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Research Article

A Study Of Innovative Technologies for Energy-Efficient Enterprise Management of Wireless Heterogeneous Networks in Collaborative Communications

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ABSTRACT

Collaborative communication technology has become a popular research area in wireless communications due to its ability to resist varying degrees of channel fading through the collaborative transmission of network nodes. This thesis focuses on energy-efficient collaborative communication systems in increasingly complex environments in heterogeneous wireless networks, with the aim of optimizing energy efficiency and improving user data rates in small areas (e.g., within an enterprise). A brief introduction to the basic technologies of wireless energy-carrying collaborative communication systems is given, summarising relay forwarding strategies, three basic communication models, and energy and information co-transmission reception mechanisms before proposing an ED-OEH relaying protocol at the end of the section that integrates energy classification and opportunity energy harvesting. Immediately afterwards, the heterogeneity of network nodes in terms of computation and storage is pointed out, and a sensor network security protocol based on a hybrid encryption regime is designed. Finally, the problem of intra-enterprise resource allocation and energy efficiency optimization in heterogeneous wireless network scenarios based on deep augmented learning algorithms is investigated. Nature DQN is used as the core algorithm, and the input dimension and loss function in traditional neural networks are improved to reduce the complexity of the algorithm. Experimental results show that the Nature DQN algorithm converges faster than traditional algorithms such as Q-learning, and the energy efficiency ratio can reach up to 300%.

Keywords: Heterogeneous Networks, DQN, Collaborative Communication, Resource Optimisation, Enterprise Management.

INTRODUCTION

The concept of collaborative conversation can be traced lower back to lookup on relay channels in the 1960s. In the aforementioned study, the hassle of data supply node-relay node-destination node conversation was once specified, and in addition, potential bounds for the relay channel have been given. Subsequently, the literature [1] pointed out that a three-terminal device ought to be decomposed into a multiple-access channel and a broadcast channel. Most of the early research targeted the capability bounds of the channel. However, with the introduction and improvement of coding strategies and Multiple-Input Multiple-Output (MIMO), tutorial hobby in collaborative communications has grown exponentially. Research has proven that introducing collaborative verbal exchange in standard cell networks is a high-quality capacity for growing gadget ability and information rates, decreasing strength consumption and hardware costs. Collaborative conversation permits single-antenna cellular terminals to share their antennas via sure rules, growing digital MIMO links, thereby gaining spatial variety and efficaciously mitigating the unfavourable outcomes of channel fading in the verbal exchange system[1], [2]. In collaborative communications, a massive wide variety of collaborative transmission schemes are unexpectedly emerging, based totally on the sign processing and implementation techniques of the relay nodes on the one hand,

and Laneman et al. classify relaying strategies into constant and adaptive relays, the place constant relays encompass Decode-Forward (DF) and Amplify-Forward (AF). Compared to direct transmission, constant relay schemes require two-time slots for facts transmission and may also drastically decrease throughput.

Wireless useful resource administration refers to the allocation and sharing of multi-dimensional Wi-Fi sources such as space, time, frequency, and electricity through aid scheduling algorithms to furnish providers with excellent assurance for Wi-Fi consumer terminals inside the network [3]. The simple beginning factor is to flexibly allocate and dynamically modify the on-hand sources of the Wi-Fi transmission phase and the community to maximize the utilization of the Wi-Fi spectrum, thereby stopping community congestion and preserving the smallest viable signalling load in the context of uneven distribution of community visitors and fluctuations in the channel due to fading and interference. The main research topics involved in wireless resource management include power control, channel allocation, scheduling techniques, switching control, call access control, etc.

A heterogeneous Wi-Fi community consists of nodes that have both LTE or WIFI technological know-how together. LTE, in many instances, recognized as 3.9G, has information download functionality of 100Mbps and is considered the dominant science in the evolution from 3G to 4G [4], [5]. It used to be delivered as a completely packet-switched optimized gadget primarily based on the Internet Protocol and radio to get admission to community architecture, as distinct in the 3GPP specification. The key science of the LTE machine is the orthogonal frequency division of more than one access, the place where the channel bandwidth is divided into a couple of useful resource blocks.

With the rapid deployment of low-power nodes in macro base stations, heterogeneous wireless networks have become increasingly complex but have also seen performance improvements. These low-power nodes include cellular cells (for improved indoor coverage, traffic offloading, and cost reduction) and latency nodes (for improved cell edge performance, reduced power consumption, and increased user capacity) as well as pico-cells (which rely on the same backhaul and access functions as macro-cells and are deployed in a centralized manner), which form the main components of a heterogeneous wireless network. Figure 1 illustrates the architecture of a heterogeneous network consisting of these nodes and devices.

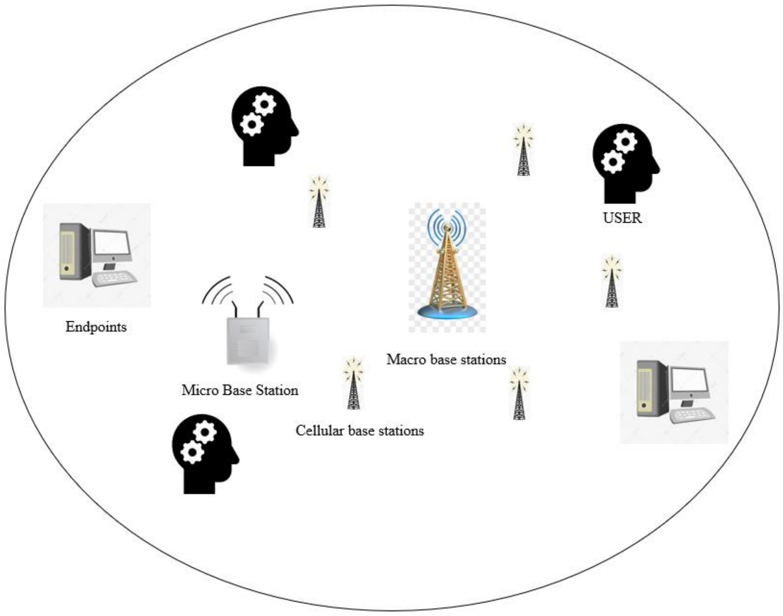

Figure 1. Heterogenous Network Architecture Diagram

LITERATURE REVIEW

Analysis of Energy-carrying Collaborative Communication Technology

During the research of collaborative communication, scholars have proposed a variety of collaborative communication models, which can be divided into the following models from the perspective of topology. As shown in Figure 2 is a diagram of the relay management center system.

