Research on electrical power quality disturbance recognition method based on edge computing and LightGBM

Wenjun Zhu[1,*], *Tianchun* Xiang[2], *Boxiang* Shang[2], *Xiaoyan* Guo[2], and *Weihua* Zhai[2]

[1]State Grid Information & Telecommunication Co.,Ltd., Changping District, Beijing 100031, China
[2]State Grid Tianjin Electric Power Company, Hebei District, Tianjin 300010, China

Abstract. In conventional cloud computing, method that data is transmitted and calculated on the cloud cannot satisfy the real-time demand for energy quality disturbance recognition. This paper proposed a power quality disturbance recognition method based on edge computing and LightGBM classification algorithm. Our main idea is that the feature of disturbance is extracted on the edge sides and used to classified on the cloud. Firstly, a multi-group feature set was extracted at the edge side intelligent fusion terminal by wavelet transform. Secondly, we used feature training accuracy to select the optimal feature collection. Finally, the optimal feature set was selected to determine the disturbance recognition method of this paper. Experiments had shown that the proposed method meets demand on data transmission by 99.5%, and achieves 97.53% recognition accuracy. Our method not only guarantees high accuracy of the power quality disturbance recognition but also alleviates the bandwidth load pressure brought by large amounts of data transmission.

Keyword: Edge computing, Wavelet transform, LightGBM, Power quality disturbance recognition.

1 Introduction

In the power distribution Internet of Things, the traditional power quality disturbance identification process is that after the power quality acquisition device collects the disturbance signal, and the disturbance signal is transmitted to the cloud for feature extraction and recognition [1]. In recent years, with the large-scale development of distributed new energy sources in the distribution network and the increase in user-side load types, the amount of data at power quality monitoring points has shown a blowout growth [2]. In the face of distributed power quality data, traditional power quality disturbance identification methods will put tremendous pressure on network bandwidth, resulting in greatly reduced power quality disturbance identification efficiency and interaction delays, and the power grid will face higher power quality risks. Especially in the case of transient power quality

* Corresponding author: 642286996@qq.com

disturbances, the disturbances appear for a short time, and the real-time performance and accuracy of the detection algorithms are more demanding [3][4]. Therefore, the research on the identification of power quality disturbances in the distribution of Internet of Things in processing massive terminal data and realizing real-time performance is of great significance for reducing power quality risks in distribution networks.

In order to solve the pressure of transmission bandwidth caused by massive data, edge computing technology is introduced to significantly enhance the data analysis capabilities of the power distribution Internet of Things [5] [6]. Compared with technologies that directly use decision trees or convolutional neural networks in the cloud to distinguish power quality disturbances [7][8][9], edge computing is equipped with a large number of calculations and storage Functional low-cost terminal equipment, which can greatly reduce the amount of transmitted data and increase the transmission rate, has a higher real-time data processing capability, and realizes efficient identification of power quality disturbances [10]. In the power business, there are already relevant application precedents for edge computing technology. For example, a large number of power transmission and transformation IoT sensors are used in substations to collect massive amounts of data. The edge computing technology is used to process the data in real time, and the data is processed on the power IoT platform. The data is managed in a unified way to achieve self-regulation of internal temperature and humidity, and will automatically issue warnings and transmit real-time data if the standards are not met [11].

