Research on Transmission and Offloading Scheme of MEC-IRS for Distribution Network Service

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Abstract—the paper introduces IRS to assist offloading, and the propagation Environment can be intelligently changed by changing the reflection unit of the IRS. This article proposes an IRS-assisted MEC power distribution Internet of Things system, and studies the gain effect of IRS in the MEC system. In this system, the single antenna equipment can choose to unload a small part of its computing task to the edge computing node of the distribution Internet of things through the multi antenna access point with the help of IRS. In this paper, the delay minimization problem of the whole system is established, the DNQ reinforcement learning algorithm is used to solve the problem, which can effectively change the coverage of smart substations.

1. INTRODUCTION
With the rapid development of sensor measurement technology, communication technology, computing technology, automation and intelligent control technology, and smart grid, the scale of transmission lines has gradually increased, which has brought unprecedented challenges to the reliable operation of the grid [1]. Different from the traditional power business, in the distribution network, a large amount of data will be generated between various smart power devices. While meeting the low latency of the grid business, the transmission and processing of these data will bring the main station a lot of pressure [2]. As we all know, the intelligent reflective surface (IRS) has been recognized in the industry for reducing the delay of information transmission services. On the other hand, edge computing provides services near the user side, decentralizing a large number of calculations to the execution end to reduce the pressure on the main station, which can meet the real-time data analysis and processing and low-latency business requirements, reduce operation and maintenance costs, and improve system efficiency. The application of edge computing assisted by intelligent reflective surfaces to distribution network services can ensure a faster response for the distribution network terminals, thereby greatly reducing the response time of the equipment [3-5]. Literature [6-7] uses the edge calculation assisted by intelligent reflective surface to directly analyze the data of sensors and other equipment, and then screen the information threatening the stable operation of distribution network business, and then upload it to the cloud for processing. Therefore, the intelligent reflective surface assisted mobile edge computing can help the power grid avoid many risks and enable the power grid to operate more stably. This paper mainly studies the mobile edge computing offloading system of the intelligent reflective surface assisted distribution network, which can increase the reliability of the distribution network by reducing the network delay.
2. SYSTEM MODEL

Considering the distribution network MEC system operating in a single-cell scenario, where $k$ single-antenna distribution Internet of Things terminals are deployed. When faced with the computational offloading problem of a hostile communication environment, the delay performance is reduced, and auxiliary offloading is performed through IRS. Improve the overall performance of its system. Among them, the $k$ single-antenna devices select the wireless transmission path and the multi-antenna node offloads some or all of their computing tasks to the edge computing node. It is assumed that the antenna spacing at the AP and the unit spacing of the IRS are sufficiently high, so that they are connected to two different antennas. The small-scale fading associated with two different reflection units is independent.

Assuming that the equivalent baseband channels from the $k$-th power distribution IoT terminal device to the IRS and from the IRS to the AP are fully estimated and quasi-static, these channels remain almost constant when the devices are scheduled to offload their computing tasks. For IRS, for simplicity, the amplitude reflection coefficient of all reflection elements is set to 1, and the phase shift coefficient vector is expressed as $\theta = [\theta_1, \theta_2, \cdots, \theta_n]^T$, where $\theta_n \in [0, 2\pi)$ for all $n \in \{1, 2, \cdots, N\}$. The reflection coefficient matrix of IRS can be obtained as $\Theta = \text{diag}\{e^{j\theta_1}, e^{j\theta_2}, \cdots, e^{j\theta_n}\}$. Assuming that the edge computing node of the power distribution Internet of Things and the AP are located at the same location, and are connected by high-throughput, low-latency optical fibers, for simplicity, the delay imposed by the data communication between the edge computing node of the power distribution Internet of Things and the AP is negligible.

After assuming that the perfect transmission scheme for realizing capacity is invoked, the maximum achievable computational unloading rate of the $k$-th device is expressed as

$$R_k = B \log_2[1 + \gamma_k]$$

The achievable SINR is

$$\gamma_k = \frac{p_i |\omega_k^H (h_{i,j} + G\theta h_{i,j})|^2}{p_i \sum_{j \neq i} |\omega_k^H (h_{i,j} + G\theta h_{i,j})|^2 + \sigma^2 |\omega_k^H|^2}$$

where $\omega_k$ is the $k$-th column of the matrix $W$, $W$ is the multi-user detection (MUD) matrix.

