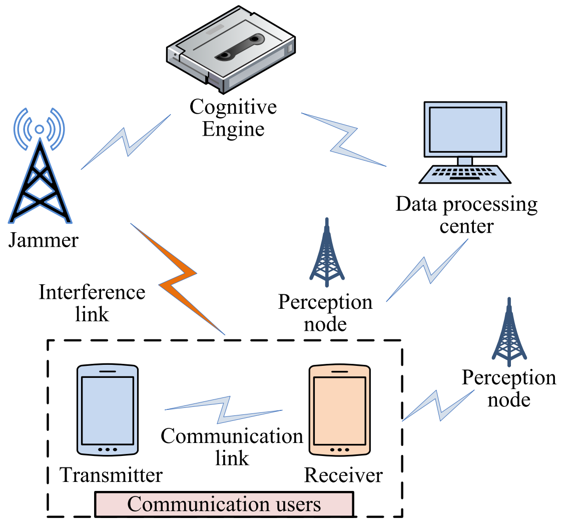

FIGURE 2. Communication interference system model under reinforcement learning.

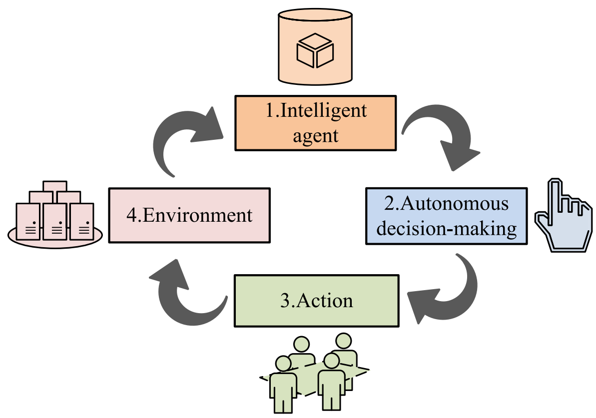

FIGURE 3. Reinforcement learning flowchart of Q-learning algorithm.

centers, and several perception nodes. The transmitter, jammer, and receiver are all built using USRP RIO software, and the functions of each part are achieved through programming software on the computer [22]. Transmitters and receivers can use different channels for communication during the communication process. For addressing the issue of channel switching in communication interference systems, the research further divides the working process of communication interference systems into two parts: spectrum sensing and interference decision-making. Firstly, by sensing nodes and data processing centers, spectrum sensing is implemented to obtain channel state information; Then, using a cognitive engine, the obtained channel state information is subjected to reinforcement learning; Next, the channel switching law between the transmitter and receiver is learned and the final interference decision is made. There are two common reinforcement learning algorithms: Q-learning and SARSA. This study will utilize Q-learning algorithm to optimize communication interference channels. Fig.3 is the reinforcement learning flowchart of the Q-learning.

Fig. 3 shows the reinforcement learning flowchart of the Q-learning algorithm. When describing the Q-learning in reinforcement learning, four keywords are generally used: intelligent agent, autonomous decision-making, action, and environment. Among them, environment refers to the physical operating state of the current intelligent agent; Autonomous strategy refers to the method of mapping agent states to actions. In reinforcement learning, the Q-learning algorithm aims to record the learned policies and inform the agent of the maximum reward value for actions taken under certain circumstances. The Q-learning algorithm does not require modeling of the environment, and even for transfer functions or reward functions with random factors, it can be learned without special modifications. As a type of reinforcement learning algorithm, Q-learning algorithm has the advantage of making optimal learning strategies without relying on environmental models, and is widely used in various decision-making problems. In the Q-learning algorithm, the intelligent agent can always achieve the optimal strategy by continuously optimizing the current state. The agent update formula of Q-learning algorithm is expressed by equation (1).

$$Q_{n+1}(s_n, a_n) \leftarrow Q_n(s_n, a_n) + \alpha\left(r_n + \gamma \max_{\alpha} Q_\pi(s_{n+1}, a) - Q(s_n, a_n)\right) \tag{1}$$

Formula (1) represents the final goal of updating the agent in the Q-learning algorithm, which is to establish a mapping between the state-action pair and the Q-value. This mapping is represented by a matrix. $Q_n(s_n, a_n)$ represents the state s and action a of agent Q at time n. $Q_{n+1}(s_n, a_n)$ represents the state and action of agent Q at time $n+1$. α represents the learning rate, with a value range of [0,1]. γ represents the discount factor, with a value range of [0,1], which is used to balance the weight between long-term and short-term returns. s_{n+1} represents the execution status of the action at time $n+1$. r_n represents the reward obtained by executing the action at n time. $r_n + \gamma \max_{\alpha} Q_\pi(s_{n+1}, a)$ represents the estimated reward value of the Q function. $Q_{n+1}(s_n, a_n)$ represents the updated Q.

