A microgrid alarm processing method based on equipment fault prediction and improved support vector machine learning

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Abstract. Microgrids are important parts of modern strong intelligent power system. In recent years, new energy sources have developed rapidly in China, and research on microgrid technologies is in the ascendant. The typical microgrid has obvious advantages such as flexible network structure and small circuit loss. With its increasing scale and increasing application in the power system, it needs to be dealt with the complex operation mode. In order to achieve efficient operation and management, microgrid control still needs to be equipped with energy management system (EMS). One of the main problems that EMS needs to solve is the generation of massive alarm information within a short period of time after equipment failure. To this end, this paper proposes a microgrid alarm processing method based on equipment fault prediction and improved support vector machine learning. Based on historical operation risk and health state evaluation, the equipment fault prediction is carried out. Then we optimize and select kernel function for machine learning and have an improved SVM model. With this model, fault equipment sets are classified and verified so we can get the accurate source alarm and fault equipment. Finally, the validity and accuracy of this method are verified by a simple example.

1. Introduction
Microgrid refers to a small distribution power system composed of distributed power sources, energy storage devices, energy conversion devices, related loads, monitoring systems and relay protection devices [1]. It can provide both electrical energy and heat energy at the same time [2]. It can be connected to a large power grid or run alone as well and nowadays it is an important part of modern strong smart power system [3]. In recent years, in order to solve the environment pollution problem, China has made great efforts to develop distributed clean energy. While wind power, photovoltaic power, biomass power, energy storage and other new energy sources are developing fast, the whole related electronic power technology gets more and more advanced. Meanwhile there are more and more microgrid systems of different types and sizes, which show many good characteristics such as flexible network structure, controllable active and reactive power, compatible with environment and small circuit loss. Research on microgrid has always been an academic hotspot since 2000[4-5]. With the increase of the penetration rate of microgrid in the entire power system, the scenes of microgrid applications are becoming more and more complex and the design requirements of microgrid control strategies and energy management systems are constantly improving. It is necessary to deal with the complex operating mode problems
and realize efficient use of multi-energy, thus a number of studies are currently being carried out in our country [6-7]. As a relatively independent and reliable power system, microgrid still needs to be equipped with traditional energy management system to achieve efficient operation management. This paper believes that for a certain scale of microgrid systems (power capacity of more than 100,000 kilowatts), in the case of failure, a large amount of alarm information will be generated in a short period of time (basically in 20 ms), such as bus node voltage exceeding, trend exceeding, delay protection device acting, switch acting, communication error, generator bus failure, etc [8]. When the size of microgrid system grows larger, the number of alarm information will increase exponentially. In order to process the alarms efficiently and accurately and locate the fault source so that operation and management measures can be taken, advanced alarm handling methods need to be studied [9]. Based on this, this paper proposes a microgrid alarm processing method based on equipment fault prediction and improved support vector machine learning. First all the important equipment of the microgrid is evaluated and the equipment fault prediction is carried out based on historical operation risk and health state evaluation. Then we optimize and select kernel function for machine learning and have an improved SVM model, with which fault equipment sets are classified and verified so we can get the accurate source alarm and fault equipment. Finally, the feasibility and accuracy of this method are verified by simulation of IEEE 9 bus system.

2. Fault prediction of the microgrid equipment
In order to predict microgrid equipment fault, the first step is to master the health status of the relevant equipment. At present, the research of equipment status assessment such as generator sets, transformers and relay protection devices has been widely carried out. The actual operating experience of microgrid shows that the more failures occur to one equipment historically and the worse its current health is, the more likely it is to fail. Therefore, this paper mainly evaluates the condition of one equipment from two aspects: the historical operating risk and the current health status evaluation.

2.1. Index of historical operation risk
The To make it simple, the historical operating risk of equipment E presented in this paper is calculated by its number of historical failures. The final results are expressed in scores, which mainly include the following indicators:

1) Ntotal: The total number of failures. It refers to the total number of failures that have occurred since the equipment was put into operation.
2) Nhy: The number of failures in the past six months. It refers to the number of equipment failures within six months before the alarm processing program is triggered.
3) Nm: The number of failures in the last months. It refers to the number of equipment failures within one month before the alarm processing program is triggered.
4) Nw: The number of failures in the last week. It refers to the number of equipment failures within one week before the alarm processing program is triggered.

