

Retraction

Retracted: Analysis on the Reform and Development of College Physical Education Teaching Service under the Background of 5G Internet Communication

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Kang, Y. Oh, and X. Li, "Analysis on the Reform and Development of College Physical Education Teaching Service under the Background of 5G Internet Communication," *Mobile Information Systems*, vol. 2022, Article ID 5725748, 11 pages, 2022.

Research Article

Analysis on the Reform and Development of College Physical Education Teaching Service under the Background of 5G Internet Communication

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The development of the Internet of Things (IoT) made it possible for technology to communicate physical education by connecting cost-effective heterogeneous devices and digital applications to uncontrolled and accessible environments. This study explores the reforms and development of college physical education teaching services under the background of the 5th Generation Mobile Communication Technology. The data channel algorithm and the Internet of things (IoT) resource allocation algorithm for deep reinforcement learning are adopted to analyze the physical education reform in colleges. The application scenario of the IoT, the Multiple Input Multiple Output (MIMO) precoding technology, and the repeated lifting coverage of transmission time interval (TTI) in data transmission are examined based on the downlink system of the Un-narrow Band Internet of Things (U-NB-IoT). Moreover, the resource allocation problem under the access of massive IoT devices is solved through the deep reinforcement learning framework. Results show that quality of service is difficult to measure the communication network centered on the integration of teachers and students, while the quality of experience can make teachers and students feel satisfied. Moreover, quality of experience can measure the quality of service by the satisfaction of teachers and students to experience teaching resources. The resource allocation algorithm proposed can improve the experience of teachers and students using teaching resources, make the satisfaction of teachers and students reach the ideal value, further optimize the traditional problems existing in teaching, and improve the quality of students in all aspects.

1. Introduction

The era of 5th Generation Mobile Communication Technology (5G) comes with the rapid development of science and technology. Besides, IoT technology is presented as the further extension of Internet technology [1]. The development and application of this technology have completely subverted the wireless network. Based on this, the reform and development of physical education in colleges are imperative. Only by pushing through the old and bringing forth the new can people break the tradition and keep up with the development trend of the mainstream society [2].

The integration of 5G technology in the creation of a college sports curriculum management guarantees not only the privacy and security of teachers' and students' personal

information but also the effective utilization of college sports curriculum resources [3]. Traditional sports network course management systems are mostly developed with static resources. However, based on the 5G environment, the course of the sports management system directly faces the actual sports course teaching and realizes the collection and storage of real-time data in the classroom. By incorporating the 5G and IoT into the field of physical education curriculum management, additional "intelligent" features may be added to the mutual interchange and cooperation of physical education curriculum data [4].

Regarding college physical education (PE) reform under Internet communication, relevant scholars worldwide mentioned that more teaching resources need to be added to PE teaching under the rapid deployment of the 5G network,

and the research of Internet communication technology in PE reform will improve the physical and psychological quality of PE students [5]. In particular, the teaching resources and terminals of colleges are data acquisition, transmission, and processing feedback between objects and machines with the development trend of IoT. Yang examined [6] and investigated student physical condition and teaching conditions and offered some recommendations for the development and reforms of university PE reform. Zhang and Zhang [7] examined the positive impact of 5G and the Internet on physical activity, educational methods, and communication modes. To investigate the reform of university sports in the context of educational information, a sports framework is designed, and a 3D mixed teaching model and a varied target evaluation system are used. Stormoen et al. [8] studied the characteristics that produce a positive experience of PE in colleges and universities by combining the key points of theory with reality. Wei-Ping et al. [9] divided the college physical education curriculum reform into three stages using literature and logical analysis: accumulation, differentiation, and deepening. They sorted out the theoretical and practical results of each stage of the college physical education curriculum and examined the positioning and direction of the college physical education curriculum reform in the new era. The author in [10] employed VRT as the research object of the IoT sports network, used the 5G network as the technical support of the IoT environment, and analyzed the VRT in sports universities, sports safety, and PE teachers and students. Lucena et al. [11] emphasized how technology evolves at a rapid pace, requiring ongoing learning. For a variety of reasons, physical education teachers find it difficult to integrate technology into their lessons. According to Hyndman [12], instructors struggle to adopt technology for several reasons, technology becomes a distraction for students, teachers require additional professional development, and technology can alter lesson time and flow.

In this study, the downlink system of the Narrow Band Internet of Things (NB-IoT) technology based on unauthorized frequency band is established to make the PE teaching equipment cover efficiently. Next, the resource allocation algorithm based on deep reinforcement learning properly handles the access problem of massive IoT devices. Moreover, the baseband processing flow of the data channel is simplified due to the shortage of authorized frequency bands, and a centralized resource allocation algorithm for deep reinforcement learning is proposed. The data channel algorithm processing of Internet communication technology and IoT resource allocation algorithm for deep reinforcement learning are adopted to share and optimize educational resources, break the imbalance of educational resources in China for a long time, improve the solidification and rigid thinking of teaching methods, supervise students in an all-round way, and improve teaching efficiency.

The rest of the manuscript is organized as follows: Section 2 is about material and methods and provides an overview of the proposed method. Different methods for data processing and collection are discussed in this section. In Section 3, the results are illustrated, and the conclusion is presented in Section 4.

2. Materials and Methods

2.1. Data Channel Algorithm Processing of Interconnected Communication Technology

2.1.1. Data Processing Flow. The common physical layer data processing flow is the same as the data channel processing flow of U-NB-IoT. To check the correctness of the transmission at the receiving end, the cyclic redundancy check (CRC) code added first without processing bits is sent down by the data link layer [13]. It is added here that the CRC of U-NB-IoT is derived from the polynomial of CRC24. Equation (1) displays the expansion of CRC24 polynomial:

$$g_{\text{CRC24}}(X) = x^{24} + x^{23} + x^{18} + x^{17} + x^{14} + x^{11} + x^{10} + x^7 + x^6 + x^5 + x^4 + x^3 + x + 1. \quad (1)$$

The CRC result is the remainder of the input bit polynomial divided by the CRC polynomial. Figure 1 displays the baseband processing flow.