Because the Q-learning algorithm relies on the Markov decision process theory, it is necessary to explain this theory before proceeding further. Markov decision-making generally includes four factors: S, A, P, and R, which correspond to the state, action, transition probability, and reward value in the decision-making process.

$$s_k = (j_k, f_k), j_k, f_k \in (1, 2, \cdots, L) \tag{2}$$

Eq. (2) is the mathematical expression of the system state in the Markov decision process. j_k represents the interference signal of the jammer at time k, f_k shows the communication channel used by the communication user, and s_k represents the state space of the system.

$$a_k = f_{k+1} \tag{3}$$

In equation (3), a_k represents the interference channel at time $k+1$ and also represents the interference action of the jammer.

$$P = \{p | (s_{k+1} | s_k, a_k)\} \tag{4}$$

In equation (4), P represents the probability that the jammer selects a_k and transitions to s_{k+1} in state s_k.

$$r_k = \begin{cases} 1 \\ 0 \end{cases} \tag{5}$$

In equation (5), r_k represents the reward obtained by the jammer when selecting a_k in state s_k. When the communication channel is consistent with the interference channel, the reward is set to 1, and if the two are not consistent, it is set to 0.

$$Q_{k+1}(s_k, a_k) \leftarrow (1-\alpha) Q_k(s_k, a_k) + \alpha\left(r_k + \gamma \max_{\alpha} Q_\pi(s_{k+1}, a)\right) \tag{6}$$

According to the Markov decision process and equation (1), the update formula for the Q-learning algorithm can be obtained as shown in Eq. (6). The time n in equation (1) is replaced by k, and the meaning remains unchanged.

$$a_k = \arg\max_{\alpha} Q_k(s_k, a) \tag{7}$$

Eq. (7) is the calculation method for the optimal action estimation value of the Q-learning algorithm. Based on the various Q-values in the Q-table, the optimal value of the current state can be estimated.

In the entire interference system, the Q-learning algorithm controls the core decision-making function of the system [23], [24]. After the data processing center processes the data, it sends it to the cognitive engine for algorithm iteration and training, and forms a Q table. The interference channel is selected by the interference opportunity following the algorithm instructions. After that, the interference signal is sent to the user, resulting in the operational flowchart of the communication interference system which is shown in Figure 4.

Fig.4 shows the operational flowchart of the communication interference system under the Q-learning algorithm. Firstly, the system will start the transmitter and receiver for data transmission, and then set the state of the jammer and determine the interference signal emitted by the interference channel [25]. At the same time, sensing nodes will also use spectrum sensing technology to obtain communication user spectrum data information and send it to the data processing center. Then the data center will process the data and send the information to the cognitive engine based on the channel conditions of the obtained communication users [24]. By transmitting signals, it is determined whether the communication channel used by the communication user is consistent with the interference channel. If it is consistent, the reward is calculated as 1, otherwise it is 0. By calculating the reward value Q table and updating the communication status, the goal of updating the Q learning algorithm and communication system is achieved.

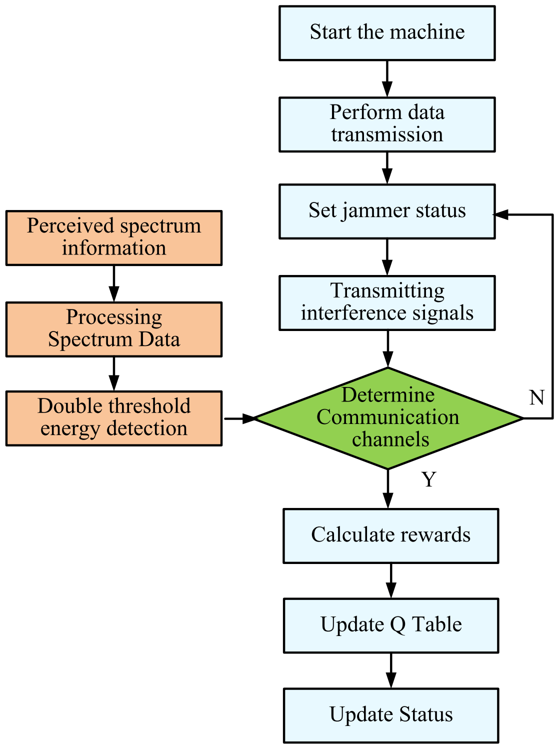

FIGURE 4. Flow chart of communication interference system operation under Q-learning algorithm.

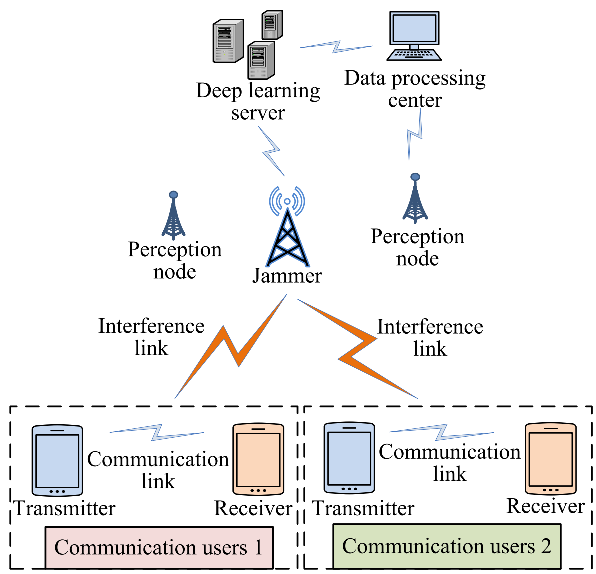

FIGURE 5. Communication interference system model diagram under CNN LSTM network prediction.

B. COMMUNICATION SPECTRUM STATE PREDICTION BASED ON CNN-LSTM NEURAL NETWORK

The communication interference system has been built using the Q-learning algorithm. To further predict the signal spectrum state during the communication process, the study attempts to use neural networks to construct a communication spectrum state prediction model. CNN and LSTM, as the two most commonly used neural network models in deep learning, can efficiently extract data features, actively learn target features, and fit complex functions. It is widely used in fields such as image processing, data classification, feature recognition, etc. [26]. Fig.5 shows a communication interference system model using CNN-LSTM neural network for spectrum prediction.