Here S is defined as equipment failure severity. According to the damage caused by each equipment failure to the operation of the microgrid, S is divided into four degrees: major, serious, harmful, and ordinary. The corresponding deduction values are 4, 3, 2, and 1 respectively.

According to the weighted average method, the historical operating risk of equipment E can be calculated by the following formula:

$$\text{History}(E) = \frac{\sum_{i=1}^{N} S(i)}{N}$$  \hspace{1cm} (1)

Where the order of N’s values quoted in this formula is Ntotal, Nhy, Nm, and Nw, which means, when Ntotal values are equal, the equipment with a larger Nhy value has a higher History value; When Ntotal and Nhy values are equal, the equipment with a larger Nm value has a higher History value; When Ntotal, Nhy and Nm values are equal, the equipment with a larger Nw value has a higher History value.
2.2. Health status evaluation

Current technology can realize the on-line real-time evaluation of equipment health status, mainly by collecting the relevant characteristic data and using offline preventive experiments data.

The final evaluation results of the equipment are synthesized from the results of evaluation of each component of the equipment, which can be divided into four levels: I health, II sub-health, III alert, and IV serious anomaly. Only when all components are evaluated as healthy, the equipment as a whole is evaluated as healthy. Otherwise, the equipment is evaluated as the worst situation.

The results of one equipment's health status are evaluated by scoring. The method is to deduct points according to the status evaluation of each component, and then sum up according to the weight of each component. The level of health of the equipment is judged according to the score.

An example of the method to evaluate the level of equipment health is shown in Table I.

The formula of this method can be described as:

\[
\text{Health}(E) = \sum \text{component score} \times \text{weight}
\]  

Table I: Equipment health status evaluation standard

| Parts 1 | \( \leq 30 \) | \( \leq 10 \) | \( > 30 \) | 12-20 | 24 | \( \geq 30 \) | Weight |
|---------|-------------|-------------|-------------|-------|-----|-------------|--------|
| Total   | Single      | Single      | Sub-health  | Single | Single | Serious abnormality | 0.1    |
| Parts 2 | \( \leq 20 \) | \( \leq 10 \) | \( > 20 \) | 12-20 | 24 | \( \geq 30 \) | 0.2    |
| 1       | 1           | 1           | 1           | 1     | 1    | 1            |        |

2.3. Fault prediction

In practice, the operating mode of microgrid is flexibly adjusted according to actual needs. Complex operating modes will affect every equipment of the microgrid and may change its health status. Therefore, the impact of operating mode changes needs to be considered.

After evaluating the historical operating risk and health status of one equipment, its failure risk can be obtained by weighted summation as following:

\[
\text{Risk}(E_i) = \alpha \times \text{Health}(E_i) - \beta \times \text{History}(E_i)
\]

This formula means the higher the historical operating risk is, the worse the health status level is, the higher the failure risk will be and equipment with poor health status is more likely to fail than equipment with high historical operating risk. In this paper, \( \alpha \) and \( \beta \) are assigned to be 0.7 and 0.3, respectively with reference to a large number of examples. According to Risk value, the likely-to-fail equipment can be picked out and a set of hypothetical fault equipment can be formed.

Equipment fault prediction is done online in real time to ensure accuracy. The History and Heath values of each equipment are obtained in real time and change whenever a fault occurs, so the set of hypothetical fault equipment is dynamically changing in various fault situations.

3. The proposed support vector machine

3.1. Basic concept

Support Vector Machine (SVM) is a small sample statistical learning theory with high generalization performance [10]. It is based on structural risk minimization principle and the VC (Vapnik - Chervenikis) concept of statistical learning theory [11]. It was originally used to study the law of machine learning under a limited learning sample and try to obtain ideal learning results with insufficient information. This method maps the input vector to a high-dimensional feature space through nonlinear function and realizes linear separability of the sample and finally obtains the optimal classification surface and the optimal solution [12]. Therefore, compared to the artificial neural network method, it can avoid problems such as excessive learning, under-study and local minima. Relatively it is a more advanced algorithm.
Suppose a linear separable sample set \((x_i, y_i)\), where \(i = 1, 2, ..., n, x \in \mathbb{R}^d\), \(y_i \in \{+1, -1\}\) is a category label. Its classification surface equation can be expressed as:

\[ g(x) = w \cdot x + b = 0 \]  

(4)

When \(|w|\) is minimum, the classification interval is the largest. If \(w\) can satisfy the following formula:

\[ y_i \left[ (w \cdot x_i) + b \right] - 1 \geq 0, (i = 1, 2, ..., n) \]  

(5)

Then this classification surface is the optimal classification surface. The samples which make the equivalent holds are closest to the classification surface and parallel to the optimal classification surface and they are called support vectors. Therefore, the optimal classification surface problem can be simplified to find the minimum value of \(|w|_2\) under the constraint of equation (5).

