Analysis of cross platform power data governance

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Abstract: With the rapid development of smart grid, how to solve the problems of professional business cooperation and information sharing, long data input time, accurate data, weak real-time, data extraction, redundant storage, low quality, privacy protection, further comprehensive management of data, mining the value of data resources has become one of the important tasks for the development of electric power enterprises. The traditional method uses edge computing for data transmission and task allocation. On this basis, we study the cross-platform power governance scheme based on edge unloading computing and deep reinforcement learning. The final experimental results show that the scheme has smaller delay and lower energy consumption.

Keywords: Edge computing; Smart grid; Deep reinforcement learning; Power data governance

1. Introduction

For many power enterprises, with the advent of the era of big data, faced with massive information and rapidly growing power data, traditional data management does not match with data organization and system, data access is difficult, data standards are not high, and data quality is not high, which cannot meet the requirements of the power industry to obtain knowledge and information analysis from massive data quickly, accurately and efficiently . How to use data governance to standardize power work flow, effectively manage structured, semi-structured and unstructured massive power data, mining and analyzing the potential value of power data, has become an urgent problem to be solved.

With the rapid development of the new generation of information technology represented by AI and the explosive growth of Internet applications, the massive information generated by mobile terminals will have a great impact on the transmission network and cloud services of mobile terminals.

Computing offloading technology has been proposed since 2000, and its core idea is always to provide highly complex services for devices with more computing resources. Mobile devices generate high latency sensitivity and high computing power to improve energy efficiency and user experience . According to different unloading methods, edge unloading strategies can be divided into full unloading and partial unloading. The purpose of the study was to determine strategies for optimizing application processing between different mobile devices and edges, which parts of the entire application could be unloaded, and how to unload to edges.

In this paper, we consider a smart grid scenario based on edge computing. Considering the unloading of user data information, we design a SDTO task unloading scheme based on reinforcement learning algorithm. The main contributions of this article are summarized as follows:

- Carry out cross platform training and analysis of power data, and use edge computing to process data.
- Based on reinforcement learning algorithm, we propose an SDTO task offloading scheme.
- Through the analysis of experimental results, the factors that affect the low latency and low energy consumption goals of the scheme are obtained.

The structure of the rest of this article is described below. Section 2 describes the application of power data in edge offloading and blockchain. In Section 3, we introduced our design methodology. Section 4 describes our experiments, as well as our experimental evaluation results and analysis. In Section 5, we summarize our work, propose some limitations, and discuss possible future work.

2. RELATED WORK

In terms of data governance practices, with the transformation of the power industry towards digitalization and informatization, data management has also been continuously implemented in various aspects of the energy industry. The research on multi source and diversified data management has become a hot topic for the further development of the power industry, and is crucial for the stable, safe, and reliable operation of the power grid. In terms of data cleaning and fusion, J. Gao proposed a response to the demand for massive multi-source data processing in smart grids. Combined with edge solutions provided by distributed computing, he proposed a distributed data fusion algorithm based on computing edges to address the existing problems of power equipment status data noise and redundant data monitoring data. On the basis of the above, Xue considered the issue of energy consumption transmission during data transmission, and proposed a low energy consumption data transmission method based on the industrial popularization of the Internet of Things fusion mechanism method. G Divya et al. introduced the application of machine learning methods in data fusion, and discussed the trend of data fusion. Y. Liang et al. combined cloud computing and data management, Dcloud's model data cloud platform, historical data cloud platform, real-time data cloud platform, and big data platform applications in data management, and data management systems based on the Dcloud model. Literature proposed entity identification for heterogeneous data cleaning, enabling data users to make good use of information from heterogeneous data sources. On the basis of traditional power entity recognition methods, literature adds bidirectional long and short term memory neural network, and uses partof speech features to recognize power corpus data.

In terms of power data security, literature uses smart contracts of blockchain technology to protect data and improve data security and data traceability. F.ZHANG et al. uses distributed consensus algorithm in blockchain technology to realize data authority confirmation, data traceability and other operations, improving power grid data governance level and open sharing ability. Literature considers the security communication in smart grid system, combines edge computing with blockchain technology, and uses group signature to ensure the legitimacy of users. Literature introduces a blockchain-based mutual authentication and key protocol, which can support effective conditional anonymity and key management, and ensure the safe transmission of data in turn. Literature considers the privacy protection of data owners and receivers, and proposes a blockchain-based multi-party computing scheme for smart grid bilateral privacy protection and smart edge support.

