POWER SYSTEM DISTURBANCE DETECTION USING FORUTH ORDER MOMENT AND SINGULAR VALUE DECOMPOSITION

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

---

Abstract - *Various unexpected events in power system, such as sudden changes in power generations or loads, a breaker failure, a tree fall, or a lightning strike, can make the system inoperative. Sometimes an oscillation arising from a disturbance at a given generator site will affect the normal operation of neighbouring generators and might cause them to fail.*

Monitoring of such events in the power system provides a great deal of understanding into the behaviour of the system. To gain knowledge about the disturbances and their impact, it is important to monitor & to properly analyse the system.

A method to detect power system disturbances in a multivariate context, using Fourth Order Moment (FOM) and multivariate analysis implemented as Singular Value Decomposition (SVD). It is based on a combination of high order statistical analysis known as FOM which is used for analysis of non Gaussian information and multivariate analysis known as Singular Value Decomposition (SVD) which helps to look at relationships between variables in an overarching way and to evaluate the relationship between variables.

***Key Words*:** Power system disturbances, multivariate, singular value decomposition, fourth order moment.

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 the power system is continuously exposed to different disturbances which range from little impact on operation to large with severe consequences, including blackout [1]. Also due to growth in power sector, the power system industry has been going through dynamic infrastructural and operational changes in recent years that have caused more prominent lightly damped electromechanical oscillations. These oscillations were initially caused by the introduction of high gain automatic voltage regulators and power electronic converters which caused a reduction in the system's mechanical inertia. The electromechanical equipment is increasingly important sources of disturbances to the process industry. Examples of electromechanical equipment in industries are the electric motors used to drive pumps and compressors [2,3,4].

The extension of process disturbance analysis to electromechanical measurements makes it essential to detect transient disturbances. The reason is that disturbances related to the electrical utility are mostly of a transient nature, caused by power imbalances in the grid which lead to momentary frequency and voltage instabilities [5].

Transmission lines and distribution lines are important parts form a vital part of the power grid, as they provide the means to transfer electric power from power plants to end users. Outage, namely a transmission line being disconnected from the grid, is one of the most common faults. Moreover, the outage 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].

In this context, the key challenges to the protection systems lie in reliably detection, classification, and analysis of the faults as well as isolating only the faulted section as quickly as possible. 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 [8].

A variety of techniques 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 [10, 11]. However, on-line estimation and visualization of modal parameters are very challenging, and may require long records of data and pre-filtering to obtain useful information [12].

Common limitation of the present methods is that the non-Gaussian information in the electrical measurements has not been much explored previously and the recorded measurements usually have a non-Gaussian distribution due to system nonlinearity and the non-Gaussian information is important for system monitoring.[12,13] Usually, the non-Gaussian information needs high order (order greater than two) analysis. As indicated in [14], fourth order moment (FOM) contains significant non-Gaussian information.

Multivariate detection method based on a combination of high order statistical analysis known as FOM and multivariate analysis known as Singular Value Decomposition (SVD). The non-Gaussianity of each electrical variable is quantified through the robust estimation of negentropy (NE) which is widely used for evaluating the extent of non-Gaussianity [15]. Then, the non-Gaussian information in the measurements of each variable is explored by FOM to provide fourth order statistics, and the obtained fourth order statistics are dealt with using SVD. Through this multivariate analysis, the presence of the same disturbance in the measurements of different variables can be jointly explored to allow a more satisfactory detection.

2. METHODOLOGY FOR FAULT DETECTION

As stated in [1] the procedure for MD-FOMSVD is now summarized below, which consists of the off-line modelling based on the training dataset and the on-line detection.

A) The off-line modelling

1. The historically recorded measurements of x_i are taken to form the training dataset.

2. The non-Gaussianity of x_i is quantified by implementing robust estimation as given below:

$$NEi = H(v) - Hi(x_i^*) \qquad (1)$$

Where, $HG(v)$ = $-\int_{-\infty}^{\infty} p_G^{(v)} \log p_G^{(v)}$ $\log pG(v)dv$ denotes the entropy of the Gaussian variable v with zero mean and unit variance, $Hi(x_i^*)$=$-\int_{-\infty}^{\infty} p_i(x_i^*) \log p_i(x_i^*) \, d x_i^*$ denotes the entropy of x_i^*, while $x_i^* = \frac{x_i - E(x_i)}{Std(x_i)}$ is the normalized version of x_i with $E(\cdot)$ and $std(\cdot)$ respectively denoting the expectation operator and the standard deviation operator, $p_i(x_i^*)$ & $p_G^{(v)}$ denote the probability density functions of x_i^* and v.

3. The time-series values c_i are calculated using (2).

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

4. The data matrix $\boldsymbol{C}$ is built and SVD is performed on $\boldsymbol{C}$ to obtain the matrices $\boldsymbol{U}$, $\boldsymbol{S}$ and V^T according to (3).

5. The *Selection Γ* is used to obtain the matrices $\boldsymbol{U}$:,1:m', $\boldsymbol{S}$1:m' and $\boldsymbol{V}$1:m',:T, and the matrix $\boldsymbol{C}$ is calculated using (4).