Define a Lagrange function as following:

\[ L(w, b, \alpha) = (w \cdot w) - \sum_{i=1}^{n} \alpha_i \left[ y_i \left( (w \cdot x_i) + b \right) - 1 \right] \]  

(6)

where \(\alpha_i > 0\) is the Lagrange coefficient. To find the minimum value of the function is to find the minimum value of the Lagrange function by \(w\) and \(b\). By finding \(L\)’s partial differentiation with \(w\) and \(b\), then make it equal to 0, this problem can be converted into a dual problem.

Assume \(\alpha_i\) is the optimal solution, the optimal classification function can be expressed as:

\[ f(x) = \text{sgn} \left\{ \left( w^* \cdot x \right) + b^* \right\} = \text{sgn} \left\{ \sum_{i \in M} \alpha_i y_i M(x_i, x) + b^* \right\} \]  

(7)

where \(\text{sgn}(\bullet)\) is a symbolic function, \(b^*\) is a threshold of the classification which can be obtained by any support vector, \(M(x_i, x)\) is a kernel function. For a given sample, the calculation of \(\text{sgn}(w \cdot x + b)\) can determine the classification to which it belongs.

3.2. The improved SVM

The kernel function \(M(x_i, x)\) plays a key role in the classification performance. For the scenarios of many samples application this method faces, Gaussian kernel function should be used to solve the problem, which can be expressed as:

\[ M(x_i, x) = \exp \left( -\frac{||x - x_i||}{2\sigma^2} \right) \]  

(8)

This is a convex programming problem. Gaussian function is used to predict mainly by determining the key parameter \(\sigma\) and the penalty parameter \(C\). In this paper, a grid search method is proposed to determine the value of \(\sigma\) and \(C\) which means: first select the appropriate step length according to the value range of \(\sigma\) and \(C\), then train each group of parameters \((\sigma, C)\) and take the best group as model parameters.

4. Process of the proposed method

The process of the proposed method is shown as Figure 1 and the specific steps are described as follows:

1) With the initial sample set, the value of \(\sigma\) and \(C\) is determined using the grid search method and then the optimal kernel function is obtained;

2) Take the set of alarm results as input and fault equipment as output, establish the SVM model of the microgrid through machine learning;

3) Receive the microgrid alarm in real time, and set synchronous action of the relay protection device and its corresponding circuit breaker as the trigger condition to start the intelligent alarm processing program and determine the fault area;
4) According to the predetermined conditions, calculate the Risk value of every equipment in the fault area and then store them in the hypothetical fault set in reverse order of the Risk value;

5) Substitute the elements of the hypothetical fault set into the SVM model, and by comparing the alarm set caused by the hypothetical fault equipment and the actual alarm set, solve the problem according to the optimal classification function. Select the qualified elements and decide the source alarm and fault equipment;

6) By comparing the alarm set caused by the hypothetical fault equipment and the actual alarm set, find the missing alarm and error warning and so on. The result of this alarm processing is put into the sample set and the SVM model is perfected through machine learning.

Fig.1. Flow chart

5. Case study
This paper takes IEEE 9-node standard system as an example and verifies the method briefly. In order to illustrate the advantages of the proposed method, the traditional fault early warning method is used for comparison. The system includes generators, buses, power lines, and loads, in which G1 is a photovoltaic unit, G2 is a wind turbine unit, and G3 is a small regular generator. Its SVM model is established according to the method referred in section 2.

Fig.2. The topology of IEEE 9-bus system

Take a simple failure as an example: assume that the G2 unit fails at 0s, and bus 3 voltage exceeds the low limit and generate one alarm, then at 0.09s relay protection acts and generate one alarm, then circuit breaker on bus 3 acts and generate one alarm which triggers the alarm processing main program. At 0.1s the program infers that G2 was the fault equipment.

