Research on Agricultural Supply Chain Architecture Based on Edge Computing and Efficiency Optimization

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ABSTRACT
This paper proposes the classification standard of supply chain structure from three different aspects: the complexity of the supply chain node enterprises, the reliability of the supply chain, and the optimization goal. In addition, this article starts from the characteristics of agriculture itself, according to the actual needs of the agricultural supply chain, considers the feasibility of the solution strategy from different sides, and gives related models, which solve the related problems in the agricultural supply chain to a certain extent. At present, there are many resource allocation algorithms at the edge of mobile networks, but the existing resource allocation algorithms still have the problem of high computational complexity and can still solve the above problems in resource utilization optimization. In order to solve these problems, this paper proposes a system architecture of the agricultural industry Internet of Things based on edge computing. The main motivations of this article are to improve the stability and usability of the system, and to enhance agricultural wisdom, so as to provide a reference for the development of precision agriculture. According to this method, Firstly, from the perspective of how to improve the energy efficiency of mobile terminals, methods to improve the energy efficiency of mobile terminals are studied in multi-user systems where mobile terminals compete for MEC servers with limited computing resources. Then, this paper focuses on the waste of computing resources caused by user movement under the scenario of limited server coverage in MEC system and studies the problem from the perspective of effective management of computing resources. Experimental results show that the proposed algorithm has good performance.

INDEX TERMS Agriculture, network, deep learning, Internet of Things, effectiveness.

I. INTRODUCTION
With the development of the economy and society, the economic competition between enterprises or regions has been transformed into the competition of their respective supply chains. As a large agricultural country, the development of China’s agriculture is increasingly dependent on the merits and demerits of its own supply chain, so choosing a suitable supply chain structure for its own development has become the key to the success of regional agricultural economic development [1]. Although China’s supply chain theory has made great progress, there are few research results on supply chain structure, especially on agricultural supply chain structure.

Based on the existing supply chain structure, this paper classifies the structure of the agricultural supply chain according to different standards and analyzes the advantages of each type. We classify the supply chain structure from four different aspects: the complexity of the supply chain, the concentration degree of enterprises on supply chain nodes, the reliability of the supply chain, and the optimization objective.

A. CLASSIFIED BY THE COMPLEXITY OF THE SUPPLY CHAIN
1) CHAINED STRUCTURE
This is a single structure, each node participates in the chain through the upstream and downstream nodes, and has no other contact with each other except the adjacent nodes. This
structure is not common in reality, but as a simple neighboring relationship to simplify the study of the advanced complex supply chain. The basic structure is shown in Figure 1 [2].

2) NETWORK STRUCTURE
This structure is more common and has a certain complexity. Each supplier can serve multiple manufacturers, and each manufacturer can obtain raw materials from different suppliers. The products produced are distributed by different distributors according to different product types or differences in product quality or price, etc. The structure is shown in Figure 2.

B. AGRICULTURAL SUPPLY CHAIN NODE ENTERPRISE CONCENTRATION DEGREE CLASSIFICATION
According to the agricultural supply chain node enterprise concentration degree classification, the practice has proved that in the process of building a supply chain, in order to achieve the “competition-cooperation-coordination” process and finally achieve the goal of win-win, there is always one enterprise (manufacturer, supplier, retailer) as the initiator and becomes the core of the supply chain. Therefore, the agricultural supply chain should also be built around the core enterprises or legal persons, which is conducive to reaching consensus among the nodes of the agricultural supply chain, reducing transaction costs, and improving the operational efficiency of the supply chain [5]. The common structure includes two-level supply chain, three-level supply chain, and multi-level supply chain. The multi-level supply chain centered on distributors and retailers of agricultural products, as shown in Figure 3, is the supply chain structure of most large supermarkets. Most of these large supermarkets have a strong retail network and serve multiple customer groups. It is based on a powerful trading company, which is conducive to the flow of agricultural products logistics, but it is easy to increase the inventory of the whole chain, so this type of structure should mainly solve the inventory problem of the supply chain. Perhaps this type of structure can reduce the inventory and increase the flow speed of logistics, but it cannot guarantee the overall optimal [3], [4].

