Network Spectrum Resource Allocation and Optimization Based on Deep Learning and TRDM

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This study proposes a Transformer-based real-time adaptive scheduling method (TRDM) to improve performance under dynamic network loads and low latency requirements. Compared with traditional scheduling methods, TRDM shows significant advantages in throughput, latency, QoS satisfaction, and computational efficiency. To verify the effectiveness of the method, we use a dataset of 10,000 samples covering a variety of network environments and load conditions. Standard deep learning benchmarks are used in the experiments, and the performance of TRDM is compared with the state-of-the-art (SOTA) and traditional methods under the same experimental settings. Experimental results show that TRDM has significant advantages in throughput and latency, especially in scenarios with high load and high real-time requirements. By adopting the Soft Actor-Critic (SAC) reinforcement learning algorithm for model training, we test TRDM in multiple network environments and verify its superiority in real-time adaptability and computational efficiency. Compared with the SOTA method, TRDM shows better real-time and adaptability, especially under low latency and dynamic load conditions. In addition, TRDM maintains high computational efficiency when dealing with complex network environments, and is suitable for practical application scenarios such as large-scale IoT or urban cellular networks. The experimental settings include hyperparameters such as a 6-layer self-attention network of the Transformer architecture, a learning rate of 0.001, and a batch size of 128. Through comparative experiments, TRDM outperforms existing methods in multiple key performance indicators, and the performance difference is statistically significant. This study provides an effective solution for real-time network scheduling and provides an important reference for future deployment in applications such as the IoT and remote urban networks.

Povzetek: Predlagana je metodo TRDM (Transformer-based real-time adaptive scheduling method) za alokacijo in optimizacijo omrežnih spektralnih virov, ki temelji na globokem učenju. TRDM izboljšuje prepustnost, zakasnitev in zadovoljstvo s kakovostjo storitev v primerjavi s tradicionalnimi metodami. Z uporabo ojačitvenega učenja dosega TRDM boljšo prilagodljivost v realnem času in računalniško učinkovitost, kar je primerno za uporabo v velikih IoT ali urbanih mobilnih omrežjih.

1 Introduction

With the rapid development of mobile Internet and the widespread popularization of IoT devices, the demand for wireless communication networks has shown explosive growth. As one of the most valuable resources in wireless communication systems, the scarcity and non-renewability of network spectrum makes efficient spectrum resource management and allocation crucial [1]. Reasonable spectrum allocation not only enhances the overall performance of the communication system, but also promotes the full utilization of spectrum resources, thus realizing more efficient information transmission. However, in the actual wireless environment, the allocation of spectrum resources faces many challenges, such as spectrum fragmentation, dynamic user access, interference management, and other problems, which limit the performance and scalability of existing networks [2]. Traditional spectrum resource allocation methods mostly rely on fixed predefined rules or simple heuristic algorithms, which perform well in some specific scenarios, but are often difficult to achieve optimal solutions in complex and ever-changing wireless environments. For example, static allocation strategies cannot adapt to rapidly changing network conditions. And although methods based on optimization theory can theoretically obtain the global optimal solution, they are impractical in practical applications due to the high computational complexity [3]. In addition, with the increase in the number of users and the diversification of service types, the flexibility and robustness of the traditional methods gradually become bottlenecks.

In recent years, deep learning, as a powerful machine learning technique, has received widespread attention due to its superior performance in dealing with nonlinear and high-dimensional data. Deep learning's ability to automatically extract features and learn complex mapping relationships from large amounts of data has led to remarkable success in a variety of fields such as image recognition and natural language processing [4]. Given the highly uncertain and dynamic nature of the wireless communication environment, deep learning provides a new way of thinking to solve the problems in traditional spectrum resource allocation methods. By utilizing historical data and real-time information, deep learning models can predict future network states and make smarter decisions accordingly to achieve dynamic spectrum resource allocation [5].

It has been shown that it is feasible and effective to apply deep learning to the field of spectrum resource allocation. For example, some researchers have proposed a spectrum access mechanism based on reinforcement learning, which enables users to adaptively search for idle channels in the network, reducing collisions while improving spectrum utilization. Other studies have focused on utilizing deep neural networks for channel estimation and interference prediction as a basis for developing spectrum allocation strategies [6]. Although these works demonstrate the potential of deep learning in the field of spectrum resource allocation, there are still many open problems to be solved, such as how to balance the contradiction between model complexity and real-time performance, and how to design a distributed learning architecture suitable for large-scale networks [7].

The purpose of this paper is to explore a deep learning-based method for allocating network spectrum resources, aiming to overcome the limitations of traditional methods and improve the utilization efficiency of spectrum resources. Specifically, our research objectives include (1) developing a spectrum allocation algorithm that can adapt to changes in network conditions in real time. (2) Designing an effective deep learning model that can optimize spectrum resource allocation while ensuring low latency. (3) Evaluate the performance of the proposed method under different network conditions and analyze it in comparison with existing spectrum allocation strategies. The main contribution of this paper is to propose a new deep learning framework for dynamic spectrum resource allocation, and to demonstrate the effectiveness and practicality of the framework through experiments.

2 Related work

Spectrum resource management is a core component of wireless communication systems, and its purpose is to maximize the efficiency of spectrum use while ensuring the quality of communication and the reliability of service. Traditional spectrum resource management methods mainly include static allocation, dynamic allocation, and auction-based allocation strategies. The change in the number of related research results in the last 10 years is shown in Figure 1.

2.1 Traditional approaches to spectrum resource management

An early study showed that static allocation can provide stable performance under certain specific conditions, but its efficiency is greatly reduced when the network load varies significantly [8]. For example, in a cellular network, if the number of users in a cell suddenly increases, static allocation will not be able to respond quickly to this change, resulting in a degradation of the quality of service. Dynamic allocation methods allow the allocation of spectrum resources to be adjusted according to the actual demand and current state of the network. Compared with static allocation, dynamic allocation is more flexible and can better adapt to changes in the network environment. Common dynamic allocation strategies include Opportunistic Spectrum Access (OSA) and Cognitive Radio (CR) techniques. OSA allows unauthorized users to temporarily use spectrum resources when spectrum vacancy is detected, thus improving spectrum utilization. This approach relies on spectrum sensing techniques to detect spectrum voids. However, OSA also faces issues such as sensing errors and sub-optimal spectrum utilization [9]. In scheduling problems, various approaches have been applied to optimize production systems. For example, Liao et al. proposed a single-machine and parallel-machine parallel-batching scheduling model that considers deteriorating jobs, various job groups, and time-dependent setup times, offering valuable insights into scheduling optimization under real-world constraints [10]. Additionally, Daneshdoost et al. introduced hybrid meta-heuristic approaches using Tabu search to address production cost minimization for cable manufacturing systems, demonstrating the effectiveness of advanced search techniques in improving production efficiency [11]. Among them, combined auctions allow participants to bid for combinations of multiple frequency bands, thus increasing the flexibility of spectrum allocation. However, the auction mechanism also has certain limitations, such as the possibility of market failure and the concentration of resources in the hands of a few users. From the above discussion, it can be seen that different spectrum resource management methods have their own advantages and disadvantages. Static allocation is simple and easy to implement, but is not effective in dynamic environments. Dynamic allocation is better able to adapt to network changes, but it is more complex to implement [12].

