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LATEST PROGRESS OF FAULT DETECTION AND LOCALIZATION IN COMPLEX ELECTRICAL ENGINEERING

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In the researches of complex electrical engineering, efficient fault detection and localization schemes are essential to quickly detect and locate faults so that appropriate and timely corrective mitigating and maintenance actions can be taken. In this paper, under the current measurement precision of PMU, we will put forward a new type of fault detection and localization technology based on fault factor feature extraction. Lots of simulating experiments indicate that, although there are disturbances of white Gaussian stochastic noise, based on fault factor feature extraction principal, the fault detection and localization results are still accurate and reliable, which also identifies that the fault detection and localization technology has strong anti-interference ability and great redundancy.

K e y w o r d s: fault detection and localization, feature extraction, WAMS, PMU, EMS

1 INTRODUCTION

With the rapid development of power generation industry in China, the scale of power grid has expanded rapidly. Meanwhile, owing to the large scale of the grid-connected renewable power plants such as solar power, wind power and etc, the implementation and realization of the west-to-east power transmission, modern power structure is becoming more and more complex. With the increasing scale and complexity of power system, the probability of system fault is also increasing in a geometric progression. The significant economic losses and social consequences will take place if it can't receive timely and effective treatment when abnormal condition of the devices is happened, so the control and protection system for power system is facing unprecedented challenges [1–3].

In order to guarantee the reliability and safety of a complex power system, efficient fault detection and localization (FDL) schemes are essential to quickly detect and locate faults so that appropriate and timely corrective mitigating and maintenance actions can be taken. FDL methods can be classified into three major categories: model-based, knowledge-based and data-driven approaches [4–6]. Since faults in complex system are hierarchical, correlation, time delay and uncertainty, the process is too complex to be modeled analytically and it is the lack of expert knowledge. The data-driven method is supposed not to require an explicit or complete model of the complex system, so it is preferred when system monitoring data for the nominal and degraded conditions is available. At present, complex power system has established a complete Supervisory Control and Data Acquisition (SCADA) system for primary and auxiliary equipments [7–10], which can provide reliable real-time data for fault detection and localization. On the other hand, as these model-based, knowledge-based and data-driven FDL methods have their pros and cons, it is a trend that these three complementary techniques are usually integrated together to achieve a better performance for complex system [11].

According to complex power systems, we have carried out large numbers of basic researches. In paper [12], in order to meet the requirements of wide area intelligent control, this paper puts forward a new fault location scheme based on Bayesian discriminant analysis theory. And BDA fault detection is proposed to give a partition for the membership of each element (healthy or faulted), in which the node status quantities are adopted as basic data provide by PMU. Paper [13] used mainly pattern classification technology and linear discrimination principle of pattern recognition theory to search for laws of electrical quantity marked changes. In paper [14], PCA theory is introduced into the field of fault detection to locate precisely the fault by mean of the voltage and current phasor data from the PMUs. Massive simulation experiments have fully proven that the fault identification can be performed successfully by PCA and calculation. In this paper, under the current measurement precision of PMU, we will put forward a new type of fault detection and localization technology based on fault factor feature extraction.

The paper is organized as follows. In Section 2, the theoretical basis of fault detection and localization is introduced. In Section 3, considering the current measurement precision of PMUs, according to fault factor feature extraction theory, the fault detection and localization in complex electric power systems is clarified in detail. Finally, the paper is concluded in Section 4.

2 THEORETICAL BASIS OF FAULT DETECTION AND LOCALIZATION

Contemporary science and technology has generated and is generating so vast amounts of data at unprecedented rate and scale, in order to classify these data, fea-

