Transformer Topology Identification Method Based on GPU Acceleration

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Abstract. Traditional transformer topology identification methods have poor accuracy and efficiency and are easy to be interfered. Aiming at these problems, this paper proposes a transformer topology identification based on GPU acceleration, which obtains and analyses the data from large quantities of smart meters and effectively identify the corresponding relationship between transformers and meters, via high performance computing technology and large data methods. Data analysis is implemented by GPU parallel accelerated grey correlation analysis method, which effectively improves the efficiency of the method. Numerical experiments show that the method proposed in this paper has high accuracy and computational efficiency, which has the value and potential of engineering applications.

1. Introduction

Region transformer is the last transformer passed by the electric energy to the users. It not only assumes the energy conversion task that converts the high-voltage power to low-voltage power used in cities, but its accessory concentrator is also responsible for collecting the electrical information of the users in the power supply range. That is to say, it is a dual hub of energy and information[1].

However, the increasing of electric loads leads to the adjustment of power facilities, such as relocation, expansion, cutting and stationing. In the operation of power grid corporation of many years, various technical reasons, unregulated management and responsibility adjustment cause the discrepancy between the accounts of the electric meters and the reality. Also, it is difficult to determine the power supply range of a certain region transformer, or to determine the region transformer that a certain user belongs to[2-3]. Further, the disordered accounts cause that the low-voltage region line loss analysis, remote cost control, remote recharge, clock timing and some other advanced applications cannot be effectively carried out.

Traditional methods for identifying the topology of transformer regions are divided into two kinds. One is artificial recognition-spot testing for every region transformer and every electric meter, which has very low efficiency. The other is to use special transformer recognition equipment, usually equipped with identification carrier communication module, which can improve the efficiency. But, the carrier signals transmit data to the surrounding area through common ground, common high voltage and parallel wiring coupling. Although the amplitude of the signal is attenuated, it can still communicate with the electric meters belong to the adjacent transformers[4-6].

In recent years, with the large-scale installation of smart meters, the power grid corporation can obtain massive and high-density data, but at present, the data has not been fully utilized. Some scholars use the large data technology to analyse the data of smart meters, so as to carry out the transformer topology identification[7-9]. For example, Ye A. et al. propose a topology identification method based on spatial-temporal correlation of data[7], and Li F. et al. propose a method based on BP neural network[8]. However, because of the large-scale data and numerous smart meters, the efficiency of these algorithms is low, which cannot meet real-time requirements of analysis of transformer topology.

In order to solve the above problems, this paper proposes a transformer topology identification method based on Graphics Processing Unit (GPU) acceleration, which aims to obtain and analyse the data from large quantities of smart meters and effectively identify the corresponding relationship between transformers and meters, via high performance computing technology and large data methods, so as to solve the problem of chaos account and topology. The specific attribution of this paper includes:

- It puts forward a transformer topology identification method from data acquisition to data analysis;
- It uses grey correlation analysis to realize data analysis and complete transformer topology identification;
- It uses GPU to parallelly accelerate the algorithm to improve computational efficiency.

Numerical experiments show that the proposed method has high accuracy and computational efficiency, which has the value and potential of engineering applications.

2. Algorithm overview and key technique analysis

2.1. Theoretical basis

There is a definite electrical connection between the transformer and the smart meter of the user. The voltage drop of the lines can be ignored in the power supply radius of the transformer. Therefore, the voltage of the user side will rise with the increase of the outlet voltage in the transformer region. These two voltage values have a high correlation and their variation trend are consistent.

According to the above analysis, corresponding method can be obtained: first, appropriate methods are applied to make the voltage fluctuation on the low-voltage side of transformers; second, the measurement data of smart meters is collected through communication technology; third, the correlation between data from smart meters and low-voltage side of transformers is analysed; finally, the similarity degree is calculated to complete transformer topology identification.

2.2. Procedure of the algorithm

According to Section 2.1, the flowchart of the proposed algorithm in this paper is shown as follows.

