Seminar Report

On

Intelligent Resource Management in Future Wireless Networks Inspired by Artificial Intelligence

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ABSTRACT

Edge computing and caching technologies are introduced to the fifth-generation wireless network (5G), In order to improve network performance, including reducing computation delay, transmission delay and bandwidth consumption. The number and complexity of tasks in the network are increasing sharply, but at the same time volume of edge resources is limited. Therefore, how to provide the most efficient service for network users with limited resources is an urgent problem to be solved. Thus, improving the utilization rate of communication, computing and caching resources in the network is an important issue. A major challenge to network management is the diversification of network resources. The joint resource allocation problem is difficult to be solved by traditional approaches. Development of Artificial intelligence (AI) technology helped to solve complex decision-making problems. These AI algorithms have been applied to joint resource allocation problems to solve complex decision-making problems. In this paper an AI-assisted intelligent wireless network architecture was introduced. Then, summarize the AI for resources allocation problem. And, based on the architecture, Deep Q-network (DQN) algorithm is used to figure out the complex and high-dimensional joint resource allocation problem. Simulation results show that the algorithm has good convergence characteristics, newly introduced architecture and the joint resource allocation scheme achieve better performance compared to other resource allocation schemes.

TABLE OF CONTENTS

CHAPTER 1
INTRODUCTION

The number and complexity of network tasks are rapidly increasing. However, edge computing resources are limited. Traditional approaches are not effective in solving the joint resource allocation problem. Major challenge in network management is the diversification of network resources and the increasing demands for higher data rates, better spectrum utilization, lower latency, and always-on connectivity to support communication between things and devices. In complex scenarios, many traditional resource optimization methods in wireless communication networks are becoming more performance constrained and complex. The development of Artificial Intelligence (AI) helped solve complex decision-making problems.

Intelligent Resource Management in Future Wireless Networks Inspired by Artificial Intelligence

Intelligent Resource Management in Future Wireless Networks Inspired by Artificial Intelligence is a new technology for future wireless network to improve network performance, including reducing computation delay, transmission delay and bandwidth consumption. Various AI technologies, mainly machine learning and deep learning, can extract useful information from wireless systems, learn and make decisions from dynamic environments and are considered as possible solutions for complex and previously intractable problems in future wireless networks. An AI-assisted intelligent wireless network architecture is was introduced, based on the architecture, Deep Q-network (DQN) algorithm is used to figure out Joint Resource Allocation.

Objective and Scope

The objective is to improve the efficiency and performance of the network.

The scope is that newly introduced architecture and the joint resource allocation scheme achieve better performance compared to other resource allocation schemes.

CHAPTER 2

LITERATURE REVIEW

5G mobile network specification release got frozen on 15 on June 2018. After this, the first nationwide commercial 5G network launched in South Korea on April 2019. During that time the study of roadmap and enabling technologies beyond 5G mobile network were in progress in both the academic and telecommunication industries.

Major challenges for 5G were the increasing demands for higher data rate and spectrum utilization, lower latency, better and always-on connectivity to support communication among things and devices. Thus, software-defined networking (SDN) and network functions virtualization (NFV) are vital in the 5G and beyond 5G mobile network architecture and implementation. For example, SDN controllers will regulate the traffic and organize the virtualized network devices, which can improve the efficiency and performance of the network. From the aspects of application scenarios, typical novel applications of Augmented Reality (AR) and Virtual Reality (VR) online game, real-time video processing and intelligent health care over the wireless network prompt the deployment of cache and fog/edge computing devices in wireless networks. The deployment and scheduling of storage and computing resources will be a lot more complicated than what came before. The development of AI technology brings convenience to different aspects of our life, such as smart medical care, smart factories, smart cities and so on.

Many traditional resource optimization method in wireless communication network are becoming more performance-constrained and complicated in complex scenarios. AI technology which mainly includes machine learning and deep learning can extract useful information from wireless systems, learn and make decisions from the dynamic environment, are considered as potential solutions for complex and previously intractable problems in future wireless network. On the basics of this observation, it is necessary to review about the application of AI technology to solve the complicated decision making problem and boost network performance. Subsequently, an intelligent wireless network with self-adaptation and self-optimization capability was introduced. An example application is addressed to illustrate the workflow. Finally the conclusion and implementation challenges of AI based wireless network resource management are also address.

