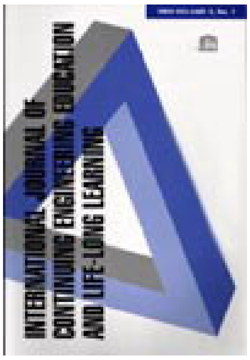

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English information teaching resource sharing based on deep reinforcement learning

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Abstract: In order to solve the problems of low energy efficiency, poor stability and low convergence in the existing teaching resource sharing methods, an English information teaching resource sharing method based on deep reinforcement learning is proposed. Firstly, a deep reinforcement learning model under super dense network is constructed. Secondly, with the support of the in-depth reinforcement model, this paper optimises the sharing interference and sharing efficiency of English information teaching resources. Finally, combined with the resource sharing model of deep reinforcement learning, the resource sample training is carried out to realise the sharing of teaching resources. The experimental results show that when the number of small base stations is 12, the average shared energy efficiency of the English information-based teaching resource sharing method based on deep reinforcement learning is about 1 bit/J, and the average energy efficiency fluctuation is ±0.05, indicating that the proposed method has good stability and adaptability.

Keywords: deep reinforcement learning; English information teaching resources; resource sharing.

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Biographical notes: Chao Han received his Master's in Principles of Pedagogy from Henan University in 2009. Currently, he is an Associate Professor of Kaifeng University. His research interests include English teaching and higher education.

1 Introduction

The development of information technology has promoted the reform of education. With the deepening of education informatisation, the informatisation of English teaching has become the primary goal of education reform. Among them, the integration and sharing of educational resources is the basis for achieving English informatisation. The so-called English informatisation teaching resources refer to the collection of various information accumulated in the process of English teaching in the context of informationisation. Compared with paper-based teaching resources, informatisation resources are highly shared, independent, and easy to store and store. Inquiries have played a huge role in improving the quality of English teaching. Therefore, English informatisation teaching resources have become one of the current research hotspots.

Wang and Wang (2021) proposed an English information-based teaching resource sharing method based on neural network. By constructing neural network, the conceptualised English information-based teaching resources are represented by symbols, and the distributed storage resources are integrated to make logical reasoning according to the serial mode to judge the optimal resource sharing strategy. However, the energy efficiency of resource sharing is low and can not meet the current energy efficiency requirements. Yang and Chen (2019) proposed an English information teaching resource sharing method based on multi-agent Q-learning, which uses the sleep strategy of the base station to enhance the energy efficiency of resource sharing, and uses the mean field method to realise resource management and distribution, but the energy efficiency has high volatility and poor stability. Wang and Huang (2019) proposed an English information teaching resource sharing method based on ergodic algorithm. The resource sharing strategy is divided into two stages by using the stage method. The geometric theory is used to analyse the relationship between resource sharing energy efficiency and base station density, so as to reduce signal interference, but the convergence is poor, so it is difficult to find the optimal resource sharing strategy, resulting in low efficiency.

Combining the shortcomings of the above three traditional resource sharing methods, this paper puts forward an English information teaching resource sharing method based on deep reinforcement learning. The overall research scheme of this method is:

- Firstly, based on the super dense network, a deep reinforcement learning model is established, and the interference and sharing efficiency of English information-based teaching resources are optimised with the support of the deep reinforcement model, so as to improve the effectiveness of English information-based teaching resources sharing.
- Secondly, based on the above optimisation results, combined with the depth enhancement model, the agent data flow is fitted, the deviation of flow data is calculated, and high-precision resource training is realised, so as to realise the sharing of English information teaching resources.
- Finally, the simulation results show that the English information teaching resource sharing method has high energy efficiency, self adaptability, stability and convergence. It can select the optimal resource sharing strategy while improving energy efficiency to meet the needs of users.

2 Construction of deep reinforcement learning model

In order to expand the scope of English information teaching resource sharing and ensure resource exchange and sharing among users, an ultra dense network based on one macro base station and N small base stations is constructed. On this basis, a deep reinforcement learning model is introduced to realise optimal resource management and sharing allocation (Wang and Xu, 2020; Wang et al., 2019; Hang et al., 2019). In the ultra dense network, the macro base station is the centre for the collection and transmission of English information teaching resources. At the same time, it can collect the collection resources and its own operation status of each small base station at any time. The deployment range of the small base station should be within the deployment range of the macro base station, and each small base station shares the whole resource, but a user can only associate with one small base station, the orthogonal method is used to upload, query and extract resources.