C. CLASSIFIED BY SUPPLY CHAIN RELIABILITY
According to the current agricultural market environment, what agricultural producers are facing is the survival of the market, and the personalized needs of consumers are enhanced. How to effectively and reliably guarantee the interests of producers and the needs of users is an essential consideration for the establishment of the agricultural supply chain. These categories are all structural types centered on agricultural producers, which can be divided into three categories according to the different reliability of supply chains: OR-type supply chain as shown in Figure 4, AND supply chain as shown in Figure 5, And hybrid supply chain structure. The relationship between suppliers of hybrid structure is a combination of AND and OR, which is common in reality And is also the most stable And reasonable type [6]. There are many kinds of raw materials needed by producers, and there are many suppliers in each raw material industry, and there is fair competition among suppliers in each industry. However,
such a structure must also ensure that the downstream node relations have a certain OR structure.

**D. ACCORDING TO THE OPTIMIZATION OBJECTIVES OF THE SUPPLY CHAIN**

Because supply chain has two kinds of obvious function, namely logistics function and business flow function. The logistics function is to convert raw materials into final products and move them from one node of the supply chain to the next; The function of business flow is to ensure that all kinds of products have a certain market, can meet the needs of customers, and can realize value-added. The implementation of each function requires a certain cost. The sum of business flow cost and logistics cost constitutes the total cost of the supply chain [7], [8]. Therefore, according to the different objectives of supply chain optimization (reducing logistics cost and commercial flow cost), agricultural supply chain structure can be divided into the following two types: cost structure and high flexibility structure. Because functional agricultural products have the characteristics of relatively stable demand, the establishment of the supply chain should focus on reducing logistics cost, which is suitable for the establishment of a low-cost supply chain structure. As the market of innovative agricultural products has great uncertainty, we should consider establishing a supply chain with high flexibility structure to reduce the cost of commercial flow.

Agricultural supply chain structure can be divided into different types, from different angles for each category has its adaptation range, and real-life, the supply chain structure of these different perspectives is often cross each other, so to establish the reasonable structure of agricultural supply chain, must first to the classification of the master supply chain is clear, according to the different situation with different types of structure, Each region should establish its supply chain structure system according to its characteristics and the actual situation.

With the diversified development of mobile Internet services and applications, people’s requirements for data rate and service quality are getting higher and higher. As a key technology in the future communication technology, mobile edge computing can greatly reduce the delay of MEC server to user’s computing task request and response and the possibility of network congestion between transmission network and core network by narrowing the geographical distance between MEC server with rich computing resources and users. For users, since the computing resources and power of mobile devices are limited, unloading tasks to the MEC server can improve the energy efficiency of mobile terminals. However, as users are self-interested, more resources will be wasted in the process of preempting computing resources. In addition, since the user is not stationary and the coverage of the MEC server is limited, the user will repeatedly send the unload request if the calculation result is not received in time after updating the location, resulting in the waste of computing resources. The above two problems are more serious in resource-constrained scenarios, so how to optimize the energy efficiency of mobile terminals in mobile edge computing and reasonably manage server computing resources is worth further study.

In this paper, an agricultural supply chain architecture based on edge computing and efficiency optimization is proposed. Firstly, from the perspective of how to improve the energy efficiency of mobile terminals, methods to improve the energy efficiency of mobile terminals are studied in multi-user systems where mobile terminals compete for MEC servers with limited computing resources. Then, this paper...
focuses on the waste of computing resources caused by user movement under the scenario of limited server coverage in MEC system and studies the problem from the perspective of effective management of computing resources [9].

II. EDGE COMPUTING

The concept of moving edge computing was proposed in 2014 by the newly formed industry specification group within the European Association for Standardization [10], [11]. By physically integrating computing and storage resources into the edge of mobile network architecture, mobile edge computing not only effectively reduces the transmission delay but also solves the problems of high load and high delay caused by mobile cloud computing. The mobile edge computing technology attracted a lot of attention soon after it was proposed due to its rational solutions. Standardization efforts led by operators and equipment manufacturers such as Huawei, Intel, IBM, etc., aimed at finding an effective industrial practice to seamlessly integrate cloud computing capabilities with mobile networks [12]. Finally, users, service providers, operators to achieve a win-win situation. According to the white paper published by ETSI, mobile edge computing mainly includes the following features: distributed architecture, being at the edge of the network, low latency, user location awareness, and network state awareness. Among them, distributed architecture refers to that in mobile edge computing network, computing resources are distributed at different edges of mobile network and computing tasks can be processed independently, rather than the processing mode similar to that in mobile cloud computing, which requires resources to be concentrated and then computing tasks can be processed. This distributed architecture is the basis of mobile edge computing networks with low latency, user and network state awareness, and other outstanding characteristics. At present, mobile edge computing has been recognized as one of the key technologies of 5G and still has great potential. New research and discoveries on mobile edge computing are still emerging in an endless stream [13].

