An Overview of Power System Disturbance Detection Method

Pooja Khurdal [1], V. R Aranke [2]

[1]PG student, Department of Electrical Engineering, Matoshri College of Engineering and Research Centre, Nashik
[2]Assistant Professor, Department of Electrical Engineering, Matoshri College of Engineering and Research Centre, Nashik

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Abstract - *The power system is continuously exposed to various disturbances that range from small with little impact on operation to large with severe consequences, including blackout. Generators in the Power system are interconnected in a distributed network so as to allow sharing of power so that if any one of the generators cannot meet the power demand, spare power is diverted from neighbouring generators. However, this approach also allows for propagation of electric disturbances. An oscillation arising from a disturbance at a given generator site will affect the normal operation of neighbouring generators, also may cause them to fail. Unexpected events, such as sudden changes in power generations or loads, a breaker failure, a tree fall, or a lightning stroke, can make the system inoperative.*

Monitoring of power system events provides a great deal of understanding into the behaviour of the system. To gain knowledge about the disturbances and their impact, it is essential to monitor & to properly analyse the system. The analysis of disturbances is a complex process that includes the study of disturbances sources, propagation and magnitude of the disturbance. Methods for detection of disturbances have been mainly addressed in two ways- Quantitative trend analysis & Numerical data driven methods. These conventional approaches are not appropriate & may provide false information.

Key Words: Fault detection; fault induced transients; disturbances; principle component analysis; nearest neighbours; singular value decomposition; multivariate.

1. INTRODUCTION

Power system operation and control are becoming more and more tangled because of the high penetration of renewable generation and increasing electricity consumption. Also, a variety of power system disturbances pose an increasingly severe threat to system security. In this challenging context, detecting these disturbances effectively plays an essential role in improving the system security and stability. To gain knowledge about the disturbances and their impact, it is necessary to monitor the system at sufficiently many geographical locations using measurement equipment of sufficient bandwidth. The collected data must also be condensed into helpful information and analyzed properly [1, 2, 6].

The electrical utility and associated electromechanical equipment such as electric motors are increasingly important sources of disturbances to the process industry. Electromechanical equipment has its own fault modes and is susceptible to power quality disturbances, that is, deviations of the voltage or current in the power supply from their ideal behaviour (4).

Outages, of a single transmission line, if not detected and treated quickly, may cascade into the breakdown of multiple lines in a few minutes, and eventually lead to a costly grid- wide outage in less than an hour [7]. Detection of power system disturbances is a difficult task because of system complexity, diversity of operating conditions and interference from noise. It places high demands on reliable, sensitive and real-time implementation and is of concern in power system monitoring and control, as indicated by present research [4]-[11]

A variety of techniques such as principle component analysis have been proposed for automatic extraction and characterization of dynamic features from measurements during ambient and transient operation. Parametric and non-parametric mode estimation algorithms have been specifically designed for detecting the impact of system disturbances on the dynamic stability margin of the system [2].

Advanced measuring devices, such as Phasor Measurement Units (PMUs), provide abundant measurements for the development of the data-driven disturbance detection. The existing data-driven approaches can be classified into three main categories according to the applications:

(1) For the protection of power systems, e.g., the hidden Markov model based method [8] and the wavelet coefficient energy based method [9];

(2) For the assessment of power quality (mainly focusing on alternate voltage), e.g., the power quality state estimation based method [7] and the wavelet packet

(3) For the wide-area monitoring of power systems, typically, the principal component analysis based methods [11]

Usually, the first two categories of methods take a univariate approach to deal with electrical variables separately, whereas the third category of methods use multivariate analysis to handle all the electrical variables together.

It has been reported in [14], [15] that the recorded measurements usually have a non-Gaussian distribution due to system nonlinearity and the non-Gaussian information is important for system monitoring. Usually, the non-Gaussian information needs high order (order greater than two) analysis. As indicated in [16], fourth order moment (FOM) contains significant non-Gaussian information is combined with multivariate analysis to meet the requirement of the wide-area monitoring.