For the super intensive English information-based teaching resource sharing network considered in this paper, a deep reinforcement learning model is constructed with the base station as the agent, and the optimal sharing of English information-based teaching resources is realised through the interactive learning between the agent and the environment. The state space, action space and return function of the i^{th} agent are defined as follows.

State space: in order to strengthen the close combination between agents and improve the efficiency of cooperative training, the action selection of agents needs to refer to the characteristics of shared teaching resources and the local environment state of the network, that is, the agent needs to obtain the shared resource information and user information in the base station, and collect the throughput and shared resource transmission power of other base stations at time *t*, The state S_i^t of agent *i* can be expressed by the following formula (1).

$$S_I^T = \left\{X_i^t, P_i^t, M_i^t, R_i^t\right\} \tag{1}$$

where P_i^t represents the shared transmission power of English information teaching resources of agent *i* at time *t*; R_i^t represents the resource capacity of agent *i* at time *t*; M_i^t represents the set of users arriving at agent *i* at time *t*.

Action space: in order to jointly optimise the shared resources and their transmission power under the deep reinforcement learning model, each agent needs to determine the local offline English information teaching resources and reasonably allocate the transmission power according to the resource type. At the same time, in order to minimise the action space, the transmission power is allocated by discrete method and divided into S levels. Therefore, at time *t*, the action a_i^t of agent *i* can be expressed as:

$$a_i^t = \left\{X_i^t \in \{0, 1\}\right\} \tag{2}$$

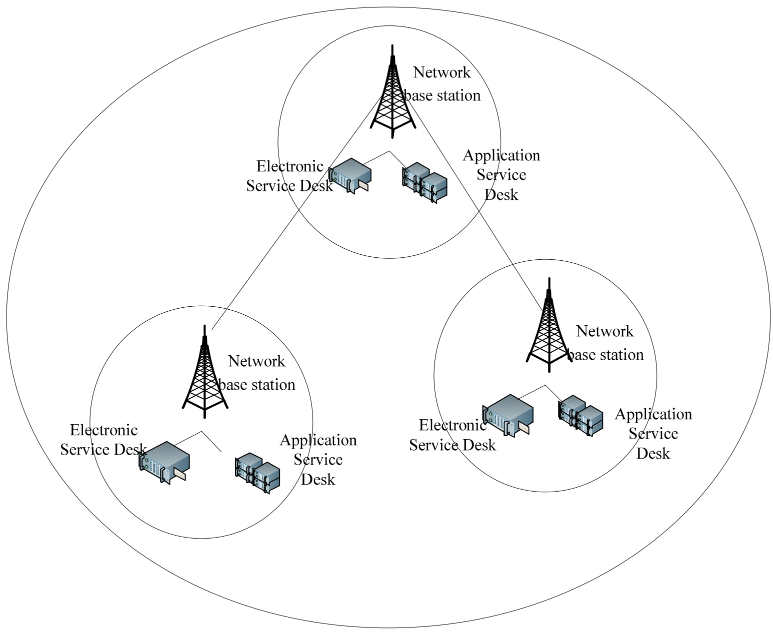
Return function: to some extent, the final return reward calculated by the return function represents the optimisation goal of the model. In the process of resource training, the interaction between multiple agents has a certain impact on the convergence of the model. Therefore, the determination of the return function should comprehensively consider the local energy efficiency of the base station itself and the local energy efficiency of other base stations, that is, the final optimisation goal can be regarded as the optimal energy efficiency solution of the whole model. At time *t*, the return function r_i^t is defined as follows:

$$r_i^t = 6\left(tlS_i^t\right) \tag{3}$$

where lS_i^t represents the real-time reward obtained by the agent from the state executing the corresponding action at time *t* (Ma, 2019).

Establish the network topology model and use the network topology model to realise the management of English information teaching resources. The topology model of English information teaching resource management is shown in Figure 1 below.