ARCHITECTURE OF 5G-BASED AI-ASSISTED INTELLIGENT WIRELESS NETWORK

In this is about a 5G-based AI-assisted intelligent wireless network architecture. The communication, computing and caching resources are virtualized as resource pools, then orchestrator jointly manages and orchestrates the three resources through AI algorithms dynamically according to the changing environment. This section also introduced various AI based resource allocation scheme.

ARCHITECTURE AND APPLICATION

The system architecture could be divided into four parts, which include physical infrastructure, logical infrastructure, software network functions and orchestrators. The system architecture is shown in the below Figure 1.

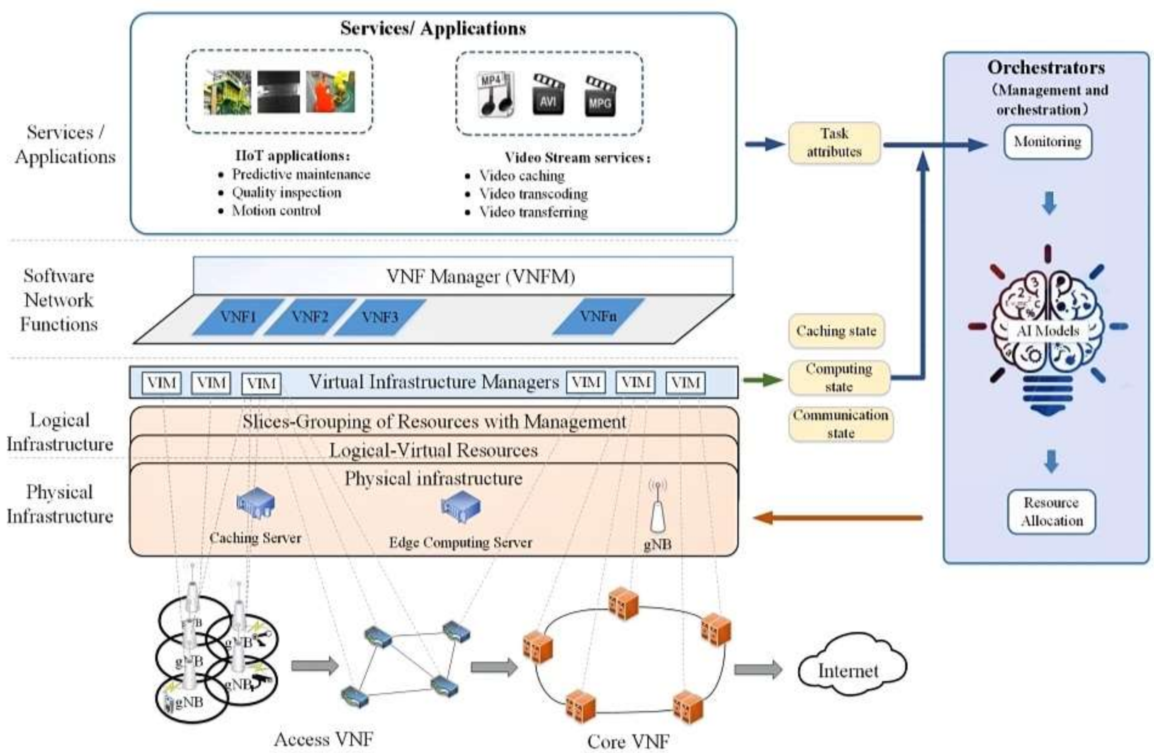

Figure 1 : AI-assisted intelligent wireless network architecture

The physical infrastructure layer consists of caching servers, edge computing servers and gNodeB (gNBs), which are responsible for caching content, executing computing tasks, and provide network access for users, respectively. The physical infrastructures are abstract into logical-virtual resources in the logical infrastructure layer. Moreover, the logical resources are changes according to the requirements. Virtual Infrastructure Managers (VIMs) dynamically monitor and manage the infrastructures.

In the software network functions layer, Virtual Network Functions (VNFs) are software that provide some kinds of network services. And Virtual Network Function Manager (VNFM) is responsible for Virtual Network Function lifecycle management.