The total delay of edge computing includes computing offloading, edge computing, and return. The end-to-end delay of the calculation result is jointly constituted. The waiting time of the $k$-th device can be calculated by selecting the maximum value between the maximum value imposed by the local calculation and the edge calculation, which is specifically expressed as follows

$$D_l(a, \theta_{l}, f_e) = \max\{D_l(a), D_l(a, \theta_{l}, f_e)\}$$

$$= \max\left\{\frac{L_i - L_j}{f_e}, \frac{L_j}{X(a, \theta_{l})} + \frac{L_e}{f_e}\right\}$$

3. PROBLEM DESCRIPTION

In order to minimize the delay, increase its computational unloading rate, and establish the problem of minimizing the weighted computational delay of all devices, so as to verify the delay performance of the IRS-assisted MEC in the distribution network, the weighted delay minimization problem is expressed as
where $\omega$ represents the weight of the k-th device, (4a) Represents the phase shift range of IRS, (4b) means that for the kth device, The calculated unloading amount is an integer between 0 and $L_k$, (4c) and (4d) are expressed as limiting the range of edge computing resources allocated to each device.

The above-mentioned problem is an online optimization problem. The state changes from time to time during the operation of the system and cannot be solved by static methods. Therefore, we model the problem as MDP, and then obtain the optimal solution.

4. OPTIMIZATION OF THE DELAY MINIMIZATION PROBLEM

A Markov Decision Process

MDP can be expressed as a triplet $\{S,A,R\}$, S stands for state space, A represents action space, R is the reward function. A detailed description is given below.

The state refers to the state of the current environment. For the system, the state is defined as the task offloading of each power distribution Internet of Things terminal in the system and the edge computing resources of each device, so the system state can be expressed as

$$S = [l_1, l_2, \ldots, l_k, f_1^e, f_2^e, \ldots, f_k^e]$$

(5)

Action is the drive that causes the environment to transfer from one state to another. In this system, the action that affects the performance of the system is the phase shift change of the IRS. By changing the phase shift, its computational offloading ability is enhanced, so the actions under the system can be expressed for

$$A = [\theta_1, \theta_2, \ldots, \theta_k]$$

(6)

Reward refers to the feedback given by the environment to the action imposed by the agent. In MDP, the agent selects an action $A$ in the state $s(t)$, gets a reward $R(t+1)$ and enters the next state $S(t+1)$. Among them, $R(t+1)$ is a single-step reward, and the reward is defined as the maximum delay between local computing and edge computing of IoT terminal devices, it can be expressed for

$$R(t + 1) = -\sum_{k=1}^{K} \omega_k D_k(\omega_k, \theta, l_k, f_k^e)$$

(7)

The purpose of deep reinforcement learning is to maximize the cumulative reward. In this system, because the research goal is to minimize the weighted calculation delay of all Internet of things devices, So defined reward as

$$-\sum_{k=1}^{K} \omega_k D_k(\omega_k, \theta, l_k, f_k^e)$$

(8)

B the design of Algorithm

The overall environment of the system is that the edge computing node of the power distribution Internet of Things assists k power distribution Internet of Things terminals to calculate and unload through the IRS. The IRS is used as an agent to observe the state of the system environment, and the phase shift is appropriately adjusted to issue an action to apply the action to the current state. The environment gives feedback on the new offloading decision, rewards the agent, and enters a new state, and so on, iteratively, until the minimum calculation delay is obtained.

In this paper, DQN is used as a method to find offloading decisions to minimize the calculation delay. DQN is a type of deep reinforcement learning. DQN is evolved from Q learning.
In the Q table, the agent can take \( \epsilon \) strategies according to the Q table. If the \( \epsilon \) greedy strategy is adopted, the probability of the agent choosing the best Q value is \( \epsilon \), and the probability of adopting a random strategy is \( 1-\epsilon \). At the same time, DQN uses neural network to simulate the Q value, then the Q function in DQN is \( Q(S_t, A_t, \zeta) \), and \( \zeta \) is the weight of the neural network. In order to improve learning efficiency and accelerate convergence, DQN also uses experience replay and target networks.

1) Experience playback: Suppose a tuple \( V_t = (S_t, A_t, R(S_t, A_t), S_{t+1}) \), the set \( V \) is stored in a memory buffer, and the agent selects a small batch of tuples from the memory buffer to update the weight of the neural network.