The existing power quality disturbance identification methods can be basically divided into empirical rule-based and machine learning-based [12]. The recognition method based on empirical rules is mainly designed by the power quality disturbance analyzer based on fuzzy logic, and the structure is recognized through massive data samples to ensure that the recognition results are true and reliable. The specific steps are roughly divided into: determining the input quantity and domain, determining the membership function, determining the fuzzy logic classification rules, and using the disturbance signal test sample for classification verification [13][14][15][16]. This type of recognition method has slightly higher classification accuracy, slightly less computational complexity, and slightly higher robustness, but it has the problems of general learning ability and poor generalization ability. The recognition methods based on machine learning are divided into power quality disturbance classifier based on neural network and power quality disturbance classifier based on support vector machine [17]. Neural network-based recognition mainly includes two processes: automatic network learning and disturbance recognition and classification. This type of method has high classification accuracy and strong applicability in real-time applications; but the learning speed, robustness and classification accuracy are easily affected by the network structure, weight adaptive algorithm and noise content, and are not suitable for high-dimensional feature vectors. Disturbance problem classification [18]. Standard support vector machine (SVM) can only solve two classification problems, and power quality disturbance is a multi-class problem, so it is necessary to convert the multi-class problem into multiple two-class problems to consider [19]. In order to reduce the amount of calculation and reduce the complexity of the solution, the least square support vector machine and the direct support vector machine have been proposed. The latter has a shorter total classification time and higher classification accuracy, with stronger generalization ability [20][21]. However, SVM algorithms are prone to overfitting. LightGBM is an algorithm under the Boosting framework, which supports high-efficiency parallel training. When processing large-scale data, it has faster training speed, lower memory consumption and higher accuracy, which is suitable for the current analysis of massive power quality data [22].

This paper proposes a power quality disturbance identification method based on edge computing and lightGBM classification algorithm. The main idea of this method is to extract disturbance features from massive power quality data at the edge, reduce the dimensionality of the data and then transmit it to the cloud, and perform classification training on the extracted data features in the cloud. First, the Mallat algorithm of wavelet transform is used to extract features of part of the simulation data, and then the extracted multiple sets of features are classified with ligthGBM, the accuracy of classification is compared, and the optimal feature set is selected. Secondly, the Mallat algorithm is placed at the edge intelligent fusion terminal, feature extraction is performed on all data, and the optimal feature set is retained. Finally, the optimal feature set is transmitted to the cloud, and the ligthGBM algorithm is used to classify and recognize it. Through actual measurement and simulation data experiments, it is proved that the method can relieve the bandwidth load pressure of a large amount of data transmission under the premise of ensuring the accuracy of power quality disturbance identification, which meets the need of real-time processing the transient data.

2 Data set introduction

According to the research results in the existing literature and the international power quality standards [23]. Random parameters were used to generate eight single disturbance signals and four kinds of composite disturbance signals in the simulation environment with a signal-noise ratio between 20 and 50 dB which is white Gaussian noise (including normal signals). Among them, the sampling rate is 6400 Hz, the fundamental frequency is 50 Hz, and the sampling period is 10 cycles (0.2 s). The simulation model of the power quality disturbance signal is shown in Table 1.

Various power quality disturbance signals generated randomly are shown in Figure 1. We generated 1000 sets of one-dimensional data for each type of signal, and divided these data into training set, verification set and test set. There are 800 groups of each type of signal in the training set, 100 groups of each type of signal in the verification set and 100 groups of each type of signal in the test set. The various types of disturbance signals in the training set, validation set and test set are randomly distributed.

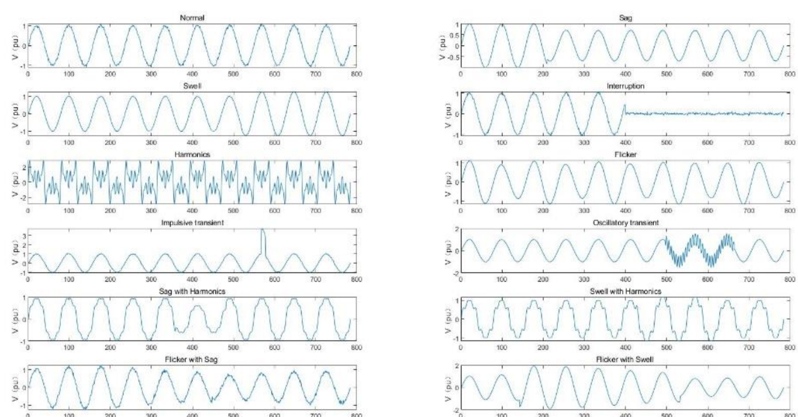

Fig. 1. Power quality disturbance signal diagram.