The new transmission bit consists of CRC verification code and unprocessed bits. Then, this combination is subjected to channel coding processing [14]. For this purpose, tail-biting convolutional codes with a rate of 1/3 and a constraint length of 7 are adopted. Figure 2 shows the principles of tail-biting convolutional code.

U-NB-IoT uses tail-biting convolutional codes to overcome the code loss of ordinary convolutional codes. Its advantage is that it can set the end of the register and the initial state to the same value [15]. As shown in Figure 2, the convolution polynomial is expressed as G , and it is exclusive OR processed with the original value of the bit to obtain the channel encoded data. Through the optimization process of rate matching, a data stream twice as many as the original bits is generated, but this is the result obtained after CRC and tail-biting convolution process of the original data. Rate matching occurs to adapt the bearing capacity of the convoluted data stream and the air interface [16]. The bitstream of scrambling airport bearing force is added after the rate matching. The U-NB-IoT system scrambles the code sequence and scrambles the codeword bit by bit through or program. Equation (2) represents the initialization seed of the scrambling sequence:

$$C_{\text{init}} = \{U\text{Frame}[1 : 0], U\text{SubFrame}[3 : 0], \text{Frame}[3 : 0], \text{CellID}[5 : 0]\}. \quad (2)$$

In equation (2), the U frame is 2 bits, the U subframe is 4 bits, and the uplink and downlink frames are 4 bits. This means the frame number is corresponding to scrambling. The unit index $\text{CellID}6\text{bit}$ is the cell index (ID). Scrambling is adopted to improve the stability of data transmission. The function of this is to whiten the transmitted signal, interfere at the transmitting end, and remove the interference at the receiving end [17].

Local pilot generation and air interface mapping are components of downlink resource mapping of the U-NB-IoT system [18]. In the frequency domain resource pattern

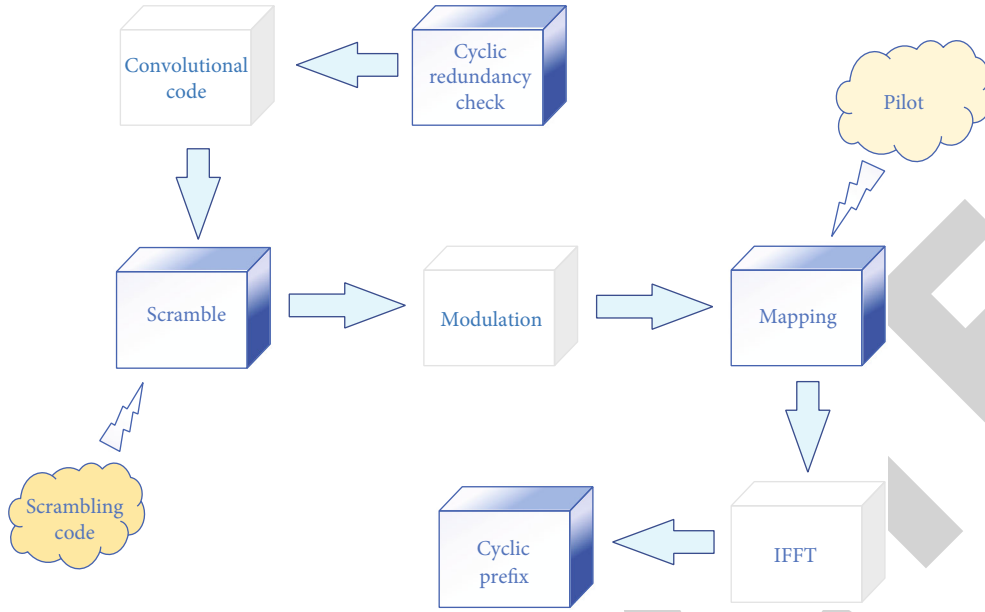


FIGURE 1: Baseband processing flow.

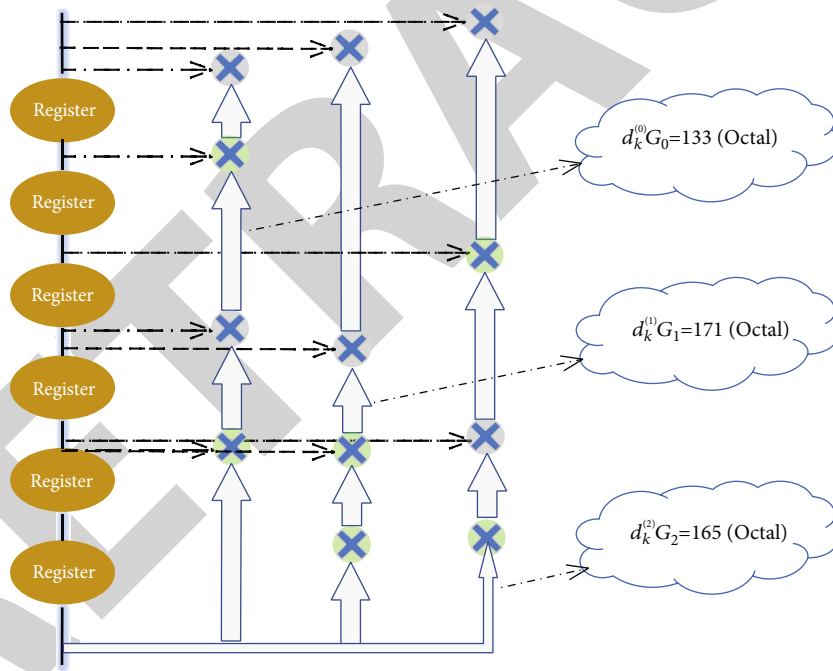


FIGURE 2: Principle of tail-biting convolutional code.

shown in Figures 3 and 4, subcarriers are corresponding to the frequency domain. One time slot corresponds to seven Orthogonal Frequency Division Multiplexing (OFDM) symbols. The green unmarked block is the data RE, and the white R_0 represents the resource element (RE) occupied by the reference signal on the antenna port 0. Figures 3 and 5 show the mapping of transceiver (1T1R) time-domain reference signals [19].