2) Target network: The target network is a clone of the evaluation network. The difference is that the target network obtains a Q value every \( \square \) iterations, which is denoted as \( Q^\tau \). And the target network is used to calculate the loss with the evaluation network, and \( L(\zeta) \) is used to update the weight of the evaluation network. \( Q^\tau \) can be expressed as:

\[
Q^\tau(S_t, A_t, \zeta^-) = R(S_t, A_t) + \max_A Q^\tau(S_{t+1}, A_{t+1}, \zeta^-)
\]

\( \zeta^- \) is the weight of the target network. The loss function \( L(\zeta) \) is expressed as

\[
L(\zeta) = (Q^\tau(S_t, A_t, \zeta^-) - Q(S_t, A_t, \zeta))^2
\]

Algorithm 1: DQN algorithm based on offloading decision

1. Initialize the evaluation network \( Q \) and its weight of \( \zeta \), initialize the target network \( Q^\tau \) and its weight \( \zeta^- = \zeta^- \), and initialize the experience playback;
2. for each episode \( k \) do
3. for each step \( t \) do
4. Observe system status \( S_t \);
5. Use the greedy strategy to select an action of \( A_t \) according to the probability \( \epsilon \), otherwise select an action randomly;
6. Perform action \( A_t \) and observe reward \( R(S_t, A_t) \);
7. Obtain \( V_t \) and store \( V_t \) in the experience pool;
8. Randomly select samples from the experience pool;
9. if episode \( k \) stops at step \( t+1 \);
10. \( y_t = R(S_t, A_t) \)
11. else
12. \( y_t = R(S_t, A_t) + \max_A Q(S_t, A_t, \zeta^-) \)
13. end if
14. Perform gradient descent with \( L(\zeta) = (y_t - Q(S_t, A_t, \zeta))^2 \) for network parameter \( \zeta \);
15. Reset \( Q^\tau = Q \) in every \( Z \) step;
16. end for;
17. end for.

5. SIMULATION ANALYSIS

The power system is a hierarchical physical network that carries massive amounts of information [13]. The distribution network presents the characteristics of wide coverage, long transmission distance, and fault conflict. This paper introduces IRS to assist its computational offloading. With the aid of IRS, it can effectively reduce the delay and improve the overall stability of the distribution network. In this system, the coverage area of AP is \( R=350m \). The influence of mobile edge computing tasks on delay is explored, and the influence of the number of IRS on delay is explored.
fig 1 shows the relationship between latency and edge computing resources, respectively considering the IRS-assisted communication and non-IRS-assisted communication systems. First of all, due to the passive beamforming gain, the scheme with IRS is better than the scheme without IRS. The performance of the system with IRS is significantly reduced. At the same time, with the increase of edge computing tasks, the delay gradually increases and performance decreases, because with the increase of edge computing tasks, processing tasks increase, processing delays, and transmission delays Correspondingly will increase and reduce latency performance, and offloading calculations through IRS-assisted power distribution IoT edge computing nodes can greatly reduce latency and improve latency performance.

fig 2 further shows the relationship between the total delay and the number of IRS units under finite and infinite cloud capacity. It can be observed that the total delay of all schemes decreases monotonically with the increase of the number of IRS elements. Because in the process of IRS assisted unloading, the received SINR can be improved by deploying the IRS for calculating unloading. In addition, in the case of unlimited cloud capacity, the performance of TDMA is slightly better than that of noma. In the case of limited cloud capacity, the total delay of TDMA decreases more obviously than that of noma due to the multiplexing gain of transmission calculation based on TDMA scheduling. It is obvious from the figure that the performance advantages of the IRS auxiliary system fully confirm the performance advantages of the IRS auxiliary MEC system.
6. CONCLUSION
With the rapid development of information and the huge growth of Internet of things equipment, its calculation and unloading delay is too large, which has a great impact on the inspection, coverage and image transmission of intelligent substation. In this paper, the IRS assisted MEC is proposed to improve its coverage, reduce the delay and improve the overall stability performance. In this paper, the weighted delay minimization problem is established, and the dqn algorithm is used for iteration. Finally, the influence of the number of IRS reflective elements on the system delay is discussed, and it is fully proved that IRS assisted unloading can improve the performance of the whole power grid system.

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