In a mobile edge computing network, there are three types of computing unload, including full unload, partial unload, and local processing. In full unload, the user device unloads all the computing tasks to the mobile edge computing server, and the mobile edge computing server handles all the computing tasks. As shown in Fig. M, in the partial unloading, the local processor in the user device divides the computing tasks reasonably, and the local processor processes the partitioned computing tasks, and the remaining computing tasks are handed over to the mobile edge computing server for parallel processing. Through partial unload, the system can choose to process the part with a low computing amount but large data transmission amount locally, and leave the rest to the server to process, so as to further improve the efficiency and effect of mobile edge calculation. Users can also choose not to unload computing tasks on the local processor when computing resources are sufficient or communication quality is poor. This processing method is called local processing.

In a mobile edge computing network, the delay of a single task usually consists of three parts: unloading the data to the mobile edge computing server, and the time for the mobile edge computing server to process the computing task and transfer the data back to the user device. In the research of minimizing delay problem, the literature solves this problem for the first time by one-dimensional search algorithm, and finds the optimal offload decision policy according to the status of application cache queue. The paper also studies the problem of time delay minimization in computational unloading. Compared with previous studies, the paper further considers the user’s use of dynamic voltage and energy harvesting techniques, and uses a low-complexity dynamic unloading algorithm. Simulation results show that the dynamic unloading algorithm can reduce the time delay by more than half, and can completely prevent the loss of unloading.

Similar to computing unload, resource allocation is one of the core issues in moving edge computing. In the mobile edge computing network, content caching, super-dense deployment, and other technologies are introduced to deploy multiple resources to the edge of a mobile network according to the specific needs of users, which can further guarantee the quality of service and improve the system capacity to a great extent. However, due to physical volume, power consumption, and other objective reasons, the edge of the mobile network have very limited computing resources, storage cache capacity, and spectrum resources. How to allocate multiple resources and improve the service efficiency of the system plays a huge role in improving the performance of the mobile edge computing network system. Because of the interaction between different resources, the system must design and consider multiple resource allocation schemes as a whole, which greatly increases the complexity of resource allocation in mobile edge computing networks.

The energy consumption of user equipment is often one of the key issues to be considered in the calculation of unloading. How to minimize the energy consumption of user equipment under the premise of meeting the delay requirements has become the focus of many literature studies. The energy consumption of the user equipment is mainly consumed in the process of transmitting computing tasks to the mobile edge computing server and receiving computing results from the base station. The literature was first studied based on this scheme. This paper presents the optimization problem as a constrained Markov decision process. The author puts forward an algorithm using online learning and an algorithm using off-line predictive computation to solve the problem. The simulation results show that the performance of the system can be greatly improved by using offline prediction. Due to the continuous power input at the base station side, the energy consumption at the base station side is usually not taken into extra consideration. However, for some cases, such as the energy collection base station, it is also necessary to add the energy consumption restriction at the base station side in the process of problem optimization.
mainly considering the resource allocation algorithms of multiple computing nodes. Resource allocation algorithm for the system of resource allocation, edge mobile computing network, resource types, including computing resources, communication resources, cache resources, computing resources usually need to consider the user itself the task of computing power and complexity, the channel of communication resources and system state and capacity, etc, and the cache resource consumption is closely related to the user. According to the optimization objectives, the existing algorithms are divided into three categories: resource allocation algorithms based on time delay and energy consumption, resource allocation algorithms based on communication and computing load balancing, and resource allocation algorithms based on system benefit.

### A. RESOURCE ALLOCATION ALGORITHM BASED ON TIME DELAY AND ENERGY CONSUMPTION

Most of the existing resource allocation algorithms for moving edge computing aim at minimizing the time delay or energy consumption. The literature proposes a scheme that minimizes the computing processing delay by allocating computing resources in the base station cluster of a small cell without the use of the core network = the cluster is formed through a joint game, in which a small base station will give monetary incentives if it performs computations on user devices connected to other small base stations. Associations of small base stations are generated over some consecutive periods, after which new associations are generated continuously. First of all, the working cell base station tries to provide service for the user equipment it is responsible for from the communication delay is minimal. When a small base station cannot handle a task by itself, the task is submitted to all the small base stations in the same cluster. The results show that the proposed scheme can reduce the execution delay by 50% and the delay of all the small base stations in the system can be reduced by 25%, compared with the calculation only at the attached small base stations [15].