3 Method introduction

The power quality disturbance recognition process is generally divided into three stages: signal noise reduction processing and feature extraction, feature selection, and disturbance classification [1]. The following will briefly explain the methods and applications involved in each stage of this article.

Table 1. Disturbance signal simulation model.

Disturbance type	Model	parameter
Normal	y(t)=Asin(ωt)	A=1V,$\omega = 100\pi$; $T \le t_2 - t_1 \le 9T$
Sag	$y(t) = A[1-\alpha(u(t-t_1)-u(t-t_2))]\sin(\omega t)$	$0.1 \le \alpha \le 0.9$;$T \le t_2 - t_1 \le 9T$
Swell	$y(t) = A[1+\alpha(u(t-t_1)-u(t-t_2))]\sin(\omega t)$	$0.1 \le \alpha \le 0.8$;$T \le t_2 - t_1 \le 9T$
Interruption	$y(t) = A[1-\alpha(u(t-t_1)-u(t-t_2))]\sin(\omega t)$	$0.9 \le \alpha \le 1$; $T \le t_2 - t_1 \le 9T$
Harmonics	$y(t) = A[\alpha_1\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t) + \alpha_7\sin(7\omega t)]$	$0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
Flicker	$y(t) = A[1+\alpha\sin(\beta\omega t)]\sin(\omega t)$	$0.9 \le \alpha \le 1$; $5\text{Hz} \le \beta \le 20\text{Hz}$
Impulsive transient	$y(t) = A[1-\alpha\{u(t-t_1)-u(t-t_2)\}]\sin(\omega t)$	$0 \le \alpha \le 0.414$; $T/20 \le t_2 - t_1 \le T/10$
Oscillatory transient	$y(t) = A[\sin(\omega t) + \alpha^{-c(t-t_1)/\tau}\sin\omega_n(t-t_1)(u(t_2) - u(t_1))]$	$300\text{Hz} \le \omega_n \le 900\text{Hz}$; $0.1 \le \alpha \le 0.8$; $8\text{ms} \le \tau \le 140\text{ms}$
Sag with Harmonics	$y(t) = A[1-\alpha(\mu(t-t_1)-\mu(t-t_2))] \times [\alpha_1\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t) + \alpha_7\sin(7\omega t)]$	$0.9 \le \alpha_1 \le 1$; $0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
Swell with Harmonics	$y(t) = A[1+\alpha(\mu(t-t_1)-\mu(t-t_2))] \times [\alpha_1\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t) + \alpha_7\sin(7\omega t)]$	$0.1 \le \alpha \le 0.8$; $0.05 \le \alpha_3, \alpha_5, \alpha_7 \le 0.15$; $\sum \alpha_i^2 = 1$
Flicker with Sag	$y(t) = A[1+\alpha_1\sin(\beta\omega t)]\sin(\omega t) + A[1-\alpha_2(u(t-t_1)-u(t-t_2))]\sin(\omega t)$	$0.9 \le \alpha_1 \le 1$; $5\text{Hz} \le \beta \le 20\text{Hz}$; $0.1 \le \alpha_2 \le 0.8$
Flicker with Swell	$y(t) = A[1+\alpha_1\sin(\beta\omega t)]\sin(\omega t) + A[1+\alpha_2(u(t-t_1)-u(t-t_2))]\sin(\omega t)$	$0.9 \le \alpha_1 \le 1$; $5\text{Hz} \le \beta \le 20\text{Hz}$; $0.1 \le \alpha_2 \le 0.8$

3.1 Feature extraction method

3.1.1 Edge computing

In this paper, the feature extraction and calculation part of power quality disturbance recognition is offloaded to the edge-side intelligent fusion terminal. The edge-side intelligent fusion terminal uses a Cortex-A7 architecture single-core 4-core processor, with a main frequency of 1.2DHz, and an integrated peripheral 2GB DDR3 and 8GB FLASH memory. Compared with traditional cloud computing, edge computing has obvious advantages: (1) A large amount of data is processed at the edge intelligent fusion terminal, and all data does not need to be transmitted to the cloud server for storage. It is not only reducing the computing pressure and storage pressure of the cloud computing service center, but also easing the network bandwidth pressure; (2) Data processing is executed on the edge intelligent fusion terminal, which reduces the high latency of data upload to the cloud for processing and improves disturbance recognition response capability; (3) The privacy data generated by factory users on the edge side does not need to be uploaded to the cloud data center, so that the privacy of factory users is guaranteed.