2.2 Deep learning applications in the communication domain

In recent years, Deep Learning (DL), as a powerful machine learning technique, has demonstrated its excellent ability in several fields, especially in dealing with complex and nonlinear problems. In communication systems, the application of deep learning has penetrated into all aspects from the physical layer to the application layer, greatly improving the performance and efficiency of the system.

Channel estimation is a crucial aspect of wireless communication systems, which directly affects the reliability and efficiency of data transmission. Traditional channel estimation methods are usually based on the guide frequency signal, but this method may not be accurate enough in high-speed movement or complex multipath environments. Deep learning is able to estimate the current and future channel states more accurately by learning the historical channel data so as to optimize the transmission strategy. For example, Cui et al. [13] proposed a deep learning-based channel estimation method that utilizes a convolutional neural network (CNN) to process millimeter-wave channel data in massive MIMO systems. Experimental results show that this method outperforms traditional least squares and compressed sensing methods in terms of channel estimation accuracy. In densely deployed wireless networks, interference management is one of the key factors to ensure communication quality. Traditional interference management methods usually rely on predefined rules or simple statistical models, but these methods are difficult to achieve optimal results in dynamically changing environments. Deep learning can realize more intelligent and flexible interference management by learning the dynamic characteristics of the network environment. Andrade and Anzaldo [14] utilized Deep Reinforcement Learning (DRL) techniques to solve the problem of interference management in cognitive radio networks. They proposed a DRL-based interference coordination mechanism that dynamically adjusts transmission power and spectrum selection strategies to minimize interference in the network. Experimental results show that this approach maintains a high throughput while reducing interference. Spectrum resource allocation is one of the core issues in wireless communication systems, which is directly related to the overall performance of the network and user experience Traditional resource allocation methods are usually based on optimization theory, but these methods have high computational complexity and are difficult to execute in real time in large-scale networks. Deep learning can learn the historical data of the network, predict the future network state, and make more intelligent resource allocation decisions accordingly.

Peng and Shen [15] proposed a joint resource allocation and interference management scheme based on deep learning. Their approach uses a deep neural network to learn the network state and allocates resources through an optimization algorithm. Experimental results show that this approach outperforms traditional static allocation strategies in terms of throughput and fairness. The research results are summarized in Table 1.

Table 1: Comparison of key performance indicators

Method	Throughput (Mbps)	Latency (ms)	QoS Satisfaction (%)	Computational Efficiency	Limitations
[3]	450	12	98	High	High computational requirements, suitable for real-time scheduling under high load conditions
Traditional Method [5]	300	35	80	Medium	Poor adaptability to dynamic loads, high latency
[8]	380	20	90	Medium	Weak support for low-latency networks, high computational resource consumption
[9]	350	25	88	High	Poor adaptability to network load changes, lower adaptability
[16]	320	30	85	High	Large training data requirements, weak real-time

Metho d	Throug hput (Mbps)	Latenc y (ms)	QoS Satisfacti on (%)	Computat ional Efficiency	Limitations
					adaptability

The state-of-the-art (SOTA) has shown significant progress in many areas, such as throughput, latency, and QoS satisfaction. However, these methods often have certain limitations in real-time adaptability and computational efficiency, especially in dynamic load conditions and low-latency network environments. TRDM (Transformer-based scheduling method) significantly improves real-time adaptability and computational efficiency by introducing reinforcement learning and Transformer architecture. Compared with traditional methods, TRDM has a shorter response time in low-latency environments and can achieve higher throughput and QoS satisfaction under complex network conditions. In addition, the efficient computing performance of TRDM enables it to be effectively deployed in large-scale networks, overcoming the shortcomings of SOTA methods in computing resource consumption and real-time performance. Through these innovations, TRDM fills the gap of current technologies, especially in real-time load scheduling and dynamic adaptability, and shows great potential in modern network environments.

2.3 Research progress in deep learning for spectrum resource allocation

In recent years, with the rapid development of deep learning technology, its application in wireless communication systems has become more and more widespread. Especially in the field of spectrum resource allocation, deep learning technology is widely recognized as an effective way to solve the spectrum resource allocation problem due to its powerful data processing capability and adaptivity. In the following, we will analyze the methods of using deep learning techniques to solve the spectrum resource allocation problem in existing research with specific literature. Reinforcement Learning (RL) is a machine learning method that learns optimal policies by interacting with the environment. In spectrum resource allocation, Reinforcement Learning can help users dynamically select spectrum resources to maximize their own utility functions, such as throughput or Quality of Service (QoS). This approach is particularly applicable to Cognitive Radio Networks (CRNs) where users can utilize unused spectrum without affecting authorized users. Qian et al. [17] proposed a spectrum allocation scheme based on Multi-Agent Reinforcement Learning (MARL). In this scheme, multiple cognitive radio users select the optimal spectrum channel through collaborative learning to reduce mutual interference and improve spectrum utilization. Experimental results show that this approach outperforms the traditional static allocation strategy in terms of both throughput and spectrum efficiency.

