A Novel Resource Allocation Method for Network Slices in Power Grid

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Abstract. To allocate the network slice optimally, a two-phase optimal allocation approach is proposed to assign the network slices with users. First, the network slice allocation system in the core cloud network is modeled as a Markov process, and then the deep reinforcement learn is adopted to allocate the network slices. In the second phase, we formulate the network slice allocation problem as Lagrange multipliers problem. The iteration method is designed to achieve the optimization problem. Numerical results demonstrate that the proposed approach can allocate the network slices at a high efficiency.

Keywords. smart grid; 5th generation mobile networks (5G) power communication system; network slice; markov model; deep reinforcement learning

1. Introduction

In recent years, many countries and enterprises have devoted themselves to building smart grids and improving the intrinsic safety of the power grid. Specially, with the implementation of the "Internet +" strategy, informatization and intelligence in the power grid have been comprehensively improved. In addition, with the continuous expansion of the scale of communication services, the divergence of user requirements is increasing, and limited spectrum resources are becoming increasingly scarce. Therefore, the use of network virtualization to achieve resource sharing network slicing technology emerges from time to time. Network slicing is a key technology in 5G networks, which can flexibly configure independent virtual networks [1]. Nowadays, network slicing resource allocation has become a research hotspot in power line systems.

Recently, the research on network slicing allocation has focused on the allocation of the virtual network resources to users according to the requirements of different service types on the network speed and delay. Typically, in reference [2], in order to make infrastructure providers, service providers and users in network slicing obtain higher profits, a multiplier-based distributed resource allocation algorithm is proposed. However, this method does not take into account the different delay requirements of each slice service. For this reason, in reference [3], the author considers the service arrival and the
dynamic changes of the wireless channel in the network slicing, and on this basis, proposes a resource allocation scheme based on OFDMA for maximizing the throughput in the wireless virtual networks. Nevertheless, this method only considers time-frequency resources and does not make full use of spectrum resources. Similarly, the statistical delay QoS requirements of each network slice, and uses non-orthogonal multiple access technology to improve the effective capacity of the system [4]. However, these studies did not consider the fair sharing of network slices by users. In this case, reference [5] proposed a semi-static network slicing resource allocation scheme based on proportional fairness algorithm. Although this method considers different types of network slicing, the service requirements of the same type of slicing are fixed and cannot meet the differentiated needs of users. In order to optimize the allocation of network slicing, reference [6] models the resource allocation problem of network slicing as a biconvex optimization problem to achieve network load balancing while minimizing link costs.

However, the existing network slicing virtual resource allocation algorithm mainly focuses on the study of spectrum resource sharing, and less considers the differentiated requirements of different service types. For example, references [7] and [8] proposed an allocation mechanism with limited resource sharing ratio, which can improve the resource sharing ability of network slicing, but did not study the problem of customized resource allocation. Reference [9] proposed a resource allocation algorithm based on bankruptcy game to realize spectrum resource allocation for cloud access network slices. This algorithm can effectively improve the utilization of spectrum resources but does not consider the differentiated requirements of different services. Different service types have different requirements for network speed, delay, reliability, etc. It is a key problem to be solved in the research of network slicing resource allocation algorithm that how to allocate only the virtual network resources needed by users according to the needs of heterogeneous services [10]. In addition, in practical applications, users arrive online in sequence. Therefore, there is a need for an online slicing resource allocation method that can allocate required resources to users after submitting business requests in a timely and efficient manner and provide customized slicing services [11,12].

In this paper, we propose a network slice allocation model based on cloud and edge collaboration. Then we use Lagrange multiplier method to maximize the utility of resources allocation for network slice. For the purposes of effectively allocating the slice resources in the core cloud to different edge agents, we introduce the reinforcement learning to optimize the allocation of network slices.