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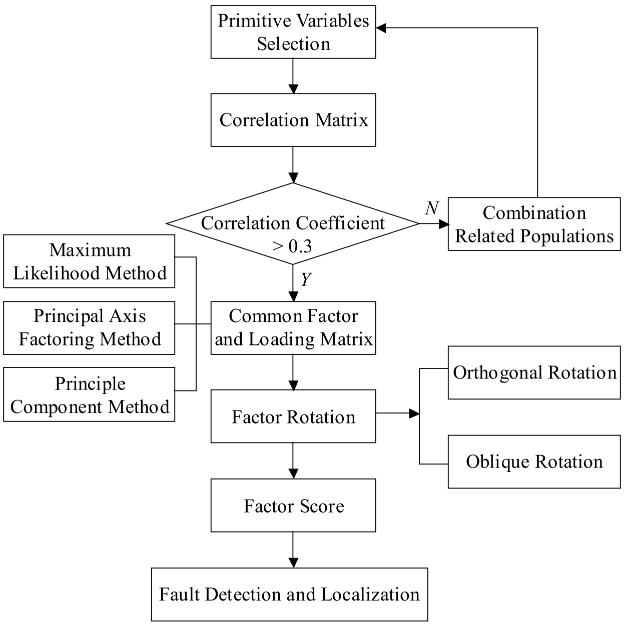

Fig. 1. Fault detection and localization algorithm flow

ture extraction has become ubiquitous. The purpose of feature extraction is to reduce the number of features of patterns and at the same time retain as much as possible of their discriminatory information [15, 16]. For this reason, a good feature extractor chooses features which are similar for patterns in the same class and very different for patterns in different classes. Now let's introduce the general process of fault detection and localization based on fault factor feature extraction [17, 18].

For factor model

$$X_i = a_{i1}F_1 + a_{i2}F_2 + \cdots + a_{im}F_m + \varepsilon_i \quad (i = 1, 2, \dots, p)\,, \tag{1}$$

we can obtain, the covariance of X_i and F_j is

$$\operatorname{cov}(X_i, F_j) = \operatorname{cov}\Big[\sum_{k=1}^{m} a_{ik}F_k + \varepsilon_i, F_j\Big] = \operatorname{cov}\Big[\sum_{k=1}^{m} a_{ik}F_k, F_j\Big] + \operatorname{cov}(\varepsilon_i, F_j) = a_{ij}\,. \tag{2}$$

Suppose the factor loading matrix is A, the sum of squares of the i-th row's elements is

$$h_i^2 = \sum_{j=1}^{m} a_{ij}^2 \quad (i = 1, 2, \dots, p)\,, \tag{3}$$

which is just the communality of variable X_i.

From the factor model, we can know,

$$\begin{aligned} D(X_i) &= a_{i1}^2 D(F_1) + a_{i2}^2 D(F_2) + \cdots + a_{im}^2 D(F_m) + D(\varepsilon_i) \\ &= a_{i1}^2 + a_{i2}^2 + \cdots + a_{im}^2 + D(\varepsilon_i) = h_i^2 + \sigma_i^2\,. \end{aligned} \tag{4}$$

The sum of squares of the j-th column's elements is

$$g_j^2 = \sum_{i=1}^{p} a_{ij}^2 \quad (j = 1, 2, \dots, m)\,. \tag{5}$$

As we know, the solution of A is not unique, here the solution will make the contribution $g_1^2 = \sum_{i=1}^{p} a_{i1}^2$ of the first common factor F_1 to X reach the maximum, the contribution $g_2^2 = \sum_{i=1}^{p} a_{i2}^2$ of the second common factor F_2 to X take second place, ..., and the contribution of the m-th common factor F_m to X is the minimum.

The corresponding contributions are in sequence of:

$$g_1^2 \ge g_2^2 \ge \cdots \ge g_m^2\,. \tag{6}$$

So, one can get

$$\sum_{j=1}^{p} \lambda_{ij} a_{jt} - \delta_{1t} a_{i1} = 0\,, \quad (i = 1, 2, \dots, p; \quad t = 1, 2, \dots, m) \tag{7}$$

$$\delta_{1t} = \begin{cases} 1\,, & t = 1\,, \\ 0\,, & t \ne 1\,. \end{cases} \tag{8}$$

Left multiplication a_{i1} and sum i, then

$$\sum_{j=1}^{p}\Big[\sum_{i=1}^{p} \lambda_{ij} a_{i1}\Big] a_{jt} - \delta_{1t} \sum_{i=1}^{p} a_{i1}^2 = 0\,, \quad (t = 1, 2, \dots, m)\,. \tag{9}$$