3.1.2 Wavelet transform for disturbance feature extraction and selection

Wavelet transform has the characteristic that the time-frequency window can be changed adaptively. It is especially suitable for analyzing sudden change signals and unstable signals and accurately analyzing the local details of the signal. Therefore, wavelet transform is very suitable for extracting transient signals of power quality disturbances, and can also accurately extract the features of complex signals and time-varying signals.

Similar to the short-time Fourier transform, the wavelet transform is essentially an improved result of the Fourier transform. The difference is that the wavelet change and the short-time Fourier change they face are not the same as the center of gravity. The characteristic of the base of the wavelet transform is that it will slowly attenuate and the length is limited, so that the frequency and time domain can be controlled at the same time. Wavelet transform is generally divided into continuous wavelet transform and discrete wavelet transform. The formula of continuous wavelet change is as follows [24].

$$Wf(a,\mathrm{b}) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} f(t)\Psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

Based on the definition of the continuous wavelet change provided in (1), Ψ(x) is a wavelet basis function, and both a and b are positive numbers.

Under the condition of a=${a_0}^m, b = n{a_0}^m b_0$, discretization is carried out on the basis of (4), and the definition formula of discrete stationary wavelet will be obtained:

$$\mathrm{W}T_f(m,n)=|a_0|^{-\frac{m}{2}}\int_{-\infty}^{+\infty} f(t)\,\Psi({a_0}^{-m}t - nb_0)dt \tag{2}$$

In order to save the computing resources of the edge-side fusion terminal and avoid the redundant calculation of continuous wavelet transform, this paper uses the Mallat algorithm commonly used in discrete wavelet transform to realize wavelet decomposition. First, the power quality disturbance signal is multi-resolution analysis:

$$i_{i+1} \ = \sum_{k=1}^{\infty} h_j(k-2_n)i_j(k) \tag{3}$$

$$d_{j+1}(n) = \ \sum_{k=1}^{\infty} g_j(k-2_n)a_j(k) \tag{4}$$

$$i_L(n) = 2^{L/2}\sum_{k=1}^{\infty} f(kT_i)\, sinc[(n-k)T_i] \tag{5}$$

In (3) and (4), h_j and g_j are the selected wavelet basis and the discrete low-pass and high-pass filter coefficients generated by the scaling function are determined by the selected wavelet basis. The voltage signal reconstruction formula is

$$i_i(\mathrm{n}) = \sum_{k=1}^{\infty} h_j(n-2_k)i_{j+1}(k) + \sum_{k=1}^{\infty} g_j(n-2_k)d_{j+1}(k) \tag{6}$$

From (3) to (6), it can be seen that the power quality disturbance feature extraction method based on wavelet multi-resolution analysis is to divide the voltage signals of different frequencies into different frequency bands according to a certain scale, and then reconstruct and separate each sub-frequency band. The perturbation information of each frequency band (as shown in Fig.2) can be obtained, so as to obtain multiple sets of perturbation characteristics of each perturbation signal. Then the extracted disturbance features of each sub-frequency band are classified and identified respectively, and a group of disturbance features with the highest accuracy is selected to realize feature selection.