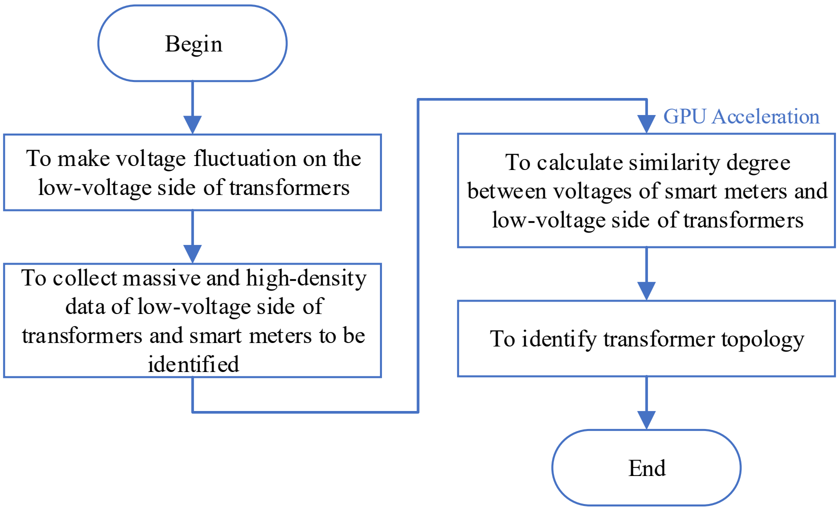

Figure 1. Flowchart of transformer topology identification method based on GPU acceleration.

The voltage fluctuation on the low-voltage side of the transformer can be realized by different ways, such as altering the voltage of the high-voltage side of the transformer, altering the parallel low capacitance impedance configuration, changing the transformer taps and adding the static var generators (SVG).

2.3. Key technique analysis

Specifically, to implement this algorithm, two key techniques need to be designed, including data correlation analysis and parallel acceleration technology.

2.3.1. Data correlation analysis algorithm. Data of the low-voltage side of transformers and smart meters required by communication technology needs similarity degree calculation. Because the voltage fluctuation on the low-voltage side of the transformer is generally difficult to describe with exact function distribution, the design of the data correlation analysis algorithm should not depend on distribution of certain samples. On the other hand, because of the large-scale data and high real-time requirements for online transformer topology identification, the time complexity of designed data correlation analysis algorithm should be as low as possible.

2.3.2. Parallel acceleration algorithm. When the number of smart meters is large, and the scale of data from smart meters is large, the sequential data correlation analysis algorithm with low time complexity is still very time-consuming. It calculates the similarity degree between every transformer and every smart meter in serial, which cannot meet the real-time requirements. Therefore, it is necessary to consider parallel acceleration processing for certain structures and steps in the data correlation analysis algorithm, to further improve the overall efficiency of the algorithm.

3. Grey correlation analysis

The grey correlation analysis is based on the data sequence of parameters to study the geometric correspondence between the parameters. That is, the higher the similarity degree of the geometric shape of the sequence curve, the higher the calculated grey correlation degree is. When using the grey correlation analysis method to analyse the voltage data, the specific steps are as follows.

a) The measurement data of the three phase voltages on the low-voltage side of the transformers in different regions is obtained as the reference sequences. Select one reference sequence as an example. Other reference sequences will be processed in the same way.

$$X_0 = \{x_0(k) \,|\, k = 1, 2, \ldots, n\} \tag{1}$$

The measurement data of smart meters to be identified is obtained as comparison sequences.

$$X_i = \{x_i(k) \mid k = 1,2,...,n\},\ i = 1,2,...,m \tag{2}$$

Where, n is the number of sampling time and m is the number of comparison sequences.

b) Dimensionless treatment for the referenced sequences and comparison sequences.

$$x_i^{'}(k) = \frac{x_i(k)}{x_i(1)} \tag{3}$$

c) Two extremums are calculated

$$p = \min_i \min_k \Delta x_i(k) \tag{4}$$

$$P = \max_i \max_k \Delta x_i(k) \tag{5}$$

Where

$$\Delta x_i(k) = \left| x_0^{'}(k) - x_i^{'}(k) \right| \tag{6}$$

d) Correlation coefficients between each comparison sequence and reference sequence are calculated

$$\Delta x_i(k) = \left| x_0^{'}(k) - x_i^{'}(k) \right| \tag{7}$$

Where ρ is the distinguishing coefficient, usually set as 0.5.

e) Similarity degrees between each comparison sequence and reference sequence are calculated

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i^k \tag{8}$$

Finally, transformer topology identification is realized according to the similarity degrees between the data from smart meters and the three phase voltage values on the low-voltage side of transformers in different regions. The larger the similarity degree between the data from a certain smart meter and from a certain phase of a certain transformer, the higher the possibility that this smart meter is used to measure the voltage of this phase of this transformer. In general, for a certain smart meter, the maximum value of the similarity degrees between the data from this meter and from different phases of different transformers can be found. It is considered that this meter is attached to corresponding transformer and corresponding phase.

4. GPU-based grey correlation analysis algorithm

4.1. GPU and CUDA

With the maturing of semiconductor technology, GPU has been developing rapidly. Initially, GPU was mainly used for graphic display. However, in 2007, NVIDIA introduced a new programming model and instruction set architecture-Compute Unified Devices Architecture (CUDA), and general-purpose GPU computing is also gradually applied to the computing areas in many disciplines [10-11].