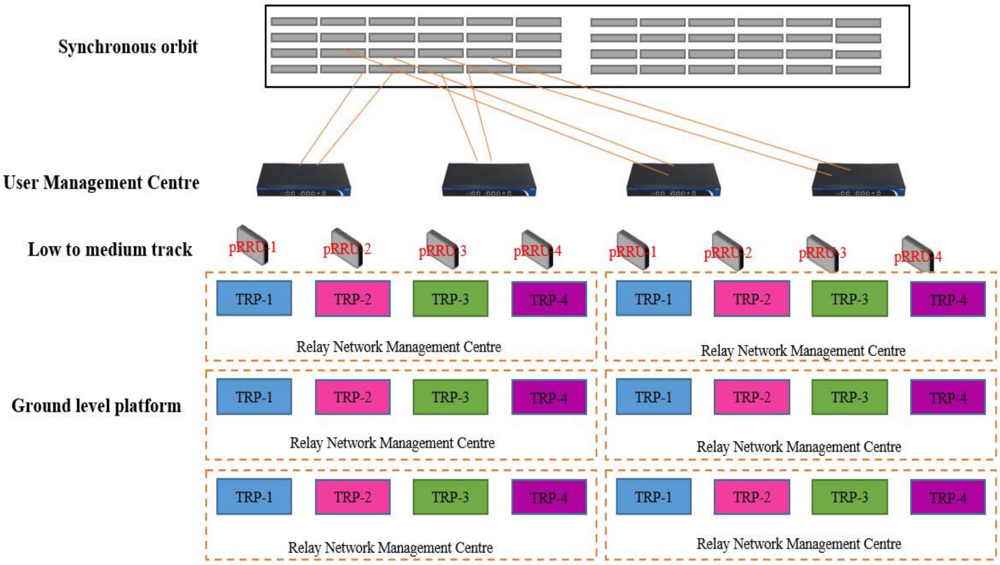

Figure 2. System Diagram of the Trunking Management Centre

Two-hop Single-trunk Model

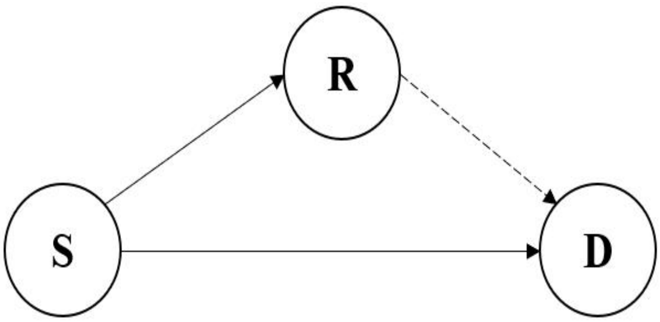

Figure 3. Two-hop Single-relay Collaborative Communication Model

The single relay mannequin is the easiest and most frequent mannequin for collaborative verbal exchange systems; as proven in Figure 3, the place all nodes protected in the model are running in a single-antenna half-duplex mode, as proven below. The facts transmission is divided into two phases; the first section is when the supply node sends the identical sign to the relay node and the goal node, i.e., the broadcast process; the 2d section is when the supply node does not ship data and the relay node forwards it to the goal node. In the 2d stage, the supply node does now not ship records, and the relay node forwards the data to the goal node, which receives the indicators in both degrees with the aid of the skill of a merging technique. During the verbal exchange method, channel fading due to transmission distance or noise makes the straight-through hyperlink; s-d can also now not exist [6].

Two-hop Multi-relay Model

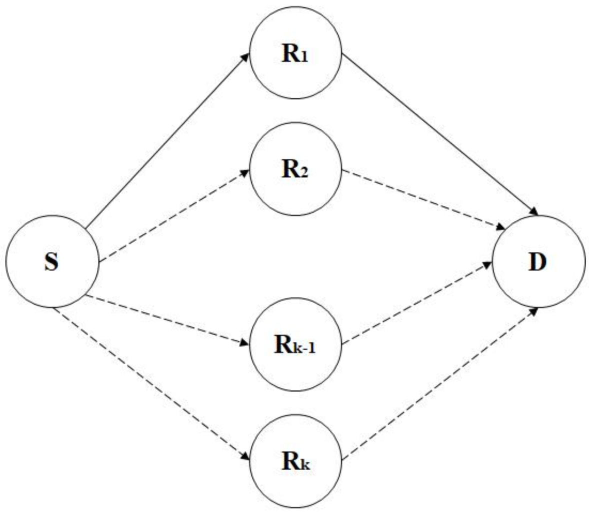

Figure 4. Two Multi-relay Collaborative Communication Models

In the single-relay model, when the signal-to-noise ratio of the receiving or forwarding hyperlink is under a positive threshold, it will lead to sign distortion at the receiving end, making the transmission error fee tons higher. In order to resolve the shortcomings of the single relay model, the conversation machine can use more than one relay to collaborate to transmit records and enhance the reliability and vast vicinity insurance of the transmission process[7], [8]. As proven in Figure 4, the machine selects one or extra relays in the relay cluster that meet the transmission prerequisites to operate statistics transmission in accordance with the relay determination scheme. The coordination procedure of relay choice normally makes use of two mechanisms: centralized and allotted coordination.

Multi-hop Multi-Relay Model

As the wireless transmission distance increases, the transmission quality of the signal will be significantly degraded. Therefore, the signal transmission process over long and medium distances requires multi-hop relaying to ensure the signal quality and avoid signal distortion. As shown in Figure 5, multi-hop relaying can effectively extend the distance of wireless transmission.

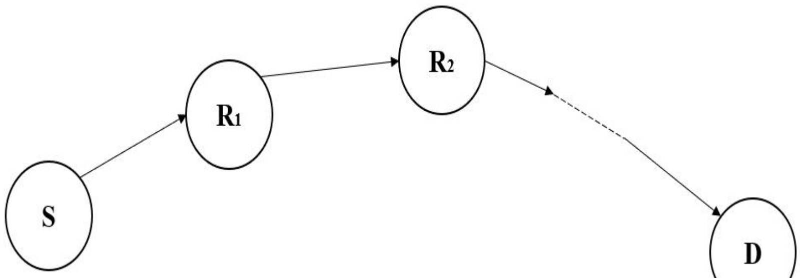

Figure 5. Multi-hop Multi-relay Collaborative Communication Model

Two-way Relay Model

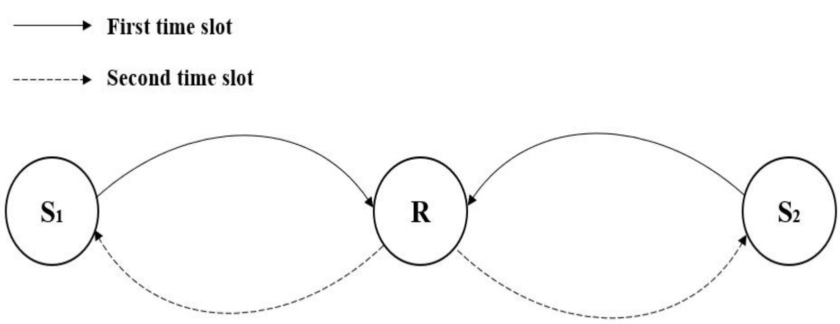

Figure 6. Two-way Relay Collaborative Communication Model

The preceding three fashions all have a half-duplex operation, which affects low spectrum utilization. In order to enhance spectrum utilization, the idea of two-way relaying, which allows statistics to be exchanged between nodes simultaneously, has been proposed in recent years. As proven in Figure 6, there is no straight-through hyperlink between the two supply nodes. In the first time slot, the relay receives indicators from two supply nodes at equal time and performs BIT or, in the second time slot, the relay encodes and modulates the acquired alerts and sends them to the two supply nodes respectively, and the supply nodes achieve the corresponding records thru self-interference cancellation.

RF Energy Harvesting Technology

Traditional energy harvesting methods mainly include solar, wind, tidal and thermal energy harvesting methods. These energy collection methods can meet the general power supply requirements, but in harsh conditions, the density of the energy source can not meet the requirements of the conversion magnitude, and it will cause communication interruption. Obviously, traditional energy harvesting methods are largely limited by environmental factors and cannot guarantee the stability of wireless portable collaborative communication systems[9]. With the rapid development of wireless communication technology, the RF signal in the environment is becoming more and more widely distributed, so the RF signal becomes a stable energy harvesting source.