Here we should take notice of

$$g_1^2 = \sum_{i=1}^{p} a_{i1}^2, \quad \sum_{i=1}^{p} \lambda_{ij} a_{i1} = \sum_{i=1}^{p} \lambda_{ji} a_{i1} = a_{ji}\,. \tag{10}$$

$$\sum_{j=1}^{p} a_{j1} a_{jt} - \delta_{1t} g_1^2 = 0 \quad (t = 1, 2, \dots, m)\,. \tag{11}$$

Similarly, left multiplication a_{it} with the former formula and sum t, then

$$\sum_{j=1}^{p} a_{j1}\Big[\sum_{t=1}^{m} a_{jt} a_{it}\Big] - \sum_{t=1}^{m} \delta_{1t} a_{it} g_1^2 = 0 \quad (i = 1, 2, \dots, p)\,. \tag{12}$$

Then, for $r_{ij}^* = \sum_{t=1}^{m} a_{it} a_{jt}$,

$$\sum_{j=1}^{p} r_{ij}^* a_{j1} = a_{i1} g_1^2, \quad (i = 1, 2, \dots, p)\,. \tag{13}$$

Or expressed as vectors,

$$\left(r_{i1}^*, r_{i2}^*, \dots, r_{ip}^*\right) \begin{pmatrix} a_{11} \\ \vdots \\ a_{p1} \end{pmatrix} = a_{i1} g_1^2 \quad (i = 1, 2, \dots, p)\,. \tag{14}$$