In this paper, We analyzed cross platform power governance based on edge computing and deep reinforcement learning. The final experimental results show that our proposed scheme has smaller latency and lower energy consumption, while analyzing the factors that affect the governance effect

3. Analysis on cross-platform power governance based on edge computing and deep reinforcement learning

3.1 Our task offloading scheme consists of two parts

(1) Decide to process tasks in the local or edge cloud based on the battery capacity of the mobile device. In addition, the availability and load of tasks are determined based on various edge clouds;

(2) The edge cloud allocates computing resources for each task . We have designed an effective solution for computing resource allocation and task allocation based on the idea of software defined networks - separating the control layer from the data layer.

3.2 Data processing process and cross-platform power governance analysis

3.2.1 Cross-platform training and analysis

(1) Each user will standardize the processed data samples in a unified format.

(2) Build a total analysis neural network on the cloud server, and randomly initialize the neural network parameters.

(3) Each user shall build a mirror neural network consistent with the cloud server on their own edge server.

(4) The cloud server passes the parameters to each user to initialize each mirror network parameter.

(5) Each user uses his or her own data samples. To train their own network model alone, training methods and DNN unity.

(6) The training cycle is unified with the above, and regularly return to the cloud server for the overall update.

(7) After the overall update of the cloud service, each user is sent to update their own mirror neural network parameters.

Each user only sends back the network model parameters. The cloud not only realizes the privacy protection of different user data, but also realizes the cross-platform uninstallation analysis.

3.2.2 THE FLOW OF EDGE-COMPUTING DATA PROCESSING

1 Determine the constraints and objective functions to be optimized;

(1) The data information collected by the user must be unloaded to the edge for processing or left locally; a represents the unloading policy, 1 represents local processing and 0 represents unloading to the edge server for processing;

(2) The computing resources allocated by local calculation shall not exceed the total amount of computing resources that can be used locally for processing data; X is the amount of computing resources allocated locally for computing resources, and Y is the total amount of computing resources that can be used locally for processing data;

(3) The total amount of computing resources allocated to all users for multimodal data processing shall not exceed the edge server and the total amount of computing resources allocated for data processing; a represents the unloading policy, b is the computing resources allocated by the edge server to the n th user data processing, and F is the total amount of computing resources allocated for data processing.(Vector is adjustable)

2. Each company collects the data of its own users in real time for data processing;

3. Vectortize the data collected in real time and convert it into a computational complexity vector;

4. Establish a deep reinforcement learning model, in which the agent of the reinforcement learning model is the deep neural network DNN, and the network parameters are randomly initialized, the computational complexity vector collected at time N into the DNN network in real time, and the unloading decision vector and resource allocation vector are obtained through DNN network calculation. Both vectors process the data through the local and edge server allocation of computing resources.

5. Take the obtained unloading decision vector and resource allocation vector as the initial data, and the input is optimized according to various constraints and objective function, and then theoptimal and constituent sample data are selected.

6. cycle execution and then train the DNN network every 10 cycles.

7. The objective function takes the shortest time in data processing in edge calculation.

3.3 Modeling of target problems

How much compute resources does the edge cloud allocate to each task. We aim to minimize the average task duration with limited battery capacity. Specifically, we define integer decision variables $m_j \in \{0,1\}$ indicating that the task is processed locally ($m_j = 1$) or in an edge cloud ($m_j = 0$). Therefore, the task placement variables are as follows:

$M = \{m_1, m_2, \cdots, m_x\}$ and $\omega = \{\omega_1, \omega_2, \cdots, \omega_x\}$ The corresponding resource allocation variables are shown as follows: $\sigma = \{\sigma_1, \sigma_2, \cdots, \sigma_x\}$ Formally, the task-unloading problem can be formulated as follows:

$$\min_{M,\omega,L} imize \sum_{j=1}^{x} \left[m_j z_j^K + (1 - z_j) z_j^A \right] \tag{1}$$

subject to:

$$m_j \alpha_j^K \le \varepsilon_j A_{\max}^j \quad \forall j = 1, \cdots, x. \tag{2}$$

$$(1 - m_j) \alpha_j^A \le \varepsilon_j A_{\max}^j \quad \forall j = 1, \cdots, x. \tag{3}$$

$$\omega_j \in E(w_j) \quad \forall j = 1, \cdots, x. \tag{4}$$

$$\sum_{j \in q_{\omega j}} \sigma_j^{\omega j} \le 1. \tag{5}$$

The objective function (1) is to minimize the total task duration. The first constraint (2) indicates that the local energy consumption is less than the remaining battery capacity of the mobile device, where the remaining energy consumption ε_j is relative to the total battery capacity $A_{\max}^j$.

