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Application of Time Series Data Clustering in Intelligent Identification of Household Transformer Relationship

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Abstract:

In order to accurately clarify the household transformer relationship of the voltage distribution network, on the basis of analyzing the shortcomings of existing verification methods in engineering applications, the rapid development of new business in the power grid puts forward the intelligence level of the low-voltage distribution network. The topological relationship of the traditional low-voltage distribution network mainly relies on manual file maintenance, resulting in low efficiency of voltage problem governance and emergency repair. It has been verified by experiments that the proposed algorithm can achieve accurate matching of the affiliation between low-voltage users and the station area, and has engineering practicability. Although the phase table has been calibrated for the phase sequence during data acquisition, due to problems such as non-standard wiring, it is inconsistent with the real phase sequence. Based on the determination of the relationship between the branch and the household meter, a household meter phase identification method that comprehensively utilizes the voltage and current data of the user meter is proposed to improve the accuracy of the household meter phase identification.

Keywords*: Time sequence; station area; identification.*

I. INTRODUCTION

In recent years, with the development of the Internet of Things technology, the low-voltage distribution Internet of Things architecture, standards and concepts have been continuously updated [1-4]. By installing smart terminals at the exit of the station area, installing acquisition and monitoring terminals at branch lines [5-7], and in conjunction with the large-scale smart energy meters installed on the user side, a large amount of user voltage, current, electricity and other operating data can be obtained. Make full use of these data to improve the depth of information perception of low-voltage distribution network, and provide more intelligent state perception, topology identification and other services for power grid companies [8-10].

Among them, the household transformer relationship is an important aspect of its topological relationship. However, due to improper management of ledger information, there are inaccuracies in the

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current household change relationship in low-voltage stations.

Due to the multi-faceted and wide-ranging low-voltage distribution transformer area and the complicated line overlap, the traditional method of sorting out household transformer relationship based on manual on-site investigation is time-consuming and labor-intensive, and the accuracy rate is difficult to guarantee [11-15]. Therefore, it is particularly important to study a practical and reliable method for verifying the relationship between household-to-household transformers in low-voltage distribution transformers. The correlation analysis method makes use of the mechanism characteristic of the correlation between the time sequence changes of the same-phase user voltage, and sets the threshold criterion of the correlation coefficient to realize the phase-sequence relationship in the station area. Automatic Identification. References [16-18] determine the user phase sequence relationship by comparing the correlation between the voltage sequence of the meter and the distribution transformer. Generally speaking, the correlation analysis method relies on the setting of the correlation coefficient threshold, and the adaptability is weak when applied in different stations. The model fitting method fits the user phase sequence relationship by minimizing the actual measurement value and the system state error. References [19-20] fit the phase sequence attribution relationship of each meter by minimizing the deviation of the total power of each phase in the station area and the sum of the power of its subordinate meters. However, in addition to the line loss, there are also situations such as electric theft and leakage in the actual station area, which lead to a large deviation of the power at the head and end of the station area, which will significantly affect the recognition accuracy.

II. THEORETICAL BASIS

Users in the distribution station area operate in a radial topology [21]. Due to the different load conditions and operating states of the system at different times, the voltage at the user end will fluctuate to a certain extent. There is a certain electrical connection between the in-phase transformer in the station area and the user's meter, so the user side voltage will rise with the increase of the outlet voltage of the transformer in the station area. The two are highly correlated and the change trend is highly consistent. That is, the voltage fluctuation law of the same phase users in the same station area has strong similarity, the electrical distance of users in different station areas is long, and the similarity of voltage fluctuation is poor. The voltage fluctuation law of users in the same phase of the distribution network in the same station area has strong similarity, and the voltage fluctuation of users in different station areas has poor similarity. Based on this feature, artificial intelligence technology and massive power big data analysis technology can be used. Carry out correlation and cluster analysis on the measurement data of smart meter at the user side and the measurement data at the low voltage side of transformer, fully mine and make use of the data of metering automation system, and realize the accurate and effective identification of station topology.