The hardware structure of RF energy harvesting mainly consists of an RF receiving antenna, impedance matching circuit, RF-DC charge pump, energy storage circuit, and load, etc., as shown in Figure 7, which requires the RF receiving antenna to operate at the same frequency as the received signal.

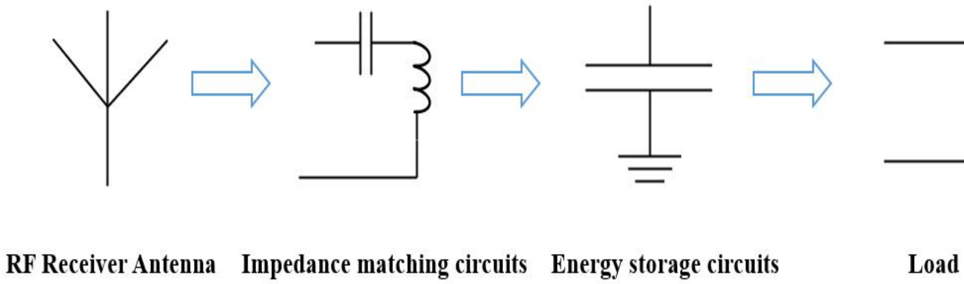

Figure 7. Hardware Architecture of RF Energy Harvesting

Relay Energy Harvesting Mechanism

(1) Time-switching Reception Mechanism

The TS receiving mechanism processes the received signal when it is received, dividing each time slot into three parts $\alpha T, (1-\alpha)T/2$、$(1-\alpha)T/2$ according to the time allocation factor α, where $0 \le \alpha \le 1$. First, in the αT time slot, the relay node uses the energy conversion circuit to collect energy from the RF signal sent by the source node; in the first (1-a)T/2 time slot, the relay node receives the source node information and processes the signal according to the corresponding relay protocol; in the latter (1-a)T/2 time period, the relay node uses the energy collected in the aT time period to assist in forwarding the signal received in the first (1-a)T/2 time period to the target node. This is shown in Figure 8.

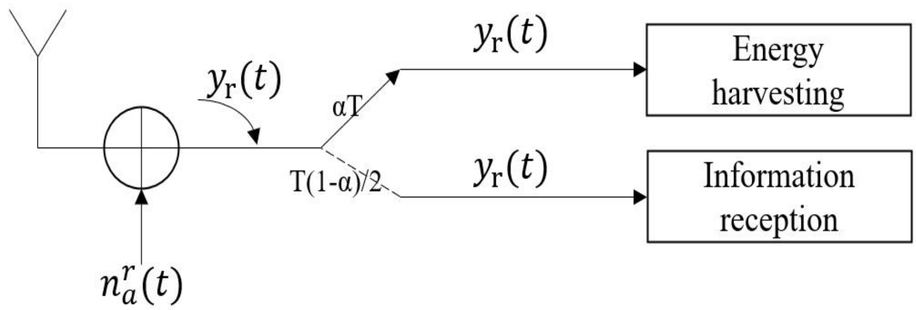

Figure 8. Time-distribution Receiver Structure

As shown in Figure 8, the relay receive signal y_r of the TS receiver structure is represented as

$$y_r = \frac{1}{\sqrt{d_{SR}^m}}\sqrt{P_s}hs(t) + n_a^r(t) \qquad (2.1)$$

Where d_{SR}^m means the distance from the source node to the relay node, m denotes the fading channel factor; P_s

is the source node transmit power, h is the channel gain, s(t) denotes the normalized signal sent from the source node to the relay node, i.e., $\mathrm{E}\{|s(t)|^2\} = 1$, $\mathrm{E}\{\cdot\}$ denotes the mean value, $|\cdot|$ denotes taking the absolute value, and $n_a^r(t)$ denotes the Gaussian white noise at the relay node. The forwarding power is denoted as

$$P_t^{\mathrm{TS}} = \frac{E_h^{\mathrm{TS}}}{(1-\alpha)T/2} \tag{2.2}$$

Where E_h^{TS} denotes the energy collected by the relay node.

α denotes the time allocation factor, and η is the energy harvesting efficiency.

(2) Power splitting reception mechanism

As can be seen from Figure 9, the PS reception mechanism divides the processing time slot into two equal parts, with the first half of the time slot first separating the received signals for energy collection and information reception, respectively, and the second half of the time slot completing the forwarding work. Let P be the power of the signal received by the relay node; in the first half of the time slot, the relay node divides P into ρP and (1- ρ)P according to the power splitting factor ρ. The receiver collects energy for the power value ρP, and the remaining power (1-ρ)P is used as the power of the received message, 0<ρ<1. In the second half of the time slot, the relay node uses the energy collected in the first half of the time slot to forward the received signal to the target node[10].

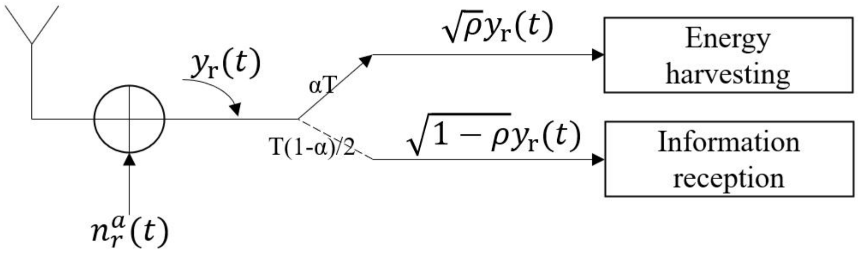

Figure 9. Power Split Receiver Structure

The PS receiver structure is shown in Figure 9, where the forwarding power is expressed as:

$$P_t^{\mathrm{PS}} = \frac{E_h^{\mathrm{PS}}}{T/2} \tag{2.3}$$

E_h^{PS} denotes the energy collected by the relay node, expressed as:

$$P_h^{\mathrm{PS}} = \frac{\rho\eta P_S|h|^2}{d_{SR}^m}(T/2) \tag{2.4}$$

METHODOLOGY

Design of Secure Communication Protocols for Heterogenous Wireless Sensor Networks

Network Initialization

The CA is an offline authentication authority, and the base station and cluster head nodes put up authentication requests to the CA earlier than becoming a member of the network and the CA verifies the identification records of the nodes to be authenticated primarily based on the records submitted by means of the base station and cluster head nodes. The CA will generate the public and personal keys for the node to be authenticated and supply them to the node to be authenticated collectively with the identification certificates of the node via the impervious channel. The base station generates a node ID for every legit frequent sensing node and information it in the official node desk T [11], [12].

The information stored in the BS of the base station includes:

(1) The public key $KEY_{CA_{pub}}$ of CA.

(2) The public key KEY_{pub} and private key KEY_{pri} of the base station itself.

(3) The identity certificate of the base station CER_{BS}.

(4) The one-way key generation function F shared by the whole network

(5) Table of legitimate sensing nodes T.

The information stored in backbone node i includes:

(1) The unique node identification IDi of the whole network

(2) The public key $KEY_{CA_{pub}}$ of CA

(3) Public key KEY_{pub} and private key KEY_{pri} of node i

(4) ID book of node I CER_i

(5) The one-way key generation function F shared by the whole network

(6) Table T of legitimate sensing nodes

The information stored in the common sensing node j includes:

(1) unique node identifier for the whole network: IDj

(2) The master key KEY_j shared with the base station

(3) The one-way key generation function F shared by the whole network

Backbone Node Joins the Network

The spine node wants to complete the two-way authentication and conversation key negotiation between the spine node and the base station to be a part of the network [13]. The two-way authentication procedure of the node is performed with the usage of a digital certificate, and the key negotiation is finished with the usage of the ECDH key alternate algorithm primarily based on ECC.