Fig. 5 shows the communication interference system model under the prediction of the CNN-LSTM network. Under the entire neural network prediction structure, the communication interference model includes two additional modules - deep learning server and communication user 2 - based on Fig. 2. The other infrastructure configuration is essentially identical to that shown in Fig. 2. The function of perception nodes in the model is still to perceive and collect spectral data information in infinite space. These data will be transmitted to the data processing center for unified processing and formed into a new dataset. The function of a deep learning server is to use these datasets for model training, in order to achieve spectrum prediction [27].

Figure 6 is the neuronal structure of the LSTM model. LSTM is optimized by the Recurrent Neural Network (RNN) and consists of three gate structures: input gate, forgetting gate, and output gate. It selectively receives information through memory units [28]. In Fig. 4, X_t represents the input data of the input layer at time t. S_t represents the neuron state of the hidden layer at time t. C_t represents the memory unit at time t. In Fig. 4, there are a total of three σ, representing the entry gate, forgetting gate, and output gate in LSTM from left to right, while f_t, i_t, and o_t represent the parameters of the three gates respectively.

$$f_t = \sigma' W_x^f \cdot X_t + W_s^f \cdot S_{t-1} + b_f \tag{8}$$

Eq. (8) is the calculation formula for the input gate parameter f_t. W_x^f and W_s^f are the weight matrix, and b_f represents the input gate bias vector. σ' represents the input gate.

$$i_t = \sigma'' W_x^i \cdot X_t + W_s^i \cdot S_{t-1} + b_i \tag{9}$$

Eq. (9) is the calculation formula for forgetting gate parameter i_t. W_x^i and $W_s^i$are the weight matrix, while b_i represents the forgetting gate bias vector. σ'' represents the forgetting gate. S_{t-1} represents the neuron state at time $t-1$.

$$o_t = \sigma''' W_x^o \cdot X_t + W_s^o \cdot S_{t-1} + b_o \tag{10}$$

Eq. (10) is the calculation formula for the output gate parameter o_t. W_x^o and W_s^o represent the weight matrix, and b_o is the output gate bias vector. σ''' is the output gate.

$$\tilde{c}_t = \tanh\left(W_x^c \cdot X_t + W_s^c \cdot S_{t-1} + b_c\right) \tag{11}$$

In equation (11), $\tilde{c}_t$ is the memory unit output obtained by calculating the forgetting gate parameter i_t through the tanh function. W_x^c and W_s^c represent the weight matrix. b_c represents the forgetting gate bias vector calculated by the tanh function.

$$c_t = i_t \odot \tilde{c}_t + f_t \odot c_{t-1} \tag{12}$$

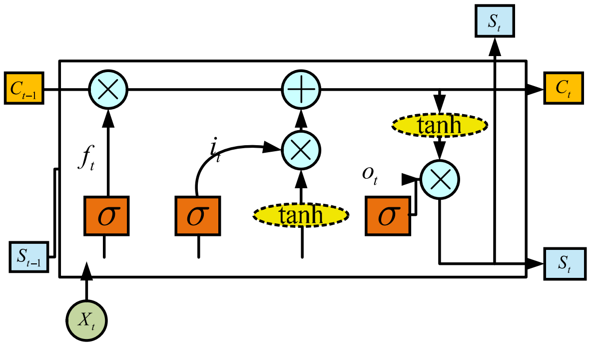

FIGURE 6. Structure diagram of LSTM neurons.

In equation (12), ⊙ refers to the Hardman product. The memory unit of LSTM can be obtained from equation (12).

$$S_t = o_t \odot \tanh(c_t) \tag{13}$$

Eq. (13) is the calculation formula for the neuron state of the hidden layer at time t. The relevant parameters in LSTM can be calculated separately through equations (8) to (13).

When building a neural network, one can choose to build a single-layer network structure or a multi-layer network structure. A single-layer neural network consists of an input layer, a hidden layer node, and an output layer, while a multi-layer neural network has more hidden layer nodes [29]. Multi-layer hidden layers' parameters can update weights in a more effective way for fitting training data. On the other hand, single-layer neural networks only have one hidden layer, which may result in poor fitting performance. Generally speaking, the performance of single-layer neural networks is worse than that of multi-layer neural networks. Single layer neural networks cannot complete complex operations, while multi-layer neural networks can use multiple layers of parameters and nonlinear relationships to fit data. Multilayer neural networks can analyze and analyze complex data from various perspectives, while single-layer neural networks can only perform simple classification and analysis. To achieve better prediction performance of communication spectrum signals, this study uses a multi-layer CNN LSTM neural network for line spectrum prediction.

Fig.7 is the structural diagram of a multi-layer CNN-LSTM neural network. The final prediction model constructed consists of a multi-layer CNN structure and a multi-layer LSTM structure. In multi-layer CNN LSTM neural networks, CNN can extract high-level data features through convolutional kernel operations, while LSTM completes data prediction tasks. Due to the fact that spectral data belongs to a type of time series data, CNN can be used for extraction. The extracted feature data is used as input to LSTM and completed spectrum prediction through LSTM. The flowchart of the communication interference system based on CNN LSTM network prediction is Fig. 8.