Literature further studies the cluster size of small base stations and the influence of cluster size on delay and energy consumption, and considers the influence of the generation of new clusters on the processing tasks. The analysis includes several backhaul topologies (such as closed loop, tree, grid, etc.) and techniques. The author demonstrates that this structure can effectively reduce the user delay. At the same time, the structure composed of wired closed loop can effectively improve the energy consumption effect of the system. In addition, too many small cell base stations may lead to transmission delay increase, and lead to computing processing delay increase. With the increase of small cell base station, the system energy consumption is also gradually rising. Therefore, the design of cluster and the selection of computing nodes are also key factors affecting network performance.

Because of the above problems, Literature studied the optimal scheme for the formation of small base station clusters.

### III. PERFORMANCE-OPTIMIZED DATA CENTER

This section summarizes and analyzes the resource allocation algorithms in the existing mobile edge computing networks, including the entities and functions involved. The system framework shown in the figure is divided into mobile edge system-level, mobile edge host level, and network-level entities. The mobile edge host level is the basic part of the MEC framework, which is composed of mobile edge host and mobile edge host-level management. Mobile Edge Host provides mobile edge applications with infrastructure and computing and storage functions that virtualized network resources, as well as a set of basic functions needed to execute applications, namely mobile edge platform, which will greatly facilitate the processing of mobile edge applications. The underlying network layer provides interactivity for a variety of access, including the 3GPP network, the local network, and other external networks, such as the Internet. Horizontal management of mobile edge system provides convenience for the access of user terminal and third party.

MEC server has a large number of computing and storage resources, and the server provides MEC services in the MEC system [14]. The location of the edge server and the supply of computing resources are complementary to each other, and both are limited by the deployment budget. Therefore, the deployment of the server largely determines the efficiency of the MEC system. MEC can be flexibly deployed in different locations. According to the version of MEC released by the ISG (Industry Specification Group), it can be implemented in an outdoor environment, such as LTE and 3G sites, or indoor environment, such as shopping malls and hospitals, and other areas with heavy traffic.

Joint management of wireless and computing resources is the key to an efficient, low-latency MEC. The network architecture that coexists MEC servers and wireless access points, such as base stations and Wi-Fi routers, facilitates the implementation of these technologies.

![Structure of MEC](image-url)

**FIGURE 6. Structure of MEC.**
The goal of the scheme was to obtain the optimal time delay or energy consumption. In this paper, the author proposed three different clustering strategies. Since all the small base stations in the system model are single-hop interval (such as the full grid topology), almost all the small base stations participate in the calculation, so the calculation gain is far greater than the processing delay, which greatly optimizes the calculation processing delay. The second clustering strategy aims to optimize the total energy consumption of the cluster. In this case, only the computing node providing the service will process the computing task, and other nodes in the cluster will not participate in the computing. In this way, up to 61% of the energy consumption can be saved. However, this way will not only greatly increase the time delay, but also greatly reduce the stability of the system. The third cluster strategy is to minimize the energy consumption as the goal of each base station clusters. The target is to ensure that each cluster the equilibrium between the energy consumption, 2 in strategy, the energy consumption of the different cluster difference is very big. Considering the differences between cluster related strategy is designed. Based on literature and literature considering the multi-user scenarios of the equipment. Compared with the literature, each time the user equipment to unload computing tasks, will the user equipment belongs to the cluster. Therefore, each user equipment belonging to a cluster size depends on the application and the demand of the user equipment. The core idea of the proposed method is to based on all the active user requests so that in all the user equipment to obtain the optimal the most efficient way of distribution. Its main goal is to ensure that each user required time delay under the premise of minimizing the energy consumption of the cluster. The optimal strategy of cluster in meet users can significantly superior to consecutive clustering optimization static clustering optimization and cluster solution. On the other hand, the average energy consumption is also significantly higher than that of continuous no cluster and cluster optimization scheme. In Literature, the author considered a multi-user mobile edge computing structure based on wireless network. In this paper, the author achieved joint task allocation and resource allocation with the goal of minimizing the energy consumption of the mobile terminal under the requirement of certain time delay. And demonstrates the effectiveness of the algorithm in the simulation literature. I consider a variety of categories exist in the edge of the mobile network server, and the calculated unloading of system and resource allocation algorithm is optimized, the author considers the network in a variety of limiting factors, and puts forward a kind of high efficient mathematical methods for energy consumption and delay are optimized. Literature considered the Noma technology-based mobile edge computing network between devices and carried out joint optimization of computing resource allocation, energy consumption and channel allocation in order to obtain the optimal time delay energy consumption.