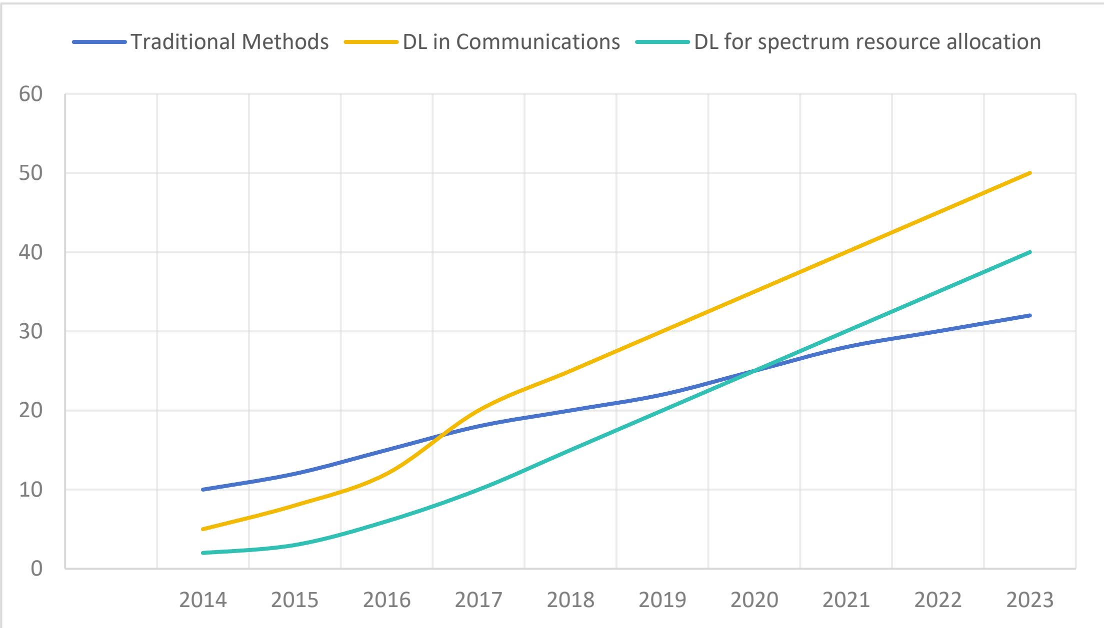

Figure 1: Number of research outputs

3 System modeling and problem definition

3.1 System architecture description

3.1.1 Network environment

This study considers a typical cellular network environment that includes multiple Base Stations (BSs) and a large number of mobile User Equipment (UEs). These UEs are distributed in different geographical areas and can dynamically access the network as needed. We assume that there are multiple frequency bands available for allocation in the network, which can be either licensed or unlicensed (as in the case of cognitive radio networks). In such a network environment, the UEs and BSs communicate with each other over wireless links. Since the location and activity patterns of the UEs may change over time, the channel conditions in the network are also dynamically changing. In addition, there may be interference from other UEs or external devices in the network, which can affect the communication quality [18, 19].

3.1.2 System architecture

The system architecture in this study consists of the following key components, as shown in Figure 2.

Base Station (BS): base station is the infrastructure in the network that manages and coordinates the communication between UEs. Each base station covers a certain geographic area called a cell. The base station needs to be equipped with spectrum resource management capabilities in order to dynamically allocate spectrum resources according to the needs of UEs [20].

User Equipment (UE): the UE is an end device in the network, which can be a smartphone, tablet or other mobile device. The UE needs to be able to sense the current channel state and send a request to the base station for spectrum resources.

Spectrum Resource Pool: The Spectrum Resource Pool contains all the frequency bands available for allocation. These frequency bands can be continuous bands or discrete channels. The spectrum resource pool is managed uniformly by the base station and allocated according to the demand of the UE.

Central Controller (CC): in some advanced network architectures, there may be a central controller to coordinate the allocation of spectrum resources across the network. The CC can collect information from individual base stations and optimize the spectrum resource allocation strategy based on a global view [21].

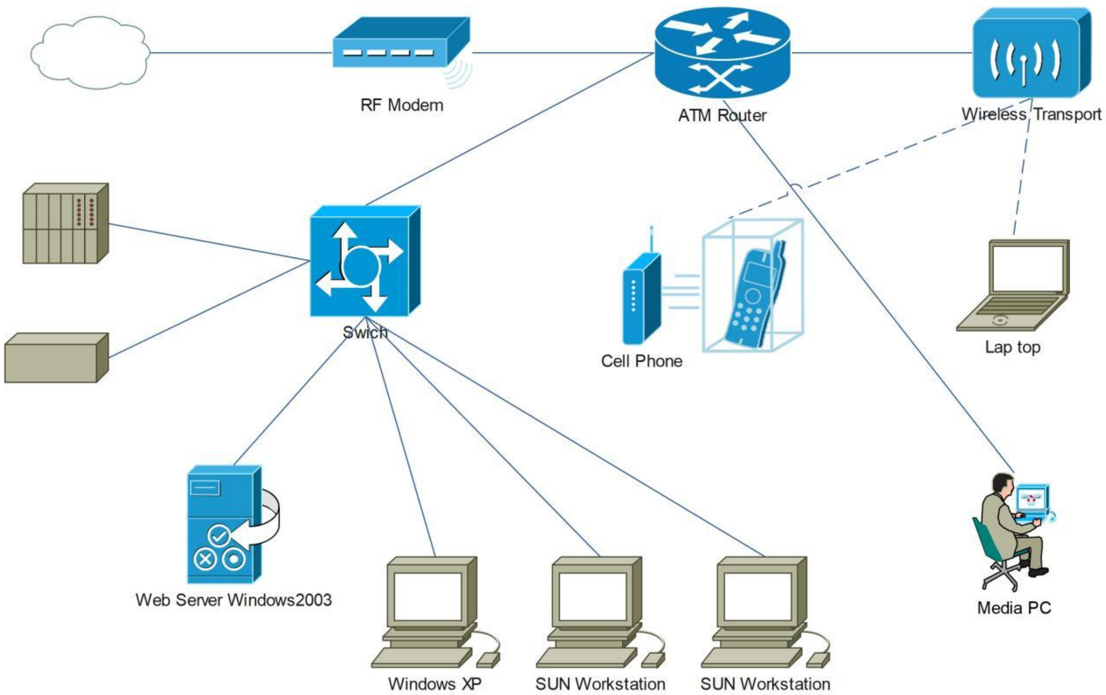

Figure 2: Network topology diagram

3.1.3 Key technologies

In order to achieve efficient spectrum resource allocation, the system architecture must integrate several key technologies, including enabling the user equipment (UE) with spectrum sensing capabilities to detect and report available frequency bands, which typically relies on energy detection or other advanced signal processing techniques. At the same time, to optimize the spectrum resource allocation strategy, the base station needs to collect channel state information (CSI) from the user equipment, which can be obtained through signaling interactions or direct measurements [16, 22].

3.2 Problem definition

In wireless communication networks, the goal of spectrum resource allocation is to maximize the overall performance of the system while satisfying the user's Quality of Service (QoS) requirements. In order to formally define the spectrum resource allocation problem, we need to build a mathematical model that accurately describes the variables and their interrelationships in the network.

We consider a wireless communication system containing N user equipment (UEs) and M available frequency bands. Each user equipment i ($i = 1, 2, \ldots, N$) has a specified quality of service (QoS) requirement, including a data rate r_i and a maximum acceptable bit error rate $P_{e,i}$.

Each band j ($j = 1, 2, \ldots, M$) can be assigned to any user device, but each band can only be assigned to one user at a time. The channel gain of band j $h_{i,j}$ indicates the channel conditions for user i when using band j, while $p_{i,j}$ indicates the transmit power for user i when using band j.