2. System model

Smart grids have business diversification and different network requirements, such as large-scale power production business and large-scale management information business. Among them, the power production area business includes distribution automation and millisecond precision load control. The management information area includes use and procurement services, which requires strict isolation requirements. Generally, power grid services require millisecond-level ultra-low latency and ultra-high reliability networks. Based on the above requirements, for smart grid services, 5G network slicing technology is used to provide on-demand deployment, high isolation, and end-to-end service guaranteed power slices to meet the needs of power services.

According to power demand, user services can be divided into three types: enhance Mobile Broad Band (eMBB), ultra-Reliable Low Latency Communications (uRLLC), and massive Machine-Type Communications (mMTC). Each network slice is composed of a series of Virtual Network Functions (VNF), resources for running these network functions, and directional links connecting these functions. In a practical power grid, due to the business’s ultra-low latency and ultra-high reliability requirements, these services, such as the distribution automation business, millisecond precision load control, distributed feeder automation and other services, use uRLLC slices. Owing to the high connection density of distributed power sources and future mass communication services, these services generally use mMTC slices. In addition, for enhanced mobile bandwidth services, eMBB slices are used due to large bandwidth requirements (Figure 1).
The allocation of network slices is divided into two stages. In the first stage, computing resources, storage resources, and NVF are allocated to different edge networks. These edge networks include different Internet of Things, mobile networks, and various business networks. In the second stage, the edge service agent allocates different slices to the required users in the edge network. In this paper, we assume that different slices are deployed in different regions, and that the same VNF deployed in different regions exhibits different performance in terms of delay and efficiency. In the second stage, the edge service provider allocates the assigned users and merges them according to their different needs. Service providers can offer a variety of virtual resources, such as virtual spectrum resources, virtual computing resources and virtual storage resources.

3. Resource allocation optimization in the edge

In order to optimally allocate slices, we introduce quality of experience (QoE) as a basis for measuring user transmission rate. Suppose $u_n$ is the $n$th type of network slice, then the throughput using this network slice is given by

$$C = \sum_{u_n} \log_2 \left[ \det \left( I_{LM} + \frac{\gamma}{L_N} H(f) R_{ss}(f) H(f) \right) \right],$$

where $I_{LM}$ is an indicator matrix with $L_M \times L_N$ dimension, $\gamma$ represents the receiving SNR, $R_{ss}$ is the correlation covariance of the signals, $f$ is the frequency for network slices, $H$ is the fading between edge service agent and the end user. Because the service program executed on the edge service agent unit (AU) is determined by the application sent by the terminal. For this purpose, we define $w_i \in \{0,1\}$ as whether the slice is accessed or not. Therefore, the channel rate for the $i$-th terminal user (TU) is given by

$$C_i = w_i \log_2 \left( 1 + \frac{p_i |h|^2}{p_I + p_n} \right),$$

where $p_n$ is the noise power, $p_I$ is interference power of, $p_i$ is the receiving power of the received signal.

We adopt proportional fair scheduling (PFS) algorithm to allocate resources to the highest QoS users. Then $k_m$ is given by

$$k_m = \arg\max_{k=1,\ldots,K} \frac{\log_2[1+\rho_k(m,f)]}{T_k(f)},$$

where $T_k(f)$ represents the throughput. In addition, $\rho_k(m,f)$ is the SNR of the $k$th TU, which is related to the $m$-th PRB and frequency. In addition, the energy consumption of the edge agent can be
expressed as \( P \).

The QoE optimally allocates network slicing resources. Then the QoE of the \( n \)-th network slicing type is expressed by

\[
V_n = g(D_n, C_n, P_n, a_n, u_n),
\]

where \( D_n \) is the total delay of the \( n \)-type network slice, \( C_n \) is the communication rate of the \( n \)-type network slice, \( P_n \) is the transmission rate of the \( n \)-type network slice, and \( a_n \) is the priority of the \( n \)-th slice. To simplify the problem, this article assumes that the core cloud can provide enough slices to be allocated to edge users. Then the network slicing optimization problem can be formalized as