(1) Two-way authentication between the backbone node and the base station.

The backbone node and the base station complete the authentication and public key exchange by exchanging digital certificates, ensuring that the authenticated party is the certificate holder through the signature mechanism and performing strong freshness authentication through the Nonce mechanism to resist replay attacks.

As shown in Figure 10, the two-way authentication process between cluster head node I and the base station when joining the network is as follows.

a. Cluster head node i sends the authentication request and its own public key certificate to the base station BS.

$$\mathrm{CH_i} \rightarrow \mathrm{BS}: REQ|CER_i \qquad (3.1)$$

b. The base station BS verifies the digital certificate of the cluster head node with the public key of CA, generates a random number N_a if the certificate is valid, and sends the digital certificate of the base station and the random number N_a to the cluster head node i.

c. Cluster head node $\mathrm{CH_i}$ uses CA's public key to verify the validity of the digital certificate of the base station; if it is valid, it generates the random number N_b finds the hash value of the received random number N_a, and then signs the hash value of N_a with its own private key, and finally sends the random number N_b and the signed value to the base station BS.

$$\mathrm{CHi} \rightarrow \mathrm{BS}: \mathrm{Sign}_{KEY_{pi}}\ (\mathrm{Hash}\ (N_a))|N_b \qquad (3.2)$$

d. The base station BS calculates the hash value of the random number N_b and verifies the signature value using the public key of the cluster head node $\mathrm{CH_i}$; if it passes, then the cluster head node $\mathrm{CH_i}$ is legitimate. The base station takes the hash value of the received random number N_b and, signs the hash value with its own private key, and sends the hash value to the cluster head node $\mathrm{CH_i}$.

$$\mathrm{BS} \rightarrow \mathrm{CH_i}; \mathrm{Sign}_{KEY_{pn}}\ (\mathrm{Hash}\ (N_b)) \qquad (3.3)$$

e. Cluster head node $\mathrm{CH_i}$ calculates the hash value of random number N_b and verifies the signed value using the public key of the base station BS; if it passes, the base station is a trusted base station, thus completing the two-way authentication between cluster head node $\mathrm{CH_i}$ and base station BS.

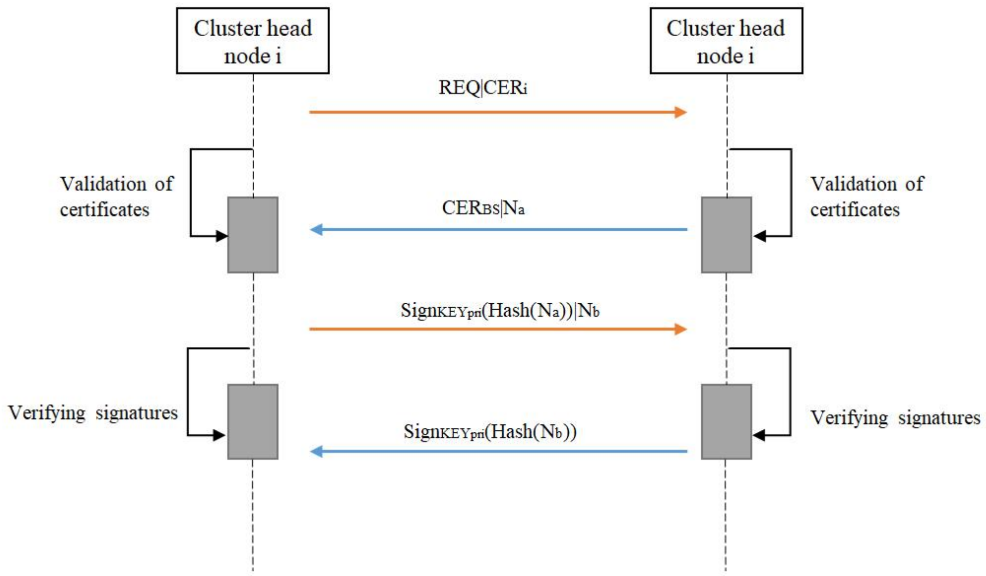

Figure 10. Two-way Authentication Process for Cluster Head and Base Station

(2) Master key negotiation between backbone node and base station

After the cluster head node $\mathrm{CH_i}$ and the base station BS have completed the two-way authentication, they need to generate a shared master key KEY_{master} to further generate the encryption key K_{enc} and authentication key K_{mac} for communication encryption. the master key is generated using the ECDH protocol based on ECC, assuming that the two sides of the negotiation are the cluster head node $\mathrm{CH_i}$ and the base station BS, respectively, $\mathrm{CH_i}$ and BS share the elliptic curve parameters (elliptic curve E, order N, and base point G), and the negotiation process of the master key between the two parties is shown in Figure 11 below[14], [15].

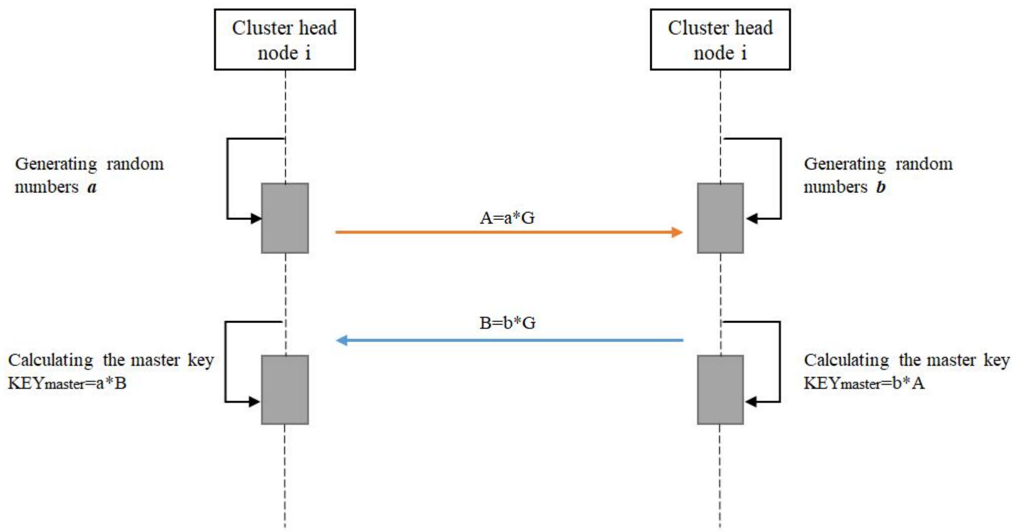

Figure 11. Cluster Head Note and Base Station Master Key Negotiation Process

a. Cluster head node $\mathrm{CH_i}$ generates a random number a and calculates $A = a \cdot G$, then sends A to the base station BS.

b. The base station BS generates the random number b and calculates $B = b \cdot G$, then sends B to the cluster head node $\mathrm{CH_i}$.

c. Cluster head node $\mathrm{CH_i}$ calculates $\mathrm{Q_A} = \mathrm{N_a} \cdot B = \mathrm{N_a} \cdot \mathrm{N_b} \cdot G$.

d. The base station BS calculates $\mathrm{Q_B} = \mathrm{N_b} \cdot A = \mathrm{N_a} \cdot \mathrm{N_b} \cdot G$

At this point, the cluster head node $\mathrm{CH_i}$ and the base station BS finish negotiating the master key, and the master key shared by $\mathrm{CH_i}$ and BS is $KEY_{master} = \mathrm{Q_A} = \mathrm{Q_B}$.