According to the same method, for IEEE 9-node system, simulate other unit faults, bus single-phase grounding, phase to phase short circuit and other types of faults respectively, and deal with the generated
alarm events. The results show that the average early warning time of the method proposed in this paper is 0.091s, and the success rate of early warning is 99.4%, while the average early warning time of the traditional method is 3.27s, and the success rate of early warning is 96.7%.

The simulation results show that the method presented in this paper has short reasoning time, high accuracy and high practicability.

6. Conclusion
With further development of distributed clean energy, more microgrids will show up in various forms and sizes. This is both an improvement of intelligent grid and one new challenge to the operation and management of power grid. For those relatively independent microgrids, it is worthwhile to research how to identify faults quickly and effectively and achieve better operation and management. This paper takes the equipment as the starting point and proposes a method improving the alarm processing speed and the accuracy by equipment on-line monitoring, pre-judging the failures and analyzing with the optimized SVM model. The simulation results show that this method has good performance and has good application prospects.

References
[1] Van der Geer, J., Hanraads, J.A.J., Lupton, R.A. (2010) The art of writing a scientific article. J. Sci. Commun., 163: 51–59.
[2] L. Che, M. Shahidehpour, A. Alabdulwahab and Y. Al-Turki. (2015) Hierarchical Coordination of a Community Microgrid With AC and DC Microgrids. J. IEEE Transactions on Smart Grid, vol. 6, no. 6, pp. 3042-3051.
[3] F. Zandi, B. Fani, I. Sadeghkhani and A. Orakzadeh. (2018) Adaptive complex virtual impedance control scheme for accurate reactive power sharing of inverter interfaced autonomous microgrids. J. IET Generation, Transmission & Distribution, vol. 12, no. 22, pp. 6021-6032.
[4] E. Harmon, U. Ozgur, M. H. Cintuglu, R. de Azevedo. (2018) The Internet of Microgrids: A Cloud-Based Framework for Wide Area Networked Microgrids. J. IEEE Transactions on Industrial Informatics, vol. 14, no. 3, pp. 1262-1274.
[5] T. Agarwal, P. Niknejad, A. Rahimnejad, M. R. Barzegaran and L. Vanfretti. (2019) Cyber–physical microgrid components fault prognosis using electromagnetic sensors. J. IET Cyber-Physical Systems: Theory & Applications, vol. 4, no. 2, pp. 173-178.
[6] A. Garcés. (2018) On the Convergence of Newton's Method in Power Flow Studies for DC Microgrids. J. IEEE Transactions on Power Systems, vol. 33, no. 5, pp. 5770-5777.
[7] J. Li, Y. Liu and L. Wu. (2019) Optimal Operation for Community-Based Multi-Party Microgrid in Grid-Connected and Islanded Modes. J. IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 756-765.
[8] A. Hussain, V. Bui and H. Kim. (2018) Robust Optimal Operation of AC/DC Hybrid Microgrids Under Market Price Uncertainties. J. IEEE Access, vol. 6, pp. 2654-2667.
[9] Z. Huang, Z. Wang and H. Zhang. (2018) A Diagnosis Algorithm for Multiple Open-Circuited Faults of Microgrid Inverters Based on Main Fault Component Analysis. J. IEEE Transactions on Energy Conversion, vol. 33, no. 3, pp. 925-937.
[10] Z. Huang and Z. Wang. (2020) A Fault Diagnosis Algorithm for Microgrid Three-Phase Inverter Based on Trend Relationship of Adjacent Fold Lines. J. IEEE Transactions on Industrial Informatics, vol. 16, no. 1, pp. 267-276.
[11] F. Ye, Z. Zhang, K. Chakrabarty and X. Gu. (2014) Board-Level Functional Fault Diagnosis Using Multikernel Support Vector Machines and Incremental Learning. J. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 33, no. 2, pp. 279-290.
[12] S. Khandelwal, L. Garg and D. Boolchandani. (2015) Reliability-Aware Support Vector Machine-Based High-Level Surrogate Model for Analog Circuits. J. IEEE Transactions on Device and Materials Reliability, vol. 15, no. 3, pp. 461-463.

[13] Y. Rahulamathavan, R. C. -. Phan, S. Veluru, et al. (2014) Privacy-Preserving Multi-Class Support Vector Machine for Outsourcing the Data Classification in Cloud. J. IEEE Transactions on Dependable and Secure Computing, vol. 11, no. 5, pp. 467-479.