Figure 1 Topology model of English information teaching resource management (see online version for colours)



According to Figure 1, the purpose of resource management is to more effectively develop and utilise English information education resources. For resource management under ultra dense network, the collected English education resources are collected, organised and classified by means of modern information technology. The overall resource management is divided into four processes: resource collection, resource transmission, resource analysis and resource storage. However, due to the distributed and intensive characteristics of small base station deployment in ultra dense network, large state space and high complexity, resource management becomes more and more difficult. Considering the above problems, for the resource management of English information education resources, combined with RL online learning in the deep reinforcement learning model and offline training in the neural network algorithm, the generated online resources are directly analysed and trained. The trained resources carry different feature factors, and the optimal classification of resources is realised by fitting the feature function, under this management model, it can effectively solve the problem of state space guarantee in ultra dense networks, overcome the instability of resource management, and further improve the security and integrity of resource storage.

3 English information teaching resource sharing

Based on the above topology model of English information-based teaching resource management, English information-based teaching resource sharing is carried out. Since each agent has different channel gains when acquiring resources from the macro base station, and a user can only obtain resources from one agent, it may be interfered by other agents with the same channel gain in the process of English information teaching resource sharing (Yang and Yao, 2021; Zeng et al., 2019; Ji and Yue, 2021). This interference caused by the same channel gain is collectively referred to as signal interference, then the signal interference noise ratio of agent i when sharing English information teaching resources can be expressed as:

$$SINR_i^t = \frac{P}{h_i^t} + \sigma^2 \tag{4}$$

where P represents the shared transmission power of English information teaching resources; h_i^t represents the channel gain of the resource acquired by the agent i, and σ represents the noise power.

When the calculated signal-to-noise ratio exceeds a certain standard value, it indicates that the sharing stability of English information-based teaching resources is threatened. The information interference can be reduced by modifying the channel gain to optimise the sharing stability of English information-based teaching resources.

In addition to stability optimisation, the efficiency optimisation of English information teaching resource sharing is also one of the important joint optimisation problems.

Firstly, from Shannon power, the rate at which agent i obtains English information-based teaching resources from Acer is:

$$R_i^t = W \log\left(1 + SINR_i^t\right) \tag{5}$$

where W represents the transmission bandwidth of English information teaching resources; The binary indicator variable $\log(1 + SINR_i^t)$ is used to indicate whether the agent i shares English information teaching resources with users. If the value is 1, it means sharing is agreed; if it is 0, it means sharing is prohibited.

The power loss of each agent is composed of English information resource sharing transmission power and hardware operation power. The overall power loss P^t of agent i can be expressed as:

$$P^t = P_i^t + P_C^1 \tag{6}$$

where P_C^1 is the hardware operating power of agent i.

To sum up, the energy efficiency of agent i can be expressed as:

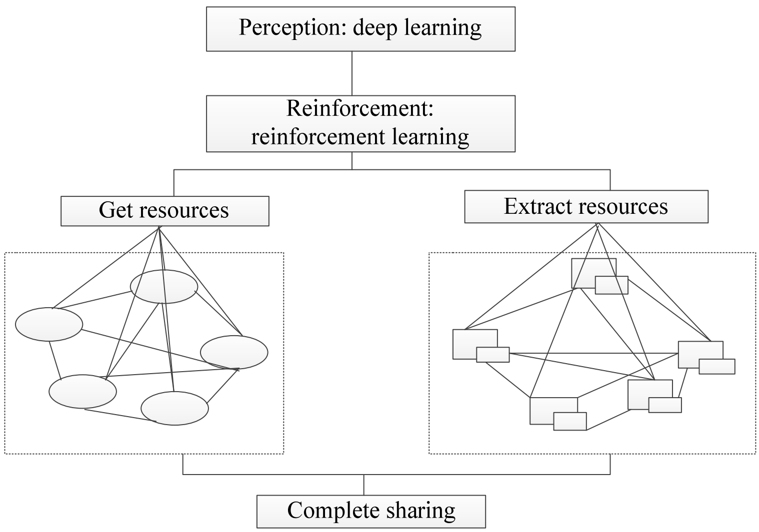
$$EE_i^t = \frac{R_i^t}{P_i^t} \tag{7}$$