Fig. 8 is the flowchart of the communication interference system predicted by the CNN-LSTM network. Firstly, it is necessary to set up several sensing nodes in the wireless environment to perceive and collect spectral energy data, and send the data to the data processing center for processing. Next, the data processing center will convert the processed data into a dataset and send it to the deep learning server. The CNN-LSTM network in the server will use the dataset

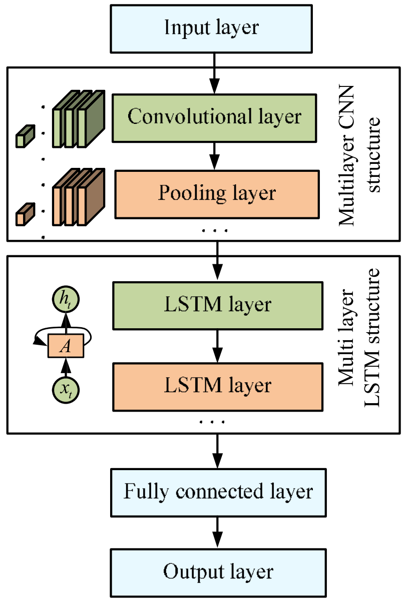

FIGURE 7. Multilayer CNN-LSTM network structure.

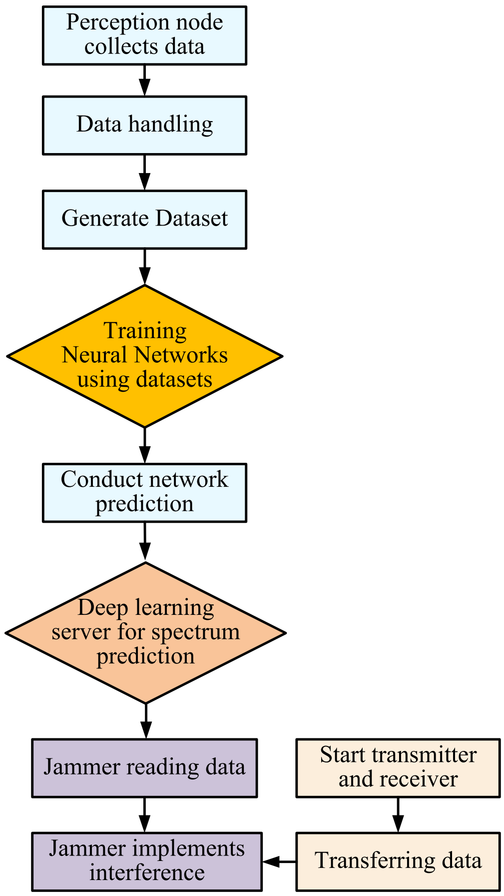

FIGURE 8. Communication interference system flowchart under CNN-LSTM network prediction.

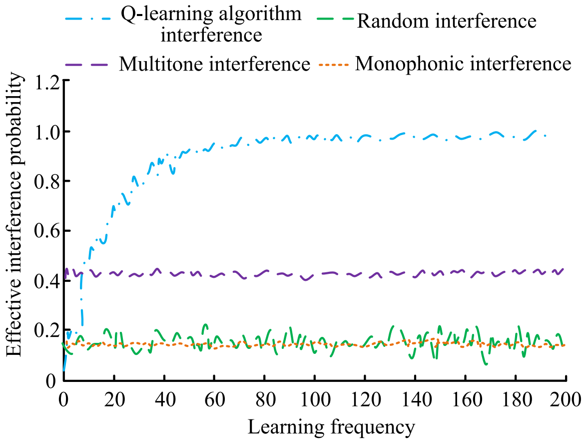

FIGURE 9. Effective interference probability of different interference patterns under fixed communication.

for network training and adjust various parameters to achieve better performance of the model. After the training of the CNN-LSTM network is completed, it can start predicting the changes in spectral state and transmit the predicted data to the jammer. The jammer executes interference decisions based on predicted data to complete the final channel interference.

IV. SIMULATION EXPERIMENT SETTINGS AND RESULT ANALYSIS

A. ANALYSIS OF INTERFERENCE CHANNEL EFFECT BASED ON Q-LEARNING ALGORITHM

To test the performance of the final designed communication spectrum state prediction network, simulation experiments were conducted on Matlab. The channel number of the system under the Q-learning algorithm is set to: $L = 7$, learning rate $\alpha = 0.1$, and discount factor $\gamma = 0.5$. Assuming that there are two strategies for fixed communication and variable communication between communication users. The study compares the probabilities of effective interference under random, single-tone, multi-tone, and Q-learning algorithm interference, all in the same experimental environment.

Fig.9 is the effective interference probabilities of different interference modes under fixed communication strategies. Among them, single tone interference refers to fixed interference on a channel. Multi tone interference refers to the fixed interference of three channels. Random interference refers to randomly interfering with one channel at a time. With the increase of system learning times, the effective jamming probability under the Q learning algorithm shows a rising trend. When the system learns 100 times, the effective interference probability under the Q-learning algorithm approaches 1 and gradually remains stable. On the contrary, with the increase of system learning times, the effective interference probability under random interference, single tone interference and multi tone interference basically does not change significantly. Random interference stabilizes below 0.2, single tone interference stabilizes around 0.16, and multi tone interference stabilizes around 0.4.

Figure 10 shows the effective interference probability of different interference modes under different communication strategies. When the communication mode of the system is no longer fixed, all four interference modes mentioned above will fluctuate within a certain range and cannot achieve 100% effective interference. With the increase of system learning times, the effective jamming probability under the Q learning algorithm still shows a rising trend. When the learning frequency of the system reaches 80, the effective interference probability under the Q-learning algorithm fluctuates around 0.8 and there is no longer a significant change. In addition, with the increase of system learning times, the effective interference probability under random interference, single tone interference and multi tone interference still does not change significantly. Among them, random interference remains stable below 0.2, single tone interference fluctuates above and below 0.2, and multi tone interference remains stable above 0.4.

