An Power Grid Things of Internet Fog Resource Scheduling Algorithm

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Abstract. In the wake of developments in computer and internet, power Internet of things technology is becoming more and more mature. As an extension of cloud computing, fog computing provides computing, network, storage and network edge communication for power grid Internet of things. Due to the limitation of its own storage and computing power and the increasing business demand, it is urgent to improve the efficient and feasible resource scheduling scheme. This paper takes the fog resource scheduling in power grid as starting point, proposes a fog resource scheduling algorithm based on time series optimization for the Internet of things in the power grid, and evaluates the proposed algorithm. The results show that the algorithm has strong application value for electricity the development of Internet of things provides the possibility.

Keywords: Fog Computing, Power Internet of Things, Resource Scheduling

1 Introduction
With the development of power grid Internet of things, a large number of data are generated in devices monitoring or power grid systems, fog computing has been widely used in each scenes[1], in order to provide instant computing support for content delivery at the edge of the network system, provide services for billions of connected devices, and real-time data processing for various applications[2]. Fog computing is widely used in power Internet of things [3]. Fog computing can replace this kind of server, which can flexibly transmit data in network topology, process massive heterogeneous edge devices, and provide services of fast response, fast transmission, low delay and low power consumption. Fog nodes at the edge collect data from sensors and devices, such as power consumption, environmental
monitoring, etc. [4,5], preprocess the data, retain useful data, and realize local control in the process of power distribution.

Resource scheduling is an important research direction of fog computing. The purpose of scheduling is to optimize resource allocation and program CPU usage time, and achieve low latency, high response, high reliability, high security, low energy consumption and cost. This paper introduces two common scheduling strategies, and proposes a fuzzy scheduling algorithm based on time series. Experiments show that this method is effective.

2 Recent work
1) Algorithm to reduce task execution time. In reference [6], Markov decision process method is proposed to reduce task processing delay. In reference [7], a task scheduling algorithm based on fog region and cloud is proposed. The scheduling problem is transformed into integer programming problem, which is combined with heuristic algorithm.

2) Algorithm to reduce task energy consumption. For the sake of reduce the energy usage in smart terminals to a large extent, the paper [8] proposes an optimal task offload and transfer scheme that considers the power consumption in mobile edge computing. Firstly, the conditional power consumption of mobile devices is analyzed, and then the system model of mobile edge computing is proposed. Finally, based on the above analysis, an optimal task offload and transfer model is designed.

3 Fog Resource Scheduling Algorithm of Internet of Things

3.1 Fog resource preprocessing
Fog computing in the Internet of things can be regarded as a virtual resource pool, in which the resources are composed of many distributed computers, which can respond to the needs of end users and complete data calculation and storage.[9] Different types of tasks have different requirements for resources. Tasks with high computing requirements focus on the need for computing power. Real-time tasks require multiple bandwidth resources. Massive data also requires a large amount of storage space. In order to meet the needs of the above businesses, we divide the resources [10]. In this section, we use the fuzzy clustering algorithm based on their multi-dimensional attributes. There are m fog nodes in the fog resource which set be \( F = \{ F_1, F_2, F_3, \ldots F_m \} \), \( F_m = \{ f_{m1}, f_{m2}, \ldots f_{mn} \} \). The resource nodes are shown below:

\[
F = \begin{bmatrix}
 f_{11} & f_{12} & \cdots & f_{1n} \\
 f_{21} & f_{22} & \cdots & f_{2n} \\
 \vdots & \vdots & \ddots & \vdots \\
 f_{m1} & f_{m2} & \cdots & f_{mn}
\end{bmatrix}
\]

In the above formula, \( f_{mn} \) represents the nth characteristic attribute of resources \( f_{in} \).

Before scheduling fogs resources, we must standardize and fuzzy cluster the original resource data. The steps for data standardization and fuzzy clustering are as follows.

3.1.1 Data standardization. Each feature attribute of the fog resource has a different dimension in the fog computing environment. If the original data is directly clustered, it will cause data disaster.
Therefore, to solve this problem, we first use the transformation standard deviation transform to normalize the resource matrix data:

\[ f'_{mn} = \frac{f_{mn} - \bar{f}_{mn}}{S_n} \] (1)

\[ \bar{f}_{mn} = \frac{1}{k} \sum_{n}^{k} f_{mn} \] (2)

\[ S_n = \sqrt{\frac{1}{k} \sum_{n}^{k} (f_{mn} - \bar{f}_{mn})^2} \] (3)

Among them, \( f_{mn} \) represents \( n \)-th dimension characteristic attribute in the mean value of each resource, \( S_n \) represents \( j \)-th dimension characteristic attribute in the standard deviation of each resource. The processed data conform to the standard normal distribution with an average value of 0 and a deviation value of 1.