Then the optimal energy efficiency after joint optimisation can be expressed as:

$$\max EE = \sum\nolimits_{i \in N} EE_i^t \tag{8}$$

The advantage of deep reinforcement learning is that it has high perception and decision-making ability. It is an artificial intelligence method close to human thinking. In essence, deep reinforcement learning is an end-to-end perception and control system with strong universality and flexibility, but it is strongly dependent on time, therefore, the main function of the resource sharing model of deep reinforcement learning is to reduce the difficulty of resource sharing and improve the efficiency of resource sharing. The specific structure of English information teaching resource sharing model under deep reinforcement learning is shown in Figure 2.

Figure 2 English information teaching resource sharing model under deep reinforcement learning



The English information-based teaching resource sharing model under deep reinforcement learning gives multiple weights to the resource samples to be trained, disrupts the original arrangement order of English information-based teaching resources, and uses the discrete method to carry out non-uniform random sampling on the disrupted English information-based teaching resource samples, so as to reduce the weight of English information-based teaching resource samples. The non-uniformity random sampling process can be expressed by the following formula (9):

$$E(f(x)) = \int_a^b f(x)p(x)dx \tag{9}$$

where $E(f(x))$ is the density value obtained from non-uniformity random sampling verification; x represents the sample of English information teaching resources; a is the weight of the total English information teaching resource sample; b is the weight of non-uniform random sampling of English information teaching resources.

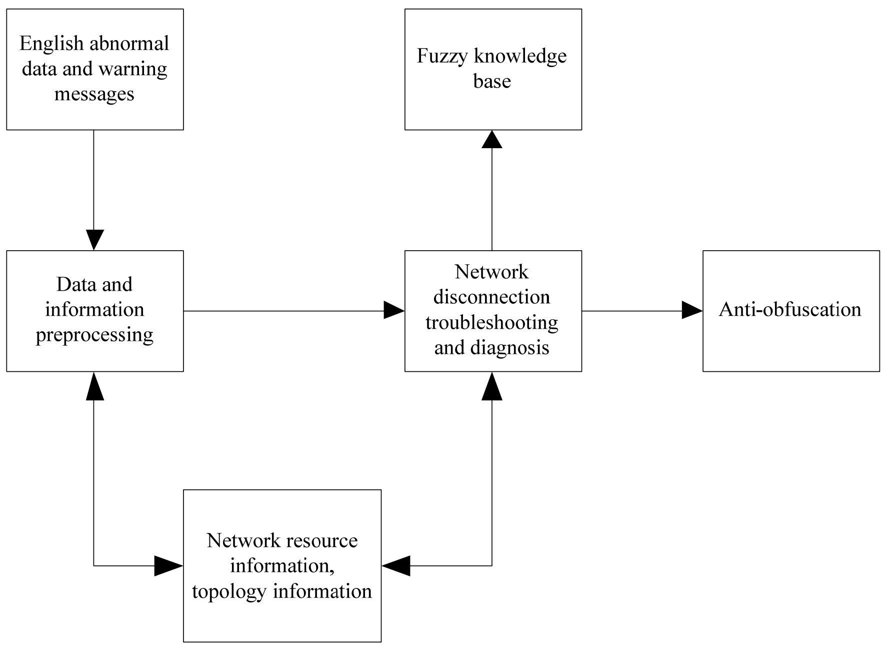
The extracted English information-based teaching resource samples are weighted, the state value of the resource sample is defined, and the state value is recursively processed and displayed. The recursive processing formula is as follows:

$$V_K = \frac{f(x_1) + f(x_2) + \ldots + f(x_n)}{n} \tag{10}$$

where V_K represents the recursive value of weighted English information teaching resource samples; $f(x_1) + f(x_2) + \ldots + f(x_n)$ is the weighting value corresponding to the English information education resources to be shared; n is the number of resources to be shared.

The sharing is completed according to the established English information-based teaching resource sharing model. The sharing process of English information-based teaching resources is shown in Figure 3.

