ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20230708000788
Original scientific paper

Distributed AC Islanding Model Detection Method Based on Integrated Learning

Wen ZHAN, Chen GAO, Hong ZHU*, Qian NING

Abstract: With the increasing demand for DC transmission from new energy sources and the increasing DC load, the original AC distribution network system cannot meet the demand for power transmission, and AC-DC distribution network has become one of the development directions of future distribution network. When photovoltaic system is connected to AC/DC distribution system, unplanned island operation may occur on both AC and DC sides of the system. When unplanned islanding occurs in the system, maintenance personnel and system equipment fail to detect islanding in time and operate normally, which may pose a great threat to the safety of equipment and personnel. Therefore, it is necessary to accurately identify the operating state of the system, and then provide accurate judgment information for the action of the micro-switch to operate the photovoltaic system with islanding phenomenon through the micro-switch integrated with islanding detection algorithm, so as to ensure the safety and stability of the distribution system and load. In order to identify the running state of the system reliably, this paper analyzes the changes of the system electrical quantity before and after the islanding, and based on this, puts forward an islanding detection method. First of all, this paper uses a variety of data preprocessing techniques to clean and extract the features of the original data, and selects six island characteristic indicators such as voltage, current and output active power as detection features to generate a feature vector set to improve the quality and accuracy of the data. Secondly, this paper adopts three classification algorithms, including KNN, random forest and XGBoost, to integrate and learn the model, so as to improve the accuracy and robustness of the islanding detection task. Finally, it is verified by experiments that the islanding detection method based on multi-classification fusion model proposed in this paper has high fault detection accuracy and robustness, and has a wide application prospect and popularization value in practical application, which can provide performance improvement and stability guarantee for micro-cluster switches.

Keywords: AC/DC distribution network; data preprocessing; distributed power supply; feature extraction; integrated learning; islanding detection; photovoltaic system

1 INTRODUCTION

Solar energy has garnered global attention due to its ubiquity, environmental friendliness, abundant reserves, and enduring usability. This growing complexity in energy utilization necessitates a corresponding evolution of our power grid. To accommodate the diverse characteristics of various energy sources, adaptations within the power system are required [1-3]. Presently, alternating current (AC) remains the primary mode of transmission within distribution networks. However, with the rapid expansion of renewable energy sources such as photovoltaic power generation and the widespread adoption of DC loads in daily applications, like electric vehicles and DC motors, the demand for DC distribution networks is increasingly conspicuous. The AC distribution network system has undergone extensive worldwide research and has matured accordingly. To address the demands of DC power supply and load transmission, an AC-DC hybrid distribution network system has emerged as a prominent trend in future power grid development [4, 5]. When connecting a photovoltaic system to the power grid, it introduces a range of safety concerns. Among these issues, unplanned islanding operations can pose significant risks to the safety of critical equipment and personnel within the system. Therefore, it is imperative that photovoltaic systems integrated into the power grid possess the capability to detect and determine if the system is isolated from the grid [6]. The term "islanding effect" pertains to the intriguing phenomenon where a current path exists within a specific area of an electronic circuit, yet no actual current flows through it. This "island effect" harbors considerable latent hazards for equipment and personnel safety, manifesting in the following aspects:

1) When the power grid is blacked out for maintenance, the maintenance personnel may not be aware of the existence of the distributed system. If the inverter of the grid-connected photovoltaic power station continues to supply power, it may badly affect the safety of the maintenance personnel.

2) When islanding occurs, the power grid cannot control the voltage and frequency of power supply islanding, and the drift of voltage amplitude and frequency will bring damage to electrical equipment.

3) If the inverter is still generating power, because of the phase difference between the output voltage of the grid-connected system and the grid voltage, surge current will be generated when the grid resumes power supply, which may cause tripping again or damage to the distributed power generation system, load and power supply system.