Orchestrator is responsible for orchestrating infrastructures based on the tasks attribute and resource status. The orchestrator with built in AI algorithm analysis the system resources status and task attributes to dynamically allocate corresponding computing, caching and communication resources for specific tasks.

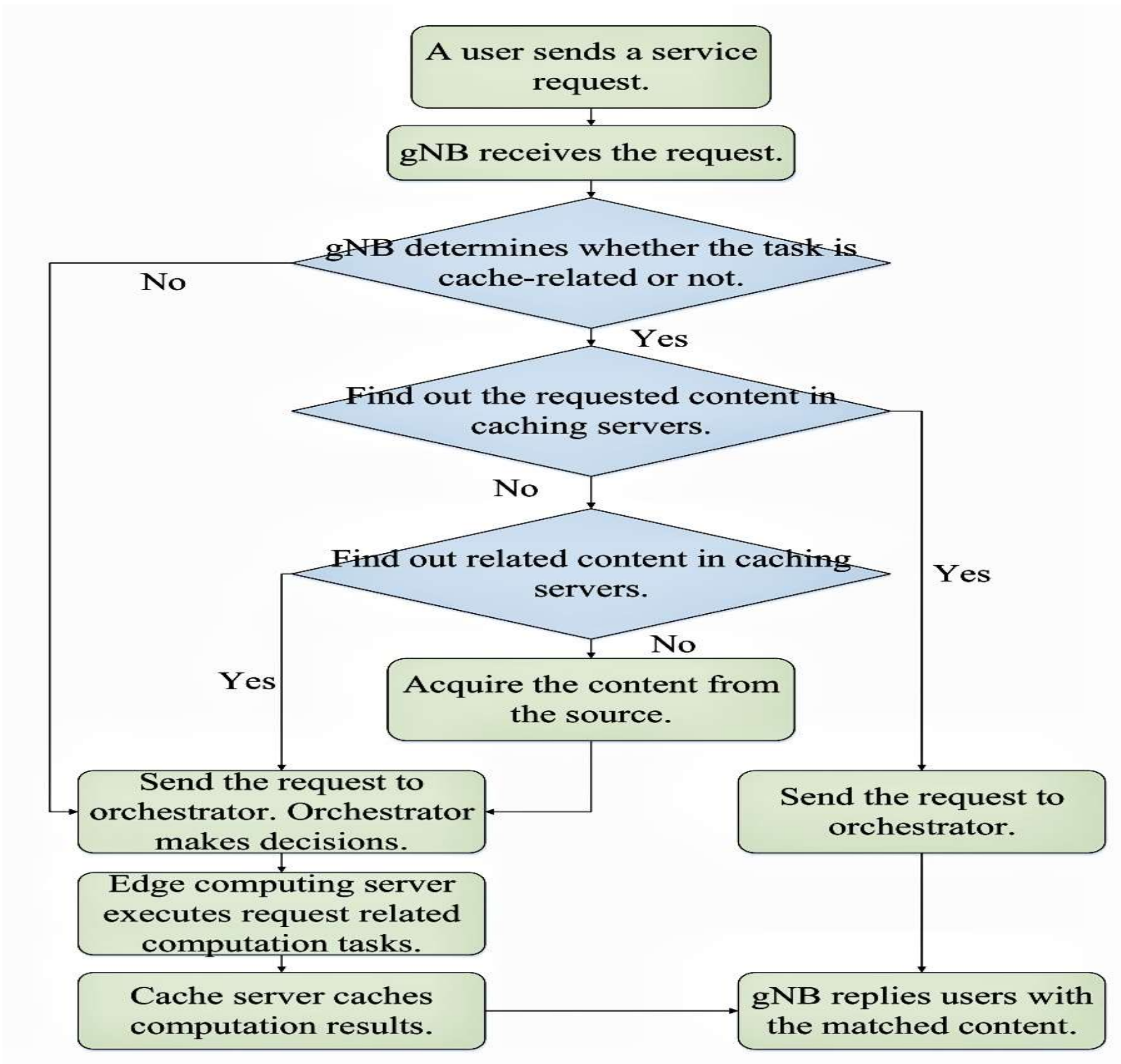

Figure 2: Workflow of AI-assisted intelligent wireless network architecture

The Video Streaming Task refers to caching a video on a caching server near the user, to fulfill numerous requests for videos from users. Generally, high bit rate videos are cached on the system. Even if the user requests the video at a lower bit rate, the Edge computing server can meet the requirement through transcoding. However, when low bit rate videos are requested at high frequency, the caching server can also cache low bit rate video to reduce the size of the edge computing. This type of work usually requires the coordination of communication, caching, and computing resources.