2. LITERATURE SURVEY

Power system transient disturbances are increasingly relevant in process industries which rely on electromechanical equipment. Existing data-driven methods for detecting transient disturbances assume a distinct amplitude or time-frequency component. That paper proposes a detection method which is more generic and handles any short-term deviation of a measurement from its overall trend, regardless of whether the trend incorporates features such as oscillations, noise or changes in operation level. [1]

Advantages of as k nearest neighbor (kNN) analysis method [17], are that it can deal with the electrical measurements with oscillatory trends and can be implemented in real time. A multivariate statistical projection method based on Principal Component Analysis (PCA) is proposed for detecting and extracting unusual or anomalous events from wide-area monitoring data. [2]. Principal component analysis (PCA) has long been used in fault detection by extracting relevant information from multivariate chemical data for a chemical process plant. In [11], multi-scale principal component analysis (MSPCA) is used for fault detection and diagnosis. MSPCA simultaneously extracts both, cross correlation across the sensors (PCA approach) and auto-correlation within a sensor (wavelet approach). The proposed MSPCA approach is able to outperform the conventional PCA based approach in detecting and identifying real process faults in an industrial process, and yields minimum false alarms.

In this paper a systematic and comparative study of various diagnostic methods from different perspectives has been presented. Fault diagnosis methods are classified into three general categories these are quantitative model-based methods, qualitative model-based methods, and process history based methods. [3]

The paper presents a method to detect transient disturbances in a multivariate context, and an extension of that method to handle multirate systems. The paper demonstrates superior results with the multivariate method in comparison with the univariate approach, and with the multirate method in comparison to a unirate method, for which the fast-sampled measurements had to be down sampled. [6]

The importance of power quality issues, due to the significant losses for poor power quality, has resulted in research being focused on extending the concept of state estimation techniques into power quality issues. The accuracy of the new transient state estimator is investigated by application to a test system to identify the cause of a voltage dip/sag in the presence of 5% measurement noise (normally distributed) in all the measurements. [7]

The problem of detecting transmission line outages in power grids can be modelled as time series of power network measurements as a hidden Markov process, and formulate the line outage detection problem as an inference problem. Due to the physical nature of the line failure dynamics, the transition probabilities of the hidden Markov Model are sparse. Taking advantage of this fact, an approximate inference algorithm using particle filtering, which takes in the times series of power network measurements and produces a probabilistic estimation of the status of the transmission line status has been developed in [8].

In the previous years, wavelet-based methodologies have been proposed as a good alternative for real-time fault detection. The drawbacks of this method can be overcome by the proposed energy analysis which is not affected by the choice of the mother wavelet, presenting no time delay in real-time fault detection. [9]

In [10], the mechanism of transient voltage instability in a typical receiving-end power system, i.e., Guangzhou power grid, is discussed and a quantitative assessment method to determine the transient voltage stability of actual large-scale power grid has been proposed.

Dynamic trend analysis [12], is used for fault detection and diagnosis which involves hierarchical representation of signal trends, extraction of the trends, and their comparison (estimation of similarity) to infer the state of the process. A novel interval-halving method for trend extraction and a fuzzy-matching-based method for similarity estimation and inferencing are also presented.

Qualitative trend analysis (QTA) [13] is a process-history-based data-driven technique that works by extracting important features (trends) from the measured signals and evaluating the trends has been used.

Direction finding techniques are usually based on the second-order statistics of the received data. In [15], two types of direction finding algorithms which use the fourth-order cumulants of the array data. One is a MUSIC like technique based on eigen decomposition of a suitably defined cumulant matrix and other is an optimal (minimum variance) estimator based on minimization of a certain cost function.

To detect power system disturbances in a multivariate context [18], method is based on Fourth Order Moment (FOM) and multivariate analysis implemented as Singular

Value Decomposition (SVD). The application results on the measurements of an actual power system in Europe illustrate that the proposed multivariate detection method achieves enhanced detection reliability and sensitivity.

3. MULTIVARIATE DETECTION BASED ON FOM AND SVD

Lianfang Cai [19] has explored correlation information in the measurements besides the non-Gaussian information, a multivariate detection method based on FOM and SVD, referred to as MD-FOMSVD. In the following, MD-FOMSVD is presented in detail by four parts.