In the framework of CUDA, the users can define the kernel function, which can execute n parallel threads when called and different threads calculate the same function instruction but with different data. The programming model of CUDA can be depicted with Figure 2. Each kernel function takes up a grid when called. Each grid is composed of multiple thread blocks, and each block executes in parallel. Each block also contains multiple threads, which execute in parallel. When the kernel function is called, the number of enabled blocks and the number of enabled threads in each block can be set.

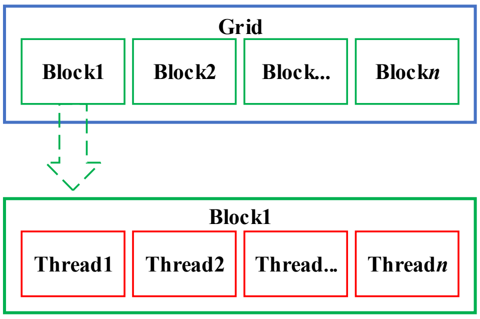

Figure 2. Model of CUDA.

4.2. Parallelism analysis of the algorithm

The parallelism of the algorithm is reflected in Expression (3)-(6) and is shown in Table 1
.

Table 1. Analysis of the parallelism of the algorithm.

	Different time of the same comparison sequence	Different comparison sequences
$x_i'(k)=\frac{x_i(k)}{x_i(1)}$	Can be run in parallel	Can be run in parallel
$\min_k \Delta x_i(k)$	Cannot be run in parallel	Can be run in parallel
$\max_k \Delta x_i(k)$	Cannot be run in parallel	Can be run in parallel
$\Delta x_i(k)=\left\|x_0'(k)-x_i'(k)\right\|$	Can be run in parallel	Can be run in parallel
$\xi_i^k=\frac{p+\rho P}{\Delta x_i(k)+\rho P}$	Can be run in parallel	Can be run in parallel
$\gamma_i=\frac{1}{n}\sum_{k=1}^{n}\xi_i^k$	Cannot be run in parallel	Can be run in parallel

From Table 1, it can be seen that many steps in the grey correlation analysis are parallelizable. The parallelism of different comparison sequences is coarse-grained parallel. All the comparison sequences are independent to each other and have no interdependence. So, all the calculations among different comparison sequences can be carried out in parallel. The parallelism of the same comparison sequence is fine-grained parallel. Some calculations require the processing of voltage data at different times respectively, and the processing is independent from the voltage data at other times, such as dimensionless processing, calculation of correlation coefficient, etc., so these steps can be carried out in parallel among different times.

4.3. GPU accelerated algorithm

According to the principle of CUDA and parallelism analysis in Section 4.2, a series of GPU kernel functions can be designed to accelerate the whole algorithm in parallel, as shown in Table 2.

Table 2. Design of kernel functions.

Number of kernel functions	Expression	Number of enabled blocks	Number of enabled threads in each block
1	$x_i^{'}(k)=\frac{x_i(k)}{x_i(1)}$	n	m
2	$\Delta x_i(k)=\lvert x_0^{'}(k)-x_i^{'}(k)\rvert$ $\max_k \Delta x_i(k)$ $\min_k \Delta x_i(k)$	m	1
3	$\xi_i^k=\frac{p+\rho P}{\Delta x_i(k)+\rho P}$	n	m
4	$\gamma_i=\frac{1}{n}\sum_{k=1}^{n}\xi_i^k$	m	1

Based on these kernel functions, GPU-based grey correlation analysis algorithm can be realized.

5. Numerical experiments

The algorithm runs in Windows10 of 64bit. The CPU used in the tests is Intel Core i7-7700K, with the 4.20GHz of main frequency and 32G of memory. The GPU used is NVIDIA GeForce GTX1080, supporting CUDA8.0 standard.

5.1. Test for accuracy of the algorithm

In order to test the accuracy of the proposed algorithm, take an actual case for instance, of which topology graph is shown as Figure 3. Take samples of voltage data within 24 hours of 1 day. The sampling interval is 1min~3h. Accordingly, the number of sampling data of each smart meter varies from 8~1440. Table 3 records the accuracy of the proposed algorithm.