The quality inspection task is usually to take pictures of the products, identify the collected images and sort the products by the identification results. This type of work usually requires coordination of communication and computing resources.

A quality-related task, such as a task quality assignment task, sends the gNB request directly to the orchestrator. The orchestrator operates AI algorithms, including the Reinforcement Learning (RL) algorithm and the DQN algorithm. AI algorithms are run by the orchestrator. With the help of AI algorithms, the orchestrator dynamically allocates computing and communication resources to the user according to task attributes, edge computing, and communication resource status. Sends data related to the task, such as product images, to user-selected gNB, and the gNB Sends data to the selected edge computing server. Once the data is received, Edge Computing nodes computing tasks such as image identification tasks to detect defects in products. Then, Edge Computing server returns the computing results to the user via the selected gNB.

If the task related to the cache. Like a video stream service, the system will detect whether the requested video version is cached on the system or not. Assume the required video version already exists and the video will be sent to the user via the selected gNB. If the requested video version is not cached on the system, the system checks whether the system with the higher bit rate version has cached video. Although there is no higher bit rate version, the system will gain content from the source. After winning the original version or higher bit-rated version, the task is sent to the orchestrator, and the orchestrator selects an edge server to transcode the video. The orchestrator decides whether to cache the transcoded video from the edge computing server. If the orchestrator decides to cache the video, a caching server will allow the video to be cached. Finally, the video will be sent back to the user via the selected gNB.

With this in mind, a resource allocation scheme operating in the orchestrator is very important. Reasonable resource allocation will bring high system benefits. However, in the network, the problem of composite resource allocation is a high-level and complex problem that is difficult to solve using a traditional algorithm. Therefore, several resource allocation schemes based on the AI algorithm have been given.

AI FOR RESOURCE ALLOCATION PROBLEM

In this section, briefly discuss recent technological advances in AI-based resource allocation schemes. AI approaches can be used not only in traditional areas but also in wireless communication areas.

- ❖ **Supervised Learning & Unsupervised Learning:** High quality training datasets are difficult to obtain in a wireless network environment, limiting supervised learning and unsupervised learning on the wireless network.
- ❖ **Deep Learning (DL):** DL is commonly used for classification or regression. However, the performance of in-depth study is closely related to model training strategies and experience.
- ❖ **Reinforcement Learning:** The RL algorithm is ideal for making decisions regarding resource allocation. However, some tabular-based RL algorithms, such as Q-Learning, store experiences on a Q-table. However, the size of the Q-table grows significantly with the levels of state space, and the conversion rate to the optimal policy is relatively low.
- ❖ **Deep Reinforcement Learning (DRL):** DRL integrates the benefits of in-depth learning and empowerment learning. In the standard DRL scheme, The Deep Neural Network (DNN) is used to study high-dimensional RAW data and calculate the performance of a functional value. This can be applied to the problem of high-dimensional state space compared to traditional reinforce learning. Thus, there are many researches focusing on this topic.

SUMMARIZED OF AI-BASED APPROACHES USED IN RESOURCE MANAGEMENT

AI categories	Characterizes	Advantages	Limitations	Application in resource management
Supervised learning(NN, SVM)	extract features from labeled data	simple and easy to deploy	sensitive to the quality of data	classification; prediction of performances
Unsupervised learning(K-Means, PCA)	learned from unlabeled data	simple and easy to deploy	sensitive to the quality of data	clustering; reducing dimensions
Reinforcement learning(Q-Learning, MDP)	learned policy from own experiences	no need of priori knowledge of data	complexity increasing with the dimension of state and action space; low convergence rate	automatic control and decision making
Deep learning(DNN)	learning from raw data	better learning performance	ininterpretable; long training time	prediction
Deep reinforcement learning(DQN)	learning policy from experiences	better performance and quick convergence	continuous state and action space; ininterpretable	automatic control and decision making; resource allocation policy