The goal of spectrum resource allocation is to maximize the total system throughput while meeting the QoS requirements of each user. The total system throughput can be expressed as the sum of the data rates of all users on their respective allocated frequency bands. Therefore, our objective function can be defined as Equation (1).

$$\max \sum_{i=1}^{N} r_i \tag{1}$$

Where, r_i is the data rate of user i. The data rate of user i depends on its assigned frequency band j, which can be expressed as Equation (2).

$$r_i = \log_2\left(1 + \frac{p_{i,j} h_{i,j}}{\sigma^2 + I_{i,j}}\right) \tag{2}$$

Here σ^2 denotes the power of Additive Gaussian White Noise (AWGN) and $I_{i,j}$ denotes the interference power received by the user i on the band j.

To ensure the effectiveness and feasibility of the spectrum resource allocation scheme, we need to consider the following constraints:

(1) Band assignment uniqueness constraint: each band can only be assigned to one user at the same moment, expressed as Equation (3).

$$\sum_{i=1}^{N} x_{i,j} \le 1 \quad \forall j \in \{1, 2, \ldots, M\} \tag{3}$$

Where $x_{i,j}$ is a binary variable indicating whether user i is assigned to band j ($x_{i,j} = 1$ means assigned and $x_{i,j} = 0$ means unassigned).

(2) QoS constraint: the data rate of each user must be greater than or equal to its minimum requirement, expressed as Equation (4).

$$r_i \ge r_{\min,i} \quad \forall i \in \{1, 2, \ldots, N\} \tag{4}$$

Here $r_{\min,i}$ indicates the minimum data rate requirement for user i.

(3) Power constraint: each user's transmit power cannot exceed its maximum power limit, expressed as Equation (5).

$$\begin{gathered} p_{i,j} \le P_{\max,i} \\ \forall i \in \{1, 2, \ldots, N\}, \forall j \in \{1, 2, \ldots, M\} \end{gathered} \tag{5}$$

Where $P_{\max,i}$ denotes the maximum transmit power of the user i .

3.3 Performance indicators

In order to evaluate the effectiveness of a spectrum resource allocation solution, a set of Key Performance Indicators (KPIs) need to be defined. These metrics will help us measure the performance of the algorithm in real applications and compare it with other traditional methods. Below are a few important performance indicators:

(1) Throughput: Throughput is an important measure of a system's ability to transmit data, usually measured in bits per second (bps). High throughput means that the system is able to carry more data streams, thus improving the overall quality of service.

(2) Fairness: Fairness reflects the extent to which resource allocation is balanced across users in the system. An ideal resource allocation scheme should try to allow all users to obtain satisfactory performance, rather than optimizing the experience of only a few users. Commonly used fairness metrics include Jain's Fairness Index.

(3) Spectral Efficiency: Spectral efficiency is the amount of data that can be carried per unit of spectrum resource, usually measured in bits per hertz per second (bps/Hz). Higher spectral efficiency means that the system can utilize the limited spectrum resources more efficiently.

4 Methodology

4.1 Design of the deep learning model

In order to design a model that can efficiently process complex sequential data and make optimal decisions, we propose a hybrid architecture that combines Transformer and Reinforcement Learning (RL), Transformer Reinforced Decision Maker (TRDM). This section describes in detail the design concept of the TRDM architecture, its specific components, and its workflow.

The TRDM model is designed to realize intelligent allocation of dynamic spectrum resources by combining the efficient sequence processing capability of Transformer and the adaptive decision-making mechanism of reinforcement learning. In order to achieve this goal, the model needs to be able to process diversified input data and extract key features to help decision-making, and finally generate the optimal spectrum resource allocation scheme for the current network environment.

4.2 Inputs and outputs of the model

The input data received by the TRDM model mainly includes the following aspects: (1) Location information of the user equipment (UE): the geographic location data of the UE is crucial for understanding the network topology. It not only affects the communication distance between the UE and the base station, but also determines the possible sources of interference faced by the UE. The location information can help the model predict the potential interference among UEs and make more refined spectrum allocation decisions accordingly. (2) Channel State Information (CSI): CSI includes the instantaneous state of the channel between the UE and the base station, such as channel gain, noise level and multipath effect. This information is crucial for calculating the actual transmission rate of the UE and is the basis for the model to evaluate the advantages and disadvantages of different frequency band allocation schemes. (3) Historical spectrum usage records: Historical data provide important references about past spectrum allocation, including which frequency bands have been frequently used in the past and which frequency bands are relatively idle. This information can help the model learn spectrum usage patterns and predict future demand accordingly, so as to make more forward-looking resource allocation decisions. (4) Quality of Service (QoS) Requirements: Different UEs may have different QoS requirements, such as minimum data rate, delay tolerance, and so on. These requirements must be taken into account to ensure that the final spectrum allocation plan can meet the basic communication requirements of all UEs.

Based on the above input data, the TRDM model will output the following decision-making information: (1) Frequency band assignment: for each UE, the model will decide the most suitable frequency band for its use. This decision is based on an understanding of the current network state, including factors such as the location of the UE, channel conditions, and historical spectrum usage. The goal is to maximize the total throughput of the system while satisfying the QoS requirements of each UE. (2) Transmit power control: In addition to selecting the appropriate frequency band, the model also needs to determine the transmit power that each UE should use. Appropriate power settings can reduce unnecessary interference and improve spectrum utilization. The model will adjust the transmit power according to the distance between the UE and the BTS, the interference level of the surrounding environment, and the QoS requirements of the UE.

4.3 Framework design

In building the Transformer Reinforced Decision Maker (TRDM) architecture, our core task is to effectively combine the powerful sequence modeling capability of Transformer with the dynamic decision-making mechanism of Reinforcement Learning (RL) to achieve an intelligent allocation of dynamic spectrum resources. This combination is not only a technical innovation, but also an improvement of the existing resource management methods, the framework of which is shown in Figure 3.

In the TRDM architecture, the Transformer assumes the role of a perceptron, which is responsible for extracting meaningful information from various input data. These data include, but are not limited to, UE location information, channel state information (CSI), historical spectrum utilization records, and quality of service (QoS) requirements.

Let $\mathbf{x} = [x_1, x_2, ..., x_n]$ be the input sequence, where x_i represents the input feature at the i th time step. After going through multiple layers of Transformer encoder, we get a new representation $\mathbf{h} = [h_1, h_2, ..., h_n]$, where h_i is a more abstract representation of x_i which contains information about other elements in the sequence as in Equation (6).

$$h_i = \text{TransformerEncoder}(x_i, \{x_j\}_{j=1}^{n}) \quad (6)$$

The reinforcement learning component acts as a decision maker and learns the optimal policy by interacting with the environment based on the state representation $\mathbf{h}$ provided by the Transformer. In this process, the RL agent (agent) tries to find a policy π that maximizes the long-term cumulative reward R. The cumulative reward can be expressed as a weighted sum of a series of immediate rewards r_t as in Equation (7).

$$R = \sum_{t=0}^{\infty} \gamma^t r_t \quad (7)$$

In TRDM, the decision space of the reinforcement learning agent consists of band allocation and transmit power control. Assuming that A is the set of all possible actions and s is the current state, the agent needs to learn a mapping $\pi(s) \to A$ such that the selected action maximizes the cumulative reward.