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III. ALGORITHM DESIGN

3.1 Phase sequence correlation analysis

This section analyzes the timing characteristics of the user voltage theoretically. In order to better grasp the timing characteristics of user voltage, this paper makes relevant simplifications in the theoretical derivation process according to the actual situation, including: (1) The offline lines of users are generally short, and their voltage loss is ignored; (2) The reactive load in the station area lower, ignoring the reactive component in the voltage drop.

3.2 household transformer relationship network topology

The network topology of the station area refers to the network structure from the public transformer in the station area to the user's electric energy meter. The low-voltage power supply lines are mostly radial wiring, and the 10kV medium-voltage busbars are reduced to 400V low-voltage busbars after passing through Taiwan transformers. The 400V low-voltage bus is divided into multiple 400V branch feeders through primary power distribution equipment to distribute power to different power supply areas. Each branch feeder ultimately supplies power to each end user through secondary power distribution equipment. There is a three-phase line between the first-level branch outlet switch in the station area and the branch box, the branch box and the meter box, and a single-phase line between the meter box and the user's electric energy meter. Through intelligent distribution transformer terminals and line data monitoring equipment, the collection of electrical energy such as voltage, current, and power can be realized in the station master meter and branches at all levels in the station area. The identification of the topological relationship in the station area includes the identification of the phase of the electric energy meter, the identification of the relationship between the electric energy meter and the last stage branch, and the identification of the topological relationship between the first branch and the second branch in the station area.

IV. ALGORITHM VERIFICATION

Low-voltage distribution network refers to the distribution network with a voltage level lower than 1kV. The voltage is further transmitted to the user through a step-down transformer. Each distribution transformer is called a station area. The low-voltage users in the station area are arranged radially through the A, B, and C three-phase feeders, and each phase feeder can be connected to multiple low-voltage users. A power supply station has a total of 100 stations, and each station is connected to several low-voltage users. If the operating status is different, select a representative user under station area 5 as the user to be matched, and mark it as low-voltage user 0. Calculate the correlation between site variables 6, calculate the blood affinity index between the user to be matched and all sites, and verify the experimental results. Through experimental verification, we propose a household meter phase identification method that comprehensively utilizes the voltage and current data of the user meter to improve the accuracy of the household meter phase identification.

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V. CONCLUSION

Aiming at the problem of inaccurate identification caused by not considering the three-phase meter in the phase sequence identification of user power supply current in low-voltage substations, the influence of the length of time series data on the identification accuracy is analyzed through an example test. On this basis, a household meter phase identification method that comprehensively utilizes the voltage and current data of the user's electricity meter is proposed, which improves the accuracy of the household meter phase identification. The method proposed in this paper has certain guiding significance for the comprehensive perception of the station area network and the lean management of the station area.

REFERENCES

[1] Li Yizhuo, Zhang Juan, Yang Dehao, Lu Shuaizheng, Wang Fang, Zhang Yunfei. Three-phase load imbalance big data analysis and governance scheme based on iterative strategy [J]. Rural Electrification, 2022(01):5-7. DOI: 10.13882/j.cnki.ncdqh.2022.01.001.

[2] Xie Qiyang. Analysis and summary of a case of electricity theft [J]. Rural Electrician, 2022, 30(01): 49-50. DOI: 10.16642/j.cnki.ncdg.2022.01.053.

[3] Cheng Yushu, Xie Zhengang, Chen Anqi. Electricity feature extraction of station area based on least squares vector machine combined with bidirectional time series long short-term memory [J]. Electronic Devices, 2021, 44(06): 1443-1449.

[4] Zhang Ruixue, Ma Zhibin, Qian Chuanwei, Hou Zhefan. Automatic identification model and algorithm of station topology based on measurement data [J]. Power Supply, 2021,38(10):73-79.DOI:10.19421/j .cnki.1006-6357.2021.10.010.

[5] Cai Yongzhi, Tang Jie, Que Huakun, Li Jian, Guo Wenchong. A method for verifying the relationship between household changes in Taiwan districts based on the analysis of voltage cluster characteristics [J]. Guangdong Electric Power, 2021, 34(08): 50-60.