In the signal diagram, white R_0 represents the RE occupied by the reference signal of the antenna port, blue represents the RE occupied by the reference signal of antenna port

1, and the remaining green is the data RE. In the same time slot, for antenna port 0, the RE position occupied by antenna port 1 can be set to 0. For antenna port 1, the RE position occupied by antenna port 0 is also set to 0. OFDM symbols are generated according to the mapped symbols processed by inverse fast Fourier transform (IFFT). The sampling rate of each channel in the U-NB-IoT system is 1.98 MHz. In 10 ms baseband data, 128 points IFFT is performed for each symbol. Figures 6 and 7 show time-domain reference signal diagrams of two transmitting antennas transmitting and receiving (2T1R).

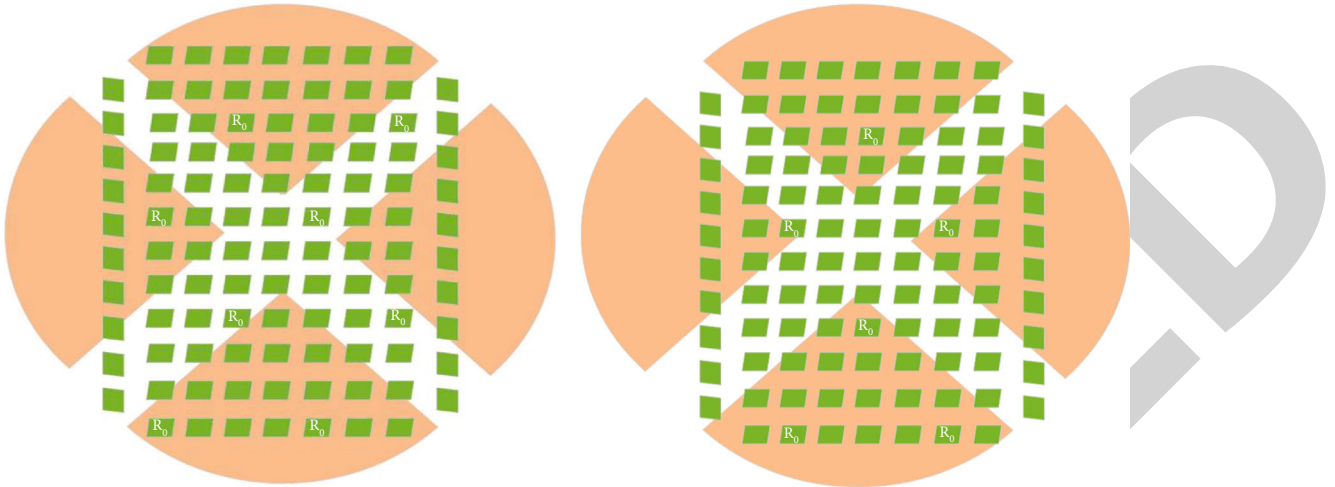


FIGURE 3: Reference signal diagram of evolution technology 1T1R.

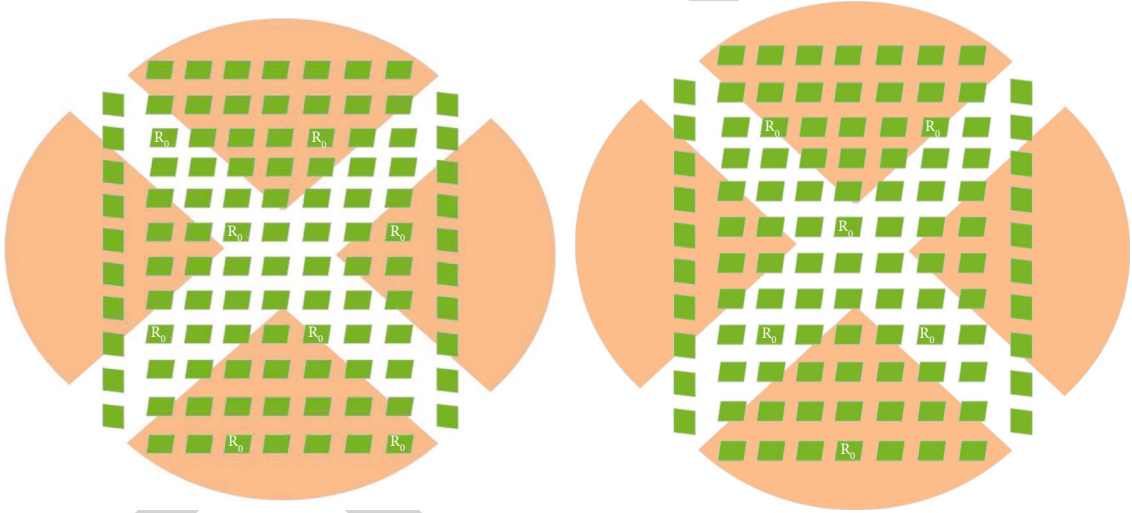


FIGURE 4: Optimization point line diagram of the QoS model.