RESULTS and DISCUSSION

Optimization of Energy-efficient Management of Heterogenous Wireless Networks Based on Nature DQN

In long-term evolutionary structures and 5G cellular verbal exchange systems, electricity and aid allocation troubles in wi-fi networks have been studied in academia. With the fast improvement of Wi-Fi communications, networks are getting larger and larger. Especially amongst heterogeneous networks, the wide variety of base stations will increase drastically as the number of customers increases[16]. The hassle of electricity allocation and useful resource allocation requires a rational solution, and an unreasonable allocation scheme can decrease device ability and strength efficiency. Cellular cells are presently being proposed by means of corporations as an answer to the indoor insurance problem. While mobile cells provide sizable advantages to each operator and user, there are a wide variety of challenges that need to be addressed if these advantages are to be totally realized. One of the most daunting challenges is the interference between macro base stations and different cell base stations. Often, cell cells are mounted by means of stop users, so their range and region are random and unknown to the community operator. Furthermore, due to the complicated and dynamic homes of the wi-fi community itself, the extended interference existing at the base stations due to the make bigger cell base stations, and the presence of non-consistent consumer behaviour, it is rewarding to talk about in addition how to allocate assets adaptively in a heterogeneous Wi-fi network[17], [18].

Theoretical Foundations of Deep Augmented Learning Algorithms

Q-learning, as a value function-based reinforcement learning algorithm, has a natural advantage in solving dynamic wireless network environment problems. In the Q-learning algorithm, each agent can converge its own action-value function through successive iterations of learning. This action-value function is generally represented by a value table $Q(s_m, a_l)$, $a_l \in A, s_m \in S$. So, the dimensionality of this value table is m × $1 Q(s_m, a_l)$. Represents the value of the reward accumulated for taking action a_l when the user is in state s_m in a finite time domain, which can be expressed by the following equation.

$$Q_\pi(s,a) = E_\pi[\sum_{k=0}^{\infty} R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) | S_t = s, A_t = a] \qquad (4.1)$$

Since user arrivals and departures follow a Poisson distribution, it is not possible to fully determine the action taken. Thus $Q(s_m, a_l)$ is essentially the mathematical expectation of the long-term reward generated by a strategy.

The goal of the Markov process is to find an optimal strategy, i.e., the one that yields the greatest payoff. the Q update follows the following formula[19], [20].

$$Q_n^{t+1}(s_m^n, a_l^n) := (1-\alpha) Q_n^t(s_m^n, a_l^n) + \alpha(R_n^t + \gamma max \underset{a' \in A}{\overset{t}{max}}(s_m^n, a')) \qquad (4.2)$$

$0 \le \alpha \le 1$ indicates the learning rate.

When the country area is large, it can be time-eating by using discovering the Q values in the Q-value table. In latest years, Deep Neural Network (DNN) has been brought in augmented gaining knowledge of frameworks in order to remedy the hassle of massive country spaces. For example, DQN is the best-known algorithm in which DNNs can match top-of-the-line insurance policies and choicest price features[21], [22].

$$Q^*(s, a, \theta) \approx Q(s,a) \qquad (4.3)$$

θ denotes the parameters of the deep neural network.

In order to ensure the stability of $Q^*(s, a, \theta)$, we train the neural network and evaluate the neural network parameters to minimize $L(\theta)$ so that we can fit $Q(s,a)$ well, where $L(\theta)$ can be expressed as.

$$L(\theta) = E[(\eta(t) + \gamma max Q(s_{t+1}, a_{t+1}; \theta^-) - Q^*(s_t, a_t; \theta))^2] \qquad (4.4)$$

Here θ^- is the parameter of the target neural network, and θ is the parameter of the action network.

In contrast with the preceding Q-leaning, the replacement of the price feature is carried out with the aid of the parameters of the neural community alternatively of the Q cost table. The neural community replace method makes use of a stochastic gradient descent algorithm, so we get that the price characteristic replace follows the following equation.

$$\theta_{t+1} = \theta_t + \alpha[r + \gamma \underset{a}{max} Q(s', a'; \theta^-) - Q(s, a; \theta) \nabla Q(s, a; \theta) \qquad (4.5)$$

Here $r + \gamma \underset{a}{max} Q(s', a'; \theta^-)$ denotes the Temporal Difference (TD) target, and $Q(s, a; \theta)$ denotes the value function target approximated by the neural network. $\nabla Q(s, a; \theta)$ denotes the gradient.

Description Of Energy-efficient Optimization Model for Heterogeneous Wireless Networks

In this subsection, we will quickly describe the bodily state of affairs of the coexistence of macro base stations and mobile base stations in a heterogeneous wi-fi community whilst constructing a mathematical mannequin and giving a mathematical expression for the optimization trouble[23], [24].

Model Description of Heterogeneous Wireless Networks

We consider a heterogeneous wireless network consisting of a macro-cell (containing a macro base station (MBS) with a single transmit and receive antenna) and N_f cellular cells (containing a cellular base station with a single transmit and receive antenna), with the physical network scenario shown in Figure 12. The macro base station is located at the center of the network, and the N_f cellular base stations are distributed within the macro cell coverage area. The geographical distribution of the cellular base stations follows a Poisson process model, assuming transmission over an orthogonal downlink, with the macro base station and cellular base stations sharing K subcarriers, and the macro base station users and cellular base station users located in the macro cell and cellular cell areas respectively, with interference between the macro base station and cellular base stations, and between the cellular base stations[25], [26]. There is also potential interference between cellular base stations. The movement of users is modeled as random wandering when the mth user at time t moves at speed $V_t^m(0 \leq V_t^m \leq V_{\max})$, and the angle of movement is denoted D_t^m as $(0 \leq D_t^m \leq 2\pi)$. Each user can only be connected to one base station at moment t. Each subcarrier can only be allocated to one user, and some of the state information is shared between cellular base stations during the learning process of improving the energy efficiency of the whole network. The channel model is assumed to be a six-path fading model, and the channel model does not affect the final simulation results.

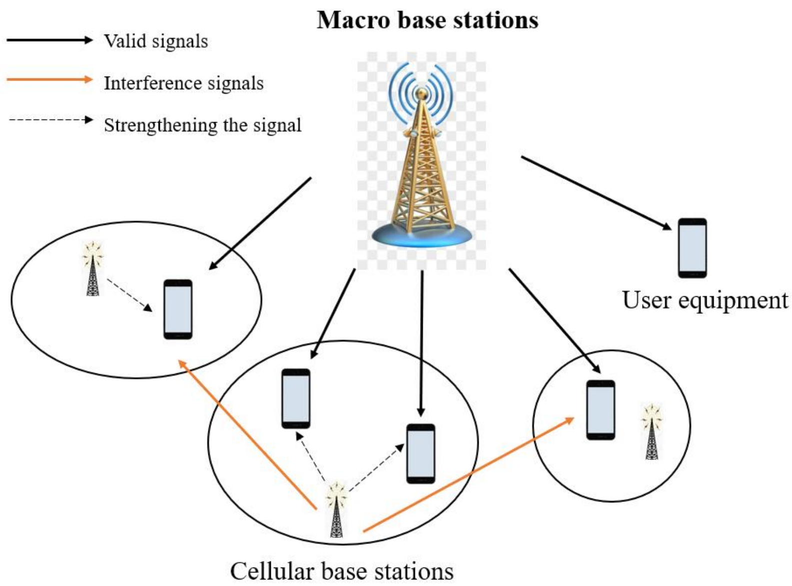

Figure 12. Coexistence Scenarios for Macro and Cellular Base Solutions

For the purpose of explanation, we assume that U_m macro base station users U_f and cellular base station users are located within the coverage area of the macro cell and cellular cell $P_0^{(k)}$, and $P_n^{(k)}$ denote the transmission power of the macro base station and the nth cellular base station on the kth subcarrier, respectively. In addition, the maximum transmission power of the macro base station and any cellular base station is denoted as P_0^{max} and P_f^{max}, respectively, so the following equations are available: $\sum_{k=1}^{K} p_o^k \leq P_o^{max}$、$\sum_{k=1}^{K} p_n^k \leq P_f^{\max}$. The channel of the ith base station and any jth user on the kth subcarrier for any transmit power. The gain is denoted as $h_{ij}^{(k)} = \frac{|G_{ij}^{(k)}|^2}{d_{ij}^{PL}}$, where d_id denotes the distance between the i-th base station and the j-th user. PL is the path loss exponent. $|G_{ij}^{(k)}|$ denotes the fading parameter generated through Rayleigh distribution.

