A FAULT DIAGNOSIS APPROACH FOR POWER GRID WITH INFORMATION FUSION

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ABSTRACT

Considering the development of power system automation and communications technology, this paper presents a fault diagnosis approach for power grid with information fusion based on multi-data resources which contain the switching-status data related to breakers and protection relays, and the continuous-time data derived from fault recorders. Fuzzy Petri nets and wavelet energy analysis are employed to extract fault features. The fuzzy integral theory is used to execute information fusion. Simulation example and calculations show that, the proposed approach significantly improves the diagnostic accuracy while effectively lowers the influence resulted from relay or breaker's mal-operation or refuse-operation, and has good application value.

INTRODUCTION

With the development of the communication and digital technology, the acquisition of the information after fault in a power system has become more and more convenient. When fault occurs in a power system, huge amount of data pours into the dispatching center, by which the dispatcher will be overwhelmed and could not make the right decision timely. Thus, a tool is badly needed to help supporting the real-time decision-making process.

To solve the problem of fault diagnosis of the power system, there are many methods proposed home and abroad, such as the expert system [1], the artificial neural network (ANN) [2], the Petri net method [3], the fuzzy set theory [4] and so on. Although the literature presents a great variety of works considering the problem in subject, few of them were totally developed and applied in real large-scale power systems. All the methods presented above are based on the operation information of circuit breakers (CB) and protection relays (PR) in the power system, namely the switching-status data. However, actually when a fault occurs in a power system, there are always the cases of the malfunctions or failure to operations of the CBs or PRs, as well as the missing of the fault information during communication. In this case, methods presented above that are based on the switching-status data may give incorrect results.

In this case, the circuit and voltage information after fault, namely the continuous-time data, has the advantage of more accuracy, more completeness and more fault tolerance comparing with the switching-status data. Then, more accurate results may acquire using both the continuous-time data and the switching-status data.

This paper presents a novel method that is based on both the switching-status data and the continuous-time data. First, the switching-status data is pre-processed using the fuzzy Petri net method to get the fuzzy fault degree (FFD). Simultaneously, the wavelet transform theory is adopted to analyze the continuously-time data and to extract the fault feature. In this paper, in order to better express the fault, three fault degrees are defined, namely the wavelet fault degree (WFD), the wavelet singular degree (WSD) and the wavelet energy degree (WED) respectively. After that, the fuzzy integral theory is employed to fuse the fault features from the pre-processing procedure. Thus the fault elements will be identified. The simulation studies have been undertaken using PSCAD and MATLAB on the IEEE 14-bus system. The results show that the proposed method can work well and give correct results.

PRINCIPLES USED FOR FAULT DIAGNOSIS

A. Pre-process of the Switching-Status Data-The Fuzzy Petri Net Theory

When faults occur in a power system, the corresponding CBs and PRs will operate to isolate the fault elements. Thus, analyzing the operation signals received in the dispatching center by SCADA, the fault elements could be found out. In this case, the fuzzy Petri net method is adopted to analyze the logical relationships among the CBs, PRs and the elements [5]. In this way, the Boolean quantity of the switching value is quantified to be a numerical value using fuzzy Petri net method. Therefore, the fault probability of the ith element can be obtained as Pi (i=1…N). To get the body of evidence, that is the FFD in the fusion method, Pi is processed by the following equation:

$$mP_i = \frac{P_i}{P_{\max}}\alpha_{mP} \tag{1}$$

where $P_{\max} = \max(P_1,...P_i,...P_N)$ and α_{mP} $(\alpha_{mP} < 1)$ is the FFD of the element corresponding to $P_{\max}$. In this paper, α_{mP} is set to be 0.75 considering the uncertainty of the diagnosis method. Comparing to the paper [6], the definition in this way is more simple and concise in calculation and more reasonable.

B. Pre-process of the Continuous-time Data-The Wavelet Transform Theory

When a fault occurs in a power system, the current and voltage will be sure to fluctuate sharply, the nearer, the severer. Thus by analyzing the waveforms of the current and the voltage, the fault place can be located. In this case, the wavelet transform theory is adopted.

Wavelet transform has been used to analyze the wave signals in many areas which does not only decomposes s signal into its frequency components, but also provide a non-uniform division of the frequency domain. The attribute to tailor the frequency resolution can greatly facilitate signal analysis and the detection of signal features, which can be very useful in characterizing the source of the transients and the state of the post-disturbance system [7]. Among all the wavelets (Haar, Cofiman, Db, etc.), Daubechies's wavelets can provide a much more effective analysis than others [8]. Thus, the Daubechies's wavelets (DB4) are used to evaluate wavelets' suitability for signal analysis and data compression.