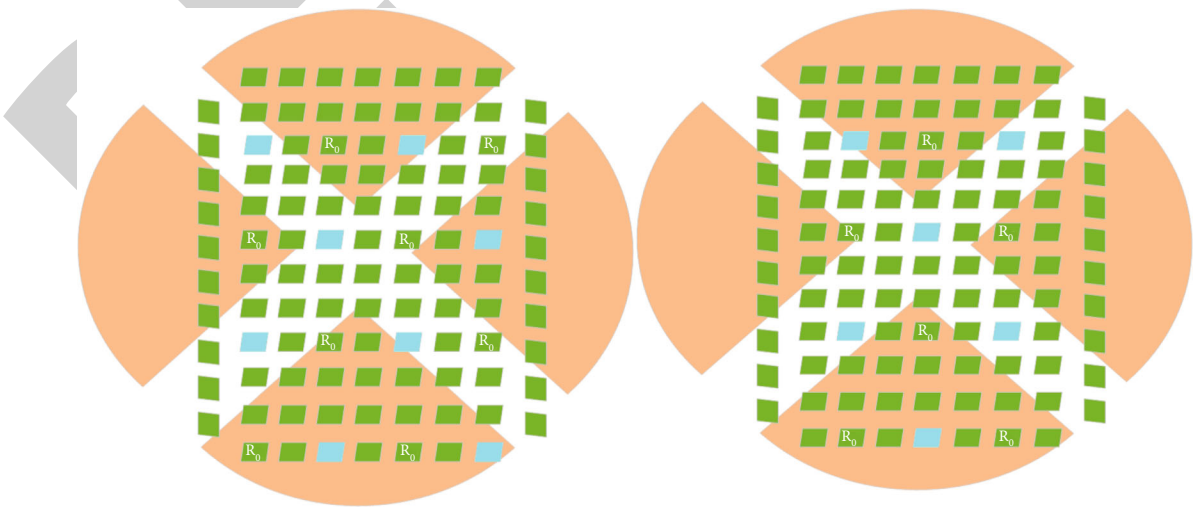


FIGURE 5: Schematic diagram of 1T1R four-slot reference signal.

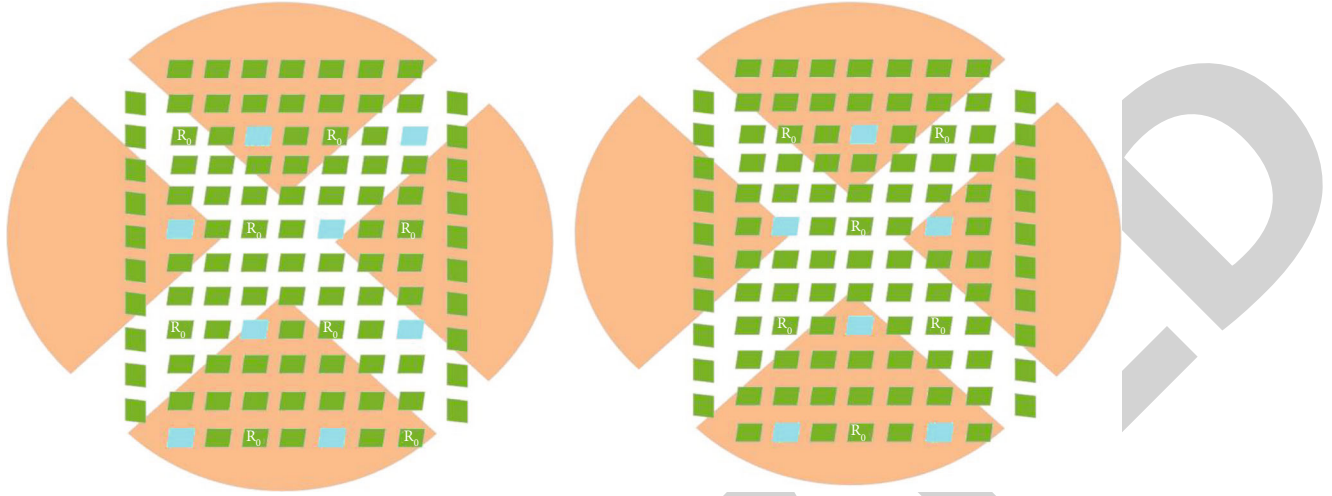


FIGURE 6: Evolution technology 2T1R reference signal diagram.

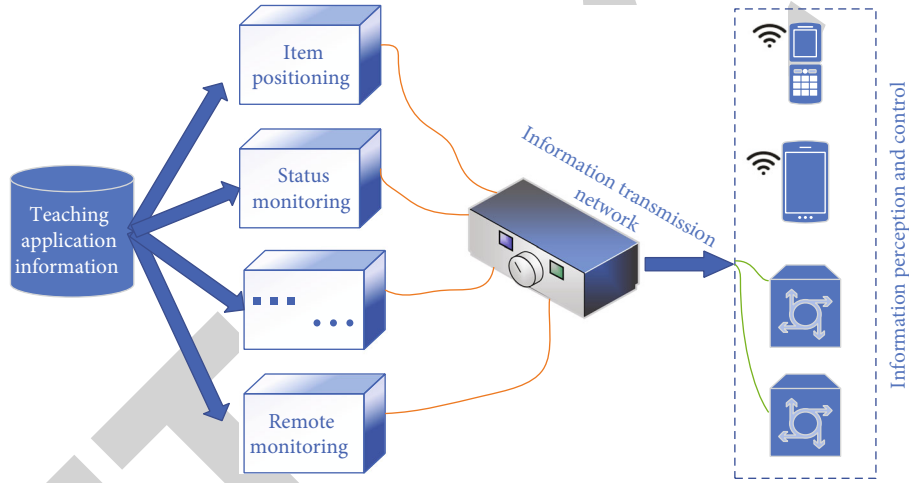


FIGURE 7: Schematic diagram of 2T1R four-slot reference signal.

2.1.2. *Data Channel Algorithm.* Transmission time interval (TTI) repetition and Multiple-Input Multiple-Output (MIMO) precoding are components of coverage enhancement processing. Physical Downlink Shared Channel (PDSCH) is a channel used by U-NB-IoT to connect service data [20].