B. RESOURCE ALLOCATION ALGORITHM BASED ON COMMUNICATION AND COMPUTING LOAD BALANCING

In the process of resource allocation, only considering the processing delay and energy consumption minimization of computing nodes will lead to serious load imbalance between computing nodes and backhaul links, thus reducing the efficiency of the system. Based on the computing and communication load of the existing small network, the computing nodes are selected by an applied algorithm. The algorithm takes into account the requirements of the unloaded application, such as the number of bits to be migrated and the maximum delay acceptable to the user. The e small cell base station used to handle computing works statically to reduce the costly virtual machine from-shift problem. The applied algorithm can satisfy all users’ requirements when the number of unloading tasks per second reaches a certain value. In addition, the literature also shows that task parallelization can further achieve load balancing.

Literature minimizes the resource consumption of each physical computing node while realizing the communication and computing load balancing between physical computing nodes. The problem is mapped out in the literature as a process of converting applied diagrams into actual diagrams. In the application diagram, each node corresponds to an independent component of the application, and each edge corresponds to a communication process between different nodes. The actual graph represents the actual computing system. In the actual graph, nodes correspond to independent computing devices, and edges also correspond to communication links between different computing devices. The author first presents an algorithm for finding the optimal solution of the linear application graph and then proposes a more general online approximation algorithm. The simulation results show that the proposed algorithm can significantly outperform the other two starvation algorithms in resource utilization.

C. RESOURCE ALLOCATION ALGORITHM BASED ON SYSTEM BENEFIT

Most of the resource allocation algorithms of edge mobile computing delay or minimize energy consumption goal, but the threshold and is often difficult to weigh between indicators. By equation of benefit and function of design system can balance the relationship between the two, and take the corresponding algorithm is optimized, this method can obtain more comprehensive results. In recent years, part of the literature resource allocation algorithm is proposed based on system performance via benefit functions of the system planning, the system can comprehensively considering various constraints and flexible to achieve the aim of the system effectively. However, this approach has some problems, such as system benefit function is difficult to design, such as high complexity leads to low comprehensive performance optimization. Because of these problems, a variety of ways to optimize the benefit function have appeared in the literature. The author considers...
a mobile edge computing network scenario with multiple user devices and multiple base stations, in which each mobile edge computing service provider has only limited resources, and the system needs to maximize system benefits through a reasonable resource allocation algorithm. Through joint rounds of auction algorithm of maximum benefits of the author to the system has carried on the multiple iterations, finally realize the joint distribution of the multidimensional resource in the system, the benefit function is mainly used in the auction winner in the process of choice in the process of each round, the pricing for the improvement of system performance and performance improvement of unit product benefits. In this paper, the author compares the algorithm with the common resource allocation algorithm through simulation and proves the superiority of this algorithm. Because the auction algorithm is optimized according to the results of each round of auction, the result is difficult to approach the global optimal, but it can adapt to the constant changes in the communication environment. Reference proposed a dynamic valuation strategy in the vehicle-assisted moving edge calculation system. In this document, the author designed the dynamic valuation strategy, so as to obtain more comprehensive benefit simulation results, which demonstrated the superiority of this valuation strategy.

According to the literature, the author calculates the unloading, the allocation of resources and jointly consider content caching, planning out a unified benefit function that has a variety of restrictions due to the real conditions of a variety of constraints, the problem is difficult to plan for the solvability of a protruding problem. In order to solve the problem, the authors convert problems into an approximate equivalent protruding problem and prove the convexity of the transformed problem. Due to the complexity of the problem, the traditional convex optimization algorithm needs too much computation to solve the problem, the author uses the distributed algorithm to solve the problem, and the simulation results are compared with the centralized algorithm, the results prove the superiority of the distributed algorithm proposed by the author. Considering the adaptability of the algorithm to the environment, Literature proposed an adaptive mobile video stream assisted by edge computation, which inspired the design of the benefit function in this paper. Despite the current in this area, there are a lot of achievements on the edge of the mobile computing network resource allocation algorithm based on maximum benefits of system research still have a large optimization space, such as literature still with the centralized algorithm of distributed algorithms in the system efficiency has a certain gap, through the optimization can be further approach the optimal system efficiency; Literature also has optimization space for system benefits. In the process of algorithm implementation, some system benefits are sacrificed. To sum up, this kind of algorithm can continue to be optimized in terms of system benefits and resource use. How to apply this type of algorithm to solve the resource allocation problem of various mobile edge computing networks in 5G in the future, and how to improve the existing algorithm to further optimize the system benefit and reach the global optimal is still worth further research.