3.1.2 Fuzzy clustering. We divide processed resource matrix data into fuzzy clusters. We use FCM to set the cluster sample set as \( X = \{ x_1, x_2, \ldots, x_i \} \in R^d \). Among them, \( x_i \) is a \( d \)-dimensional vector. To divide the sample set into class \( J \), the cluster center set is \( V = \{ v_1, v_2, \ldots, v_j \} \). And define sample points \( x_i \). The degree of belonging to class \( J \) is \( \mu_{mn} \), sample space \( X \) Fuzzy matrix of \( U = (\mu_{mn}) \). The mathematical model of FCM algorithm is a problem of finding the extremum of objective function

\[ Y = \min \sum_{m=1}^{i} \sum_{n=1}^{j} \mu_{mn} \| x_m - v_n \|^2 \] (4)

\[ s.t. \sum_{n=1}^{j} \mu_{mn} = 1 \]

\[ \mu_{mn} \in [0,1] \quad m = 1,2,\ldots,i, \quad n = 1,2,\ldots,j \]

Among them, \( \mu_{mn} \) represents the membership degree, which in the \( j \)-th class, \( i \)-th sample, \( v_n \) represents the \( j \)-th clustering center, \( \| x_m - v_n \| \) represents the Euclidean distance from the \( m \)-th sample to the \( n \)-th cluster center.

3.2. Scheduling algorithm based on time series

After clustering fog computing resources, the amount of data resources is already small. We have developed a judgment matrix for manual evaluation criteria \( C \). Used to evaluate all attribute values. Among them, \( c_{mn} \) by \( x_m \) reach \( x_n \). The relative importance of the property value.

\[ C = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{mn} & \cdots & c_{nn} \end{bmatrix} \]
We have a problem with discriminant matrix $C$. Each column vector in is normalized, and the row vectors of the new matrix are summed to get the matrix $E = [\varepsilon_1, \varepsilon_2, ..., \varepsilon_n]'$. Renormalization matrix $E$ Formation matrix $W = [\omega_1, \omega_2, ..., \omega_n]'$ is the final weight.

\[
C'_{mn} = \frac{c_{mn}}{\sum_{k=1}^{m} c_{kn}}
\]  
(5)

\[
\varepsilon_n = \sum_{m=1}^{n} C'_{mn}
\]  
(6)

\[
\omega_n = \frac{\varepsilon_n}{\sum_{k=1}^{n} \varepsilon_k}
\]  
(7)

Each task request needs different resources, including calculation, network transmission and data storage resources. In the above formula, the user demand attribute and resource demand attribute are both calculated, the scheduling algorithm of fog calculation based on time series is as follows.

**TABLE I.** Algorithm 1 time series data scheduling algorithm

| Algorithm 1 time series data scheduling algorithm |
|-----------------------------------------------|
| **INPUT** A fog dataset $F$, task dataset $T_a$, $n_t$ is the total number of clusters, $X$ is identified as an outlier |
| **OUTPUT** A outlier dataset $O$ |
| 1 Get the standardized matrix $D$, $T_a$ |
| 2 For $i=1$, $i++$: |
| 3 For $j=1$, $j++$: |
| 4 Dist($i,j$) |
| 5 For $m=1$ to $n_t$ |
| 6 Calculate the cluster center for each cluster, and generate the list of cluster centers $C[j]$. Find the max value $d_{max}$ and the min value $d_{min}$ in the $i$th cluster |
| 7 Generate subdatalist[i] |
| 8 For $n=1$ to subdatalist[i].length-1 |
| 9 If(subdatalist[i][j]>dmax || subdata-list[i][j]<dmin) |
| 10 Append the outlier into $O$ |
| 11 End |
| 12 |

**4 Experimental Result**

To better evaluate task requests and fog resource matching, the experiment platform in this chapter uses MATLAB r2018a simulation software, and we randomly set the number of fog resource nodes and task requests with the number of 10 and 10, respectively, for fuzzy clustering and resource scheduling. Using the weight matching method mentioned in this chapter, select the appropriate resources. The following figure shows the resource distribution after clustering.
In order to test the accuracy of this proposed algorithm, we run the algorithm independently for 50 times to calculate the clustering accuracy [11]. The results are shown in the table below. After clustering the fog computing resources correctly, the scope of matching resources for task requirements is narrowed. To a certain extent, the efficiency of resource scheduling will be improved.

**TABLE II.** Accuracy of clustering algorithm

| algorithm | data set | Correct cluster number | Number of error clusters | Accuracy rate |
|-----------|----------|------------------------|--------------------------|---------------|
| FCM       | Iris     | 142                    | 8                        | 94.36%        |
|           | Wine     | 130                    | 20                       | 84.61%        |

Response time is the amount of time required for a user's request before the response is completed, which usually takes less response time for a dynamic environment. Figure 2 shows the response time comparison between this method and previous methods, including BLA and graph partition, simple scheduling, left and MPG[12]. Each request takes 2500 milliseconds and increases as the number of requests increases. The proposed method takes 1800 milliseconds, which is 30% less than the graph partition and 45% less than the BLA. Simple scheduling, lift and MPG[12] algorithm do not require high task scheduling, which requires more time for scheduling.

**Fig.2 Response time comparison**

5 Conclusions

Conclusion Task scheduling is an important factor affecting system performance. This paper mainly solves the communication delay, connection failure, resource shortage and other requirements of the power Internet of things in the terminal network, and proposes a fog resource scheduling algorithm based on time series optimization. Firstly, we preprocess the fog resources (standardization, fuzzy clustering), then schedule the time series, and evaluate the response time and accuracy. The results show
that our algorithm has better performance than the previous method, which provides a new idea for the power Internet of things.

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