Figure 3 English information resource sharing process



Assuming that the sharing environment of English information-based teaching resources is always in a distributed state (Peng and Dai, 2019; Ning et al., 2021; Meng et al., 2019), Monte Carlo method is used to verify the regular density of resource samples. It is assumed that the probability density of each English information-based teaching resource sample is independent of other resource samples. The calculation method of probability density is as follows:

$$P(V_K) = K_3 \int_0^1 eK_3 dt \tag{11}$$

where K_3 represents the parameters of nonlinear ultra dense network; $e(t)$ represents the importance function.

Since the stability of resource sharing cannot be guaranteed (Liang et al., 2019), which leads to difficulties in resource sharing, the above formula needs to be corrected to obtain the probability density calculation formula of linear English information teaching resource samples as follows:

$$P(V_{KO}) = K_D \frac{de(t)}{dt} \tag{12}$$

where K_D represents the parameters of nonlinear super dense network.

Normalise the above functions, change the weight of English information teaching resource samples again to make them present a recursive state (Li and Perez, 2020), and share the resources after reaching the same resource sample. The sharing formula is as follows:

$$\left[I_x v + I_y u\right] = (x, y) \tag{13}$$

where $[I_x v + I_y u]$ represents the shared result; v represents sharing speed; u represents the shared distance; I_x represents horizontal shared resources; I_y stands for vertically shared resources.

4 Experimental simulation and analysis

4.1 Experimental scheme

In order to verify the practical application performance of English information-based teaching resource sharing based on deep reinforcement learning, a simulation experiment is designed. Selected in this paper based on the depth of reinforcement learning English the informationisation teaching resources sharing method (hereinafter referred to as the DRL sharing method) with the traditional based on multi-agent Q learning English the informationisation teaching resources sharing method (MAQ) sharing method, based on The Times calendar calculation method of English informationisation teaching resources sharing (hereinafter referred to as traversal sharing method) based on neural network and information-based teaching English Experimental simulation and comparative analysis are carried out by using NNA sharing method to analyse the practical application performance of four kinds of resource sharing simulation.

4.2 Experimental environment parameters

The ultra-dense network is established based on the 5G network standard, the Tensorflow 1.4.0 simulation platform is used to complete the modelling operation, and the MATLAB data display platform is used for experimental display. In the experiment, the location of the macro base station is fixed, the deployment of the small base station meets the randomness, and the channel model between the small base station and the user is simulated using standard Rayleigh fading. The experimental parameters set are shown in Tables 1 and 2.

Table 1 Experimental parameters 1

Parameter	*Value*
Maximum transmit power of small base station	30 dBm
Historical traffic size	5 bit
Noise power	95 dBm
Encoder size	70
Decoder size	70
Action sampling	100
LSTM layers	1

Table 2 Experimental parameters 2

Parameter	*Value*
Ultra dense network size	200 m * 200 m
Channel bandwidth	10 M
Number of resource blocks	20
Fixed operation loss of small base station	1 W
Learning rate	0.1

In addition to the above experimental parameters, the experimental parameter nodes are designed based on the ultra dense network. The node allocation of English information education resources is shown in Table 3.

Table 3 Allocation list of super dense network shared resource nodes

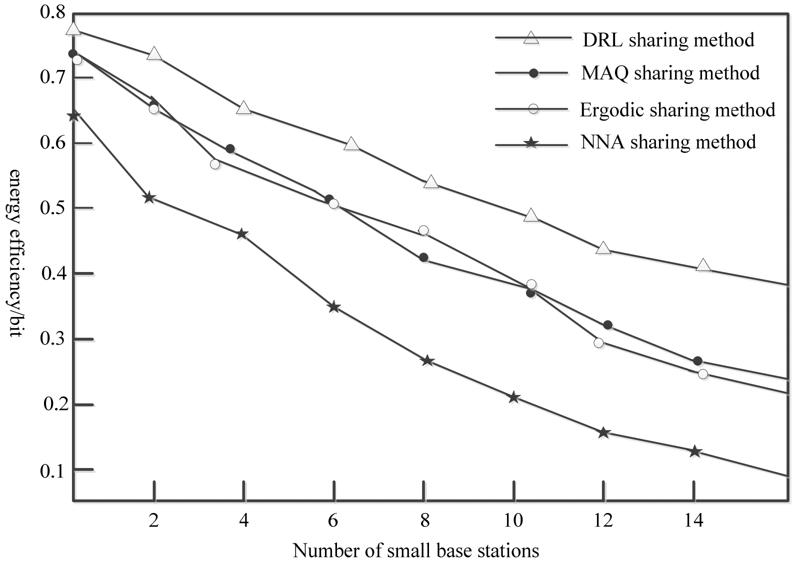
Number	*Number communication capability*	*Sharing capability*
1	0.25	230
2	0.26	196
3	0.19	235
4	0.22	245
5	0.24	210
6	0.28	247