A. Multivariate Extension Using SVD

SVD is a multivariate statistical analysis technique, which can factorize any data matrix into a product of three other matrices with specific properties as follows:

$$\boldsymbol{C}=\boldsymbol{U}\boldsymbol{S}V^{T}=\sum_{i=1}^{m} u_j\, s_j v_j^{t} \qquad (1)$$

Where, the columns of $\boldsymbol{U}$ are orthonormal basis functions for the columns of $\boldsymbol{C}$, while the rows of V^T are orthonormal basis functions for the rows of $\boldsymbol{C}$, (·)T denotes the transpose operator, and $\boldsymbol{S}$ is a diagonal matrix with diagonal elements as the descending-order singular values (SVs) of $\boldsymbol{C}$. The square of a SV is directly associated with the total variance of $\boldsymbol{C}$ along the direction defined by the corresponding row of V^T. This means that the first few rows of V^T are the directions capturing the largest variance proportion of the rows of $\boldsymbol{C}$.

The objective of applying SVD is to further identify principal features from matrix C, where principal features are those capturing the largest proportion of the variances of C. Thus, MD-FOMSVD starts from c_i generated by following equation:

$$C_i\,(k) = x_i\,(k)\; x_i\,(k-\tau_1)\; x_i\,(k-\tau_2)\; x_i\,(k-\tau_3) \qquad (2)$$

That is, based on the training dataset $\{c_i(k)\}_{k=\tau_3+1}^{N}$ of c_i are calculated using (2) and treated as the elements of the i-th row c_i^T of $\boldsymbol{C}$, and then $\boldsymbol{C}$ is factorized with SVD as the following equation:

$$\mathrm{C}=\begin{bmatrix} c_1^T \\ c_2^T \\ \vdots \\ c_m^T \end{bmatrix}=\begin{bmatrix} c_1(\tau_3+1) & c_1(\tau_3+2) & c_1(\tau_3+3) \\ c_2(\tau_3+1) & c_2(\tau_3+2) & c_2(\tau_3+3) \\ c_m(\tau_3+1) & c_m(\tau_3+2) & c_m(\tau_3+3) \end{bmatrix}=\sum_{j=1}^{m}\begin{bmatrix} u_{1j} \\ u_{2j} \\ \vdots \\ u_{mj} \end{bmatrix} s_j v_j^T \qquad (3)$$

where $m<N-\tau_3$, and $u_{r,j}$ denotes the r-th row and the j-th column element of $\boldsymbol{U}$.

In [6], two important issues are now discussed, regarding the implementation of SVD. Firstly, power system disturbances have a larger impact on principal features that account for most of the variance of the rows of $\boldsymbol{C}$. Those principal features of interest are captured by the first few basis functions of matrix $V_{m'}^T$ where $m'<m$, whereas the remaining basis functions should capture the details of comparatively less significance to the description of disturbances. Accordingly, the determination of m' should be performed to remove the basis functions of matrix V_m^T as well as the related SVs $s_m$and the column vectors U_m.

After this selection step called *Selection Γ* here, the data matrix $\boldsymbol{C}$ is formed by the retained $u_j\; s_j v_j^T$=1,2,⋯,m' as:

$$\hat{C}=\begin{bmatrix} \hat{c}_1^{\,T} \\ \hat{c}_2^{\,T} \\ \vdots \\ \hat{c}_m^{\,T} \end{bmatrix}=\boldsymbol{U}_{:,1:m'}\boldsymbol{S}_{1:m'}\boldsymbol{V}^{\mathrm{T}}_{1:m',:}=\sum_{j=1}^{m'}\begin{bmatrix} u_{1,j} \\ u_{2,j} \\ \vdots \\ u_{m,j} \end{bmatrix} s_j v_j^{\mathrm{T}} \qquad (4)$$

where $U_{:,1:m'}$ denotes the matrix consisting of the first m' columns of $\boldsymbol{U}$, while $V^T{}_{1:m';}$ denotes the matrix consisting of the first m' rows of V^T , & $s_{1:m'}$ denotes the diagonal matrix with diagonal elements as the first m' diagonal elements of $\boldsymbol{S}$.

This selection step is to retain the first m' basis functions $V_{m'}^T$ from all the m basis functions. It is performed on a multivariate level that can be quantitatively reflected by the m diagonal entries of $\boldsymbol{S}$. More specifically, the squares of these m SVs are drawn up in a chart with respect to the SV numbers 1,2,⋯,m, and the number after which the squares of the SVs are small enough to be neglected is chosen as the initial value of m' and is denoted as m'_{ini}. This can be easily understood as only larger SVs account for the main variance of the rows of $\boldsymbol{C}$ and give an obviously large trend in the former part of the chart.