Analysis of energy-efficient model optimization algorithms for heterogeneous wireless networks

Analysis of the augmented learning model

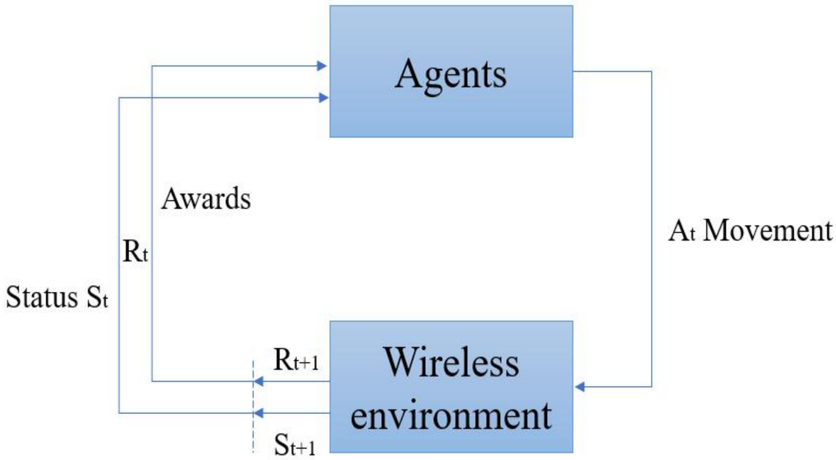

Figure 13. Diagram of the Agent-environment Interaction Process

Reinforcement getting to know views gaining knowledge of as a heuristic contrast process. As proven in Figure 13, the agent makes a motion-based totally on the environment, and when the surroundings receive this motion, the nation of the agent is in changes, and a reward is generated and fed again to the agent[27]. The agent selects the subsequent motion by way of the use of the reward price and the cutting-edge kingdom of the environment. The criterion for determination is the capacity to make bigger the agent's reward, the cumulative value so that the agent obtains the best policy, which is referred to as augmented mastering due to the property of growing reward value. The environment, country, and reward in the graph are the three key factors in augmented learning[28]. We map the residences associated with heterogeneous Wi-fi networks to the national space, motion area, and reward values of the augmented mastering framework based totally on the machine mannequin of heterogeneous Wi-Fi networks in the preceding section. In addition, macro base stations observe the equal mastering manner as mobile base stations, and there is mutual interference between macro base stations and cell base stations, which we mannequin under with mobile base stations as dealers.

Agent: BS n, $1 \leq n \leq U_f$

The state space $S = \{S_1, S_2, \ldots, S_m\}$:Due to the continuity of user mobility and transmit power, the state space of the base station is relatively large, and the size of the Q-value table in the corresponding augmented learning is different for each base station, so we redefine the Q-value table. The specific rules are as follows.

At the moment, for the nth cellular base station on the subcarrier, the state space can be defined as.

$$s_t^{n,k} = \{M_t^n, u_t^{n,k} I_t^k, P_t^n\} \quad (4.6)$$

Here $u_t^{n,k} \in \{1,2,\cdots,U_f\}$ represents the users communicating with the base station on the kth subcarrier at time t. Level of interference from the macro base station.

$$I_t^k = \{\begin{matrix} 1, & C_o^{(k)} < \beta^o \\ 0, & C_o^{(k)} \geq \beta^o \end{matrix} \quad (4.7)$$

β^o is the target capacity at which the macro base station wants to achieve QoS performance. We assume that the macro base station reports $C_o^{(k)}$ to all cellular base stations via backhaul connections .Rate discretization with the following discretization criterion.

$$p_t^n = \tau, (P_{max}^f - A_\tau) \leq \sum_{k=0}^{K} p_t^{n,k} < (P_{max}^f - A_{\tau+1}) \quad (4.8)$$

Reward value $R(s, \vec{a})$:The reward value on the kth subcarrier of the nth cellular base station is related to the magnitude of the energy efficiency that the nth cellular base station can improve the network[29]. The expression for the energy efficiency of a cellular base station is the ratio of the capacity of the cellular base station to the sum of the transmit power of the cellular base station and the macro base station, expressed using η_f. The strength effectivity of the macro base station is expressed as the ratio of the potential of the macro base station to the sum of the transmit energy of the mobile base station and the macro base station and is used collectively as the entry to the deep neural community after augmentation studying is carried out independently via the cell base station and the macro base station. The expression for the reward cost bought by using the cell base station can be described as.

$$r_t^{n,k} = \begin{cases} e^{-(\eta_f-1)^2}, & \sum_{k=0}^{K} p_t^{n,k} \le P_{\max}^f \\ -1, & \sum_{k=0}^{K} p_t^{n,k} > P_{max}^f \end{cases} \quad (4.9)$$

Analysis of the Nature DQN model

First, a deep neural network is shown in Figure 14 and consists of an input layer, a hidden layer, and an output layer. Combining information about the heterogeneous wireless network environment and starting from reducing the input dimension of the deep neural network, we define the input dimension as.

$$\text{inputs}_t = [M_t^1, \ldots M_t^n, \ldots, M_t^N, p_t^{(1,1)}, \ldots, p_t^{(n,k)}, \ldots, p_t^{(N,K)}]$$

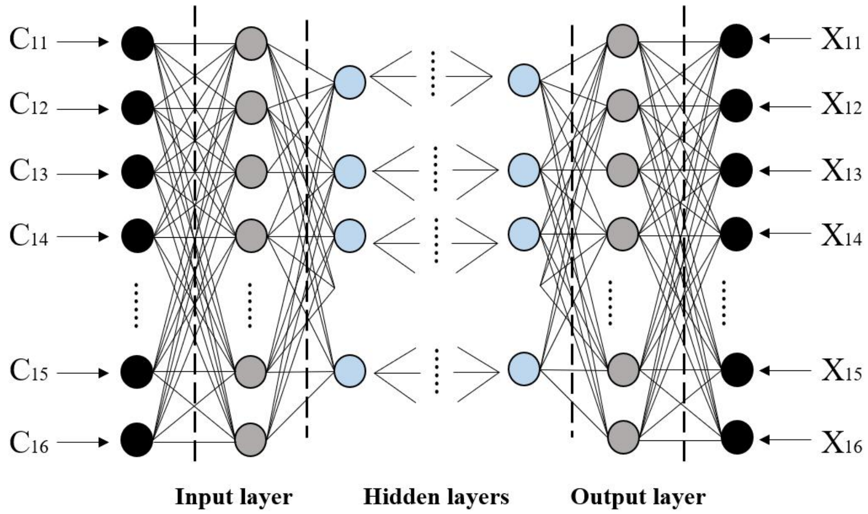

Figure 14. Deep Neural Network Model Diagram

The hidden layer can contain multiple layers of the network and is mainly used to improve the non-linearity and fitting ability of the neural network optimization. The dimensionality of the output layer can be defined as

$$\text{outputs} = [|\vec{p}_t^{(1,1)}|, \ldots, |\vec{p}_t^{(n,k)}|, |\vec{p}_t^{(N,K)}|] \quad (4.10)$$