The signal is usually being called the raw signal before being analyzed by the wavelet theory. After being processed by the DB4, the raw signal, suppose X , can be represented by the following equation:

$$\begin{aligned} X &= D_1 + D_2 + ... + D_j + A_j \\ &= \sum_{i=1}^{\alpha} D_i + A_\alpha \end{aligned} \tag{2}$$

where α is the decomposition scale in the wavelet analysis, $D_i\,(i=1...\alpha)$ is the coefficients of high-frequency components, representation of the detail information of the ith scale and $A_i\,(i=1...\alpha)$ is the coefficients of low-frequency components, representation of a coarse approximation of the ith scale. Definition is made that $D_{\alpha+1} = A_\alpha$, then (2) can be rewritten as following:

$$X = \sum_{i=1}^{\alpha+1} D_i = \sum_{j=1}^{l} x_j \tag{3}$$

where l is the sampling number if the signal, x_j is a component in D_i .

The Wavelet Fault Degree (WFD)

The extraction of this feature characteristic is based on the fact that the amplitude variation degree of the current wavelet in a line after fault is much larger than that in a healthy line. Detail representation is as follows. X_i is the signal of the ith element, the result of which after DB4 is $x_{i1}, x_{i2}, ..., x_{il}$. Then, after locating the fault moment (the kth moment), the result above can be rewritten as $x_{i1}, x_{i2}, ..., x_{ik}$ and $x_{i(k+1)}, x_{i(k+2)}, ..., x_{il}$, representing the analysis results before and after the fault respectively. Then the amplitude variation degree of the fault information before and after the fault can be obtained by the following equation:

$$V_i = \frac{\max\{F_{if}, F_{ib}\}}{\min\{F_{if}, F_{ib}\}} \tag{4}$$

where F_{ib} and F_{if} are the maximal value in the wavelet analysis results of the signal before and after the fault. Change it into the body of evidence so that the WFD is received.

$$mF_i = w_i \frac{V_i}{V_{\max}} \alpha_{mF} \tag{5}$$

where w_i is the wave index which reflect the distortion of the waveform, $V_{\max} = \max(V_1, ..., V_N)$ and $\alpha_{mF}\ (\alpha_{mF} < 1)$ is the WFD of the element corresponding to $V_{\max}$.

The Wavelet Singular Degree (WSD)

As most of the fault information is hidden in the frequency content, wavelet transform helps to obtain further information from the raw signal that is not readily available. Since the result data received after DB4 is too huge to be dealt with, the Singular Value Decomposition theory (SVD) that is able to assess the effects of the noise on the singular values and singular vectors is introduced [9]. Detail introduction of the SVD theory can be found in [10].

Suppose Λ_i is the eigenvalue matrix of the ith element, then

$$S_i = \frac{\sum_{i=1}^{\beta} \lambda_i}{\beta}, \quad i = 1, 2, ..., N \tag{6}$$

where λ_i is the singular value in Λ_i and β is the dimension value of Λ_i . To change it into the body of evidence, we can get the WSD as:

$$mS_i = w_i \frac{S_i}{S_{\max}} \alpha_S \tag{7}$$

where w_i is the wave index which reflect the distortion of the waveform, the definition of $S_{\max}$ and α_S is the same as that in WFD.

The Wavelet Energy Degree (WED)

As the energy can represent the intensity of a signal, the WED is extracted from the raw signal. First, the energy distribution of the signal in the αth scale is defined as $E_1, E_2, ..., E_m$, where $E_i = \sum_{k=1}^{l} |D_j(k)|^2$ (j=1,… α). In this way, the WED can be obtained that:

$$mE_i = w_i \frac{W_i}{W_{\max}} \alpha_{\mathrm{E}} \tag{8}$$

where w_i is the wave index which reflect the distortion of the waveform, $W = \sum_{i=1}^{\alpha} E_i \Big/ \alpha$ and the meaning of $W_{\max}$ and α_E is the same as in WFD.

C. The Fuzzy Integral Theory

In the fusion procedure, the fuzzy integral theory is adopted. Fuzzy integral is a nonlinear function based on fuzzy measures [11]. In this paper, the Choquet integral is used for data fusion. The following part gives a brief introduction of the theory [12].