[6] Wang Guantao, Gao Feng, Wu Xiaodong. Research on the method of improving the ability to resist load fluctuations in the middle platform of the distribution network [J]. Energy and Environmental Protection, 2021, 43(07): 237-242. DOI: 10.19389/j.cnki. 1003-0506.2021.07.041.

[7] Song Weiqiong, Guo Shuai, Li Ji, Liu Heng, Guo Qiuting, Hu Wei. Intelligent identification of household change relationship in distribution station area based on voltage time series data [J]. Journal of Electric Power Systems and Automation, 2022,34(01) :48-55.DOI:10.19635/j.cnki.csu-epsa.000812.

[8] Cui Jiao, Wen Yuxing, Yu Yongsheng, Ou Yuqian, Chen Meng, Gu Ziwen. Load Multi-granularity Prediction Model Based on Kernel Extreme Learning Machine [J]. Journal of Chongqing University, 2022, 45(01): 68-78 .

[9] Wang Fan. Research on the applicability of LSTM and CNN to short-term load forecasting in distribution station area [D]. Lanzhou Jiaotong University, 2021. DOI: 10.27205/d.cnki.gltec.2021.000985.

[10] Su Hang. Analysis and calculation of open capacity of distribution transformers based on big data technology [D]. North China Electric Power University (Beijing), 2021. DOI: 10.27140/d.cnki.ghbbu.2021.000512.

[11] Cai Jiahui. Research and application of data-driven line loss anomaly intelligent analysis method [D]. Jiangnan University, 2021. DOI: 10.27169/d.cnki.gwqgu.2021.000490.

[12] Shou Peiyao. Research on Tensor Completion Method for Missing Data in Low-Voltage Station Area [D]. North China Electric Power University, 2021. DOI: 10.27139/d.cnki.ghbdu.2021.000201.

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[13] Zhang Siqi. Analysis on the Cause of False Line Loss in Distribution Network and Research on Correction Method [D]. University of Electronic Science and Technology of China, 2021. DOI: 10.27005/d.cnki.gdzku.2021.001718.

[14] Zhang Pan, Gao Qiangwei, Huang Xu, Zhu Cong, Sun Weiqing. Topological structure identification method of low-voltage distribution network based on power carrier communication [J]. Electronic Devices, 2021, 44(01): 162-167.

[15] Xue Bin, Zhang Xiangdong, Wang Gang, Hu Wen, Weng Yali, Yang Mei. Research on the application of anti-stealing electricity based on time series analysis of electricity stealing behavior [C]//. Proceedings of the 2020 China Institute of Communications Energy Internet Symposium., 2020:121-124+141.DOI: 10.26914/c.cnkihy.2020.065737.

[16] Li Ning, Guo Zelin, Yuan Tiejiang, Wang Yongchao, Bai Yinping, Pan Chenglong, Yan Qiang. Power topology generation method for low-voltage stations based on power measurement information [J]. Distributed Energy, 2020,5(05):48 -55.DOI:10.16513/j.2096-2185.DE.2005006.

[17] Lu Xin, Leng Anhui, Mao Shanshan, Hong Haimin, Wang Chun. Electrical topology discovery technology for low-voltage distribution network based on high-frequency synchronous acquisition and edge computing [J]. Telecommunications Science, 2020, 36(08): 184- 192.

[18] Huang Mengjia. Research on the multifunctional improvement potential of cultivated land in Jiutai District, Changchun City [D]. Jilin University, 2020. DOI: 10.27162/d.cnki.gjlin.2020.004976.

[19] Lv Haican, Wang Weifeng, Zhao Bing, Zhang Yi, Guo Qiuting, Hu Wei. Short-term load forecasting based on Wide&Deep-LSTM model [J]. Power Grid Technology, 2020,44(02):428-436.DOI :10.13335/j.1000-3673.pst.2019.0558.

[20] Huang Xu, Wang Weiheng, Wu Shuang, Hu Wei. Research on the identification method of the relationship between Taiwan and households based on the big data of electricity consumption [J]. Power Supply, 2019, 36(10): 22-29. DOI: 10.19421/j .cnki.1006-6357.2019.10.004.

[21] Li Yu. Improved calculation method of grid power loss considering new energy access [D]. Huazhong University of Science and Technology, 2017.