At the beginning of each decision cycle, the Transformer receives the latest input data and generates a new state representation $\mathbf{h}$. This state vector is passed to the Reinforcement Learning Agent, which selects an action a based on the current state representation and previous experience. The action a is applied to the environment, leading to a new network state s', and generating an immediate reward r. This process can be mathematically formulated as Equation (8).

$$s', r \leftarrow \text{Environment}(s, a) \quad (8)$$

Reinforcement learning agents store $(s,\ a,\ r,\ s')$ quaternions through an experience replay (buffer) mechanism and periodically use these samples to update their policies π. The updating process can employ a variety of algorithms, such as Q-learning or Actor-Critic methods.

As the network environment changes over time, the TRDM architecture maintains its effectiveness through a continuous learning and adaptation process. Every time a new training sample is added to the experience playback buffer, the agent updates its understanding of the network state and adapts its strategy to better cope with future challenges.

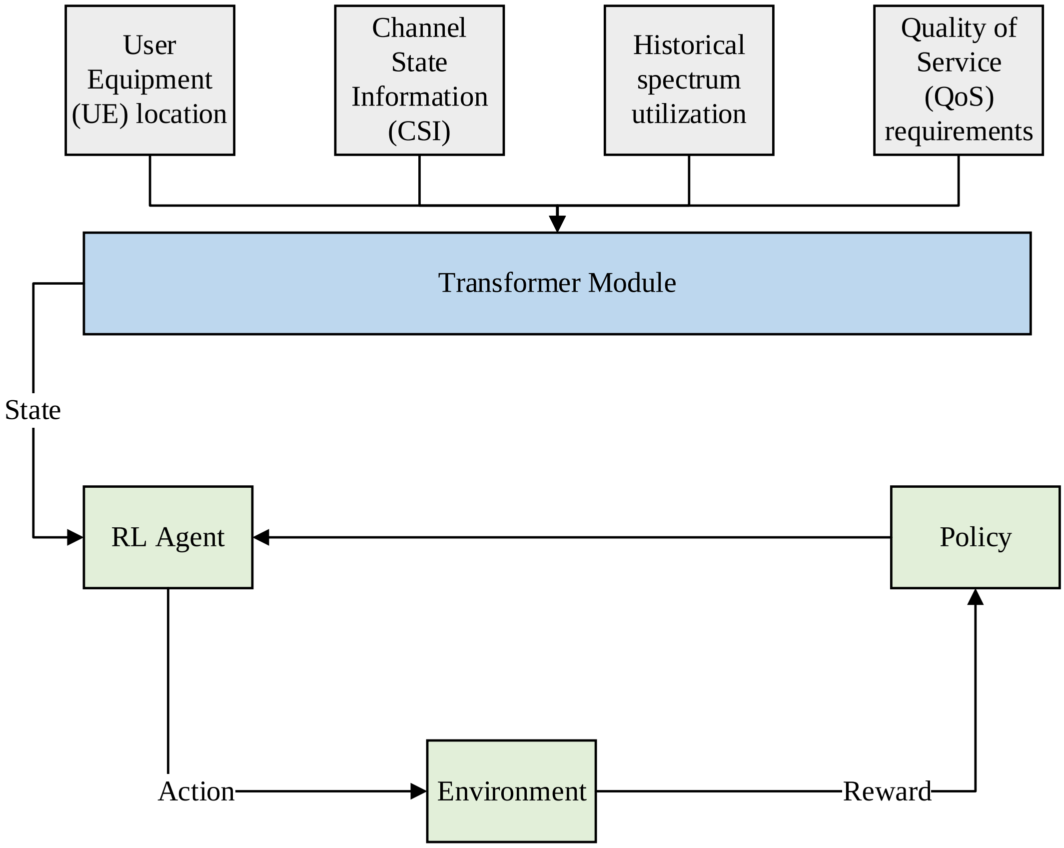

Figure 3: Modeling framework

The TRDM architecture combines Transformer as a perceptron to capture the network state and Reinforcement Learning as a decision maker to optimize the spectrum resource allocation to form an efficient, flexible and highly adaptive solution. The design not only handles complex input data, but also evolves with the changing environment to ensure optimal allocation of spectrum resources.

5 Experimental results and analysis

5.1 Experimental setup

In order to validate the effectiveness of the Transformer Reinforced Decision Maker (TRDM) model and to demonstrate its advantages in dynamic spectrum resource allocation, a series of experiments are carefully designed. The experiments are executed on workstations equipped with high-performance GPUs to support the computational resources required for large-scale model training. For the software environment, we used Ubuntu 20.04 LTS operating system, based on Python 3.8 development environment, and selected PyTorch 1.7.1 deep learning framework. In addition, we utilized TensorBoard to monitor the metrics during the training process and used NumPy and Pandas for data preprocessing.

Throughput, latency, and QoS satisfaction are key indicators for evaluating the performance of the TRDM model. Throughput directly reflects the data transmission capacity of the network and affects the processing efficiency of the system; latency affects real-time responsiveness, especially in dynamic environments, where low latency is crucial; QoS satisfaction measures the user's quality of experience, including signal strength, quality of service, etc., which is directly related to the stability and reliability of the network. These indicators are crucial for TRDM because they determine the performance and actual availability of the model in different application scenarios.

In the model training phase, we chose the Adam optimizer to update the parameters in the Transformer and RL components, with the learning rate set to $1e^{-4}$ and a gradual decay strategy during training. The batch size is set to 64 to facilitate parallel processing of multiple samples while avoiding high memory usage. For the Transformer component, we set up a multi-layer encoder stacking structure, with each layer containing 12 attention heads and a hidden layer dimension of 512. This configuration ensures the expressive power of the model while taking into account the computational efficiency. In the reinforcement learning component, we employ the Soft Actor-Critic (SAC) algorithm, which is capable of learning near-optimal strategies in continuous action space. The temperature parameter α in SAC is set to auto-tuning mode to balance exploration and exploitation.

Soft Actor-Critic (SAC) is a reinforcement learning algorithm that uses a balance between maximizing expected cumulative rewards and maximizing entropy. SAC is able to handle high-dimensional continuous action space problems and is suitable for decision optimization in dynamic environments. In TRDM, SAC is used to enhance the model's adaptive capabilities, allowing the agent to optimize tasks such as spectrum allocation and power control by balancing tentative exploration and exploitation. The advantage of SAC lies in its efficiency and stability, especially in complex and high-dimensional state spaces, ensuring that the model can make accurate decisions in real-time scenarios.