Table 1: Summarized of AI-Based Approaches Used In Resource Management

This table summarizes the al-based approaches used in resource management. In general, supervised learning and non-supervised learning are ideal for performing the regression, classification, and clustering tasks to assist the resource management. At the same time, the Reinforcement Learning algorithm is ideal for making resource allocation decisions on less complex wireless networks. DQN was recently deployed to address integrated resource allocation issues in a variety of situations, including vehicle network and satellite-to-ground integrated networks.

CHAPTER 3

METHODOLOGY

DEEP Q-NETWORK (DQN)

In this paper, the deep Q-Network algorithm is used to solve the joint resource allocation problem. Well-trained neural networks can guide orchestrator resource allocation. On this network system, orchestrator resources must be allocated for communication, video content caching, and computation task execution.

DQN is a type of reinforcement learning that differs from traditional tabular RL algorithms. It a kind of reinforcement learning algorithm based on function approximation, which mainly calculates the value function of the reinforcement learning problem using artificial neural networks and statistical curve fittings.

Therefore, before introducing DQN, this section will first introduce a type of traditional tabular RL algorithm called Q-Learning. In Q-learning, there is an interaction between the environment and the agent during the process. First, the environmental condition is understood by the agents. The agent then decides to select an activity based on the appropriate policy under the Environment State. Action-State Value Function is the evaluation of a policy. A policy with a generally high state-of-the-art value is the best policy. Then, we can adjust the parameters as we are more likely to select the action with the highest action-state value. The learning process of Q-learning is a continuous repetitive process of value function.

Q-learning algorithm in tradition, action-state value. Can also call it the Q-value, which is stored in a Q-table. However, joint resource allocation issues have a high dimensional state space, and the size of the queue table increases exponentially as the state increases. It is difficult to include all states and activities in the Q-table. Therefore, use a neural network to evaluate Q-values. Neural network parameters including load and biases are trained to minimize loss function. Weights and biases are updated during the training process to achieve positive evaluation results.

DQN requires a data set to train neural networks. DQN's data set comes from the interaction between the agent and the environment. A portion of the data generated from each interaction is stored and used to train the neural network. However, the order of the data is interrelated. In order to train neural networks, interconnections need to be removed. Thus, the Experience Replay mechanism is introduced. Experience Replay is a biologically motivated mechanism that minimizes the interrelationship of sequences obtained during the training process. Furthermore, the novel DQN Pro puts forward another mechanism called Fixed Target Deep Networks, which is used to minimize interactions with the target, thus ensuring the stability of the integration process. Thus, the DQN approach is shown in below Algorithm.

DEEP Q-NETWORK BASED JOINT RESOURCE ALLOCATION ALGORITHM

Initialization:
Initialize evaluated Q-networks and target Q-networks with parameters w and w'.
for $t = 1 : T$ **do**
  Orchestrator receives the task request $T_u^{v_i}(t)$.
  Orchestrator senses the current environment state $S(t)$.
  while $S(t)! = S_{terminal}$ **do**
    Orchestrator selects action $a(t)$ according to $T_u^{v_i}(t)$ and $S(t)$
    Orchestrator obtains reward $R(t)$ and next state $S(t+1)$.
    Orchestrator stores $(S(t), a(t), R(t), S(t+1))$ in the experience replay memory.
    Randomly sample some pieces of experiences from the experience replay memory.
    Estimate target Q-value $Q_{target}(k)$ based on target Q-networks:
    if $S(k+1) == S_{terminal}$
      $Q_{target}(k) = R(k)$,
    else
      $Q_{target}(k) = R(k) + \gamma_q \max_{a'} Q(S(k+1), a', w')$.
    Train evaluated Q-networks to minimize $L(w)$.
    Every some steps, update target Q-networks.
    $S(t) \leftarrow S(t+1)$
  end while
end for

CHAPTER 4
RESULTS AND ANALYSIS

The DQN-based integrated resource allocation algorithm aims to optimize resource allocation decisions based on task attributes and resource status. In general, need to analyze the performance of the algorithm to measure whether the algorithm is suitable for solving such problems. Therefore, here will analyze the DQN based integrated resource management algorithm in two steps. First, the cohesiveness performance is analyzed. Second, analyze the performance of the algorithm to improve system reward.