Therefore, it is of profound significance to realize the reasonable application of micro-metering switch in distributed photovoltaic access scenarios by studying the application technical scheme of micro-metering system [7-10]. Through the research on the design of multifunctional integrated micro-metering switch, the new micro-metering switch which can replace the traditional smart meter is developed by integrating the functions of metering, sensing and protection. With the new micro-metering switch, the direct interaction with photovoltaic inverter equipment through the downlink interface can not only solve the problems of equipment redundancy and cost caused by adding photovoltaic grid-connected switches and other equipment on site, but also solve the problems of high operation and maintenance cost, large space occupation and poor operation reliability. When the power of distributed photovoltaic grid-connected exceeds the absorptive capacity of the power grid, it will have a great impact on the power quality and safety of the power grid. The micro-metering switch integrated with islanding detection is used to detect and control the power consumption characteristics, so as to realize the observability, measurability, controllability and adjustability of all photovoltaic grid-connected elements, ensure the safe and stable operation of photovoltaic equipment, and eliminate the harm of islanding to distributed power generation system, load and power supply system. Traditional islanding detection methods are divided into three categories: remote method, local passive method and local active method. These methods have some problems, such as large detection blind area, high cost and complex design, which affect the power quality output by inverter. Data mining technology can not only query the historical operation data of power system, but also find out the potential relationship between the data, make a higher-level analysis, and better solve the problems of island decision-making and prediction. Therefore, scholars at home and abroad have carried out different degrees of research on data mining technology. Literature [11] proposes a hybrid islanding detection technology for distributed generation grid-connected. The scheme is based on three different determinants, which are derived from negative sequence voltage (NSV) by applying Hilbert transform, wavelet transform and standard normal distribution function. Even in the case of complete power balance, the scheme can accurately detect the island state. In addition, the proposed scheme provides better stability in the case of specific types of non-isolated events. Literature [12] proposes an islanding detection method for microgrid based on sliding window discrete Fourier transform (SDFT) - empirical mode decomposition (EMD) and attention mechanism optimized long-term and short-term memory (LSTM) network. In this paper, the output current of inverter and the voltage at point of common coupling (PCC) are transformed by SDFT. The symmetrical component method (SCM) is used to calculate and reconstruct the positive sequence, zero sequence and negative sequence components of voltage and current harmonics. Literature [10] mixes down-sampling empirical mode decomposition (DEMD) and optimized random forest (RF) machine learning methods to detect islanding with reduced NDZ and classify non-islanding power quality events in distributed power generation systems with high wind energy penetration. Aiming to solve the problem of islanding detection, combined with the data information of AC islanding collected by simulation, this paper puts forward an AC islanding detection method based on integrated learning fusion model, which improves the performance of machine learning model, reduces the risk of over-fitting, enhances the robustness and generalization ability of the model, and can handle large-scale data sets. In this paper, firstly, an AC islanding simulation subsystem is built, and nine kinds of electrical data including voltage and voltage change rate are collected as the original database, and the data are cleaned. Then, the key features reflecting the operation of distributed AC islands are extracted and a feature vector set is generated. Finally, the classification results of multiple classifiers are fused by weighted average method, and an AC islanding classification detection method based on ensemble learning is proposed. The results show that this method can improve the accuracy of AC islanding detection, has high accuracy and robustness, and has a wide application prospect and popularization value in practical application.

2 ANALYSIS AND FEATURE EXTRACTION OF KEY ELECTRICAL CHARACTERISTICS OF ISOLATED ISLAND OPERATION

Island feature is the inherent embodiment of island operation, which is directly related to the accuracy of island detection, so extracting effective island feature is the key to island detection. At the moment of islanding, the active power P, reactive power Q, frequency F, voltage U and power factor $cos\varphi$ of AC power grid all change, so they can be selected as the key features of AC islanding detection. In order to construct islanding detection method suitable for AC/DC distribution network, it is necessary to analyze the variation law of each electrical quantity before and after islanding. There are abundant information such as voltage, active power, frequency and reactive power in AC system. By analyzing the changing rules of the above-mentioned electrical quantities before and after the islanding, we can get the characteristic electrical quantities that change obviously after the islanding. Compared with AC system, DC system lacks the information of reactive power, frequency and phase, so we need to analyze the limited electrical quantities such as voltage, current and active power to find out the suitable electrical types in DC islanding. Because of the differences between AC system and DC system in electrical quantity analysis, the distribution network system is divided into two subsystems when the islanding problem of AC/DC distribution network is detected, as shown in Fig. 1 and Fig. 2.