To summarize, the communication model that uses the Q-learning algorithm can attain a channel interference probability of 100% after a certain number of training iterations in a fixed communication strategy, whereas it can attain an effective interference probability of 80% under a transformed communication strategy. By comparing several different interference methods, it can be proven that Q-learning algorithm can enhance the interference effect of communication systems to a certain extent.

B. ANALYSIS OF COMMUNICATION SPECTRUM STATE PREDICTION EFFECT BASED ON CNN-LSTM

To test the effect of CNN-LSTM network for communication spectrum state prediction, the study used USRP RIO software radio platform and computer hardware equipment to build the simulation experimental environment, while Matlab was used to write the simulation code. In addition, the study uses a homemade network communication dataset as the experimental training dataset to complete the testing of model performance. Through extensive radio measurements and signal collection, 2000 pre-processed sample data were selected as the final training data set. The dataset used includes the date and time of data collection, records of the state of each channel at a specific point in time, signal strength, location information, frequency information, and specific communication patterns. To confirm the number of layers and performance of the final CNN-LSTM network, the study set up the network model parameters as shown in Table 1, respectively, and tested the model performance under different parameters.

According to Table 2, three different CNN-LSTM networks were ultimately constructed, namely CNN1-LSTM1, CNN1-LSTM2, and CNN1-LSTM3. In a CNN network, the number of convolutional kernels is set to 32, and the pooling layer adopts average pooling. In the LSTM network, the number of LSTM units in the hidden layer is set to 32, 64, and 128, respectively. To test the performance of CNN-LSTM networks under different layers, the study first analyzed the

TABLE 1. Comparison table of the literature.

Author Name	Research Title	Research Areas	Number
Wang. J, Liu. C, and Chen. X	Spectrum prediction in wireless communication using deep neural networks	Spectrum prediction, deep learning	[4]
Li. Z, Zhang. H, and Luo. J	Spectrum prediction in wireless communication using LSTM recurrent neural networks	Historical spectrum data prediction, deep learning	[5]
X. Ding, L. Feng, Y. Zou, and G. Zhang	Deep Learning Aided Spectrum Prediction for Satellite Communication Systems	Satellite, spectrum data prediction, deep learning	[7]
M. Bhowmik, and P. Malathi	A hybrid model for energy efficient spectrum sensing in cognitive radio	Hybrid predictive models, radio	[8]
J. Silva, G. Wikstrom, R. K. Mungara, and C. Fischione	Full Duplex and Dynamic TDD: Pushing the Limits of Spectrum Reuse in Multi-Cell Communications	Cellular networks, prediction	[9]
C. Ren, H. Zhang, J. Chen, and C. Tellambura	Exploiting Spectrum Access Ability for Cooperative Spectrum Harvesting	Wireless spectrum prediction	[10]
F. Li, K. Y. Lam, Z.Sheng, W. Lu, and L. Wang	Agent-Based Spectrum Management Scheme in Satellite Communication Systems	Satellite spectrum optimization	[11]
W. Wang, X. Zhao, and D. Liu	Design and Optimization of 1D-CNN for Spectrum Recognition of Underwater Targets	Neural networks, spectrum identification	[12]
Z. Chen, Y. Q. Xu, H. Wang, and D. Guo	Deep STFT-CNN for Spectrum Sensing in Cognitive Radio	Spectrum sensing, neural networks	[13]
C. Liu, J. Wang, X. Liu, and Y. Liang	Deep CM-CNN for Spectrum Sensing in Cognitive Radio	Spectrum sensing, neural networks	[14]
T. Huynh-The, C. H. Hua, V. S. Doan,Q. V. Pham, and D. S. Kim	Accurate Deep CNN-basedWaveform Recognition for Intelligent Radar Systems	Spectrum waveform recognition, neural network	[15]

lag time step size RMSE variation results. The lag time step size RMSE variation diagram under different CNN-LSTM networks is Figure 11.

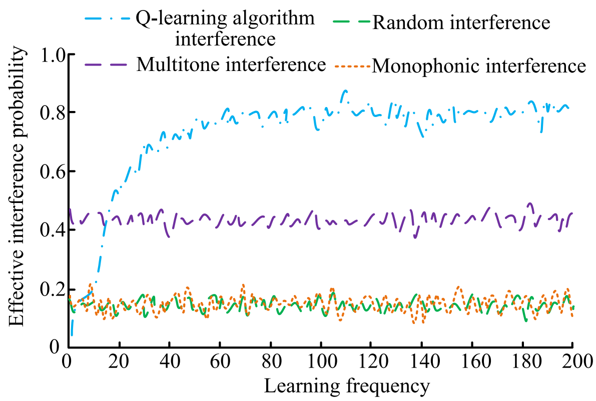

FIGURE 10. Effective interference probability of different interference patterns under transformed communication.

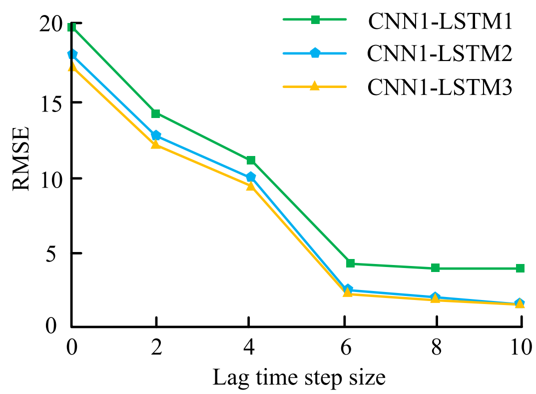

FIGURE 11. Lag time step size RMSE variation diagram for different CNN-LSTM networks.