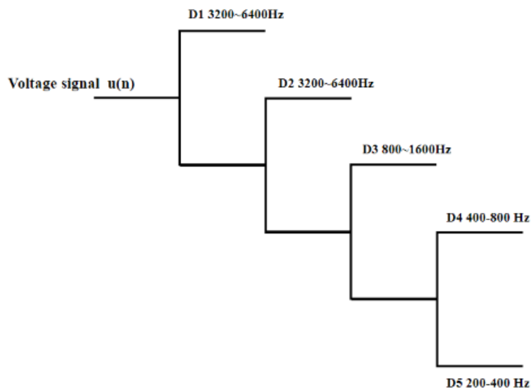

Fig.2. Orthogonal wavelet multi-resolution decomposition of voltage signal.

3.2 Disturbance classification method

LightGBM (Light Gradient Boosting Machine) is an open source framework developed by Microsoft to implement the GBDT (Gradient Boosting Decision Tree) algorithm and support efficient parallel training. GBDT is an enduring model in machine learning. Its implementation principle is to use decision tree (weak classifier) iterative training to obtain the best model. This model has many advantages such as not easy to overfit and good training effect. The background of LightGBM is that GBDT is not effective in processing massive amounts of data, and it is difficult to quickly and well participate in industrial practice. It mainly has but not limited to the following advantages: faster training speed; lower memory consumption; better accuracy; faster processing of massive data.

The LightGBM model is characterized by the advantages of histogram algorithm and leaf-wise strategy with depth limitation. This section uses the histogram algorithm to normalize all features, as shown in Fig.3. The histogram algorithm feature information gain calculation only needs to traverse k bins. Since the decision tree is a weak model, the segmentation point with lower segmentation accuracy has the effect of regularization. The number of bins determines the degree of regularization. In each split, leaf-wise strategy with depth limitation finds the leaf with the largest gain to split and loop. At the same time, the complexity of the model is reduced and overfitting is prevented through the depth of the tree and the limit of the number of leaves. During the construction of the weak learner, the histogram of the leaf node can be obtained by the difference between the father node and the sibling node, and only k bins need to be traversed, which further improves the training speed.

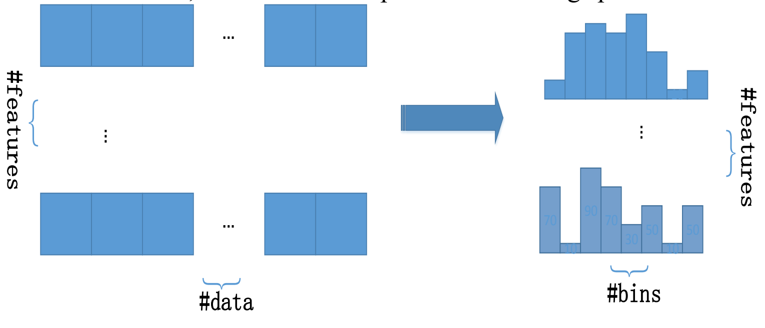

Fig. 3. Normalization of feature bins.

4 Simulation experiment and results analysis

4.1 Feature extraction and selection experiment

Wavelet transform is the most effective method for analyzing the non-stationary signals or the singular mutant signal, which is suitable for applications where electrical quality disturbance transient mutation signals [25]. Selecting a suitable mother wavelet for signal analysis, which has a great impact on energy quality disturbance recognition. The tight endurance of the mother wavelet can reduce the leakage of signal energy between the adjacent decomposition stage to ensure its localization. The larger the vanishing moment of the mother wavelet, the better the accuracy and integrity of the extracted signal by discrete wavelet transform (DWT). In addition, the selected wavelet should have orthogonality to allow reconstruction signals. The dbN wavelet system (N is a wavelet serial number) has all the above characteristics so that it is very suitable for the analysis of transient signals. After selecting a variety of mother wavelets including dbN wavelets, it was found that the difference between the signal feature amount after db5 wavelet processing was the most obvious, and its electrical quality disturbance recognition effect is the best. So the db5 wavelet is used as the mother wavelet function of this paper. As shown in Fig. 4, a waveform diagram of the five-layer decomposition of the flicker with sag composite power quality disturbance signal is performed. The approximation function of each layer is performed on the left side, and the right side is a detail function.