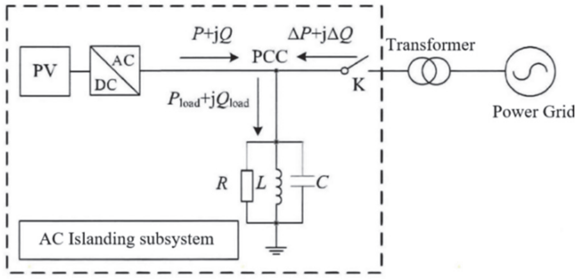

Figure 1 Simplified diagram of isolated island operation of AC distribution network

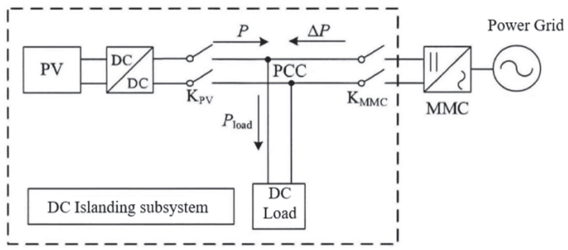

Figure 2 Simplified diagram of isolated island operation of DC distribution network

Fig. 1 is a simplified model of the AC islanding subsystem. The photovoltaic unit is connected to the power grid through a DC/AC converter and a main transformer. The load of the photovoltaic unit can be equivalent to an AC local load connected to PCC. When the AC switch $K$is turned off for some reason, the AC islanding subsystem is formed. Fig. 2 is a simplified model of DC islanding subsystem. Photovoltaic units are connected in parallel by DC/DC converter and then connected to AC power grid by MMC. In the follow-up research of this paper, the power grid connected with AC system and DC system has enough capacity to ensure the stability of voltage and frequency under normal grid-connected operation. When the photovoltaic AC system shown in Fig. 1 is in normal operation, the photovoltaic output power is $P + jQ$, the local load consumption power is $P_{load} + jQ_{load}$, and the power output from the power grid to the AC system is $\Delta P + j\Delta Q$. At this time, because the photovoltaic system is connected to the power grid, the amplitude of the voltage at point of common coupling (PCC) is determined by the power grid under the clamping action of the large power grid.

Influenced by the current control strategy adopted by photovoltaic AC grid-connected inverters, the phase difference between output current and voltage will not change in the stable state before and after islanding:

$$\begin{cases} I = I_0 \\ \varphi = \varphi_0 \end{cases} \tag{1}$$

where I represents the output current value of grid-connected inverter after islanding; I_0 represents the corresponding steady-state value in normal operation state; φ represents the phase difference of output current and voltage of grid-connected inverter after islanding; φ_0 represents the corresponding steady-state value under normal operation.

In order to maximize the photovoltaic output efficiency, the photovoltaic system does not output reactive power, and the corresponding reactive power is provided by the power grid and reactive power compensation equipment. Therefore, most photovoltaic systems adopt unit power factor control, so that the phase difference approaches zero, that is, the above φ and φ_0 are about equal to 0. Under this condition, the system analysis before the island occurs can be obtained:

$$\begin{cases} I = \dfrac{P_{load} - \Delta P}{U_0 \cos \varphi_0} \\ \varphi \approx 0 \\ R = \dfrac{{U_0}^2}{P_{load}} \end{cases} \tag{2}$$

where U_0 represents the output voltage value of grid-connected inverter under normal operation; R represents the equivalent local load of the system. The circuit system after islanding is analyzed:

$$U = IR \cos \varphi \tag{3}$$

where U represents the voltage amplitude at PCC after island operation. Simultaneous 2 and 3 types are available:

$$U = U_0 \left(1 - \frac{\Delta P}{P_{load}} \right) \tag{4}$$

When ΔP is not 0, it is deduced from Eq. (2) to Eq. (4) that the voltages U and U_0 are not equal before and after islanding, and the difference between them is related to the size of ΔP, which can be used as the theoretical basis of passive over/under voltage method. When the voltage is 85% - 110% times the rated voltage, the system can still run normally and continuously. According to Eq. (4), it can be calculated that when the ΔP is less than 15% of the local load, islanding occurs at this time, and the corresponding voltage value is still in the normal range, that is, the over/under voltage method will enter the detection blind area and cannot accurately identify the occurrence of islanding. Through the analysis of the changes of electrical quantities in AC/DC system, it can be known that there are many kinds of electrical quantities in AC system, and there are many available characteristic quantities. However, according to the requirements of national standards, there are inherent detection blind spots in traditional passive islanding detection, and at the same time, the active method has an impact on the power quality of the system, so it is necessary to find an AC islanding detection method that can avoid affecting the power quality and greatly reduce the detection blind spots: compared with AC system, there are fewer kinds of electrical quantities. f passive method is used in DC system, it is difficult to solve the problem of large detection blind area. Therefore, active method is generally chosen as island protection scheme in DC system, but active method has problems of affecting power quality and multi-machine cooperation. It is necessary to find a DC island detection method that can reduce the influence of active method on the system and ensure accurate operation in multi-machine system.