At the beginning of the simulation, here start with the State Transition Probability Metrics to show the computing, caching, and communication status. State Transition Probability Metrics indicate the order of the environment in which the agent is to be studied. Let the content size of the task be 2 Mbits, the number of CPU cycles required is 5 Mcycles. The bandwidth between the user and gNB is 5 MHz. The user's unit pay-fee for caching, edge computing server and wireless spectrum usage is 5 units / MB, 7 units / Mic and 2 units / MHz. And charging-fees from used users Caching, computing, and communication resources are all 0.2 units / Mbps.

Here, compare the performance of four simulation schemes.

• DQN based joint allocation scheme.

• DQN based scheme except edge computing.

• DQN based scheme except caching.

• Static allocation scheme.

Under the DQN based joint resource allocation algorithm, the time required for DQN to train 4000 episodes is 227s, and each episode includes 50 steps. After the training process, the well-trained neural networks are used for generating the resource allocation policy.

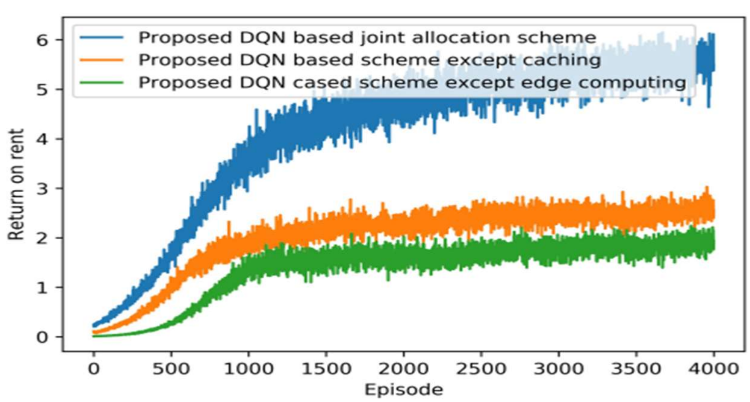

Figure 3: Return on rent versus episode under different scheme.

Figure 3 shows the return on rent varies with the training episodes. Considering the cohesive nature of the algorithm, neural networks are trained for 4000 episodes in this simulation. Initially, the

ROR of all three schemes increases, indicating that the neural network parameters are still being updated repeatedly. At the same time, it can be seen that the DQN based composite scheme has the highest growth rate. This is because the rewards for each iteration are relatively high. After 1500 episodes, the curves begin to flatten, i.e. the DQN-based algorithm begins to converge. This shows that neural networks are well trained to guide the agent towards optimized action selection strategy. Note that a larger ROR indicates a higher utilization of resources. It is clear that the DQN based joint allocation scheme is performing well.

Here need to know if the algorithm works well under different task attributes. So dynamically change the number of CPU cycles required to see the performance changes under different schemes. As CPU cycles increase, the ROR under different schemes decreases. Furthermore, the computing server takes longer to execute the task of the required CPU cycles and the computing rate is reduced. Thus, the system receives lower fees from users and pays more for computing, which reduces the total rental revenue. This shows that in the charging approach defined in this paper, the system can achieve greater benefits in handling tasks with smaller computing requirements. But it is clear that the DQN-based joint allocation scheme achieves the highest ROR. This means that communication, computing and caching resources need to be combined.

CHAPTER 5
CONCLUSION

In this paper, An Al-Assisted Intelligent Wireless Network Architecture based on 5G is was introduced. By studying the environmental status and task attributes through algorithms, the Al-Algorithm-based orchestrator is able to allocate resources to different situations. Among them, The DQN algorithm is used to solve the complex and highly complex resource allocation problem. The simulation results show that the newly Introduced resource allocation scheme has good integration characteristics and the combined share of communication, computing and caching resources will yield high returns. Future operations should focus on improving the mobility of the system.

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