\[
\begin{align*}
\max & \quad \sum_{u_n} C_i I \{l \geq \tau\} + k_m I \{l < \tau\} \\
\text{s.t.} & \quad C_i \geq R_{th} \\
& \quad \sum_{u_n} C_i \leq R_n, \\
& \quad \sum_{n} P_{AU} < P_{max} \\
& \quad P_t = \sum_{j=0}^{N_n} P_{j}/h_j^2 < I_{max} \\
& \quad \omega_i \in \{0,1\}
\end{align*}
\]

where \( \tau \) is a real number for delay sensitive. \( I \{l < \tau\} \) is used to indicated the delay demand, if \( l < \tau \), then \( I \) is equal to zero, otherwise \( I \) equal to 1. In addition, \( R_{th} \) is the capacity of the channel for users, \( N_n \) is adjacent network numbers, \( P_t \) is the interference from adjacent agent units, \( P_{j} \) is the sum of the transmission power and and \( h_j \) is channel gain, \( I_{max} \) are the total interference threshold. We then convert (6) to

\[
\begin{align*}
\max \sum T \log_2 \left( 1 + \frac{p_i|h_i|^2}{p_{max}I_{max}\|l\|_1} \right)
\end{align*}
\]

the objective function in (6) is transformed into

\[
G(p, r) = \sum_{u_n} -T \log_2 \left( 1 + \frac{p_i|h_i|^2}{p_{max}I_{max}+P_n} \right) + rB(p),
\]

where \( r \) is the penalty coefficient, \( p \) is the vector composed of the transmission power of AU, and \( B(p) \) is given by

\[
B(p) = -\sum_{u_n} \ln (R_{th} - C_i) - \ln (R_n - \sum_{u_n} C_i) - \sum_{u_n} \ln (P_{max} - \sum_{u_n} P_{AU}) - \sum_{u_n} \ln (I_{max} - P_i|h_j|^2) - \sum_{u_n} \ln P_t
\]

To solve (7), we adopt an iterative algorithm to achieve the sub-optimal solution.

4. Slice allocation optimization in the cloud

4.1. MDP modeling

Due to limited infrastructure resources, a lot of effort has been invested in managing the allocation of resources to a slice in the radio access network. This paper introduces the system evaluation parameter, which involves four parameters based on the consideration of resource utilization and QoE satisfaction,
expressed as

\[ \xi = \eta / \eta_{th} + \vartheta / \vartheta_{th}, \]  

where \( \eta \) and \( \vartheta \) represent resource utilization and QoE, respectively; \( \eta_{th} \) and \( \vartheta_{th} \) are the thresholds of \( \eta \) and \( \vartheta \), respectively.

State: The state of the system can be expressed by

\[ S = \{ s | s = \sum_{N} f(\xi, f_{NN}(O_E)) \}. \]  

where \( f_{NN} \) represents the neural network.

Action: According to the geographic distribution of TUs in the cell, AU is divided into clusters. Each cluster should only be assigned to one service. Therefore, actions are defined as

\[ A = \{ a_1, a_2, a_3, \ldots, a_M \}_N, \]

where \( N \) is slice number and \( a_i \) indicating whether the \( i \)-th cluster belongs to \( N \).

Reward: According to its characteristics, the reward for the system is defined as

\[ r = \begin{cases} +10, & s \geq 0.8 \\ +1, & 0.5 \leq s < 0.8 \\ 0, & 0.3 \leq s < 0.5, \\ -1, & s < 0.3 \end{cases} \]  

where \( s \) represents the state, see formula (11) for details. At this point, the system can be modeled as an MDP.

4.2. Assignment algorithm with reinforcement learning

The algorithm can be formulated as a tuple \( \langle S, A, P, R, \gamma \rangle \), where \( S \) is a finite state set, \( A \) is a finite set of actions, \( P \) is a state transition probability matrix, \( R \) is a reward function, and \( \gamma \) is the penalty factor. The algorithm description is shown in Figure 2.