3 THE ENSEMBLE LEARNING METHOD FOR THE MULTI-CLASSIFICATION OF SMART METER FAULT TYPES

Because of the richness of electrical information in AC system, the research on islanding detection in AC system is also comprehensive and perfect. Although there are many available electrical quantities in AC system, according to the islanding operation standard in the national standard, the passive method of detecting the variation law of electrical quantities has the problem that the detection method fails when the power matching degree is high, while the active method of actively breaking the power balance through injection has the problem of affecting the power quality. At the same time, for the traditional islanding detection methods, it is necessary to manually set the threshold, and the judgment result is obtained by comparing the detection quantity with the threshold. The threshold setting needs to consider various operating States of the system to avoid misoperation and refusal of islanding protection scheme. Therefore, in the AC system, the traditional active and passive islanding detection has corresponding disadvantages. It is necessary to find a new islanding detection method to realize accurate identification and avoid interference to the power quality of the system. Considering the good applicability of intelligent algorithm in the process of data mining optimization, combining intelligent algorithm with islanding protection can greatly improve the efficiency and accuracy of islanding detection. In this paper, an ensemble learning method is designed and applied to islanding detection, and its flow chart is shown in Fig. 3. The purpose of the ensemble learning is to integrate the advantages of base classifiers, and then improve the fault classification accuracy of the model. In addition, it can reduce the risk of over-fitting, improve the generalization and stability of the model. As shown in Fig. 3, assuming that there are J base classifiers used to build the ensemble learning model, the sample dataset is as shown as:

$$D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_M, y_M)\} \tag{5}$$

The classification accuracy of each type in the training results of the *j-th* model a_j is:

$$a_j = \left[a_j^1, a_j^2, \ldots, a_j^N \right] \tag{6}$$

Then the prediction results of the multi-classification ensemble learning model for the n_{th} fault type $\hat{y}^n$ is:

$$\hat{y}^n = arg\max\left(\sum_{j=1}^{J} y_j^n\right) \tag{7}$$

where *argmax* represents the type with the highest score as the final prediction result; y_j^n represents the classification result of the j_{th} base classifier for the n_{th} fault type. Soft Voting Classifier is used in our method by taking the averages produced by all the base classifiers as the evaluation values, and the corresponding type with the highest value is the final prediction result.

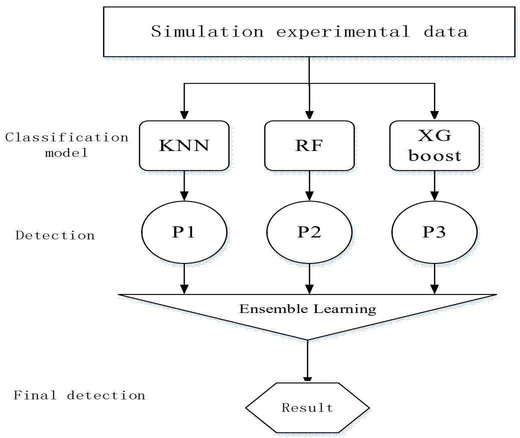

Figure 3 The flowsheet of the Ensemble Learning Method for the Multi-classification of Smart Meter Fault Types

4 SIMULATION VERIFICATION AND EXPERIMENTAL RESULT ANALYSIS

The accuracy of the classification result of intelligent algorithm is related to the completeness of the original data. Therefore, in order to ensure the correct classification result of the islanding detection method based on intelligent algorithm, it is necessary to collect a complete original database. The original data usually comes from the recorded data of the actual operation of the system and the experimental data of the simulation system. However, in order to ensure that the original data can cover all possible operating conditions, but the actual recorded data can not meet this requirement, so the original data collected in this study are all from the experimental data of the simulation system.

4.1 Simulation System Model and Original Data Collection

Our experiments are carried out on a 64 - bit Windows 10 operating system and a 2.5 GHz Intel(R) Core(TM) i5-7300HQ CPU. Considering that at present, there are few cases where there are multiple islanding detection methods in the original data collection based on intelligent algorithm, in order to ensure the accuracy of islanding detection, there are cases where active and passive islanding detection methods are used in the same system, and the active islanding detection method may also affect the recognition accuracy of intelligent algorithm because of injecting disturbance into the system. Therefore, in order to verify the recognition accuracy of the proposed method, passive and active detection methods need to be included in the training model. At present, the common passive islanding detection scheme is over/under voltage method, and the common active islanding detection method is Q-f feedback method, so the above two detection methods are adopted in the simulation system. In addition, because the different number of parallel units will also cause the changes of related electrical quantities, the simulation system of AC isolated island subsystem is established by Matlab/Simulink, as shown in the figure. Because the passive method can reduce the detection blind area by determining the system state together with various electrical information, the simulation system collects nine electrical data including voltage, voltage change rate, phase difference between voltage and current, active power, active power change rate, reactive power change rate, frequency and frequency change rate as the original database, and all the above electrical data are collected at PCC point. In the simulation system, the rated output power of a single photovoltaic unit is 500 kw, which is connected to the 220 kV power grid after being boosted in parallel, and the number of parallel photovoltaic units is 2 - 4. In each case, passive data with only passive islanding detection method and active data with Q-f feedback method are collected respectively.