Deep neural networks use the dropout technique to improve the generalization ability of the network, reduce the network neuron parameters and avoid overfitting. In addition, we use the Adam optimizer to perform backpropagation. To hasten the convergence, the loss function of the deep neural network is defined as.

$$\text{Loss} = \frac{1}{s}\sum_{i=0}^{s}(q_z - o_z)^2 + \frac{1}{min(o_2)} + c \parallel \theta \parallel_2 \quad (4.11)$$

Nature DQN algorithm strategy

In this area, we advise a new algorithm known as Nature DQN. A cutting-edge Q community Q price for choosing the motion and updating the mannequin parameters and a goal Q community Q fee for calculating the goal Q value. Instead of iteratively updating the community parameters of the goal Q-network, the community parameters are up to date. A time is copied from the present-day Q-network Q-value, i.e., delayed update, which reduces the correlation between the goal Q-value and the cutting-edge Q-value and improves the convergence pace of the algorithm. The main difference with DQN is: Nature DQN collects m samples to calculate the current target value y_j by the formula.

$$y_j = \begin{cases} R_j & \text{is\_end}_j \text{ is true} \\ R_j + \gamma \max_{a} Q'(s_j', a_j', w') & \text{is\_end}_j \text{ is false} \end{cases} \quad (4.12)$$

Where w' denotes the parameter value copied from the current Q-network to the target Q-network after a period of time. To reduce the correlation between the target computation and the current value, the loss function can then be computed.

$$Loss = (R + \gamma \max_{a} Q(s', a', w') - Q(s, a, w))^2 \quad (4.13)$$

The above loss function can solve some of the problems of DQN very well, but Nature DQN is not very perfect; it has some drawbacks like DQN, such as the problems caused by random sampling, the accuracy of evaluating action values individually, and the accuracy of target Q values. In order to adapt to the dynamic environment of heterogeneous wireless networks, this paper focuses on optimizing Nature DQN in terms of its convergence speed so that it can reach convergence faster.

Simulation of energy-efficient Nature DQN algorithms for wireless heterogeneous networks

In this section, we evaluate Nature DQN to solve the problem of dynamic resource allocation for heterogeneous wireless networks and thus improve the energy efficiency of the system. First, we present a network distribution diagram for a scenario of multiple cellular base stations coexisting under a macro base station. Then, a Keras architecture diagram of the simulation part of the Nature DQN deep neural network is given. The spectral and energy efficiencies of the three algorithm implementations are then analyzed and explained. The simulation results show that our proposed Nature DQN has better performance than Water-filling and Q-learning. We then compare the two simulation models of Nature DQN implemented under the same random seed after training several times. We then compare the spectral efficiency of Nature DQN for a heterogeneous wireless network system with three levels of power discretization. Finally, we also compare the training time of the Nature DQN after optimizing the DQN with that of the unoptimized DQN by means of a histogram.

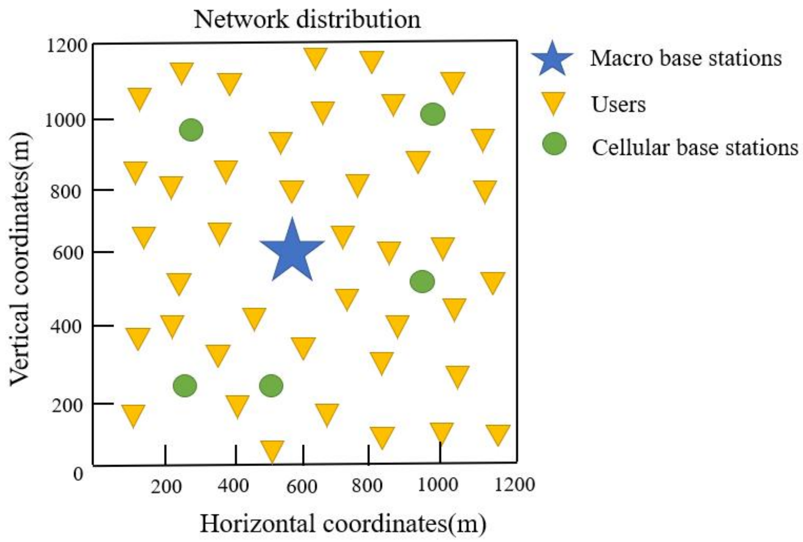

Figure 15. Simulation of the Coexistence Distribution of Multiple Cellular Base Stations Under a Macro Base Station

Figure 15 represents a simulation simulation diagram of the coexistence distribution of macro base stations and multiple cellular base stations in a heterogeneous wireless network. In the diagram, the macro base station is located at the positive center, multiple cellular base stations are distributed around it via Poisson, users are distributed in a 1000*1000 square network via Poisson, and users follow certain rules to walk around randomly.

We set up the relevant experimental platform, as well as the relevant deep learning framework, to compare our proposed Nature DQN algorithm with other algorithms and evaluate them so as to verify the merits of this section.

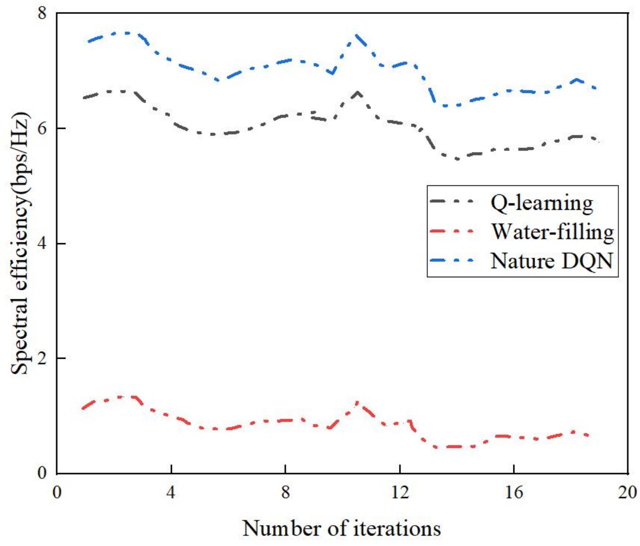

Figure 16. Comparison of the Spectral Efficiency of the Three Algorithms

The spectral efficiency of the three algorithms after simulation is shown in Figure 16, where the spectral efficiency of the three algorithms can be seen for each iteration, i.e., after the user has moved and the network topology has been updated. From this figure, it can be seen that Nature DQN achieves higher spectral efficiency than the Water-filling and Q-leaning algorithms.