In the U-NB-IoT system, 10 ms is not only an ordinary transmission time interval but also the basic resource scheduling unit of the system. According to the uniqueness of IoT equipment transmission, generally, the data of each TTI cannot touch the SNR threshold after decoding when it reaches the receiving end; so, it is essential to improve the received signal-to-noise ratio [21]. The method of TTI repetition is to send the same data frame repeatedly, and it can repeat multiple times, such as 1 time and 5 times, which is based on the integer multiple principles of TTI. Its disadvantage is to reduce the code rate and data transmission rate. Its advantage is to improve the demodulation performance of the receiver, improve the received signal-to-noise ratio, and strengthen the coverage.

MIMO precoding is performed after data modulation. However, there is a problem; that is, OFDM technology is limited, such as the offset of carrier frequency and the offset of average power ratio [22]. Furthermore, OFDM has the advantage of reducing the complexity of receiver design. From the aspect of the signal-to-noise ratio of the receiver, flat fading cannot improve the signal-to-noise ratio of the receiver. Hence, the use of various diversity technologies can partially eliminate the disadvantages of fading channels. Figure 8 displays the composition of teaching resources in IoT structure [23].

A precoding technology in the MIMO system is called space frequency block code (SFBC). SFBC can increase the redundancy of the signal so that the signal can obtain diversity gain. The SFBC is expressed in equation (3).

$$\begin{pmatrix} D^{(0)}(2i) & D^{(0)}(2i+1) \\ D^{(1)}(2i) & D^{(1)}(2i+1) \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} d(2i) & d(2i+1) \\ -\text{conj}(d(2i+1)) & \text{conj}(d(2i)) \end{pmatrix}. \quad (3)$$

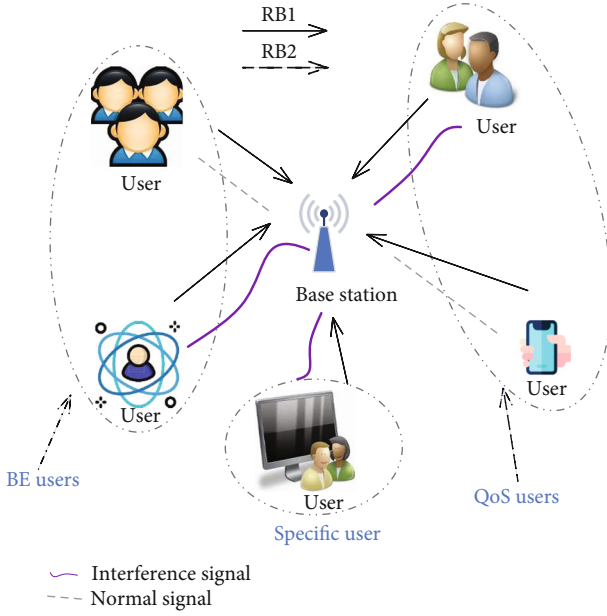


FIGURE 8: Composition of teaching resources in IoT structure.

2.2. IoT Resource Allocation Algorithm for Deep Reinforcement Learning

2.2.1. Resource Allocation System Model

(1) *Qos-Oriented System Model.* In this study, the research objects selected are the power allocation and the selection of uplink spectrum resources. The research scenario is the category of massive IoT teacher-student access and various teacher-student services [24]. Figure 9 depicts the model of the proposed system.

The transmission power and time slot change of user equipment (UE) are set to be positively correlated. Then, the location and number of UE will change dynamically. Meanwhile, few frequency bands can be used in IoT equipment; so, the number of teachers and students considered in the algorithm is greater than the number of resource blocks (RB) that can be used. Cofrequency interference between IoT equipment is the main interference source of the system [25]. To sum up, equation (4) is used to express of signal to interference plus noise ratio (SINR) of teachers and students.

$$\text{SINR}_i = \frac{G_{n,k}P_{n,k}}{\sum_{i \in N \setminus \{n\}} x_{j_1,k} G_{j_1,k} P_{j_1,k} + \sigma^2}, \quad (4)$$

where $P_{i,k}$ and $P_{j,k}$ are the transmission power of the multiplexing the RB k of IoT teacher-student n and teacher-student j . $G_{i,k}$ and $G_{j,k}$ are the channel gains of teacher-student n and teacher-student j to the base station and multiplexing the RB k . $X_{i,k}$ is the pointer of teacher-student n on the RB k . $X_{i,k} = 1$ means that the n -th teacher and student use the k -th RB. In addition, $X_{i,k} = 0$. σ^2 repre-

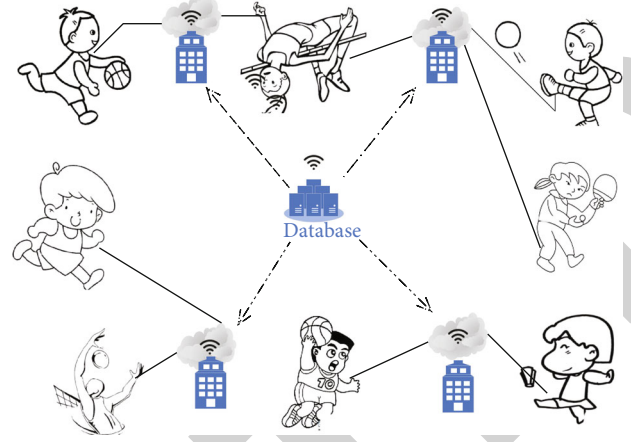


FIGURE 9: System model.

sents the additive white Gaussian noise (AWGN) power of RB. Equation (5) shows the channel capacity of receiving SINR of a single teacher and student:

$$C_n = B \log_2(1 + \text{SINR}_n). \quad (5)$$

(2) *Utility Function for QoE (Quality of Experience).* From the beginning of wireless technology to today's 5G technology, teachers' and students' requirements have also changed from simple service needs to various fast services. The types of service requirements for teachers and students are even more diverse today. From simple real-time message sending and receiving to intelligent control and complex personal LAN configuration, there are various restrictions on the communication system, which is based on each service request. 5G is the foundation of all mobile Internet, creating value for teachers and students through a sustainable service environment. Therefore, focusing on teachers and students is the most crucial service concept of 5G. The previous response of network performance is reflected by the QoS. The indicator measurement of QoS is usually realized by hardware such as packet loss rate and spectral efficiency. However, QoS is difficult to accurately measure teacher and student-centered communication networks because of the increase of service categories. QoE refers to the satisfaction of teachers and students when using the Internet to complete teaching tasks. This shows the feelings of teachers and students for different services. Therefore, QoE indicators are adopted to optimize the management of wireless resources. Nevertheless, it is difficult to model and solve the optimization problem of QoE, which is due to the immaturity and imperfection of the modeling system. Hence, at present, it still needs to rely on the QoS parameters to evaluate the network performance and map them to the QoE function to achieve the effect of optimizing the resource allocation algorithm.