4.3 Analysis of experimental results

4.3.1 Resource sharing performance analysis

Use energy efficiency as the evaluation index to judge the sharing performance of the four sharing methods. The comparison of energy efficiency of the four sharing methods under different base station densities is shown in Figure 4.

Figure 4 Comparison of energy efficiency of four sharing methods under different base station densities

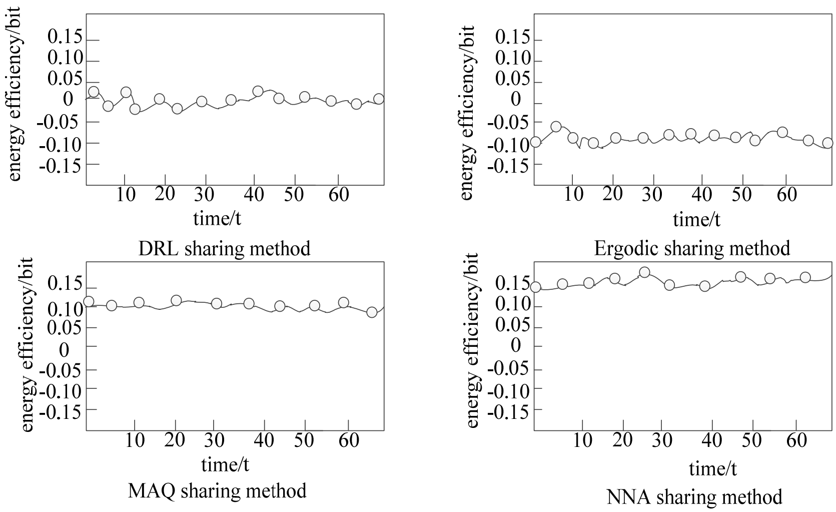


As can be seen from Figure 4, the energy efficiency of the four resource sharing methods decreases in varying degrees with the increase of base station density. Among them, the decline of NNA sharing method is the largest, and the decline of MAQ sharing method and traversal sharing method is smaller. Compared with the above three sharing methods, the DRL sharing method studied in this paper has less decline. When the number of small base stations increases to 12, the average sharing energy efficiency is about 1bit/J, which has better energy efficiency performance. The reason for this phenomenon is that with the increase of the number of small base stations, the noise interference in the process of resource sharing is more serious, and the energy consumption of data sharing is increased. Three traditional resource sharing methods, such as NNA, MAQ and traversal sharing method, ignore the signal interference, resulting in the decline of energy efficiency. The DRL resource sharing method studied in this paper jointly optimises the depth enhancement model, calculates the signal-to-noise ratio and modifies the channel gain, so as to effectively reduce the signal-to-noise intensity and ensure the energy efficiency of resource sharing.

4.3.2 Adaptive capability and stability analysis of resource sharing

The number of fixed small base stations is 12. Regardless of the signal interference in resource sharing, the energy efficiency fluctuation curves of the four resource sharing methods in the same period are shown in Figure 5.