Assume that X is the set of criteria, $X = \{x_1, x_2, ..., x_n\}$, and Y is the power set of X . The definition of $u\,|\,Y \to [0,\infty]$ is a non-negative real-valued set function and is called the fuzzy measure. The λ-fuzzy measure which is represented by g_λ, has the following properties:

(1) $\forall A$ and $\forall B$, $A \subset u$, $B \subset u$, $A \cap B = \varnothing$

(2) $u(A \cup B) = u(A) + u(B) + \lambda u(A)u(B)$

(3) $\lambda > -1$

The measure is defined in a single-point set as $g^i = g(\{x_i\})$, $i = 1, 2, \ldots n$, where g^i is a fuzzy density or weight of the ith membership. The fuzzy densities of other elements are obtained using the following functions:

$$1 + \lambda = \prod_{i=1}^{n} (1 + \lambda g^i)$$

$$g_\lambda(\{x_1, x_2, \ldots, x_n\}) = \sum_{i=1}^{n} g^i + \lambda \sum_{i_1=1}^{n-1} \sum_{i_2=1}^{n} g^{i_1} g^{i_2} + \ldots + \lambda^{n-1} g^1 g^2 \ldots g^n = \frac{1}{\lambda} \left| \prod_{i=1}^{n} (1 + \lambda g^i) - 1 \right|$$

$$g_\lambda(\{x_1, x_2 \ldots x_n\}) = 1$$

where $\lambda > -1$ and $\lambda \neq 0$.

As for the function $f(x)$, the elements in the finite set X are ranged based on the monotonicity in the following order: $f(x_1) \geq f(x_2) \geq \ldots \geq f(x_n)$. In this way, the Choquet fuzzy integral of f with respect to g is obtained:

$$E = \int f \bullet g = \sum_{i=1}^{n} (f(x_i) - f(x_{i+1})) \bullet g(A_i)$$

where $f(x_{n+1}) = 0$, $g(A_i)$ represents the weight of importance of the set of criteria A and E is the fault probability index of the fault element.

D. The Procedure of the Diagnosis System

The following picture is the main structure of the diagnosis system.

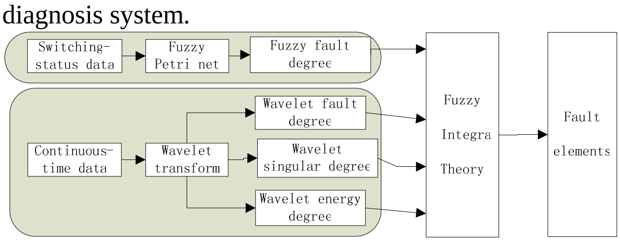

Figure 1 The main structure of the system

CASE STUDY

In this section, the IEEE 14-bus system is used to validate the proposed method. Fig. 2 shows the topology of the IEEE14-bus system. In this case, the protection relays for transmission lines are the main protection, the primary backup protection and the secondary backup protection.

A complicated fault is supposed to occur in the system and the operation order of the fault is presented as follows:

1) Suppose faults occur in line 15 and 16;
2) The main protection relays and the primary backup protection relays on both sides of L16 act;
3) CB29 trips while CB30 refuses to trip;
4) The second backup protection of L16 on side of Bus-14 acts, resulting in the operation of CB31;
5) The main protection relays on both sides of L15 act and CB27 and Cb28 trip;
6) The second backup protection relay of L15 on side of Bus-13 malfunctions and CB17 trips;
7) During the whole procedure, the operation information of the main protection relay of L15, on side of Bus-13 missing.