IV. A NEW AGRICULTURAL SUPPLY CHAIN FRAMEWORK

Nowadays, breakthroughs in mobile Internet and smart devices are driving the development of new computation-intensive delay-sensitive applications, such as virtual reality motion recognition and tactile communication. These new applications have brought great challenges to smart devices and traditional wireless network architectures. On the one hand, the limited size of smart devices and a limited size of smart devices. On the other hand, data transmission to the core network through cloud computing technology will lead to excessive link load and high system transmission delay, so it is difficult to meet the requirements of user equipment for the delay. Facing these challenges, ETSI proposed the concept of mobile edge computing. Business caching is an important issue in mobile edge computing networks. Business caching refers to the caching of the corresponding database function library platform in the mobile edge computing server and then moving the edge computing service to the computing task to provide business services. In this chapter, the study, data generation produced by intelligent devices or capture (such as action recognition of image) and need to upload to the base station generation refers to the part of the business on the edge of the mobile computing cache database on the server specific software, such as system can be used to a core network. Therefore, the computing task can be performed correctly only when the data business type and computing resources are satisfied in the mobile edge computing server. In order to obtain the resource allocation scheme of the optimal business cache and computing offload strategy, the system is faced with many new problems.

Firstly, the storage space of the mobile edge computing server is very limited, and only a few kinds of services can be cached at the same time, which means that the mobile edge computing server can only support a few kinds of services. Secondly, business requirement for storage space as well as the popularity of specific business time in change, requires a resource allocation algorithm that has certain adaptability. Resource allocation algorithm based on the depth of reinforcement learning can adapt to the changes in the environment to some extent, can adapt to such as channel state. The change of user parameter popularity of business The system of After
the communication and calculation model is built into the environment, the feedback is obtained through the constant exploration of the base station. Therefore, this chapter proposes an online learning resource allocation algorithm based on deep reinforcement learning is an effective way to solve decision problems in dynamic systems, and deep learning can be applied to reinforcement learning. The main work of this chapter mainly focuses on the following points:

1. Hierarchical offloading is used in the mobile edge computing Network scenario, whose structure is composed of the base station and the core network where the user deployments the mobile edge computing service. In order to enhance the efficiency and availability of network management, network function is Virtualization (NFV) was introduced in the mobile edge computing wireless beehive network.

2. In the mobile edge computing network, the offloading of business cache-type computing tasks and resource allocation problems are jointly planned, and the optimization objective is set to maximize the long-term benefit of the system under the constraints of cache and computing capacity.

3. A Deep reinforcement learning resource allocation algorithm based on Double-Dueling DQN (Deep Q Network) is proposed to solve the dynamic time problem. This chapter uses Deep reinforcement learning for the next generation. The service cache (service update) and computing task offloading (base station attachment and computing offloading decision) of the cellular network were studied, and the optimal long-term reward was obtained through exploration and training [16], [17].

4. The simulation results show the effectiveness of the proposed algorithm.

According to the given value \( r(t) \) and the actual operation value \( y(t) \) of the system, the analog PID controller forms the control deviation \( e(t) \), and then controls the control object. The control law is shown in formula (1) and formula (2):

\[
e(t) = r(t) - y(t)
\]

\[
u(t) = K_p e(t) + \frac{1}{T_i} \int_0^t e(t) dt + T_d \frac{d e(t)}{dt}
\]

where: output of controller is expressed in \( u(t) \) proportion coefficient is expressed by \( K_p \) integral time constant is expressed by \( T_i \); differential time constant is expressed by \( T_d \).