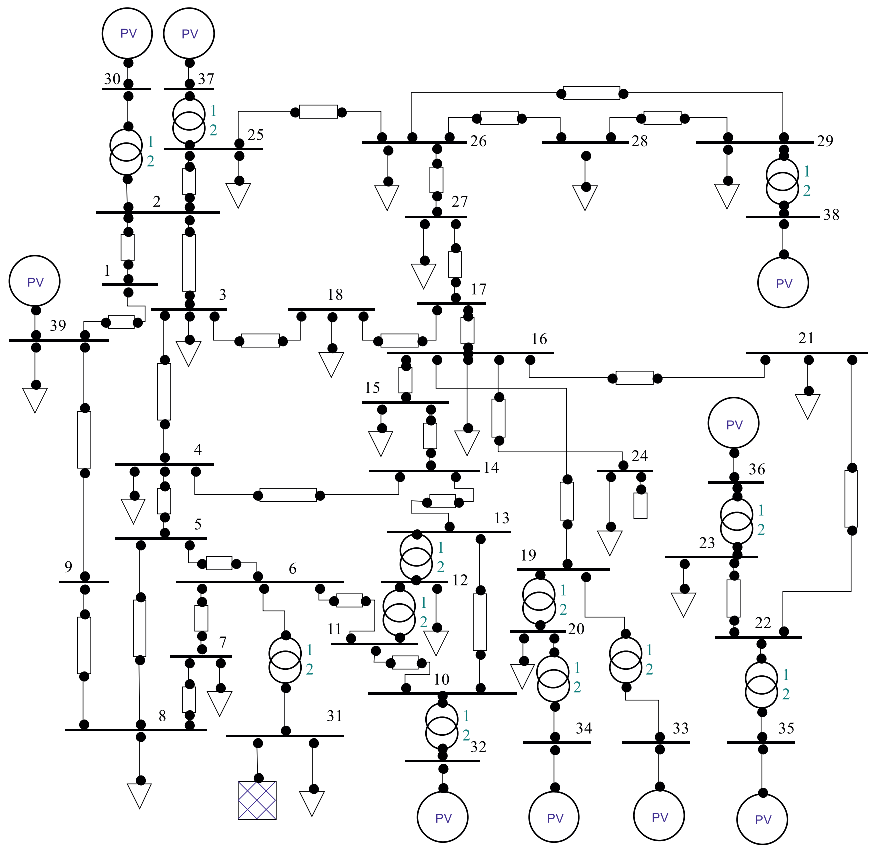

Fig. 2. Electric diagram of IEEE 39-node system

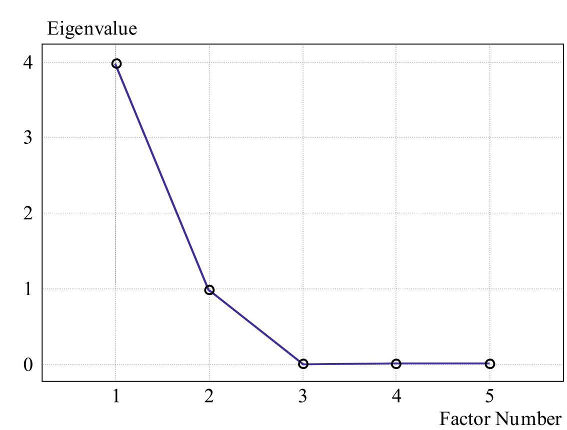

Fig. 3. Screen plot of all eigenvalues

$$(R^* - Ig_1^2)A_1 = 0\,. \tag{15}$$

Therefore g_1^2 is the biggest eigenvalue of approximate correlation matrix R^*, and A_1 is the eigenvector that corresponds to g_1^2.

Obviously, A_1 is still an eigenvector that corresponds to λ_1^*, and satisfies $A_1' A_1 = \lambda_1^* t_1^{*\prime} t_1^* = \lambda_1^* = g_1^2$.

In order to obtain the rest of $m-1$ columns in the factor loading matrix A, we should introduce the decomposition formula of spectrum of R^*,

$$R^* = \sum_{i=1}^{p} \lambda_i^* t_i^* t_i^{*\prime} = A_1 A_1' + \sum_{i=2}^{p} \lambda_i^* t_i^* t_i^{*\prime}\,. \tag{16}$$

Particularly, R^* can also be decomposed into

$$R^* = AA' = (A_1, \ldots, A_m) \begin{pmatrix} A_1' \\ \vdots \\ A_m' \end{pmatrix} = \sum_{t=1}^{m} A_t A_t'. \tag{17}$$

That is to say, after A_1 is obtained, subtract $A_1 A_1'$ from R^*, one can get

$$R^* - A_1 A_1' = \sum_{t=2}^{m} A_t A_t'\,. \tag{18}$$

In this way, one has solved the factor loading matrix A from R^*. Combining the researches in this paper, we have put forward the following fault detection and localization algorithm flow, see Fig. 1.

3 FAULT DETECTION AND LOCALIZATION IN COMPLEX POWER SYSTEM BASED ON FAULT FACTOR FEATURE EXTRACTION

In order to illustrate the specific procedure of fault detection and localization, let us take IEEE 39-node system as example. The electric diagram of IEEE 39-node system has been present in Fig. 2. In the power network structure, Node-18 appears single-phase short circuit fault. By BPA simulations, utilizing the actual measurement information of corresponding node negative sequence voltages, we will carry out fault detection and localization of fault component and non-fault component.