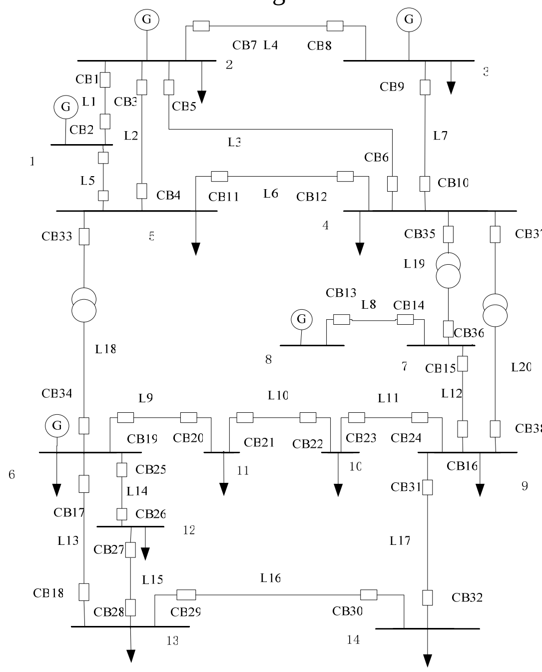

Figure 2 IEEE 14-bus Power System

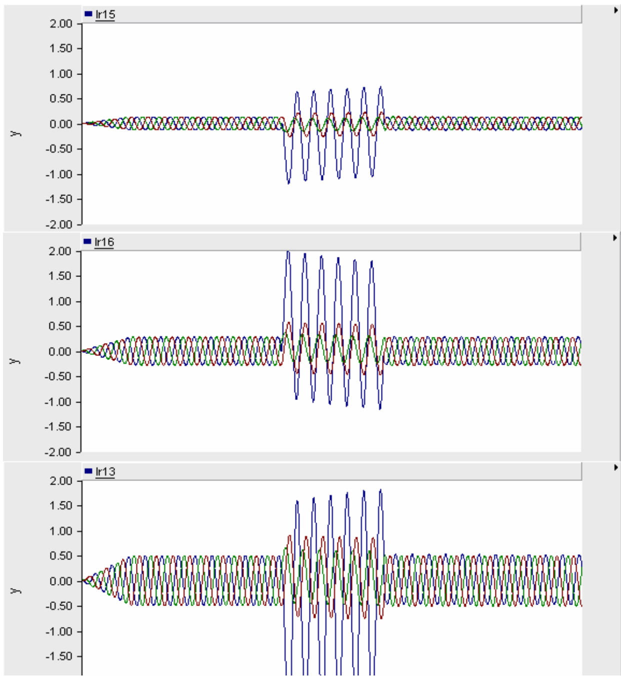

Figure 3 The current waveforms in case 1.

During the diagnosis procedure, the current information is employed as the continuous-time data to extract the fault features. The following figure shows the current waveform of the fault lines: Line 15 and Line 16 and the waveform of Line 13 which is healthy in cases that the phase A of Line 15 and phase A of Line 16 are in fault with the grand.

From Fig 3, it can be seen that although Line 13 is healthy, the current wave of Line 13 fluctuates sharply than that of Line 15 which may cause mistake if only the continuous-time data is adopted for fault diagnosis. In this case, the switching-status data can help to avoid mistakes. The following part discusses the diagnosis procedure.

The fault densities of the four fault degree WFD, WSD, WED and FFD are 0.85, 0.9 0.95 and 0.7 respectively in this paper. WFD and WSD are obtained using the data of the current waveform selected in 0.1s (total 0.2s) before and after the fault, while WED is obtained using the data of the current waveform in 0.1s after the fault.

Table 1 Diagnosis Results

Line	FFD	WFD	WSD	WED	*m*
L1	0	0.0586	0.0122	0.00066	0.0562
L2	0	0.0663	0.04359	0.00474	0.0649
L3	0	0.05246	0.08464	0.0169	0.0795
L4	0	0.0300	0.0049	0.0002	0.0287
L5	0	0.0485	0.0365	0.00312	0.0477
L6	0	0.045	0.0452	0.00478	0.0449
L7	0	0.0602	0.0909	0.0201	0.086
L8	0	0.0495	0.0764	0.0135	0.072
L9	0	0.0525	0.1557	0.0303	0.1400
L10	0	0.0497	0.0446	0.0047	0.04915
L11	0	0.05630	0.03601	0.0062	0.05507
L12	0	0.0737	0.0843	0.01757	0.08228
L13	0	0.1526	0.37	0.37	0.3667
L14	0	0.1526	0.3617	0.3494	0.3569
L15	0.75	0.4247	0.3163	0.1354	0.6504
L16	0.75	0.3384	0.5029	0.3844	0.6704
L17	0	0.37	0.2532	0.1909	0.3636

The calculation results using the method proposed in this paper has been listed in Table1, including the fault features of FFD, WFD, WSD, WED and the final fusion result m. From the table, it can be seen that the L15 and L16 are the fault elements, the fusion results of which are much larger than the healthy elements. In this case, although there is missing operation information, the proposed method can still give the right result which indicates the applicable of the proposed method.

CONCLUSION

This paper presents a novel method for fault diagnosis of power systems. Different from the conventional methods that are based on the switching-status data only, the proposed method uses both the switching-status data and the continuous-time data which conquers the problem of missing information. Testing results show that the proposed method could work well in fault diagnosis of power systems.

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