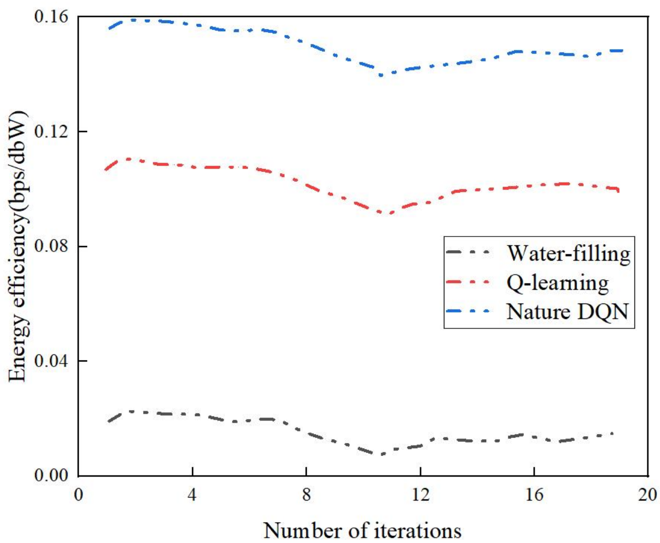

Figure 17. Comparison of the Energy-efficiency of the Three Algorithms

Figure 17 indicates the variant in electricity effectivity of the three algorithms. From the figure, it can be considered that for every iteration, the person strikes and updates the community topology, and the Nature DQN algorithm is capable of reaping greater strength effectivity every time. The Water-filling algorithm, on the different hand, can minimize the transmit strength when the channel prerequisites at some base stations are poor, ensuing in a discount in the power efficiency of the entire network. On the different hand, Nature DQN can adapt to the wi-fi network surroundings and regulate the energy in time, which can enhance the electricity effectivity higher than the Q-learning algorithm. It is in a position to operate higher in the complicated surroundings of Wi-fi networks.

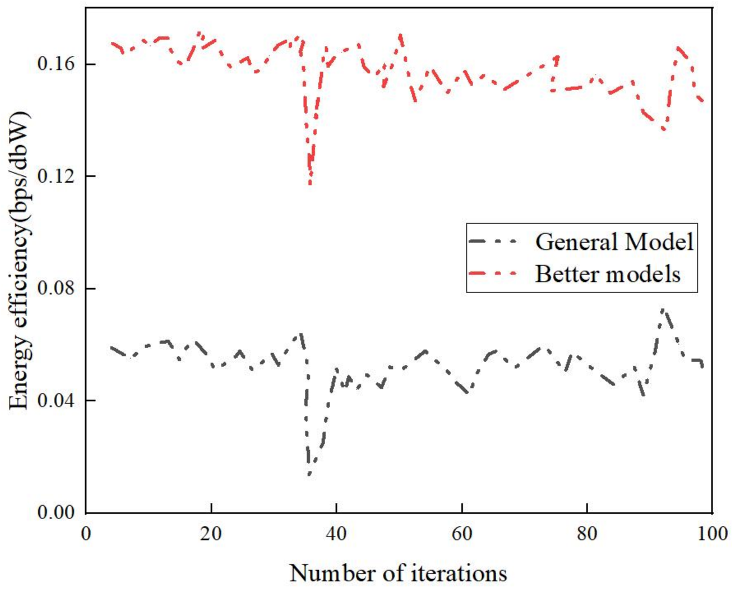

Figure 18. Comparison of the Performance of the Better Training Model and the General Training Model

Figure 18 shows the change in the energy efficiency of the system after multiple Nature DQN trainings for the same random seed case. We have chosen a better-trained model and an average model, and we can see from the simulation results of the two models that the performance of the model may show different results in each training, but after multiple pieces of training, there will be the more robust model, and This better model is the one we need.

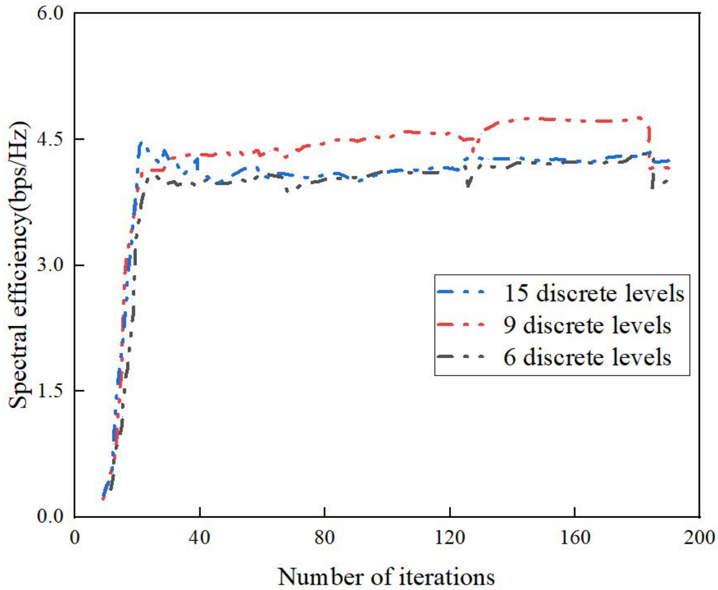

Figure 19. Nature DQN Convergence Plots at Different Discrete Power Levels

Figure 19 shows the trend of the spectral efficiency obtained by Nature DQN after discretizing the base station transmit power at three levels. The results show that when the transmit power is discretized to 15 intervals, it can achieve a more stable spectral efficiency than when the transmit power is discretized to 9 intervals and 6 intervals. When the transmit power is discretized to 9 intervals, it achieves higher spectral efficiency than when the transmit power is discretized to 15 intervals and 6 intervals, but there are significant fluctuations in the convergence process, and the model is unstable. When the transmit power is discretized into 6 intervals, its spectral efficiency is lower than that of the transmit power discretized into 15 and 9 intervals, and the convergence process has obvious fluctuations. In general, the level of discretization can represent the real change in the environment, so we need to find the trade-off of the level of discretization between the training target and the training time.

CONCLUSION

As the modern B5G Wi-Fi community is nonetheless in the exploration stage, how to make certain its community excellent service, electricity efficiency, extension and implementation fees, and different overall performance indications are the key troubles that want to be addressed urgently. In current years, collaborative conversation has turned out to be an essential candidate for technological know-how to tackle these problems by way of correctly taking part in community nodes to make the most variety of good points and effectivity improvements. In view of this, this paper addresses the desires of wi-fi cell verbal exchange to enhance the electricity efficiency, minimize latency and implementation value of organization structures thru collaborative communication, and conducts in-depth lookup on three aspects: the underlying model, the diagram of invulnerable verbal exchange protocols for heterogeneous wi-fi sensor networks and energy-efficient administration optimization algorithms. The principal work is summarised as follows.

(1) Through the evaluation of three present regular safety protocols, such as SPINS, Huang, and CERT, two shortcomings of the lookup on protection protocols for sensor networks in Phase A are pointed out: first, the protocols proposed are often homogeneous, ignoring the heterogeneity of node overall performance and protection requirements; second, the node overall performance is typically based totally on a symmetric key system, which makes the authentication and crypto mining administration complicated. This paper addresses the shortcomings of before protocols and proposes a heterogeneous sensor community safety protocol primarily based on a hybrid key regime by means of analyzing the heterogeneity of the I of sensor networks.

(2) A corresponding energy efficiency optimization model is established based on the physical scenario of the heterogeneous wireless network, and then we discretize the transmit power and use the throughput constraint of the macro base station to reduce the network state space size while improving the input dimension and network parameters of the deep neural network, the loss function, and choosing Nature DQN as the training algorithm, and finally simulating and verifying the improved optimization algorithm with The final simulation verifies that the improved optimization algorithm has substantially improved the performance and stability of Nature DQN compared with Water-filling and Q-learning, and the energy efficiency ratio can reach more than 300% and the convergence speed is more than twice as fast.

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