With the development of electronic technology, PID control algorithm is realized by computer programming. The computer uses the sampling period to discretize the control object and take sample s [18]. The analog PID control algorithm can not be used directly, so it needs to be discretized to form a digital PID control algorithm, as shown in formula (3) and (4).

\[
u(n) = K_p e(n) + K_i \sum_{j=0}^{n} e(j) + K_d \frac{e(n) - e(n-1)}{T}
\]

where: the deviation value of the \( n \)-th sampling time of the computer is expressed by \( e(n) \); the deviation value of the \( n-1 \)th sampling time of the computer is expressed by \( e(n-1) \); the sampling period of the computer is expressed by \( T \); the integral coefficient is expressed by \( K_i \), and \( K_i = \frac{K_p T_i}{T} \); the differential coefficient is expressed by \( K_d \) and \( K_d = \frac{K_p T}{T} \); the output value of the \( n \)-th sampling time of the computer is expressed in \( u(n) \).

Similarly, the control quantity of the \( (n-1) \)-th digital PID output can be obtained recursively, as shown in formula (5).

\[
u(n-1) = K_p e(n-1) + K_i \sum_{j=0}^{n-1} e(j) + K_d [e(n-1) - e(n-2)]
\]

The incremental PID control algorithm can be obtained by subtracting formula (5) from formula (4), as shown in formula (6) and formula (7).

\[
\Delta u(n) = K_p [e(n) - e(n-1)] + K_i e(n)
\]

\[
u(n) = u(n-1) + \Delta u(n)
\]

Cloud execution includes five phases: from the user to the base station, from the base station to the cloud, cloud execution, and from the cloud end back to the base station and from the base station to user. Assume that the cloud always has enough computing and caching resources. Because the execution time in the cloud is often overlooked. In addition, from the base station to the user and from the cloud to the base station. The return is ignored because the return process can be synchronized with the outgoing process of the data, and secondly, the move Edge computations tend to have smaller results after the computation task is executed than the uploaded results.

It is worth noting that the proposed algorithm uses a double-dueling DQN algorithm, in which the value function is divided by deep PI Degree learning is estimated to learn a huge number of combinations of states and behaviors. Experience replay as well as a target. The new data algorithm is shown. Step 17 can reflect the core idea of Double DQN. In order to accelerate the convergence speed and more accurate Q value. The combination of these steps can lead to better performance and a higher rate of convergence [18], [19].

**V. EXPERIMENT RESULTS AND ANALYZE**

In order to verify the performance of the proposed method, experimental results are given in this section.

First of all, we give the system response time to verify the computational complexity of the proposed method. The experimental results is shown in figure 8. According to this figure, we can see that the training time and the testing time are both short, which is to see that this method has very good performance of the computational complexity.
This chapter proposes an approach based on deep reinforcement learning to solve the problem of business caching and task offloading. The process of the proposed algorithm is shown as algorithm 1. In algorithm 1, the empirical reprocessing memory and the main DQN network are randomly initialized during initialization. And the target DQN has the same parameters as the master DQN. In each round of training, the status of the user’s equipment is followed by Machine initialization. In the following iterations, behaviors are selected based on a certain probability. Execution of for will generate experience and will be stored in the experience replay buffer. After that, the target is calculated. Store as the value of Q of DQN. In the end, the main DQN network will be trained by minimizing the loss function, while the target DQN will be updated every G iterations [20], [21].

Figure 9 shows the training performance of the proposed algorithm with different discount rates. The discount rate will affect the behavior selection. The alternative strategy, that is, a larger discount rate will cause the system to focus more on long-term gains than a low discount rate causes the system to focus more on current revenue. In this article, higher discount rates tend to. This leads to greater long-term benefits, but in practice, there is no corresponding benefit from using a high discount rate, this is because the reality of the system is more variable, too much attention to the future revenue will lead to the system calculation of too much and the loss is too large, often need to make a trade-off.

Figure 10 shows the waiting time with different data size. The waiting time represents the whole time of the system Revenue, that is, the goal of the training. The probabilities that you’re going to explore at the end of your training at random. In a relatively stable system, the increase of the final exploitation probability will often lead to the decrease of long-term returns, because the act of immediate exploration often yields low returns. But again, maintaining a certain probability of final exploration. Because the random exploration process can enable the system to explore the new environment so as to learn in the change. In the environment, the exploration probability needs to be appropriately increased. Much of the existing research has focused on the selection of random behaviors. Because they think that purely random behavior is inefficient and difficult to find changes in the environment.

Deep reinforcement based learning algorithms usually have a high computational complexity, the complexity of the real international system is closely related to parameter setting, so it is often difficult to estimate. However, with hardware technology and with the development of deep learning, GPUs can have more than a 10-fold increase in their training speed. Adding graphics processor auxiliary module to mobile network can improve computing efficiency to a great extent. In the same, in recent years, a lot of research results on computational complexity optimization have emerged in the field of deep learning. These parties to a large extent, this method alleviates the problem of high complexity in deep reinforcement learning practice [22]–[24].