The measurement of teacher-student service experience adopts a utility function as a data processing tool. The mean

opinion score (MOS) can show the distance between teachers' and students' expectations and the current network quality and also energize teachers' and students' sense of the experience of the network. The transmission rate is very crucial for QoE; so, this exploration focuses on the feedback of rate to the satisfaction of teachers and students and uses the utility function to get the MOS evaluation.

There are three different types of services for teachers' and students' requests, including QoS constraint services, best effort (BE) services, and services with special requirements. BE refers to services without QoS restrictions. Most teachers and students of such service requests do not require a delay. The second type of service request is QoS limited, and it has requirements for the number of resources [26]. The last one is the service request with the highest complexity and QoS requirements. Given the above situation, the sigmoid function is adopted to express the MOS of the utility function, and it is computed as

$$U_c = \frac{1}{A + D e^{-E(C-C_0)}} + F, \quad (6)$$

where A , D , E , and F represent the parameters of the slope. E will affect the slope of the curve, and A , D , and F will affect the mapping range from the utility function to MOS. C_0 represents another form of resource needs of different groups of teachers and students.

The three different types of services above are naturally different based on different utility functions and different rate requirements. For BE service, there is a positive correlation between teacher-student experience and resource scheduling [27]. Therefore, this is a convex function with monotonically increasing characteristics. The stability condition of this function is that the rate reaches the threshold required by the transmission rate. The utility function is a monotonic increasing function and has the characteristics of QoS traffic. QoS requirements should be met; so, the utility function grows rapidly. The high priority of teacher-student resource requests is based on the fact that the resources obtained by teachers and students are less than the QoS requirements. The low priority of teacher-student resource requests is because the resources obtained by teachers and students are greater than the critical value of QoS requirements. In this case, the growth of the utility function is very slow. The last case is teachers and students with special QoS requirements. Their satisfaction is difficult to reach the maximum unless the rate exceeds a certain value. Then, the opposite situation is that the satisfaction is 0. Figure 10 is the schematic diagram of the college physical education resource system for IoT.

(3) *Optimization Model*. The construction of the QoE optimization model is based on the utility function. Constraints and optimization objectives constitute the optimization model. The minimum QoS guarantees the upper limit of optimization constraints. Equation (7) shows the resource allocation model of the n -th teacher and student:

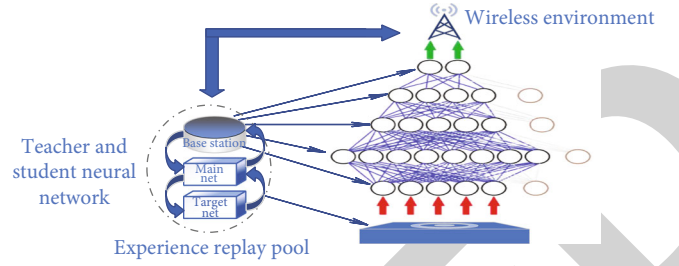


FIGURE 10: Physical education teaching system based on IoT.

$$\begin{aligned} & \max_{p,x} U_n(C) \\ \text{s.t.} & \quad C1 \quad U_n(C) > U_{\min}, \\ & \quad C2 \quad \sum_{k=1}^k x_{n,k} p_{n,k} < P_{n,\max}, \\ & \quad C3 \quad \sum_{k=1}^k x_{n,k} p_{n,k} < P_{n,\max}. \end{aligned} \quad (7)$$

Each teacher and student is not lower than the utility function threshold, guaranteed by C1, and the maximum transmission power of each IoT teacher and student is limited by C2. The condition that each teacher and student can only select one RB is C3, but multiple teachers and students can select the same RB.

2.2.2. Resource Allocation Algorithm for Deep Reinforcement Learning. Based on the research scenario, the discrete-time Markov decision process with continuous action space can be adapted to represent the hidden optimal stochastic control problems of power allocation and teacher-student scheduling. The teachers and students of the terminal cannot obtain accurate conversion information because of the complex transformation of the external environment. In addition, it is difficult to obtain the optimal solution with low complexity by the previous method given in equation (7). Therefore, the resource allocation of massive IoT devices under the deep reinforcement learning algorithm is studied below.