Table 1. The white Gaussian stochastic noise $N(0, 0.005^2)$

No.	1	2	3	4	5
1	0.0065	0.0078	−0.0080	−0.0029	0.0071
2	0.0012	0.0130	−0.0057	−0.0116	0.0047
3	−0.0013	0.0019	0.0023	0.0009	−0.0062
4	0.0009	0.0081	0.0012	−0.0017	0.0012
5	0.0019	−0.0022	0.0039	−0.0053	0.0059
6	0.0062	−0.0075	−0.0087	0.0011	−0.0077
7	−0.0008	−0.0050	−0.0017	−0.0044	0.0017
8	0.0007	0.0045	−0.0072	0.0023	−0.0004
9	−0.0006	−0.0131	−0.0068	0.0072	0.0021
10	−0.0005	0.0001	−0.0059	−0.0019	−0.0070
11	−0.0059	−0.0027	−0.0004	−0.0041	−0.0088
12	−0.0015	0.0042	0.0065	0.0062	−0.0036
13	0.0032	0.0048	−0.0031	0.0033	−0.0057
14	−0.0010	−0.0031	−0.0018	0.0007	−0.0014
15	0.0023	−0.0046	−0.0035	0.0027	0.0002
16	0.0040	−0.0072	0.0013	0.0038	−0.0028
17	0.0063	0.0029	0.0060	−0.0008	0.0060
18	−0.0037	0.0051	−0.0067	0.0005	−0.0001
19	0.0028	−0.0056	0.0003	0.0016	−0.0106
20	0.0056	−0.0078	−0.0031	0.0050	0.0059
21	0.0102	−0.0066	−0.0051	−0.0013	−0.0099
22	0.0027	0.0030	0.0009	0.0042	−0.0007
23	−0.0050	−0.0074	−0.0028	0.0077	−0.0041
24	0.0032	0.0030	−0.0082	0.0057	0.0061
25	−0.0071	0.0021	−0.0013	−0.0025	−0.0030
26	0.0017	0.0066	0.0011	0.0048	0.0079
27	−0.0044	0.0072	−0.0009	0.0009	−0.0032
28	0.0033	−0.0010	0.0011	−0.0020	−0.0033
29	0.0035	0.0056	0.0036	0.0059	0.0000
30	0.0083	0.0009	−0.0013	0.0097	−0.0024
31	0.0039	−0.0052	0.0022	−0.0005	0.0022
32	0.0000	0.0008	−0.0031	−0.0007	0.0047
33	−0.0056	−0.0008	0.0057	0.0115	0.0009
34	−0.0048	−0.0100	0.0053	0.0052	0.0019
35	0.0045	−0.0012	−0.0024	0.0009	−0.0058
36	−0.0022	−0.0014	−0.0028	0.0035	0.0014
37	−0.0054	−0.0105	0.0025	0.0077	−0.0034
38	0.0002	0.0067	−0.0165	0.0045	0.0001
39	0.0018	−0.0022	0.0032	0.0075	−0.0092

Table 2. The factor score based on fault factor feature extraction

Node	Factor 1	Factor 2	Factor 3	Factor 4
Node-1	−0.44395	−0.49280	0.87553	0.24133
Node-2	0.57297	−0.04003	−1.22361	−1.19348
Node-3	1.40257	1.11664	0.38385	0.37991
Node-4	0.06630	−0.21294	−0.09277	−1.03919
Node-5	−0.46603	0.38499	−0.00612	0.50921
Node-6	−0.26291	−0.54509	1.28537	0.42549
Node-7	−0.60332	−0.18063	−0.38719	−0.44588
Node-8	−0.33602	−1.62879	0.31398	0.35989
Node-9	−0.65318	−1.35568	−0.38614	−1.13082
Node-10	−0.39315	0.10149	0.86692	1.20142
Node-11	−0.70409	1.62940	0.18193	0.11525
Node-12	−0.26625	−0.61454	−0.17091	0.42017
Node-13	−0.34271	0.38639	0.24177	−0.02006
Node-14	−0.06004	−0.21223	0.16999	−0.08811
Node-15	0.46920	−0.61847	−0.22849	−0.16308
Node-16	0.68312	0.42142	−0.42142	−0.79325
Node-17	2.26504	0.53895	0.56081	0.76377
Node-18	4.27460	−0.36171	−0.14535	0.21392
Node-19	−0.56137	1.81217	0.77326	−0.32941
Node-20	−0.74520	0.34073	0.00268	−0.50687
Node-21	0.12791	0.86519	1.05526	0.21332
Node-22	−0.22920	−0.02865	−0.57716	−0.23579
Node-23	−0.17407	0.30401	−0.74267	−0.58871
Node-24	0.78669	−0.14123	0.12440	0.98113
Node-25	0.09824	0.44440	−0.09947	0.12809
Node-26	0.55588	1.50461	−0.13367	−0.54253
Node-27	1.27936	0.62832	0.00489	−0.80362
Node-28	−0.02434	0.48766	0.03051	0.26376
Node-29	0.05982	−0.67112	−0.75002	−0.34172
Node-30	−0.59569	0.50746	−1.33860	0.25895
Node-31	−0.83349	−0.40088	0.42127	−0.32255
Node-32	−0.86409	0.02037	0.70302	0.60860
Node-33	−0.54070	−0.66954	−1.40588	0.77547
Node-34	−0.62377	−1.00744	−0.20210	−0.75602
Node-35	−0.69769	0.48405	0.66287	0.53551
Node-36	−0.73154	−0.41790	−0.14615	0.32858
Node-37	−0.37451	0.07010	−0.79960	−1.18108
Node-38	0.29366	−3.48841	0.62058	1.22821
Node-39	−1.40804	1.03975	−0.02157	0.53016