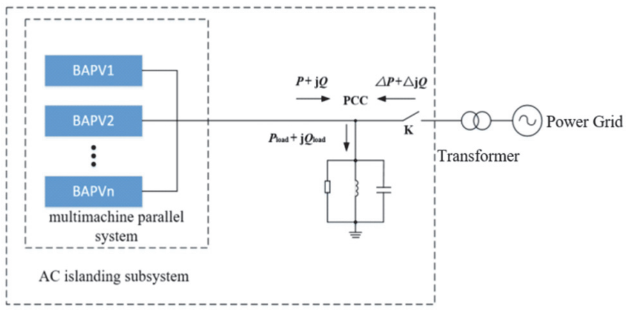

Figure 4 Simulation system diagram of AC isolated island subsystem

In the passive data, 2 - 4 photovoltaic units are connected in parallel and adjustable. Under island operation and normal grid connection, the active power and reactive power of local load are 10% - 190% of the rated load of photovoltaic output power, respectively, and change in steps of 10%, totaling 228 groups: active data, 2 - 4 photovoltaic units are adjustable, under island operation and normal grid connection, The active power and reactive power of local load are 10% - 190% of the rated load of photovoltaic output power, respectively, changing in steps of 10%, and the feedback coefficient ranges from 102 to 702, with steps of 102, totaling 1596 groups. In addition, in order to test the anti-disturbance ability of the research algorithm under normal operation conditions, the voltage rise (5% - 30% rated voltage, step 5%), voltage sag (5% - 30% rated voltage, step 5%) and grounding fault (grounding resistance 0 - 302, step 5%) occurred when 2 - 4 photovoltaic units were connected in parallel under normal operation conditions. The above data are randomly divided into verification data and training data according to the ratio of 1/3, wherein the training data is used to train the algorithm, and the verification data is used to test the recognition ability after verification. Sure, I can introduce you to the K-Nearest Neighbors (KNN), Random Forest (RF), and XGBoost algorithms.

4.2 Introduction of Basic Algorithms

K-Nearest Neighbors is a simple and intuitive machine learning algorithm used for classification and regression tasks. In KNN, the "k" stands for the number of nearest neighbors to consider. Given a new data point, KNN identifies the "k" closest data points from the training dataset based on a chosen distance metric (e.g., Euclidean distance). For classification, KNN assigns the class label that is most common among the k-nearest neighbors. For regression, it calculates the average (or weighted average) of the target values of these neighbors. KNN's performance depends on the choice of "k" and the distance metric. A smaller "k" makes the model more sensitive to noise, while a larger "k" makes it smoother. Random Forest is an ensemble learning method that combines multiple decision trees to make more accurate predictions. It's used for both classification and regression tasks. A Random Forest is constructed by creating a collection of decision trees during the training phase. Each tree is trained on a random subset of the data (bootstrapped sample) and a random subset of features, which helps to reduce overfitting. When making predictions, the results from individual trees are aggregated. For classification, the most popular class is chosen, while for regression, the average of the predictions is taken. Random Forest is known for its robustness, generalization, and resistance to overfitting. It often provides high accuracy and works well with a variety of data types. XGBoost (Extreme Gradient Boosting) is a powerful gradient boosting algorithm that has gained popularity in machine learning competitions and real-world applications. It is an ensemble technique that builds a strong predictive model by combining multiple weak models, typically decision trees, sequentially. XGBoost uses gradient boosting, which means that it trains each new tree to correct the errors made by the previous ones. It optimizes a specific loss function and employs regularization techniques to prevent overfitting. XGBoost is highly customizable with various hyperparameters to control the model's behavior, and it can handle missing data effectively. It is known for its speed and accuracy and is widely used in tasks like classification, regression, ranking, and more. In summary, K-Nearest Neighbors is a simple and interpretable algorithm that relies on the similarity of data points. Random Forest is an ensemble method that combines decision trees for better predictive performance. XGBoost is a sophisticated gradient boosting algorithm that excels in many machine learning tasks and competitions due to its speed and accuracy.