Fig. 11 is the variation of lag time step size RMSE under different CNN-LSTM network structures. As the lag time step increases, the RMSE values of CNN1-LSTM1, CNN1-LSTM2, and CNN1-LSTM3 all decrease. When the lag time step is 6, the RMSE values of the three neural networks begin to stabilize and no longer significantly decrease. When the lag time step is 10, the RMSE values of CNN1-LSTM1, CNN1-LSTM2, and CNN1-LSTM3 are 4.5, 2.8, and 2.6, respectively. Due to the high relationship between the RMSE value and the final prediction accuracy of the model, an appropriate step size should be selected for model performance testing. Finally, the lag time step value of the experiment was determined to be 6, and the spectral prediction results of the three CNN-LSTM networks were detected separately, ensuring that other experimental environmental conditions were the same.

Fig.12 is the spectrum prediction results of the CNN1-LSTM1 network. Fig.12 (a) shows the comparison between the spectrum prediction results and actual results of the CNN1-LSTM1 network. Fig.12 (b) shows the spectral prediction error values of the CNN1-LSTM1 network under different time slots. In Fig.12 (a), as the number of samples changes, the actual values of the communication spectrum can basically overlap with the predicted values of the spectrum under the CNN1-LSTM1 network, but there is still some error. The final spectral prediction accuracy of the

TABLE 2. CNN-LSTM network parameters setting table.

Parameter Setting	Component Structure	Final Model
Filters=32，Units=32	Layer 1 CNN+Layer 1 LSTM	CNN1-LSTM1
Filters=32，Units=32，64	Layer 1 CNN+Layer 2 LSTM	CNN1-LSTM2
Filters=32，Units=32，64，128	Layer 1 CNN+Layer 3 LSTM	CNN1-LSTM3

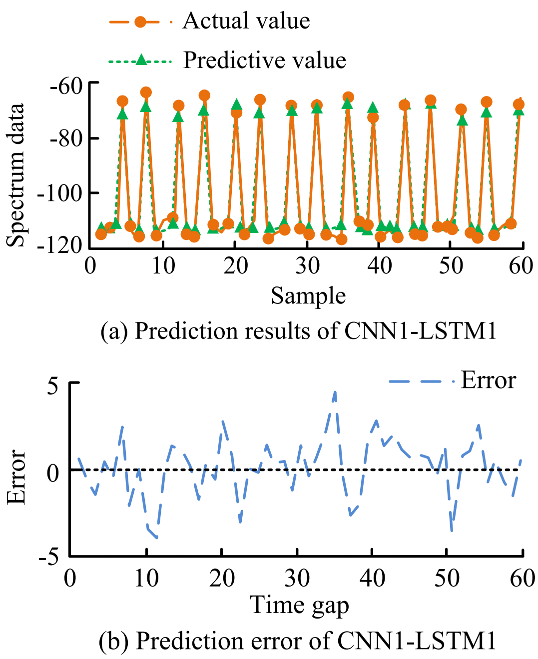

FIGURE 12. Spectral prediction results of CNN1-LSTM1 network.

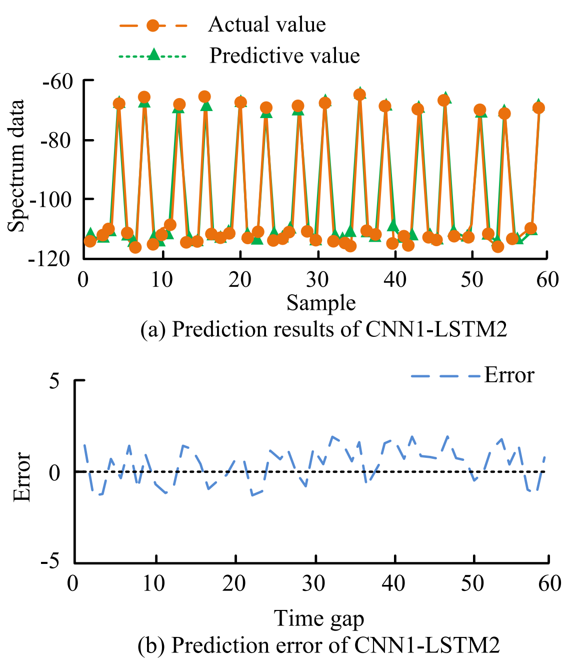

FIGURE 13. Spectrum prediction results of CNN1-LSTM2 network.

CNN1-LSTM1 network is 88.6%. In Fig.12 (b), as the time slot increases, the error value of the CNN1-LSTM1 network model fluctuates between -5 and 5, and the fluctuation amplitude is relatively large. This indicates that the error performance of the CNN1-LSTM1 network is poor.