![Figure 2. Network Slice with Deep Learning.](image)

\[ Q \] function is a sample of the interaction between the training medium and the environment, given by

\[ Q_t(s_t, a_t) = Q_t(s_t, a_t) + \rho \left[ r_t + \gamma \max_{a_t' \in A} Q_{t+1}(s_{t+1}, a_{t+1}) - Q_t(s_t, a_t) \right]. \]  

where \( r_t \) is the reward of the \( t \)-th time slot, \( s_t \) is the system state for \( t \)-th slot, and \( a_t \) is selected action of the \( t \)-th slot.

In each time slot, the agent can calculate the best \( Q \) value based on the current state and rewards.
before choosing an action. According to the current state and the selected action, the system will switch to the new state in the next time slot. In this way, the $Q$ function can be updated for each time slot. The environment usually changes dynamically. For example, the system can adjust the transmission data rate, modulation scheme, and channel coding rate according to the channel capacity. Therefore, QoE is used as the main parameter of the environment. The channel quality index uploaded via the uplink indicates the data rate. The rate is determined by the signal to interference plus noise ratio and the characteristics of the receiver.

5. Experiment and result analysis

In this section, this article evaluates the performance for the proposed system with simulations. First, we set the word carrier bandwidth as 15 kHz and the time slot as 1000 milliseconds. In our simulation system, one frame is the signals transmitted within one time-slot. Second, the transmitting power for base station is set as 4W. In addition, 0.8W are used as the maximum power for PRB [13]. For the wide-area level, it is assumed that the maximum output power is below 46dBm to ensure that it is not affected by radiation. We suppose the 5G cellular system works with the millimeter with band around 30GHz-300GHz. In addition, the spectral density of the noise power is 174dBm/Hz.

(1) Fixed resource allocation (FRA): According to tenants and their priorities, AUs are divided into different levels. The user equipment is received according to their status and then associated with the remote radio front. (2) Dynamic resource allocation (DRA): The priorities of tenants and user equipment are different. (3) Environment-based resource allocation (RRA): The machine learning method is used for dynamic executing allocation.

![Figure 3. Performance of Slicing Allocations Methods.](image)

![Figure 4. Efficiency Allocation mechanisms.](image)

In the simulation, 50 end-user devices are used for distribution, and the distribution result is shown in Figure 2. In Figure 3, $\xi$ is the user satisfaction measurement. In this experiment, considering the data
rate, power, radio resources of the user equipment, and the priority weight of each parameter in each service, the overall performance of RRA is the best. It can be seen from Figure 3 that the performance of the RRA proposed in this paper is slightly better than that of DRA. The reason is due to the fact that Figure 2 only plots the service performance. Secondly, as the signal-to-noise ratio increases, the performance of FRA becomes worse, and its resource utilization rate is also getting lower and lower. Third, when the service is sensitive to delay, RRA is superior to other algorithms in fairness and delay. In delay-sensitive slices, the quality of experience in a high SNR region is much lower than the demand threshold. Therefore, $\xi$ reduces gradually. Figure 4 shows the optimization problem that solves the cloud system. This paper uses scenarios that include three services, including voice, video, and ultra-reliable low-latency communications, to evaluate the performance of using reinforcement learning to solve problems. In addition, the user delay is 5ms, 5ms and 0.5ms respectively. It can be seen from Figure 4 that by optimizing the system resource utilization and the weighted sum of slice QoE, the proposed RRA can achieve the best performance.

6. Conclusion
Based on network slicing, this paper proposes a network slicing allocation model based on cloud-edge collaboration in power line networks. In order to cooperate with this cloud-side collaborative system and improve the efficiency of network slice allocation, a two-stage slice allocation algorithm is proposed. In the first stage, the system is modeled as a Markov model, and then the DRL is adopt to realize the effective allocation of slices. In the second stage, the local network slice allocation method was optimized in combination with the actual benefits of users. The simulation results verify that the proposed two-stage optimized network resource allocation method can effectively allocate network slices.

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