In addition to the intuitive chart, the percentage of $\sum_{j=1}^{m'} s_j^2$ in $\sum_{j=1}^{m} s_j^2$ is calculated as the cumulative percentage variance (η). Usually, $\eta \geq 90\%$ is sufficient to signify that most variance of the original data is well captured.

Secondly, some of the basis functions retained in Selection *Γ* may show little similarity to the behavior of the rows of $\boldsymbol{C}$ because the corresponding elements in $U_{:,1:m'}$ are very small. This can lead to the degraded detection sensitivity. Hence, another selection step is needed to remove from each row $\hat{c}_r^T$ of $\hat{c}$ the term $u_{r,jr}\; s_{jr} v_{jr}^T$, $jr \in$ {1,2,⋯,m'} that is not relevant to the corresponding row c_r^T of $\boldsymbol{C}$, for r from 1 to m. After this selection step called *Selection ΓΓ* here, the data matrix Ĉ is further adjusted to $\boldsymbol{C}$ as (5):

$$\boldsymbol{C} = \begin{bmatrix} \tilde{c}_1(\tau_3+1) & \tilde{c}_1(\tau_3+2) & .... & \tilde{c}_1(N) \\ \tilde{c}_2(\tau_3+1) & \tilde{c}_2(\tau_3+2) & .... & \tilde{c}_2(N) \\ \vdots & \vdots & & \vdots \\ \tilde{c}_m(\tau_3+1) & \tilde{c}_m(\tau_3+2) & .... & \tilde{c}_m(N) \end{bmatrix} =$$

$$U_{:,1:m'}\, S_{1:m'}\, V^T{}_{1:m'}; \tag{5}$$

The selection $\Gamma\Gamma$ is carried out on an individual level for the selection of relevant terms. Specifically, the following index is constructed to evaluate the m' terms $u_{r,1}s_1 v_1^{\mathrm{T}}, u_{r,2}s_2 v_2^{\mathrm{T}}, \cdots, u_{r,m'}s_{m'}v_{m'}^{\mathrm{T}}$:

$$\mu_{r,j_r} = \frac{u_{r,jr}^2}{\sum_{j=1}^{m'} u_{r,j}^2} \times 100\%, j_r \in \{1,2,\cdots,m'\} \tag{6}$$

Hence this step only retains the scores making obvious contribution to the rows of $\boldsymbol{C}$ and removes the ones making little contribution.

B. Monitoring Statistic and Detection Threshold

To detect disturbances in the context of multivariate analysis, a monitoring statistic for the i-th electrical variable x_i can be built by the variable $\tilde{c}i$ as (7):

For a system-wide monitoring statistic providing a global characterization of the group of variables with respect to the disturbances can be built as (8):

$$MD(k) = \frac{1}{m}\sum_{i=1}^{m}|\tilde{c}_i(k)| \tag{8}$$

In order to discover whether a disturbance occurs or not, the detection thresholds of MDi and MD with the confidence level α need to be determined is presented in paper [19].

Specifically, based on the training dataset, the time-series values of $\tilde{c}i$ are calculated using (5). Then, the time-series values $\{MD(k)\}k{=}\tau3{+}1N$ of MDi are calculated using (7), while the time-series values of $\{MD(k)\}_{k=\tau_3+1}^{N}$ MD are calculated using (8). Finally, the δ-th highest value of $\{MD_i(k)\}_{k=\tau_3+1}^{N}$ is taken as the detection threshold MDi, for MDi, and the δ-th highest value of $\{MD(k)\}_{k=\tau_3+1}^{N}$ is taken as the detection threshold $MD\alpha$ for MD.

3. CONCLUSIONS

Methods of fault detection/ disturbance detection such as Model based methods and Process history based methods have been reviewed in the first part of the paper. This also reveals that no single method has all the desirable features. But some of these methods can complement one another which may give better results.

In this paper the use of multivariate disturbance detection technique. Also higher order analysis used for disturbance detection overcomes problems such as to explore non Gaussian information. And with the help of multivariate analysis, the presence of different disturbance can be detected by measurement of different variables.

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