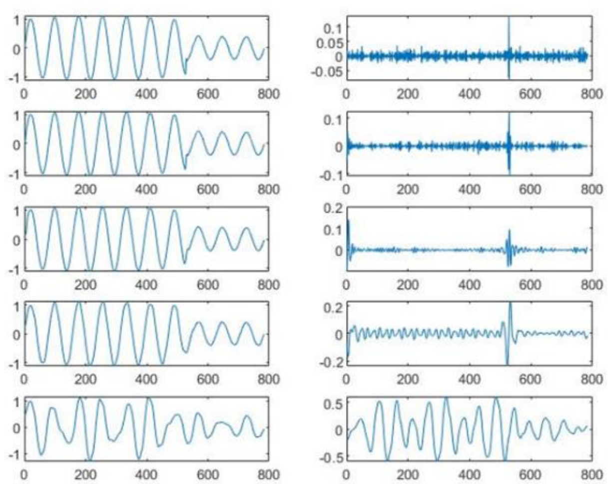

Fig. 4. Schematic diagram of Flicker with Sag composite energy quality disturbance signal after wavelet transform.

According to classification accuracy and hardware work real-time requirements, the power quality disturbance signal sampling frequency is set to 6400 Hz. First, the MALLAT algorithm is used to decompose the fourteen disturbance signals. The frequency bands of each detail component D1-D5 are as follows: Layer 1 (D1): 3200 ~ 6400Hz; Layer 2 (D2): 1600 ~ 3200 Hz; Layer 3 (D3): 800 ~ 1600 Hz; Layer 4 (D4: 400 ~ 800 Hz; Layer 5 (D5): 200-400 Hz. Reconstruct each layer’s signal characteristics after breaking to achieve the effect of noise reduction and feature extraction. The LightGBM algorithm is then used to classify and verify each layer, and the result is shown in Table 2. Therefore, after feature extraction and noise reduction on the edge side, this paper selected the D4 (400 to 800 Hz) group feature set to transfer to the cloud for classification recognition.

Table 2. Comparison of disturbance recognition performance of different frequency characteristics.

Group	Accuracy /%	Recall rate /%	elapsed time /s
D1（3200~6400Hz）	78.14	75.98	1.62
D2（1600~3200Hz）	80.66	80.12	2.06
D3（800~1600 Hz）	89.01	88.56	1.43
D4（400~800 Hz）	95.13	94.73	0.62
D5（200-400 Hz）	90.11	90.25	1.25

4.2 Disturbance recognition experiment

After feature extraction and noise reduction on the edge side, the extracted feature data is transmitted to the cloud server which is trained and tested by the LightGBM. The cloud experiment platform is the GeForce MX150, and the experimental environment is Python 3.7. To ensure the accuracy of the model and reduce the fit, the model parameters are set in Table 3.

Table 3. LightGBM parameter setting.

Para-meter	learning_rate	max_depth	num_leaves	min_data_in_leaf	feature_fraction	bagging_fraction	bagging_freq	min_split_gain
Para-meter Value	0.07	6	32	20	0.5	0.5	3	0.1

To analyze the availability of reducing network bandwidth by edge calculation, we compared the data transmission rate required for the original signal, noise reduction signal, and optimal feature set. We supposed the sample rate is 6400 Hz and a single disturbing sampling waveform 50 cycle. And we assumed that the data transmission time is controlled within 1s and the data transmission rate requires 40% of the margin [26]. The data transmission rate required for uploading one set of the original signal, the denoising signal, and the D4 group feature collection is shown in Table 4. As can be seen from Table 4, when a conventional cloud computing method is used, the data transmission rate requires approximately 1565.3kbit/s. When the denoising signal is uploaded to the cloud, the data transmission rate is about 1211.6kbit/s. When the D4 group feature set is uploaded on the edge side, the data transmission rate requires approximately 7.8kbit/s. This method which is compared to the traditional cloud computing model reduces data transmission rate requirements by 99.5%. To a large extent, the network bandwidth pressure in the process of power quality disturbance recognition is alleviated, and the energy quality disturbance recognition efficiency is improved.