(1) *Reinforcement Learning Model*. In the case of discrete-time, the present optimization problem aims to form a conventional reinforcement learning problem with the interaction between environment E and intelligent modules. The real-time reward R_t is obtained based on the timely action taken by the intelligent module after receiving the observation results in each time slot t . State-space S is the product of the resource allocation scenario. It means the current environmental state of the intelligent module. According to the reinforcement learning model of massive teachers and students, RB represents the data transmission pointer and access pointer. S_t represents the state in each period set, and it is expressed as

$$S_t = [e_1(t), e_2(t), \dots, e_K(t), I(t)], \quad (8)$$

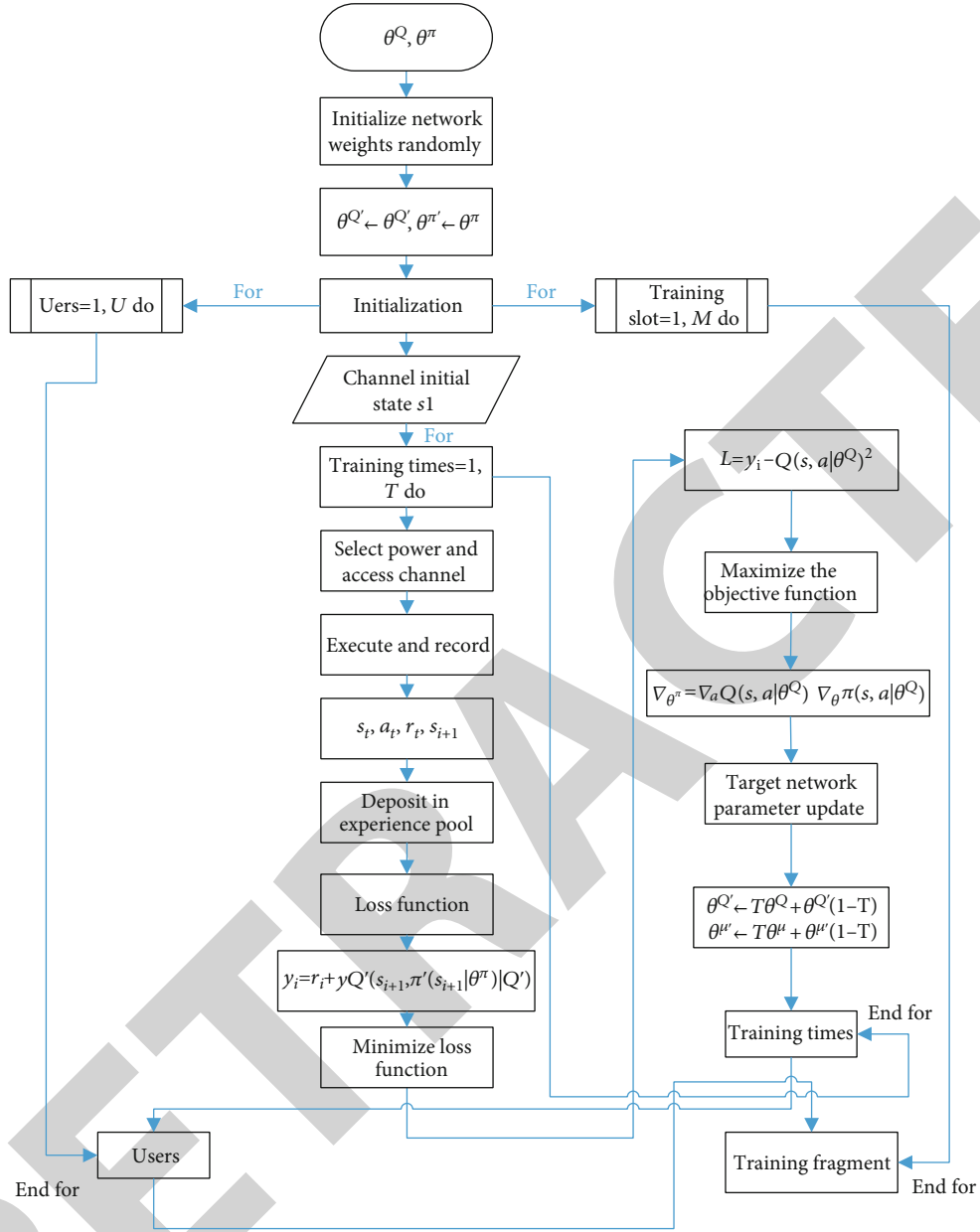


FIGURE 11: PE student-teacher algorithm framework.

where $e_k(t)$ is the expression of channel access, which means the number of teachers and students occupying RB, and $I(t)$ is the data transfer pointer. If the value of the teacher-student utility function is less than the minimum threshold, the transmission will fail, and $I(t) = 0$. On the contrary, $I(t) = 1$. The intelligent module action of time slot t is defined as

$$a_t = [c_t, p_t], \quad (9)$$

where a_t consists of RB index and transmission power of intelligent module equipment multiplexing current RB. The reward is a kind of evaluation, which specifically refers to an evaluation of the current state and behavior. The intelligent module can be adjusted according to the reward situation.

The reward here can be defined as the utility function in equation (6). The reward $R_t = r(s_t, a_t)$ is expressed as follows:

$$r_i = (s_t, a_t) = \begin{cases} u_i(t), & \text{if } u_i(r) \geq u_i(r)_{\min} \text{ and } p_{i,k} \leq p_{i,\max}, \\ C, & \text{otherwise} \end{cases}, \quad (10)$$

where C is a constant negative reward value, which is adapted to punish the action of intelligent selection. For example, if the intelligent module has the limit of the maximum power in the system model, and the intelligent module selects the transmission power greater than the threshold, the intelligent module will be punished.

(2) *Deep Reinforcement Learning Algorithm.* The purpose of introducing a nonlinear function approximation into the machine learning algorithm is to better deal with the problems of continuous action space and multidimensional state space. The frequency resources of the unauthorized frequency band cannot properly deal with these problems for ordinary linear function approximation [28, 29]. In the algorithm framework shown in Figure 11, the framework based on the integration of teachers and students is the main structure of the algorithm. Student network in PE inputs the status into S_t and outputs action. The environment is triggered by the subsequent triggering action of the intelligent module under the action of the environment and feeds back the new state S_{t+1} . Finally, the loss function is calculated according to the data. Equation (11) is used to compute the loss function.

$$L = r_t + \gamma Q'(s_{i+1}, \pi'(s_{i+1} | \theta^\pi) | \theta^{Q'}) - Q(s, a | \theta^Q)^2. \quad (11)$$

The way of updating parameters in the teacher network differs from that in the student network. Teachers update the parameters according to the gradient descent, while students update the parameters according to the gradient rise. The empirical replay method is adopted for data generalization, such as the experience pool of data storage in the figure. To achieve the purpose of algorithm convergence, the method of replaying experience in the experience pool is used to block the correlation among different data. Figure 11 shows the basic framework of the algorithm.