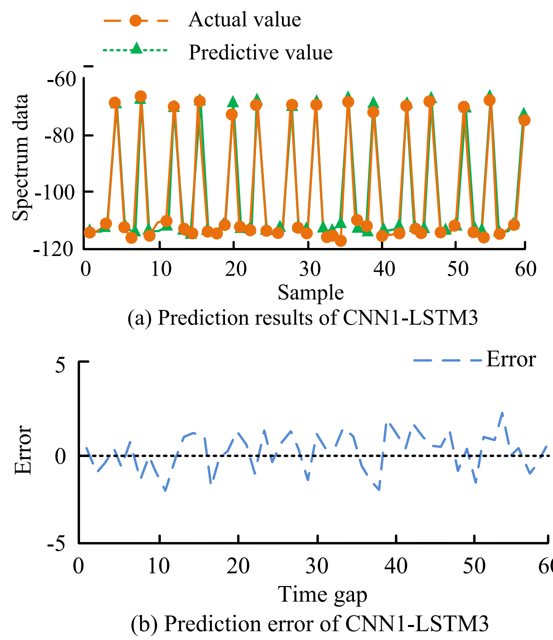

FIGURE 14. Spectral prediction results of CNN1-LSTM3 network.

Fig.13 is the spectrum prediction results of the CNN1-LSTM2 network. Fig.13 (a) is the comparison between the spectrum prediction results and actual results of the CNN1-LSTM2 network. Fig.13 (b) shows the spectral prediction error values of the CNN1-LSTM2 network under different time slots. In Fig.13 (a), as the number of samples changes, the actual values of the communication spectrum can mostly overlap with the predicted values of the spectrum under the CNN1-LSTM2 network, resulting in a smaller prediction error of the model. The final spectral prediction accuracy of the CNN1-LSTM2 network is 95.2%. In Fig.13 (b), as the time slot increases, the error value of the model fluctuates between -2 and 2. Compared to the CNN1-LSTM1 model, the error fluctuation amplitude and error value of the CNN1-LSTM2 network are smaller.

Fig. 14 shows the spectrum prediction results and error performance of the CNN1-LSTM3 network. In Fig.14 (a), as the number of samples increases, the actual value of the communication spectrum is basically consistent with the predicted trajectory of the spectrum under the CNN1-LSTM3 network, and the prediction error of the model is also small. The final spectral prediction accuracy of the CNN1-LSTM3 network is 95.6%. In Fig.14 (b), as the time slot increases, the error value of the model fluctuates between -3 and 3. Compared to the CNN1-LSTM1 model, the error fluctuation amplitude and error value of the CNN1-LSTM3 network are smaller. Compared to the CNN1-LSTM2 model,

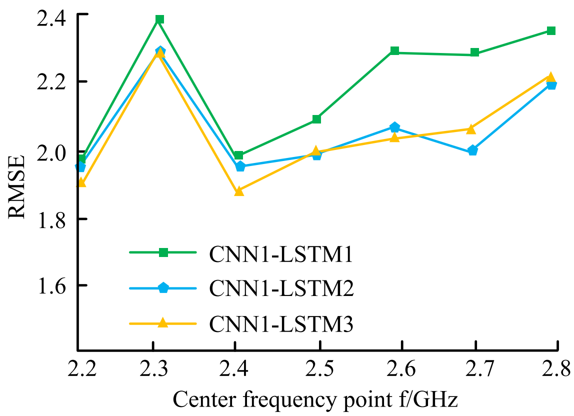

FIGURE 15. RMSE variation of three CNN-LSTM networks.

TABLE 3. Spectrum prediction performance of different models.

Final Model	Precision	Recall	F1	MAE
CNN1-LSTM1	9.02	8.95	8.98	4.23
CNN1-LSTM2	9.69	9.61	9.65	2.12
CNN1-LSTM3	9.58	9.60	9.59	2.08

the prediction accuracy and error range of both models are similar. However, the CNN1-LSTM3 model has an additional layer of LSTM compared to the CNN1-LSTM2 model, which will require more time to train the network.

Fig. 15 shows the RMSE changes of three CNN-LSTM networks. As the center frequency of the system increases, the RMSE values of all three models change. When the center frequency point is 2.3f/GHz, the RMSE values of the three network models CNN-LSTM1, CNN-LSTM2, and CNN-LSTM3 are the highest, with values of 2.38, 2.31, and 2.29, respectively. When the center frequency point is 2.4f/GHz, the RMSE values of the three network models are the smallest, they are 1.97, 1.95, and 1.88, respectively. Compared to the CNN-LSTM2 and CNN-LSTM3 models, the RMSE values of the CNN-LSTM1 model are both higher, indicating that the spectrum prediction performance of the model is poor.

The spectral prediction performance of the three models under the same data set is shown in Table 3. From Table 3, the spectrum prediction accuracy, recall, F1 value and MAE value of CNN1-LSTM1 are 9.02, 8.95, 8.98 and 4.23, respectively. The spectrum prediction accuracy, recall, F1 value and MAE value of CNN1-LSTM2 are 9.69, 9.61, 9.65 and 2.12, respectively. The spectrum prediction accuracy, recall, F1 value and MAE value of CNN1-LSTM3 are 9.58, 9.60, 9.59 and 2.08, respectively. In summary, comparing the spectrum prediction effects of the three models, it is found that CNN-LSTM2 and CNN-LSTM3 have better prediction effects than CNN-LSTM1. To reduce the training times of the model, CNN-LSTM2 is finally selected as the spectral prediction model.

V. DISCUSSION

By analyzing the interference channel effect under Q learning algorithm and analyzing the prediction effect of different CNN-LSTM communication spectrum states, the study was able to obtain the following discussion results:

1. When analyzing the interference channel effect, the Q-learning algorithm can accomplish nearly 100% and 80% effective interference probability for fixed and transformed communication strategies, respectively, after a certain number of training sessions. This performance is significantly better than that of other methods such as random, single-tone, and multi-tone interference. This demonstrates the significant advantage of Q-learning algorithm in enhancing the interference effect of communication systems.