Table 4. Data volume comparison of different transmission types.

Transmission type	Single disturbance feature data amount (Byte)	Data transfer rate demand（kbit/s）
original signal	117395	1565.3
denoising signal	90873	1211.6
D4 group feature collection	584	7.8

In terms of identification accuracy, as shown in FIG. 5, it is compared to the accuracy of the original signal, the noise reduction signal, and the D4 group feature set. The original signal classification accuracy can reach 90.62%. The denoising signals classification accuracy is 94.63%. The D4 group feature collection which is after feature extraction and noise reduction processing classification accuracy is 97.53%. It can be seen that the disturbance recognition method used herein increases the classification accuracy to a certain extent while ensuring the transmission rate.

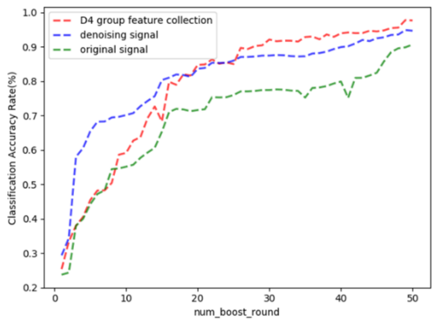

Fig.5. Comparison of accuracy ratio of different data sets.

5 Conclusion

This paper proposes the energy quality disturbance recognition method based on edge computing and LightGBM. First, the partial simulation data is extracted on the edge side by the Mallat algorithm of the wavelet transform, and then the extracted multi-group feature is classified by ligthGBM. The optimal feature collection is selected by the accuracy of the classification. Next, the Mallat algorithm is arranged at the edge intelligent fusion terminal where all data is extracted and the optimal feature collection is retained. Finally, the optimal feature collection which is classified by the ligthGBM algorithm is transmitted to the cloud. It is ultimately proved that the method proposed in this paper makes data transmission rate demand by 99.5%, and the accuracy of disturbance recognition reaches 97.53%. With the premise of ensuring the accuracy of power quality disturbance recognition, it not only relieves the bandwidth load pressure of a large amount of data transmission but also meets the needs of the real-time response of power quality disturbance in new distribution materials.

The methods used in this paper have achieved good results on the real-time and classification accuracy of power quality disturbance recognition, but only partial composite disturbances are currently trained. Therefore, the next work in this paper is to increase more types of composite disturbance data to train the model and verify the data in the actual application scenario to achieve accurate identification of the power quality disturbance type of the actual power supply scenario.

This work is financially supported by the National Key Basic Research Program of China (2020YFB0905900).

References

1. W Fei, Dynasty, R Lin Tao. Summary of Research on Power Quality Disturbance Detection and Identification Method [J]. Proceedings of the Chinese Society for Electrical Engineering, 2021, 41 (12): 4104-4121.
2. X Xiangning, L Kunyu, T Songhao, F Wenjie. New Development and Ultra Harmonic Problem of Electric Power Electronicization [J] .Journal of Electrician Technology, 2018,33 (04): 707-720.