Table 3. The factor score based on fault factor feature extraction

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.974	79.483	79.483	3.965	79.306	79.306	3.835	76.694	76.694
2	0.988	19.758	99.241	0.090	1.792	81.098	0.220	4.404	81.097
3	0.016	0.320	99.561	0.008	0.158	81.256	0.005	0.104	81.201
4	0.012	0.236	99.797	0.002	0.047	81.303	0.005	0.102	81.303
5	0.010	0.203	100.000						

According to the current measurement precision of PMU, suppose the standard deviation of voltage vector is 0.005, and the mean error is 0 [19]. Let us introduce a white Gaussian stochastic noise $N(0, 0.005^2)$, the influence on IEEE 39-node system is present in Table 1.

By the principal of fault factor feature extraction, the correlation matrix and the communalities of variables have been calculated. Based on this, one has obtained initial eigenvalues, see Table 3. In this place, the feature extraction method is principal axis factoring. In the total variance explained, the eigenvalue of the first factor is 3.974, the proportion of variance is 79.483 %, of course, the cumulative proportion of variance is also 79.483 % (close to 80 %). The eigenvalue of the second factor is 0.988, the proportion of variance is 19.758 %, and the corresponding cumulative proportion of variance is 99.241 % (close to 100 %). The eigenvalue of the third factor is 0.016, the proportion of variance is 0.320 % (it is very small), and the corresponding cumulative proportion of variance is 99.561 %, and so on. Figure 3 is the screen plot of these eigenvalues.

Likewise, using principal axis factoring feature extraction method, one can further solve factor matrix, rotated factor matrix and factor score coefficient matrix. Finally, the factor score results based on fault factor feature extraction are obtained, see Table 2.

According to the ultimate factor score results, the fault feature is obvious. In the anterior studies, the first factor corresponding to the cumulative proportion of variance is 79.483 %, the eigenvalue is 3.974. So, the first factor is our focus. At the same time, let us pay attention to the factor score of factor 1 in Table 2, there are 39 nodes altogether, and the score of Node-18 is 4.27460, which is the biggest one. As we have known, the Node-18 is just the actual fault component.

In these simulations, although there are disturbances of white Gaussian stochastic noise, based on fault factor feature extraction principal, the fault detection and localization results are still accurate and reliable, which also indicates that the fault detection and localization based on fault factor feature extraction principal has strong anti-interference ability and great redundancy.

5 CONCLUSIONS

Feature extraction for classification achieves this dimensionality reduction by maximizing a suitably chosen objective function, thus preserving or enhancing the class separability in the feature domain. Efficient feature extraction and classification techniques are essential for analysis of multivariate statistical data [15, 18].

The new type of smart grid can utilize different kinds of information in a larger scale. In the researches of complex electrical engineering, efficient fault detection and localization schemes are essential to quickly detect and locate faults so that appropriate and timely corrective mitigating and maintenance actions can be taken. In this paper, under the current measurement precision of PMU, we have put forward a new type of fault detection and localization technology based on fault factor feature extraction. The results of massive simulations have confirmed, although there are disturbances of white Gaussian stochastic noise, based on fault factor feature extraction principal, the fault detection and localization results are still accurate and reliable. The researches have also identified the strong anti-interference ability and great redundancy of the fault detection and localization technology presented in this paper.

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