4.3 Analysis of Experimental Results

After the passive training data is input into the ensemble learning islanding detection algorithm, the algorithm after training is compared with the over/under voltage method. Taking the passive islanding detection method for two photovoltaic units in parallel as an example, the comparison results of ACC are shown in Tab. 1 and Fig. 5. Input the active data into the training of integrated learning islanding detection algorithm, and compare the trained algorithm with Q-f feedback method. Take the active islanding detection method of two photovoltaic units in parallel as an example, the feedback coefficient is 502, and the comparison result of ACC is shown in Tab. 2 and Fig. 6.

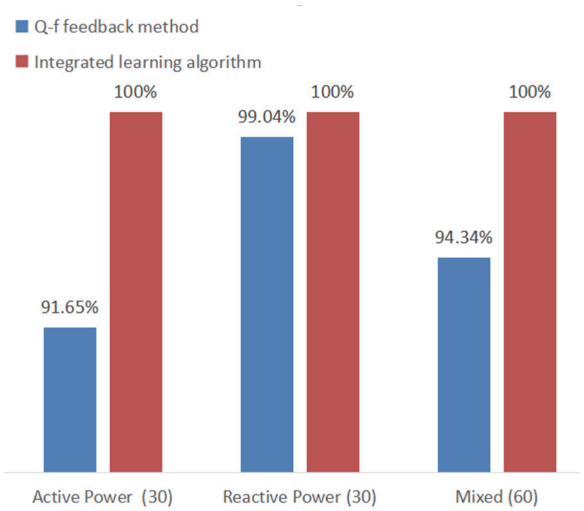

Figure 5 ACC comparison results of over/under voltage method and ensemble learning classifier

In order to compare the accuracy of islanding recognition between the research algorithm and the original algorithm, different training data are substituted into three basic classifiers for training, in which all the mixed data are a mixture of passive data and active data. The comparison results of ACC are shown in Tab. 3. Because the research algorithm combines the multi-dimensional data processing ability of KNN algorithm, the iterative cycle ability of RF algorithm and the nonlinear feature processing ability of XGBoost algorithm, Although the random forest algorithm improves the detection accuracy through cyclic iteration, because the data is multi-dimensional, the wrong update of weights will reduce the accuracy of the classification model, while the KNN algorithm itself is not as accurate as the random forest algorithm, and XGBoost algorithm is unstable for some linear problems. Therefore, it can be seen from Tab. 3 and Fig. 7 that the research algorithm has great advantages over the original algorithm in recognition of various data. The simulation results show that compared with traditional passive and active methods, the recognition accuracy of this research algorithm is significantly improved; Compared with the original algorithm, the detection accuracy of the research algorithm has also been greatly improved. Moreover, ensemble learning methods are less susceptible to the instability caused by a single algorithm.

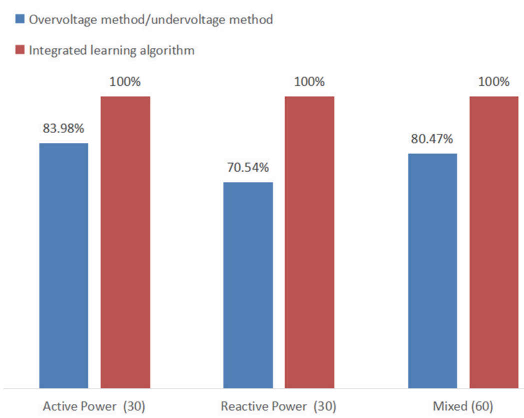

Figure 6 ACC comparison results between Q-f feedback method and ensemble learning classifier

Table 1 ACC comparison results of over/under voltage method and ensemble learning classifier

Type of verificationdata	Over-voltagemethod / Under-voltage method	Integrated learning algorithm
Active Power Fluctuation Data (30)	83.98%	100%
Reactive Power Fluctuation Data (30)	70.54%	100%
Passive mixed data (60)	80.47%	100%

Table 2 ACC comparison results between Q-f feedback method and ensemble learning classifier

Type of verificationdata	Q-f feedback method	Integrated learning algorithm
Active Power Fluctuation Data (30)	91.65%	100%
Reactive Power Fluctuation Data (30)	99.04%	100%
Passive mixed data (60)	94.34%	100%

Table 3 ACC comparison results of three basic classifiers and ensemble learning classifier