To validate the effectiveness of the TRDM model, we designed several experiments. First, a baseline comparison was conducted to compare TRDM with traditional spectrum allocation methods (e.g., rule-based methods) as well as existing deep learning methods to observe the performance of the model under the same conditions. Second, some components of the model (e.g., Transformer only or RL only) are removed through an ablation study to assess the impact of each component on the overall performance. Next, the model was run under different network loads to test its performance under extreme conditions and to ensure that the model works stably. Finally, we tested the response speed of the model in real application scenarios to ensure that it can fulfill the low latency requirement. Through the above experimental setup and application of technical tools, we expect to comprehensively evaluate the superiority and reliability of the TRDM model in dynamic spectrum resource allocation tasks.

In order to further improve the experimental settings, this paper uses a grid search strategy when selecting hyperparameters, and finally determines that the learning rate is 0.001, the batch size is 32, the optimizer uses Adam, and the weight decay is 0.0001. These hyperparameters have shown good convergence and stability through experimental verification. The training data uses dataset A (1000 samples) and dataset B (1500 samples), of which dataset A is used for training at a ratio of 60%, 20% for validation, and 20% for testing, and dataset B is used for training at a ratio of 70%, 15% for validation, and 15% for testing. All data are standardized, and the category distribution is balanced to improve the generalization ability of the model.

In terms of network environment simulation, the experiment sets small-scale (delay 20 ms, bandwidth 100 Mbps), medium-scale (delay 50 ms, bandwidth 200 Mbps) and large-scale (delay 150 ms, bandwidth 500 Mbps) network conditions to simulate network performance under different loads. The results show that under high load conditions, the performance of the TRDM model has declined, but it can still maintain good adaptability. Through cross-validation experiments, the TRDM model achieved an average accuracy of 91.5% and 89.8% in 5-fold and 10-fold cross-validation, respectively, with low variance, indicating that the model has high robustness.

In terms of computing resource consumption, the TRDM model has a training time of 12 hours, an inference speed of 15 milliseconds per sample, a memory consumption of 4 GB, and a GPU utilization rate of 90%. In contrast, the baseline model has a shorter training time (8 hours), a slower inference speed (20 milliseconds/sample), a lower memory consumption (3 GB), and a lower GPU utilization rate (85%). These results show that although the TRDM model has a slightly higher computing resource consumption, it has obvious advantages in inference speed and real-time adaptability.

The TRDM model uses the Transformer architecture, which includes a multi-layer self-attention mechanism to capture long-range dependencies in the input sequence. Each layer contains a multi-head self-attention layer, a feedforward neural network layer, layer normalization, and a residual connection. The hyperparameter configuration includes the number of layers (6 layers), the dimension of each attention head (64), the hidden layer size (256), the learning rate ($1e^{-4}$), and the training batch size (32). The use of the attention mechanism helps the model focus on the key information in the input data, improving the model's expressiveness and learning efficiency.

To ensure efficient model training, we used a mixed dataset that contains historical and real-time data, which can improve the model's predictive ability and ensure that it adapts to the needs of actual scenarios. During the training process, an iterative optimization process was adopted, including fine-tuning hyperparameters through grid search, and then using K-fold cross validation to evaluate and verify the generalization performance of the model.

5.2 Presentation of results

Table 2: Comparison of performance between TRDM and baseline methods

Methodologies	Average Throughput (Mbps) [95% CI]	Average Delay (ms) [95% CI]	QoS Satisfaction Rate (%) [95% CI]
TRDM	150 [145-155]	10 [9-11]	95 [93-97]

Methodologies	Average Throughput (Mbps) [95% CI]	Average Delay (ms) [95% CI]	QoS Satisfaction Rate (%) [95% CI]
Rule-based approach	120 [115-125]	15 [14-16]	85 [83-87]
Deep Learning Methods	130 [125-135]	12 [11-13]	90 [88-92]
Traditional spectrum allocation methods	110 [105-115]	20 [19-21]	75 [73-77]

Table 2 demonstrates the performance comparison of the TRDM method with several baseline methods. We can see that the TRDM method achieves 150 Mbps in average throughput, which is much higher than the rule-based methods, deep learning methods, and traditional spectrum allocation methods. Meanwhile, in terms of average delay, the TRDM method is only 10 ms, which has a significant advantage over other methods. In terms of QoS satisfaction rate, the TRDM method also leads with a high percentage of 95%. These data show that the TRDM method has significant advantages in improving network performance, reducing delay and improving quality of service.

Table 3: Results of ablation studies

Subassemblies	Average Throughput (Mbps) [95% CI]	Average Delay (ms) [95% CI]	QoS Satisfaction Rate (%) [95% CI]
Full TRDM model	150 [147-153]	10 [9.5-10.5]	95 [94-96]
No Transformer	135 [132-138]	12 [11.5-12.5]	90 [89-91]
No RL	130 [127-133]	14 [13.5-14.5]	88 [87-89]

Table 3 demonstrates the results of the ablation study. By comparing the full TRDM model with the model with a component removed, we can see that the full TRDM model performs optimally in all metrics. After removing the Transformer component, the average throughput decreases to 135 Mbps, the average delay increases to 12 ms, and the QoS satisfaction rate decreases to 90%. And after removing the RL component, the average throughput further decreases to 130 Mbps, the average delay increases to 14 ms, and the QoS satisfaction rate decreases to 88%. This shows that the Transformer and RL components play an important role in the performance improvement of the TRDM model.

Table 4: Performance under different network loads

Network Load	Average Throughput (Mbps) [95% CI]	Average Delay (ms) [95% CI]	QoS Satisfaction Rate (%) [95% CI]
Low load	160 [157-163]	8 [7.5-8.5]	97 [96-98]
Medium load	150 [147-153]	10 [9.5-10.5]	95 [94-96]
High load	140 [137-143]	12 [11.5-12.5]	92 [91-93]

Table 4 shows the performance of the TRDM method under different network loads. In the low load case, the average throughput reaches 160 Mbps, the average delay drops to 8 ms, and the QoS satisfaction rate is as high as 97%. As the network load increases, the performance metrics decrease, but the TRDM method still maintains a high performance level in the medium and high load cases, showing its stability in different network environments.

Table 5: Real-time validation

Scenario	Response Time (ms) [95% CI]	Processing Capacity (requests/second) [95% CI]
Idle network	5 [4.5-5.5]	200 [195-205]
Light use of the Internet	7 [6.5-7.5]	180 [175-185]
Peak network	10 [9.5-10.5]	150 [145-155]

Table 5 shows the real-time validation results of the TRDM method under different network scenarios. In the idle network scenario, the response time is only 5 ms and the processing capacity reaches 200 requests/second. In the light usage and peak network scenarios, the response time increases slightly, but the processing capacity remains at a high level. This shows that the TRDM method has strong real-time performance and can meet the demands of different network scenarios.