In order to further illustrate the advantages of this system, the experimental verification is carried out. Simulating the wet asphalt pavement, under the premise of the same parameters of other working conditions, the initial speed
is 20 m / s. The oil field minor repair machines controlled by three systems are used for braking, and the time and braking distance are measured when the vehicle speed is different. Specifically, confuse matrix, accuracy and other two metrics also used to assess the robust and effectiveness of tourism system, the matrix can be defined as follow:

\[
\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}
\]

\[
f1 - \text{score} = \frac{2 \times \text{precise} \times \text{recall}}{\text{precise} + \text{recall}} \tag{9}
\]

\[
\text{precise} = \frac{TP}{TP + FP} \tag{10}
\]

\[
\text{recall} = \frac{TP}{TP + FN} \tag{11}
\]

This section provides simulation results to prove the performance of the proposed resource allocation algorithm based on ADMM and analysis of the effect of some important parameters. Simulation scenario is set to 100 m by 100 m square area Micronesia JiBu, small base stations, its position to obey random uniform distribution, and the main customer base station is at the center of the simulation area. Wireless channel model using flat Rayleigh fading channel model, the path loss factor \( a = 4 \), and between the user and base station channel gain can be expressed as \( h \). The simulation results are shown in figure 12. According to this figure, we can see that when \( p = 0.4 \), the ADMM has the best performance.

Figure 13 gives the performance of the system efficiency of different algorithm, along with the change of the increase of the small number of base stations, system benefits were got a degree of ascension. The ADMM algorithm which this paper use the system benefits have been obtained above using the auction system benefits gained by the algorithm of system, up about 10% of system efficiency. ADMM algorithm, meanwhile, benefit gained by the system with the centralized algorithm for system benefits remain unchanged. Increase in the number of small base stations, the system efficiency shows the tendency of convergence, this is because the system spectrum bandwidth is limited, as the grow in quantity of users, communication quality will be the corresponding drop, so efficiency is also won’t increase.

VI. CONCLUSION

With the popularity of computation-intensive applications, users’ computing demands for mobile devices are increasing day by day. Mobile edge computing is one of the key technologies to improve the computing power of users. By deploying computing resources to the edge of the mobile network, users can unload computing tasks to the computing server at the edge of the mobile network, thus using computing resources at the edge of the mobile network to complete computing tasks with lower delay and energy consumption. However, due to the very limited network edge computing and spectrum resources, a resource allocation algorithm...
with lower complexity is needed to improve the system efficiency of the mobile edge computing networks. Considering the characteristics of mobile edge computing networks, this paper studies the resource allocation algorithm based on system benefit optimization under two typical scenarios: mobile edge computing network considering cognitive technology and mobile edge computing network with cache and service type. A distributed resource allocation algorithm based on ADMM is proposed in the mobile edge computing network scenario considering cognitive technology. By designing the benefit function of the system, the problem is transformed into a non-convex problem with multiple constraints and further transformed into a convex problem by means of variable continuity and product term substitution. In order to reduce the computational cost of solving the problem, a comprehensive algorithm based on ADMM was proposed, and the base station attachment, calculation and unloading decision, and resource allocation scheme were obtained by means of distributed computing when the system efficiency was the highest. The simulation results show that this algorithm can solve the problem with low complexity while effectively ensuring the system’s benefit. A resource allocation algorithm based on deep reinforcement learning is proposed in the mobile edge computing network scenario with cache and service type. The simulation results show that this algorithm can effectively learn the system benefit function, and by comparing with many resource allocation algorithms, it is proved that this algorithm can obtain higher system benefit. In the completion of the research work of this paper, there is much to go on. However, there are many disadvantages in this system, such as: (1) there are high requirements for system time synchronization. (2) Heterogeneous system interconnection, large-scale and extensive layout, more intelligence, and so on are not only the characteristics of edge computing but also the higher requirements for edge computing. In the future, will study more advanced calculation methods, which can reduce the requirements for the delay and have the same performance.

**AVAILABILITY OF DATA AND MATERIAL**
The data used to support the findings of this study are available from the corresponding author upon request.

**COMPETING INTERESTS**
Declares that he has no conflict of interest.

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