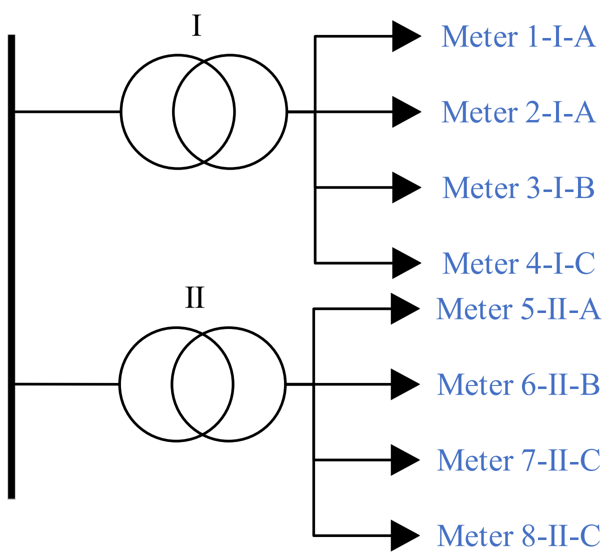

Figure 3. Topology graph of an actual case.

Table 3. Accuracy of transformer topology identification.

Sampling interval	Number of samples of each smart meter	Different comparison sequences
3h	8	50.0%
2h	12	75.0%
1h	24	100.0%
15min	96	100.0%
5min	288	100.0%
1min	1440	100.0%

Take 1h of sampling interval as an example. Table 4 records detailed similarity degrees.

Table 4. Similarity degree between voltage data from different phases of transformers and smart meters

Region	Phase	Meter 1	Meter 2	Meter 3	Meter 4	Meter 5	Meter 6	Meter 7	Meter 8
I	A	0.93	0.92	0.80	0.80	0.26	0.33	0.31	0.30
I	B	0.82	0.82	0.96	0.84	0.28	0.36	0.33	0.33
I	C	0.85	0.85	0.84	0.97	0.24	0.37	0.29	0.29
II	A	0.37	0.36	0.45	0.32	0.98	0.84	0.80	0.81
II	B	0.30	0.31	0.42	0.35	0.82	0.97	0.81	0.80
II	C	0.35	0.34	0.39	0.37	0.83	0.84	0.93	0.93

From Table 3, when the number of smart meters is fixed, the more the sampling number of the smart meter is, the higher the accuracy of the topology identification is. When the sampling number reaches 24, the recognition accuracy of this algorithm can reach 100%, which shows the importance of the massive and high-density data for transformer topology identification.

Table 4 reflects the calculation results of the similarity degrees between voltage data from different phases of transformers and smart meters. It is not difficult to find that the similarity degree between a smart meter and the corresponding transformer is large, more than 0.80, while the similarity degrees between this smart meter and other transformers are small, about 0.20~0.40. In addition, among different phases of a same transformer, voltage data of a smart meter and its corresponding phase has the largest similarity degree, over 0.90. Implementing topology identification according to the data in Table 4 can achieve the same results as Figure 3.

5.2. GPU acceleration effect test

In order to test the effect of GPU acceleration in the proposed algorithm, a large number of smart meters are simulated by computer.

Table 5. GPU acceleration effect analysis.

Number of kernel functions	Number of smart meters	Number of samples of each smart meter	CPU time cost /*ms*	GPU time cost /*ms*	Speedup ratio
1	500	50000	733	1	733
	800	80000	1877	1	1877
2	500	50000	45	1	45
	800	80000	127	1	127

3	500	50000	126	1	126
	800	80000	330	1	330
4	500	50000	62	1	62
	800	80000	150	1	150

As can be seen from Table 5, compared with CPU serial computing, the efficiency of the algorithm is improved significantly, after parallel acceleration based on GPU. For all the cases in Table 5, GPU time cost is around 1*s*. Generally, kernel function 1 and 2 have larger speedup ratio, because coarse and fine-grained parallelism can be simultaneously implemented, as shown in Table 1 and 2. Table 5 shows that the powerful parallel ability of GPU can significantly improve the efficiency of the algorithm, thus satisfying the real-time requirements of online transformer topology identification.

6. Conclusions

This paper proposes a transformer topology identification method based on GPU acceleration. The proposed method has the following characteristics:

- Grey correlation analysis method has high accuracy, especially when the sampling number reaches a certain scale, the accuracy of the topology identification can reach 100%.
- Compared with tradition CPU serial algorithm, the efficiency of the parallel algorithm based on GPU is significantly higher. For some large cases, the speedup ratio is more than 1800 times. Therefore, the proposed algorithm can fully meet the needs of massive and high-density data analysis and computation, and further meet the requirements of online transformer topology identification.

In the future, for one thing, the proposed transformer topology identification algorithm in this paper can be applied to the engineering application. For another thing, the GPU parallel computing techniques can be applied to other computing areas of energy systems and Internet of things.

Acknowledgments

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