Figure 5 Energy efficiency fluctuation curves of four resource sharing methods in the same period

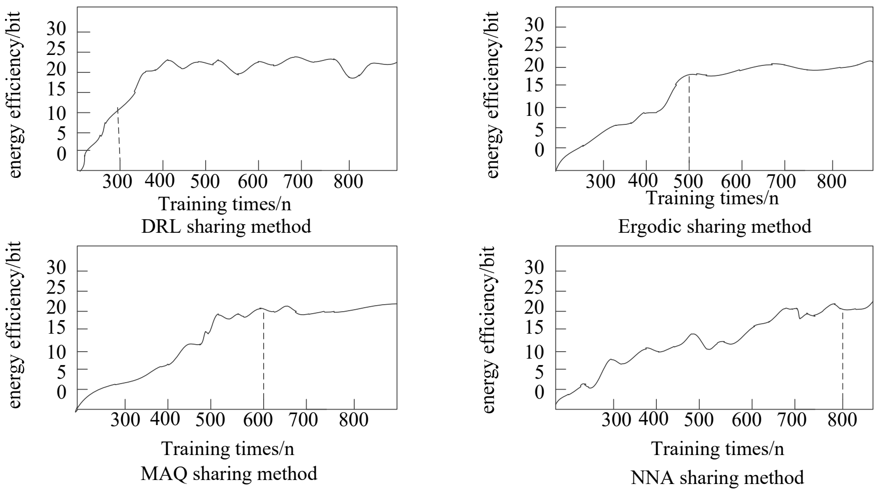


It can be seen from Figure 5 that when the number of small base stations is 12, the average energy efficiency fluctuation of NNA sharing method is +0.1, the average energy efficiency fluctuation of MAQ sharing method is +0.15, the average energy efficiency fluctuation of traversal sharing method is –0.1, and the average energy efficiency fluctuation of DRL sharing method studied in this paper is ±0.05, It can be concluded that the DRL sharing method studied in this paper has stronger adaptability and higher stability of resource sharing. The reason is that at every moment, the number of users in the ultra dense network is in a dynamic state, and the agent constantly adjusts the resource sharing strategy according to the changes of the network environment, resulting in a certain degree of energy efficiency fluctuation. The NNA sharing method has poor adaptability and is not sensitive to the change of the number of users, resulting in large fluctuations in energy efficiency. The MAQ sharing method and traversal sharing method have the problem of improper adjustment of resource sharing strategy, resulting in poor stability of resource sharing. The DRL sharing method studied in this paper can sensitively respond to the dynamic change of the number of users, use the Monte Carlo simulation method to predict the flow direction of resources, correct the node parameters with reference to the prediction results, and modify the parameters only for the resource sharing model of deep reinforcement learning without affecting the operation of other structures, so as to maintain the stability of resource sharing.

4.3.3 Convergence comparison

Convergence determines the efficiency of resource sharing. This paper compares the convergence of four resource sharing methods when the number of small base stations is 12. The convergence comparison results are shown in Figure 6.

Figure 6 Comparison of convergence of four resource sharing methods



According to Figure 6, the NNA sharing method converges when the number of resource training reaches 800, the MAQ sharing method and the ergodic sharing method converge when the number of resource training reaches 600 and 500 respectively, while the DRL sharing method studied in this paper converges when the number of resource training reaches 300. Therefore, it can be concluded that the DRL sharing method studied in this paper has better convergence, resource sharing is more efficient. The reason for this difference is that the DRL sharing method studied in this paper is based on the joint optimised deep reinforcement learning model, combined with the resource sharing model to train the resource samples, simplify the training process, conduct resource analysis based on error calculation, and use test data to verify the accuracy of model training, which greatly improves the efficiency of resource training, the other three traditional forms of resource sharing methods have too many training steps and difficult algorithm calculation, resulting in poor convergence and low resource sharing efficiency.

5 Conclusions

In the super dense network, in order to ensure the stability and energy efficiency of English information education resource sharing and reduce signal interference, this paper proposes English information teaching resource sharing based on deep reinforcement learning. Firstly, the deep reinforcement learning model is constructed to define the state space, action space and return function of the agent. It also expounds the resource sharing mechanism between the macro base station and the small base station, uses the joint optimisation method to optimise the model and improve the application performance of the model, generally summarises the English information teaching resource sharing process based on deep reinforcement learning, and discusses the application mechanism of the resource sharing model of deep reinforcement learning. It can be seen from the experimental analysis, compared with the other three resource sharing methods, the resource sharing method studied in this paper has stronger application performance and higher practical value, and is more suitable for the construction of English information education.

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