3. R. Vinotha and K. K. Poongodi. Power Quality Improvement Using D-statcom[J]. International Journal of Innovative Research and Development, 2013, 2(4) : 176-185.
4. PardoZamora Oscar N et al. Power Quality Disturbance Tracking Based on a Proprietary FPGA Sensor with GPS Synchronization.[J]. Sensors (Basel, Switzerland), 2021, 21(11)
5. C Yueming, F Xiyong, D Hongwei, L Mingxiang, D Xiaohua, Y Road. Method for perceived adaptive data processing for the edge node of power network [J] .Chiza Technology, 2019,45 (06): 1715-1722
6. C Haoyong et al. Distributed sensing and cooperative estimation/detection of ubiquitous power internet of things [J]. Protection and Control of Modern Power Systems, 2019, 4(1): 1-8.
7. Sindi Hatem et al. An adaptive deep learning framework to classify unknown composite power quality event using known single power quality events [J]. Expert Systems With Applications, 2021, 178
8. L Jinsong et al. Classification of Power Quality Disturbance Based on S-Transform and Convolution Neural Network [J]. Frontiers in Energy Research, 2021,
9. GonzalezAbreu ArtvinDarien et al. A Novel Deep Learning-Based Diagnosis Method Applied to Power Quality Disturbances [J]. Energies, 2021, 14(10): 2839-2839.
10. L Xuejun, G Jianhua, Z Lu, Z Zhennan, W Kai, Y Tiejiang. Electrical Quality Analysis of Optimization of Edge Calculation Task Allocation Optimization [J] .Electrical and Energy Efficiency Management Technology, 2021 (06): 92-98.
11. Z Lijing, S Ge, J Xiuchen.Application Analysis and Research Prospect of Power Network in Substation in Electricity Network [J] .Hiqi Electric, 2020,56 (09): 1-10.
12. Khokhar, S., Zin, A. A. B. M., Mokhtar, et al. A comprehensive overview on signal processing and artificial intelligence techniques applications in classification of power quality disturbances [J]. Renewable and Sustainable Energy Reviews, 2015, 51(0):1650-1663.
13. Mahela O P, Shaik A G. Recognition of power quality disturbances using s-transform and fuzzy c-means clustering[C]//2016 International Conference on Cogeneration, Small Power Plants and District Energy (ICUE). IEEE, 2016: 1-6.
14. Mahela O P, Sharma U K, Manglani T. Recognition of Power Quality Disturbances Using Discrete Wavelet Transform and Fuzzy C-means Clustering[C]//2018 IEEE 8th Power India International Conference (PIICON). IEEE, 2018: 1-6.
15. Chakravorti T, Dash P K. Morphology based fuzzy approach for detection & classification of simultanious power quality disturbances[C]//2016 IEEE Annual India Conference (INDICON). IEEE, 2016: 1-6.
16. Das D, Chakravorti T, Dash P K. Hilbert huang transform with fuzzy rules for feature selection and classification of power quality disturbances[C]//2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON). IEEE, 2017: 439-445.
17. Rumelhart, David E., Geoffrey E. Hinton, et al. Learning representations by back-propagating errors. Nature, 1986, 323(0): 533-536.
18. Q Hezuo,L Xiaoming,C Chen,et al． Classification of power quality disturbances using convolutional neural network[J]． Engineering Journal of Wuhan University,2018,51(6)：534-539.
19. C Wei, H Jiahuan, P Xiping. Application of Deep Belief Network in Power Quality Compound Disturbance Identification[J].Proceedings of the CSU-EPSA, 2018 , 30(9): 75-82

20. D Yuanhang, C Lei, Z Weiling, et al. Power System Transient Stability Assessment Based on Multi-Support Vector Machines [J]. Proceedings of the CSEE, 2016, 36(5): 1173-1180.
21. X Zhichao, Y Lingjun, L Xiaoming. Power quality disturbance identification based on clustering-modified S-transform and direct support vector machine [J]. Electric Power Automation Equipment, 2015, 35(7): 50-58.
22. Z Ting,Y Jun,Z Qiangming,et al．Power system transient stability assessment method based on modified LightGBM[J]．Power System Technology,2019,43(6)：1931-1940.
23. IEEE Recommended Practice for Monitoring Electric Power Quality, IEEE Standard 1159-2019, Jun. 2019.
24. H Ming, C Yu. Stranstective Detection and Positioning of Electrical Power Quality Based on Wavelet Transform Modularity [J] .Prural Technology, 2001 (03): 12-16.
25. Hanif M,Dwivedi U D,Basu M,et al.Wavelet based islanding detection of DC-AC inverter interfaced DG systems[C]//UPEC2010.45th International Universities' Power Engineering Conference. Cardiff: Cardiff University, 2010:1-5.