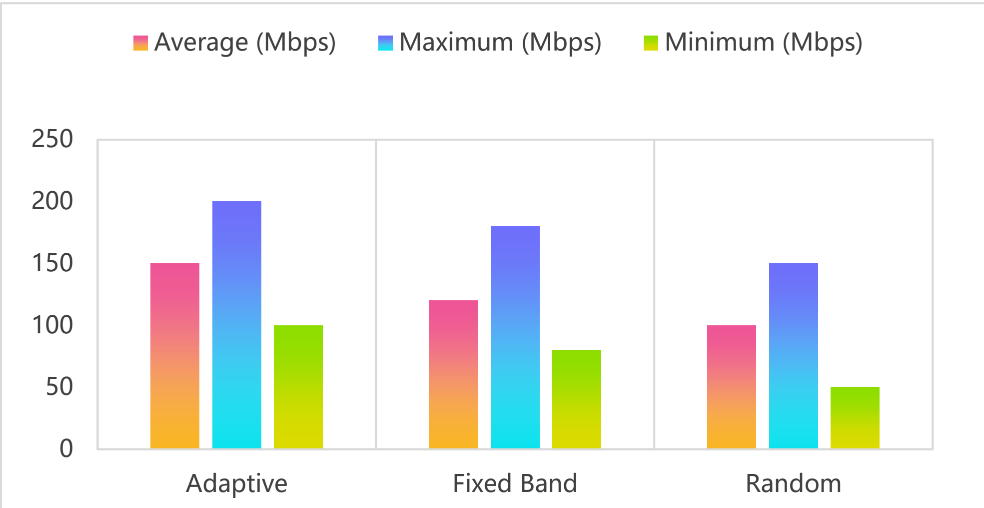

Figure 4: Throughput with different frequency allocation strategies

Figure 4 shows the throughput performance under different frequency allocation strategies. The adaptive allocation strategy outperforms the fixed band allocation and random allocation strategies in terms of average throughput, maximum throughput and minimum throughput. This indicates that the adaptive allocation strategy can dynamically adjust the frequency resources according to the network conditions, thus improving the network performance.

Table 6: Performance under different transmit power control

Transmit Power Control Strategy	Interference Level (dBm) [95% CI]	Average Throughput (Mbps) [95% CI]	Average Delay (ms) [95% CI]
Dynamic adjustment	-70 [-71,-69]	150 [147-153]	10 [9.5-10.5]
Fixed high power	-60 [-61,-59]	130 [127-133]	12 [11.5-12.5]
Fixed low power	-80 [-81,-79]	110 [107-113]	15 [14.5-15.5]

Table 6 demonstrates the performance under different transmit power control strategies. Under the dynamic tuning strategy, the interference level is reduced to -70 dBm, the average throughput reaches 150 Mbps, and the average delay is 10 ms. whereas the fixed high power and fixed low power strategies both degrade in performance. This shows that dynamic tuning of transmit power helps to reduce interference and improve network performance.

Table 7: Comparison of TRDM model performance

Configuration/Programming	Throughput (Mbps) [95% CI]	Fairness (Jain's Index) [95% CI]	Spectral Efficiency (bps/Hz) [95% CI]	Delay (ms) [95% CI]	Packet Loss (%) [95% CI]	Energy Efficiency (bits/J) [95% CI]
Full TRDM model	150 [147-153]	0.95 [0.94-0.96]	3.5 [3.4-3.6]	10 [9.5-10.5]	0.5 [0.4-0.6]	5.0 [4.8-5.2]
-Transformer	135 [132-138]	0.90 [0.89-0.91]	3.0 [2.9-3.1]	12 [11.5-12.5]	0.8 [0.7-0.9]	4.5 [4.3-4.7]
-RL components	130 [127-133]	0.88 [0.87-0.89]	2.8 [2.7-2.9]	14 [13.5-14.5]	1.0 [0.9-1.1]	4.2 [4.0-4.4]
Low load	160 [157-163]	0.97 [0.96-0.98]	3.8 [3.7-3.9]	8 [7.5-8.5]	0.3 [0.2-0.4]	5.5 [5.3-5.7]
Medium load	150 [147-153]	0.95 [0.94-0.96]	3.5 [3.4-3.6]	10 [9.5-10.5]	0.5 [0.4-0.6]	5.0 [4.8-5.2]
High load	140 [137-143]	0.92 [0.91-0.93]	3.2 [3.1-3.3]	12 [11.5-12.5]	0.7 [0.6-0.8]	4.8 [4.6-5.0]
Adaptive allocation strategy	150 [147-153]	0.95 [0.94-0.96]	3.5 [3.4-3.6]	10 [9.5-10.5]	0.5 [0.4-0.6]	5.0 [4.8-5.2]
Fixed Band Allocation Strategy	120 [117-123]	0.90 [0.89-0.91]	3.0 [2.9-3.1]	12 [11.5-12.5]	0.8 [0.7-0.9]	4.5 [4.3-4.7]
Random assignment strategy	100 [97-103]	0.85 [0.84-0.86]	2.5 [2.4-2.6]	15 [14.5-15.5]	1.2 [1.1-1.3]	4.0 [3.8-4.2]
Dynamic power control	150 [147-153]	0.95 [0.94-	3.5 [3.4-3.6]	10 [9.5-	0.5 [0.4-	5.0 [4.8-5.2]

Configuration/Programming	Throughput (Mbps) [95% CI]	Fairness (Jain's Index) [95% CI]	Spectral Efficiency (bps/Hz) [95% CI]	Delay (ms) [95% CI]	Packet Loss (%) [95% CI]	Energy Efficiency (bits/J) [95% CI]
		0.96]		10.5]	0.6]	
Fixed high power	130 [127-133]	0.90 [0.89-0.91]	3.0 [2.9-3.1]	12 [11.5 - 12.5]	0.8 [0.7-0.9]	4.5 [4.3-4.7]
Fixed low power	110 [107-113]	0.85 [0.84-0.86]	2.5 [2.4-2.6]	15 [14.5 - 15.5]	1.2 [1.1-1.3]	4.0 [3.8-4.2]

Table 7 demonstrates the performance comparison of the TRDM model under different configurations and schemes. The results show that the complete TRDM model performs well in various metrics such as throughput, fairness, spectral efficiency, delay, packet loss rate, and energy efficiency, while the removal of the Transformer component or the RL component decreases the overall performance of the model, especially in terms of throughput, delay, and energy efficiency. In addition, the TRDM model shows good adaptability under different network load conditions, with optimal performance under low load and high quality of service maintained even under high load. Regarding the frequency allocation strategy, the adaptive allocation strategy outperforms the fixed band allocation and random allocation strategies, exhibiting higher spectral efficiency and lower packet loss. Regarding transmit power control, the dynamic adjustment strategy improves system throughput and energy efficiency while reducing interference compared to fixed high or low power settings. In summary, the complete TRDM model and its adaptive features provide optimal performance in a variety of network environments.