The second constraint (3) states that the energy consumption for transferring tasks to the edge cloud is limited by the mobile device battery. The third constraint (4) indicates that the relevant BS are those constraints j that provide services to user w. Last one condition (5) assigned to ω should not exceed the amount of calculation to calculate total amount, including $q_{\omega j}$ says On the edge of cloud ω computing tasks set j.

Objective functions and constraints

In this section, we demonstrate an effective task unloading scheme based on the optimization problem mentioned in (7). We first defined the objective function as follows:

$$h(M, \sigma, \theta) = \sum_{j=1}^{x} \left[m_j \frac{\gamma_j}{h_j^k} + (1 - m_j) \left(\frac{\gamma_j}{\sigma_j^{\omega j} h_{\omega j}^d} + \frac{r_j}{s_{j,\omega j}} \right) \right] \tag{6}$$

For simplicity, we define that $\theta = (m, \omega)$ Let L and F represent σ and θ :the feasible set of the sum.The problem in Equation (1) is a mixed-integer nonlinear optimization problem.

From formula (7), the resource allocation can only be obtained when the task is uninstalled to the edge cloud $m_j = 0$. We set up $i = \omega_j^0$ and $m_j^0 = 1$.Then the objective function (7) can be converted to the following equation:

$$h(\sigma, \omega^0) = \sum_{j=1}^{l} \left(\frac{\gamma_j}{\sigma_j^i h_i^d} + \frac{r_j}{s_{j,i}} \right) \tag{7}$$

Where $h(\sigma, \omega^0)$ is a function of the relative to $\sigma = \{\sigma_1, \sigma_2, \cdots, \sigma_x\}$ Then we can get its Hessian matrix as follows:

Of these, each specific element is:

$$\frac{\eta^2 h}{\eta \sigma_j \eta \sigma_i} = \begin{cases} \dfrac{2\gamma_j}{(\sigma_j^i) 3 h_i^d} & if \quad j = i \\ 0 & otherwise \end{cases} \tag{8}$$

The parameters in (8) are all positive numbers for 0. Thus, we conclude that all eigenvalue matrices F are positive and F is a symmetric positive definite matrix.

$$K(\sigma, b) = \sum_{j=1}^{k} \left(\frac{\gamma_j}{\sigma_j^i h_i^d} + \frac{r_j}{s_j} \right) + \sum_i b_i \left(\sum_{j \in o_i} \sigma_j^i - 1 \right) \tag{9}$$

$$\sigma_j^* = \frac{\sqrt{\gamma_j}}{\sum_{j \in q_i} \sqrt{\gamma_j}} \tag{10}$$

$$h(\sigma^*, \omega^0) = \sum_{i=1}^{y} \sum_{j \in q_i} \left[\frac{\sqrt{\gamma_j} \sum_{j \in q_i} (\sqrt{\gamma_j})}{d_i} + \frac{r_j}{s_{j,i}} \right] = \sum_{i=1}^{y} \left[\frac{\left(\sum_{j \in q_i} \sqrt{\gamma_j} \right)^2}{d_i} + \sum_{j \in q_i} \frac{r_j}{s_{j,i}} \right] \tag{11}$$

3.5 problem formulation

Through the above discussion,we give that $\theta = \theta^0 \in F$ .We can get the optimal solution in (11). On this basis, the original optimization problem is transformed into an integer planning problem for M and ω, as follows:

$$\min_{M,\omega} imize \quad h(M, \sigma^*, \omega) \tag{12}$$

subject to:

$$m_j \alpha_j^K \le \varepsilon_j A_{\max}^j \quad \forall j = 1,2,\cdots,x. \tag{13}$$

$$(1 - m_j)\alpha_j^A \le \varepsilon_j A_{\max}^j \quad \forall j = 1,2,\cdots,x. \tag{14}$$

$$\omega_j \in E(w_j) \quad \forall j = 1,2,\cdots,x. \tag{15}$$

The optimization questions about and in (12) can be rewritten as optimization problems as follows:

$$\min imize \quad | (WZC)^Z |_2^2 + SZR \tag{16}$$

subject to

$$m_{ji} \in \{0,1\} \tag{17}$$

$$\sum_{i=1}^{y+1} m_j = 1 \quad j = 1,2,\cdots,x. \qquad n_{ji} \ge 0, \quad \sum_{i=1}^{y+1} n_j = 1, \quad j = 1,2,\cdots,x. \tag{18}$$

4. EXPERIMENT

4.1 Analysis of experimental results

In this paper, for task unloading, we assume that the computational quantity and data size are generated by a probability distribution. The total computing resource of the edge cloud is 30 GHz, while the total computing resource is 15 GHz.