Fault Type	KNN	RF	XGBoost	EL
Passive mixed data (60)	89.45%	93.73%	91.87%	100%
Actively mixed data (400)	95.82%	98.32%	96.21%	100%
All mixed data (460)	83.78%	97.24%	94.36%	99.54%

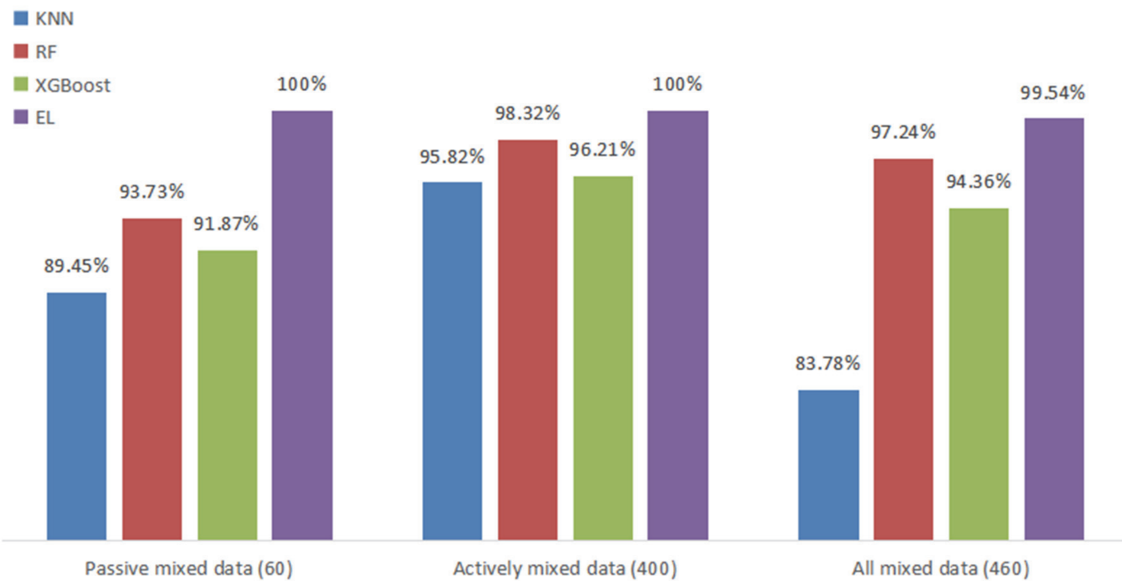

Figure 7 ACC comparison results of three basic classifiers and ensemble learning classifier

5 CONCLUSION

When photovoltaic system is connected to AC/DC distribution network, unplanned islanding may occur on both AC side and DC side. In order to reduce the threat of unplanned islanding to equipment and maintenance personnel, it is of great significance to identify the occurrence of islanding in AC system and DC system respectively. In this paper, the problem of islanding identification in AC distribution network is analyzed, and the changes of electrical quantities before and after islanding in AC system are analyzed, and the corresponding islanding detection methods are put forward. The main results of this paper are as follows:

1) In this paper, the islanding operation of AC/DC system is analyzed separately, and the variation laws of voltage, frequency, active power, reactive power and phase angle before and after islanding operation in AC/DC system are expounded, and the changes of each electrical quantity with different islanding degrees are also analyzed. Finally, the variation law of each electric quantity is obtained in the AC system, which provides the basis for the follow-up research.

2) In the research of islanding detection in AC system, this paper adopts three classification algorithms, including KNN, random forest and XGBoost, to integrate and learn the model, so as to improve the accuracy and robustness of islanding detection task. The research algorithm uses the characteristics of incomplete overlapping of blind spots of multiple electric quantities to judge the system state together, which improves the accuracy of passive islanding detection. The simulation results show that the recognition accuracy of the research algorithm is obviously improved compared with the traditional passive method and the traditional active method; the detection accuracy of the research algorithm is also greatly improved compared with the original algorithm.

Future Work:

While the paper focuses on AC system analysis and detection methods, future work could include a detailed analysis of islanding in the DC distribution network. This is especially relevant when dealing with renewable energy systems like photovoltaics, as there may be unique characteristics and challenges in the DC side of the system. Developing islanding detection methods specific to the DC system would be valuable. Investigating the potential for hybrid islanding detection methods that combine both AC and DC system characteristics could be meaningful. Combining information from both sides of the system can lead to more robust and accurate islanding detection, as unplanned islanding can manifest differently in AC and DC components.