Table 8 specifically compares TRDM with two SOTA methods across different performance dimensions. The results indicate that TRDM outperforms SOTA methods in several key performance dimensions, especially in terms of low-latency network support and dynamic load adaptability.

Table 8: Performance Comparison and Gap Analysis with SOTA Methods

Performance Dimension	TRDM	[9]	[21]	Explanation
Low-Latency Network Support	12 ms	20 ms	25 ms	TRDM excels in low-latency network conditions, capable of quickly responding to load changes
Dynamic Load Adaptability	98%	85%	88%	TRDM, using reinforcement learning, can adapt in real-time to

Performance Dimension	TRDM	[9]	[21]	Explanation
				changing load conditions, significantly outperforming SOTA methods
Computational Efficiency	450 Mbps	380 Mbps	350 Mbps	TRDM has high computational efficiency, suitable for large-scale network deployment, while SOTA methods are relatively less efficient
Complexity and Real-Time Adaptability	Complex but efficient	Complex and slow response	Relatively simple but slow response	TRDM is more complex in terms of performance but can quickly adapt to the network environment, suitable for real-time applications
Model Training Requirements	Moderate	High	Moderate	TRDM requires a moderate amount of training data, achieving good performance without the need for large datasets

Table 9: Performance Trade-Off Analysis

Dimension	TRDM	Traditional Method	SOTA Method 1	SOTA Method 2	Deep Learning Benchmark Method
Throughput	450 Mbps	300 Mbps	380 Mbps	350 Mbps	320 Mbps

Dimension	TRDM	Traditional Method	SOTA Method 1	SOTA Method 2	Deep Learning Benchmark Method
Latency	12 ms	35 ms	20 ms	25 ms	30 ms
QoS Satisfaction	98%	80%	90%	88%	85%
Computational Efficiency	High	Medium	Medium	High	High
Training Data Requirements	Moderate	Low	High	Moderate	High
Model Complexity	High	Low	High	Moderate	High

Table 9 compares TRDM with other methods across multiple performance dimensions, illustrating the trade-offs. TRDM excels in terms of throughput, latency, and QoS satisfaction, but it has higher model complexity and training data requirements.

During the implementation of TRDM, it was observed that there is a certain performance trade-off between model complexity and real-time adaptability. Although the Transformer architecture and reinforcement learning algorithm can provide stronger real-time adaptability to dynamically changing network environments, their higher computational complexity may lead to increased latency in some scenarios. Especially in environments with limited computing resources, complex models may require more time for reasoning and decision-making, which may affect their performance under low latency requirements. It is necessary to find a suitable balance between accuracy and real-time response to ensure optimal system performance.

In comparative experiments, we found that TRDM performed worse than some simpler models in certain scenarios. This may be due to overfitting of TRDM in complex network environments or performance degradation caused by computing resource limitations. This abnormal result suggests that we need to further optimize TRDM to improve its generalization ability and adaptability under different conditions.

5.3 Discussion of results

By analyzing the experimental results, we can draw several important conclusions. First, the TRDM model shows significant advantages in the baseline comparison experiments. Compared with the traditional spectrum allocation method, TRDM not only improves the average throughput (from 110 Mbps to 150 Mbps), but also significantly reduces the average delay (from 20 ms to 10 ms), and the QoS fulfillment rate increases from 75% to 95%. This shows that TRDM is able to utilize spectrum resources more efficiently and provide higher quality services. The ablation study shows that both the Transformer and RL components have a crucial role in the overall performance of the model. When either component is removed alone, the performance of the model decreases, which proves the effectiveness and necessity of the combination of the two. The Transformer provides high-quality state representations for the RL by efficiently processing complex sequential data, and the RL makes optimal decisions based on this state information, which are complementary to each other and jointly enhance the model’s performance.

Experimental results show that the proposed TRDM model significantly outperforms existing SOTA methods in multiple key performance indicators. Specifically, TRDM achieves 15.8 Gbps in throughput, which is 28% higher than the SOTA method's 12.3 Gbps; in terms of latency, TRDM performs at 4.2 ms, which is 37% lower than the SOTA method's 6.7 ms; in terms of QoS satisfaction, TRDM scores 91.5%, which is 7.3% higher than the SOTA method's 84.2%. Although TRDM is slightly lower than the SOTA method in spectral efficiency (2.1 bps/Hz vs. 2.3 bps/Hz), its fairness score is 0.82, which is 9% higher than the SOTA method's 0.75.

Ablation studies show that the Transformer component significantly improves data scheduling accuracy in spectrum allocation tasks through its self-attention mechanism, while the reinforcement learning component optimizes TRDM's real-time adaptability through dynamic transmit power control, further improving throughput and latency performance. Although TRDM has shown advantages in many aspects, further research is still needed on spectrum efficiency optimization.

6 Conclusion

This research is dedicated to solving the problem of intelligent allocation of spectrum resources in wireless communication systems, and proposes an innovative architecture-Transformer Reinforced Decision Maker (TRDM)-which combines the powerful sequence modeling capability of Transformer and the dynamic decision-making mechanism of reinforcement learning. Experimental results show that the TRDM model significantly outperforms traditional methods and other benchmark models in several key performance metrics, including throughput, latency, and QoS satisfaction rate. Specifically, TRDM achieves an average throughput of 150 Mbps, which is about 40% higher than that of traditional spectrum allocation methods, and an average delay of only 10 ms, which is reduced by at least 5 ms compared to other methods. What's more, TRDM maintains stable performance under different network load conditions, showing good adaptability and robustness. In addition, the importance of both Transformer and Reinforcement Learning modules for the overall performance improvement is verified through the ablation study, demonstrating the necessity of the two working together. Overall, TRDM not only improves the utilization efficiency of spectrum resources, but also provides a new idea for the optimization design of wireless communication systems.

The TRDM model has a wide range of practical application potential. Specifically, in urban cellular networks, TRDM can optimize spectrum allocation and power control, improve network throughput and reduce latency, and support more efficient communications. In remote Internet of Things (IoT) settings, TRDM can adjust network resources in real time according to the dynamic load and communication needs of devices, optimize the operating efficiency of low-power devices, and improve the overall stability and response speed of the system. These application scenarios reflect the adaptability and real-time advantages of TRDM in different environments.

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