Figure 11 shows that Main Net and Target Net appear in both teacher networks and student networks. The same grid structure is adopted to construct a target and evaluation network with the same structure but different parameters. The evaluation grid will allocate the target grid after a certain time. The algorithm flow chart in the figure below summarizes the procedures for each module to implement the in-depth teacher-student integration framework. The algorithm used updates the target network at each step. Figure 12 is a flow chart of a resource allocation algorithm based on the integration of teachers and students.

3. Result

3.1. *Analysis of QoS Model in PE-IoT Mode Based on 5G Internet Communication.* The performance of traditional networks is reflected by QoS. However, QoS is generally measured by spectrum efficiency, packet loss rate, and other indicators. With the increase of service categories, QoS is difficult to measure the communication network centered on the integration of teachers and students. Figure 4 shows the optimization point line diagram of the QoS model.

Figure 4 suggests that the utility function changes with the change of rate. Different teachers and students have different service needs. In the BE service, teacher-student experience is directly proportional to resource scheduling. The function shown in the figure is monotonically increasing, and the required stability condition is that the rate reaches

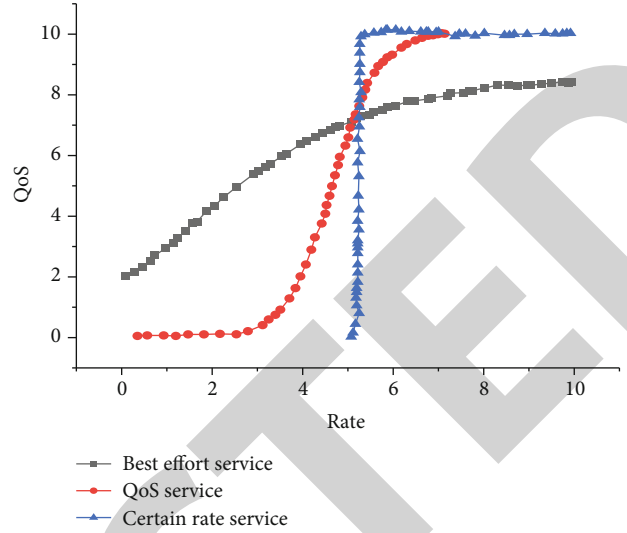


FIGURE 12: Resource allocation algorithm based on the integration of teachers and students.

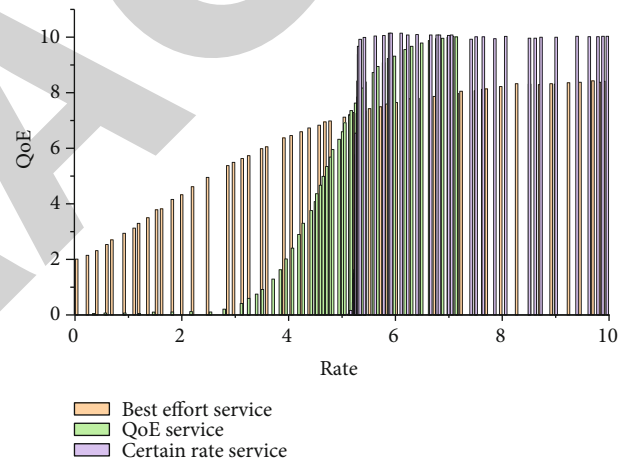


FIGURE 13: QoE optimization model for different teacher-student requests.

the relevant threshold. The characteristics of QoE flow between teachers and students are also monotonically increasing, and the rapid growth of its utility function is based on the fact that the resources obtained by teachers and students are less than the required value of QoE. For teachers and students with special QoE needs, if the rate is greater than a specific value, their satisfaction can reach the maximum, but this is difficult to achieve.

3.2. *Analysis of IoT Model Based on College Sports Organization.* Unlike the traditional QoS optimization algorithm, the teacher and PE student network uses the utility function approximation to evaluate the value function. The use of this method greatly improves the experience praise index and satisfaction of college teachers and students. Figure 13 shows the QoE optimization model of different teacher-student requests.

Different types of services correspond to different utility functions and different rate requirements. For the BE service, there is a positive correlation between teacher-student experience and resource scheduling. The above situation shows that this function has the characteristics of monotonic increase, and the utility function of QoE traffic characteristics is also a monotonic increasing function. The priority of teacher-student resource requests should be higher to meet the rapid growth of utility functions. The reason for the low priority of teacher-student resource requests is that the resources obtained by teachers and students are greater than the critical value required by QoE. In this case, the growth of the utility function is very slow. In the last case, it is difficult for teachers and students with special QoE needs to reach the maximum value of their satisfaction. On the contrary, the satisfaction is 0.

4. Conclusion

The advent of IoT and 5G made it possible for technology to improve PE by connecting low-cost heterogeneous devices and digital applications to uncontrolled and accessible environments. In the IoT environment, 5G technology was used to improve the teaching methods of PE, and good progress has been made. This study adopted an IoT resource allocation algorithm and deep reinforcement learning to analyze the reform and development of college PE teaching services. Based on the narrowband U-NB-IoT downlink system, the precoding technology of MIMO and the repeated lifting coverage of TTI in the data transmission were examined. The resource allocation problem under the access of massive IoT devices was solved through the deep reinforcement learning framework. The results show that the resource allocation algorithm proposed can improve the experience of teachers and students on teaching resources, make the satisfaction of teachers and students with different service requests reach the ideal value, further reform the physical education teaching mode, and optimize the problems existing in teaching. However, the allocation algorithm is relatively single, and its diversity is insufficient. Therefore, the subsequent future work will focus on distributed resource allocation algorithm.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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