Acknowledgement

This research was supported by the science and technology project of State Grid Fujian Electric Power Co., Ltd.: Research on Micro-metering System for New Power System (52130X22000H).

6 REFERENCES

[1] Ahmed, N. & Khan, M. (2021). Logistic Regression based Islanding Detection for Grid-Connected Inverter. *2021 IEEE Kansas Power and Energy Conference (KPEC)*, 1-4. https://doi.org/10.1109/KPEC51835.2021.9446257
[2] Khan, M. A., Haque, A., Kurukuru, V., & Saad, M. (2022). Islanding detection techniques for grid-connected photovoltaic systems-A review. *Renewable and Sustainable Energy Reviews, 154*, 111854. https://doi.org/10.1016/j.rser.2021.111854
[3] Singh, O., Urooj, S., Gupta, S. K., & Sagar, J. (2020). Pattern Recognition Technique based Islanding Detection Scheme in Grid-connected PV System. *INDICON 2020*, 1-7. https://doi.org/10.1109/INDICON49873.2020.9342592
[4] Kishor, S., Rajesh, K., Ram Kumar, A. M., & Priya, P. (2021). Analysis and control of a grid interfaced hybrid grid tied inverter based PV system with anti-islanding grid protection. *Materials Today: Proceedings*. https://doi.org/10.1016/J.MATPR.2021.02.782
[5] Lu, G., Wu, Q., Wu, C., Cheng, H., & Shi, X.(2019). Islanding detection of grid-connected PV system based on bi-direction voltage harmonic variation. *Electric Power Automation Equipment*.
[6] Smitha, J. P. & Gayadhar, P. (2015). Wavelet technique based islanding detection and improved repetitive current control for reliable operation of grid-connected PV systems. *International Journal of Electrical Power & Energy Systems, 67*, 39-51. https://doi.org/10.1016/j.ijepes.2014.11.008
[7] Badr, M. M., Ibrahem, M. I., Mahmoud, M., & Fouda, M. M. (2022). Detection of False-Reading Attacks in Smart Grid Net-Metering System. *IEEE internet of things, 9*(2), 1386-1401. https://doi.org/10.1109/JIOT.2021.3087580
[8] Dikty, M., Sternal, J., & Haack, A. (2022). The self-cleaning rotary valve from Kreisel: an essential infeed and metering system for the pneumatic transport of bypass dusts of a cement rotary kiln fired with secondary fuels. *Cement international*, 2-20.
[9] Lee, S., Jin, H., Nengroo, S. H., Doh, Y., Lee, C., Heo, T., & Har, D. (2021). Smart Metering System Capable of Anomaly Detection by Bi-directional LSTM Autoencoder. *arXiv e-prints*. https://doi.org/10.1109/ICCE53296.2022.9730398
[10] Kebotogetse, O., Samikannu, R., & Yahya, A. (2021). Review of key management techniques for advanced metering infrastructure. *International Journal of Distributed Sensor Network, 17*(8), 48-56. https://doi.org/10.1177/15501477211041541
[11] Sareen, K., Bhalja, B. R., & Maheshwar, R. P. (2017). A Hybrid Multi-feature based Islanding Detection Technique for Grid Connected Distributed Generation. *International Journal of Emerging Electric Power Systems, 18*(1), 20160042. https://doi.org/10.1515/ijeeps-2016-0042
[12] Xia, Y., Yu, F., Xiong, X., Huang, Q., & Zhou, Q. (2022). A Novel Microgrid Islanding Detection Algorithm Based on a Multi-Feature Improved LSTM. *Energies, 15*, 2810. https://doi.org/10.3390/en15082810

Contact information:

Wen ZHAN, SN ENGR
State Grid Fujian Electric Power co, LTD.
No. 9 Qinyuan Bypass, Jin'an District, Fuzhou City, Fujian Province, China
E-mail: zhan_wen@fj.sgcc.com.cn

Chen GAO, SN ENGR
State Grid Fujian Marketing Service Center,
No. 9 Qinyuan Bypass, Jin'an District, Fuzhou City, Fujian Province, China
E-mail: gao_chen@fj.sgcc.com.cn

Hong ZHu, SN ENGR
(Corresponding author)
Wahlap Technology Corporation Limited,
No. 181 Wuchang Avenue, Wuchang Street, Yuhang District, Hangzhou, China
E-mail: zhuhong198112@126.com

Qian NING, ENGR
Wahlap Technology Corporation Limited,
No. 181 Wuchang Avenue, Wuchang Street, Yuhang District, Hangzhou, China
E-mail: qian.ni@holley.cn