2. This study explores communication spectrum state prediction using a CNN-LSTM network and optimizing its parameters to improve prediction accuracy. The initial phase of the study involved testing the CNN-LSTM network's performance under various network structures and thoroughly analyzing the lag time step-RMSE variation of the networks. The study constructed three different CNN-LSTM network models, namely CNN1-LSTM1, CNN1-LSTM2, and CNN1-LSTM3, which varied in the number of hidden layer units. The models, namely CNN1-LSTM1, CNN1-LSTM2, and CNN1-LSTM3, had different numbers of hidden layer units, respectively. The analysis of experimental data showed that the Root Mean Square Deviation (RMSE) scores of the three network models decreased as the lag time step increased. However, the scores started to stabilize when the lag time step was at 6, and no significant decrease was observed after that. As a result, researchers concluded that 6 is the appropriate step size setting. Then, the study conducted a comparative analysis of the spectral prediction results of the three CNN-LSTM networks. The results show that the CNN1-LSTM2 and CNN1-LSTM3 models have more accurate prediction results and smaller error ranges compared with the CNN1-LSTM1 model, which proves that adding more hidden layers can improve the prediction accuracy of the models. It should be noted, however, that although the prediction accuracy of the CNN1-LSTM3 model is slightly higher than that of the CNN1-LSTM2, its additional hidden layer results in longer training times. The changes in the RMSE values of the three models were compared. It was concluded that the RMSE values were highest when the central frequency point was 2.3f/GHz and lowest when the central frequency point was 2.4f/GHz. This suggests that the models' prediction effectiveness varies with the central frequency point of the system. In conclusion, the CNN1-LSTM2 model can be identified as the ultimate spectrum prediction model. It ensures prediction accuracy and avoids time loss caused by overtraining.

In general, this paper demonstrates the potential power of Q-learning algorithms and CNN-LSTM networks in applications concerning interference and spectrum prognosis in communication systems. Subsequent studies could improve on the used results by optimizing the algorithms further and exploring more intricate communication scenarios to design more flexible and resilient communication systems.

VI. CONCLUSION

To accurately predict the spectral changes during the communication process and combat various communication interference technologies, the study attempts to apply reinforcement learning and neural networks to the field of communication interference. Therefore, a spectrum state prediction model based on CNN-LSTM network was constructed, and a communication interference system framework based on Q-learning algorithm was designed. To test the performance of the Q-learning algorithm and determine the final structure of the CNN-LSTM network, a series of simulation tests were conducted and the following results were obtained. Compared to random interference, single tone interference, and multi tone interference, the communication model under the Q-learning algorithm has a better effective interference probability. In fixed communication strategies, the effective interference probability is as high as 100%. While in the transformation communication strategy, it is as high as 80%. Comparing the prediction accuracy of CNN1-LSTM1, CNN1-LSTM2, and CNN1-LSTM3 in the same experimental environment, it was found that the spectral prediction accuracy of the three models was 88.6%, 95.2%, and 95.1%, respectively. The error performance of CNN1-LSTM2 and CNN1-LSTM3 is better than that of CNN1-LSTM1. In summary, to achieve high-precision prediction in the shortest possible time, the CNN1-LSTM2 model was ultimately adopted as the spectrum prediction model. This study constructed a CNN-LSTM network for communication spectrum prediction and achieved high prediction accuracy. However, in the future, other deep learning methods can be attempted to construct prediction models to compare the prediction results under different deep learning models.

VII. LIMITATION AND FUTURE WORK

Although this study has made significant advances in the field of communication spectrum prediction and interference optimization, there are still some obvious shortcomings. First, the Q-learning algorithm and CNN-LSTM network model used in this study were optimized and tested under specific environments and conditions. However, the complex and changing environments in real-world applications may lead to a decrease in prediction accuracy and interference capability in new environments. For this problem, future research can try to test and optimize the model more extensively under diverse environments and conditions. Second, the experimental data in this study were mainly collected based on the USRP RIO radio platform, which limits the generalization capability of the model to some extent. Exploring ways to include data from a broader range of devices and platforms for training and testing could enhance the model's generalizability and robustness. This line of inquiry is crucial for future research. Furthermore, although the study concluded that the CNN1-LSTM2 model outperforms other models with respect to prediction accuracy, its high computational complexity and operational inefficiency may pose a challenge for practical applications. Especially, the inefficiency of the model may significantly impact its suitability for scenarios where it is necessary to make real-time predictions and interferences. Therefore, how to improve the operational efficiency of the model while maintaining high accuracy will be a problem that future research needs to focus on.

Future research directions can be approached from several perspectives. First, new deep learning models can be researched and developed or existing models can be improved to improve the accuracy of communication spectrum prediction and communication interference. The transformer model using attention, which has seen significant development in recent years, performs well in various intricate tasks and might also find use in predicting communication spectrum and optimizing interference. Second, future research can consider testing and optimizing the models on more communication environments and devices to improve the generalization capability of the models. As an illustration, one can gather data from distinct wireless communication devices, various frequency bands, and a variety of geographic locations to test and optimize the model thoroughly. Research efforts should optimize current deep learning algorithms or employ new computational techniques, for instance, parallel computing or distributed computing, to address the efficiency of operation, enhance computational efficiency, and real-time performance of such models.

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