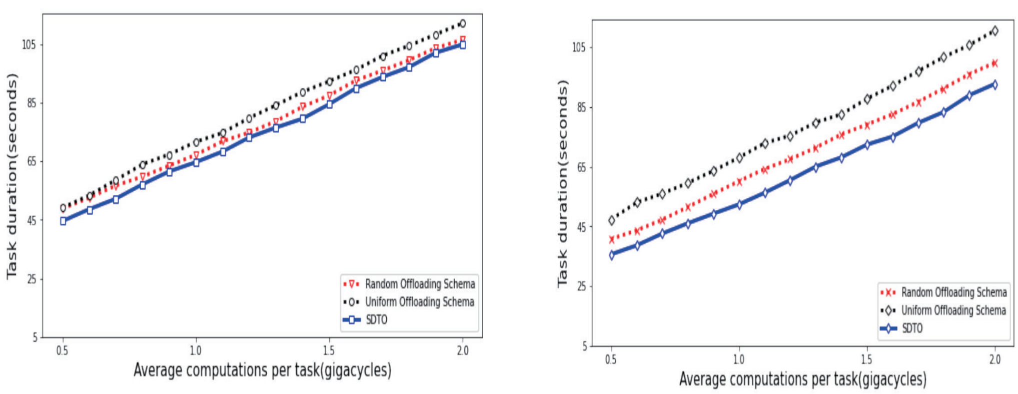
This section presents simulation experiments on the task unloading of mobile computing. Experimental results compare the task duration and energy cost of the proposed SDTO with other task unloading schemes.

Random offloading scheme: When the user proposes the task, the computing task is uninstalled to the edge cloud for processing or local random processing. We build a random generator that can generate numbers 0 and 1 with equal probability and then unload the computational task to the edge cloud or perform local random processing according to the random generator. Then, based on the random task allocation strategy, the resource allocation is given using formula(12).

Uniform unloading scheme: when the user put forward tasks, we according to the user's battery capacity all tasks are divided into two parts, part is the edge cloud processing, the other part is the local local processing, and then resource allocation, similar to the random unloading scheme, based on the unified task allocation strategy, use formula(12) gives resource allocation.

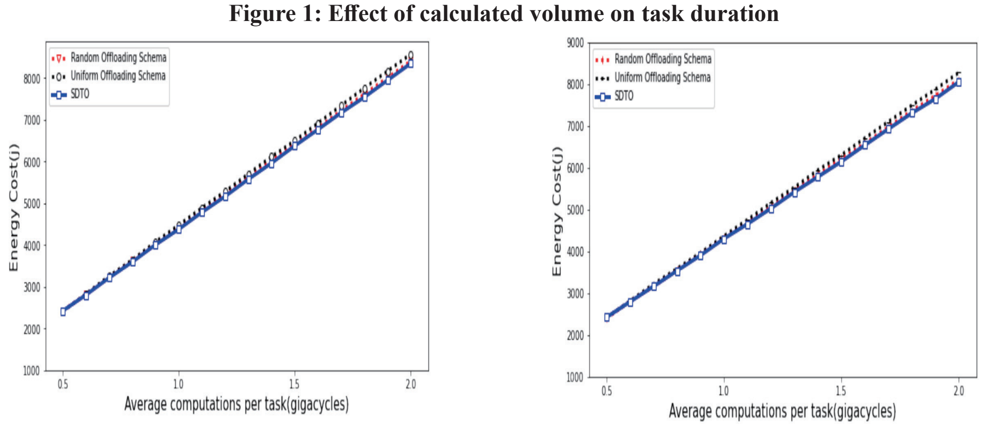
We set the task data size to follow a normal distribution with a mean of 10 MB. In computational terms, a uniform and normal distribution were used

As shown in Figure 4, we can conclude that the larger the computation of a task, the longer the task duration, the greater the energy expenditure.



(a) Normal distribution **(b) Uniform distribution**

Figure 1: Effect of calculated volume on task duration



(a) normal distribution **(b)Uniform distribution**

Figure 2: Impact of the calculated quantities on the energy costs

In Figure 1 (a) and Figure 2(a), when the random unloading, the results show that our proposed SDTO can reduce task duration by 30% and energy cost by 10%. A 41% reduction in task duration and 11% in energy expenditure compared to the unified unloading scheme. As shown in Figure 1(b) and Figure 2(b), when the calculated quantities follow a uniform distribution, the results are similar to the situation based on the normal distribution.

5. CONCLUSIONS

In this paper, we use reinforcement learning and edge computing technology to effectively analyze edge power data, and measure the two factors of task delay and energy consumption. We propose a solution for offloading edge cloud tasks or local processing. Experimental results show that our method works well. However, this article also has many shortcomings. Data security implications were not considered. This is also a follow-up study that needs improvement.

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