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

6. The *Selection ΓΓ* is used to obtain the matrix $\boldsymbol{U}$:,1:m', and the time-series values $\{\tilde{c}_i(k)\}_{k=\tau_3+1}^{N}$ are calculated using (5).

7. The time-series values $\{MD_i(k)\}_{k=\tau_3+1}^{N}$ are calculated using (6), while the time-series values $\{MD(k)\}_{k=\tau_3+1}^{N}$ are calculated using (7), and the detection thresholds MDi,α and $MD\alpha$ are determined

$$MD_i(k) = |\tilde{c}_i(k)|,\ i = 1,2,\cdots,m \qquad (6)$$

$$MD(k) = \frac{1}{m}\sum_{i=1}^{m} |\tilde{c}_i(k)| \qquad (7)$$

B) The on-line detection

1. The present measurement $x_i(p)$ of x_i is taken to calculate the present value c_i (k) of c_i using (2).

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

2. The present value $c_i(p)$ of c_i obtained in previous step is used in (14) to calculate the present value $\tilde{c}(p)$ of $\tilde{c}i$.

3. The present value $\tilde{c}(p)$ of $\tilde{c}i$obtained in step 2, is used in (6) and (7) to calculate the present value $MDi(p)$ of MDi and the present value $MD(p)$ of MD, respectively.

4. If MDi, is exceeded consecutively for a number of sampling time points, an alarm is given for x_i. If $MD\alpha$ is exceeded consecutively for a number of sampling time points, disturbance is detected.

3. SIMULATION & RESULTS

For analysis of disturbance, a system consisting of Generation, transmission & distribution unit has been considered. The system consists of a generator of rating 10 MVA, 15kW as shown in fig (1). This output of the generator has been given to two parallel system – i.e. step up from 15kW to 132 kW and another as 15kW to 6.6 kW. In this simulation, fault is injected in generator and disturbances in the system are observed by measuring parameters (current, voltage, active power, reactive power, apparent power) of two substations as shown in simulink model.

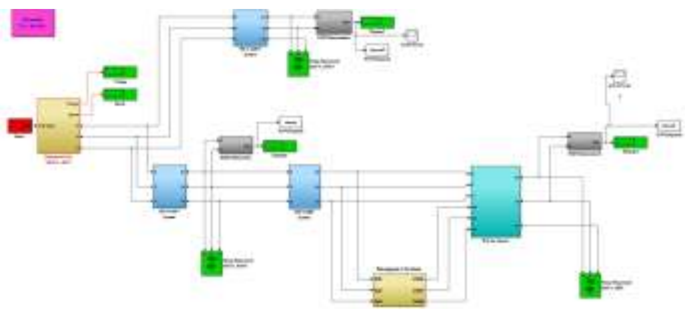

Fig -1: Simulink model

The obtained waveforms of the Singular value decomposition matrix & are given in figures below. Fig (2) shows the waveforms of the Fourth order movement & power spectral density at the time of occurrence of disturbance. The data obtained after fourth order moment is the dealt with SVD. As cited in [1], the obtained data matrix is split into Matrix **U, S & V** which are shown in fig (3).

The combined form of Fourth order moment & Singular value decomposition is then used for disturbance analysis. At the time of occurrence of disturbance, there is deviation in system parameters of adjacent/ parallel system too. Hence the parameters of two substations are taken for analysis. After dealing with FOM and SVD, the disturbance can be detected by visualizing different system parameters. Fig (4) shows parameters variations at the time of occurrence of disturbance.

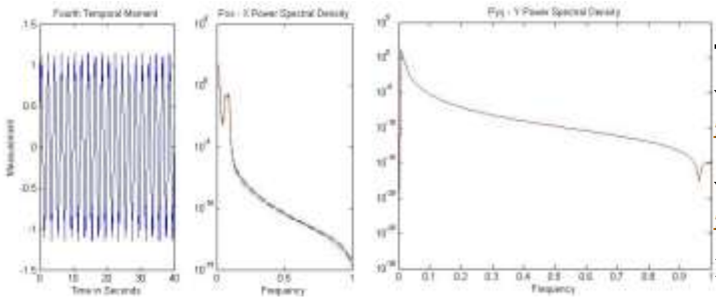

Fig -2: First graph shows fourth order Moment (x axis: time, y axis: Measurements), Second & Third graph shows Power spectral densities

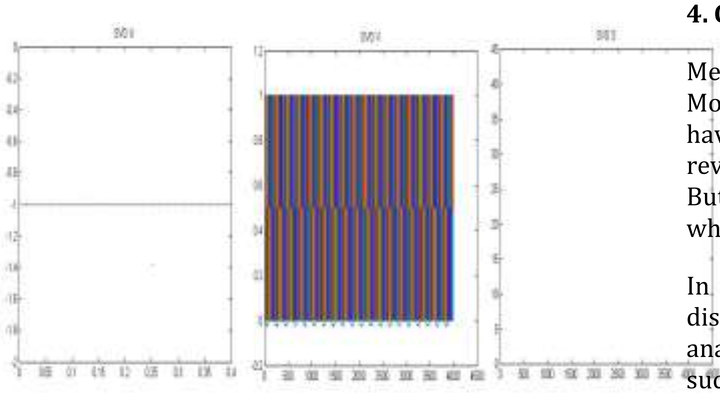

Fig -3: Singular value decomposition matrix

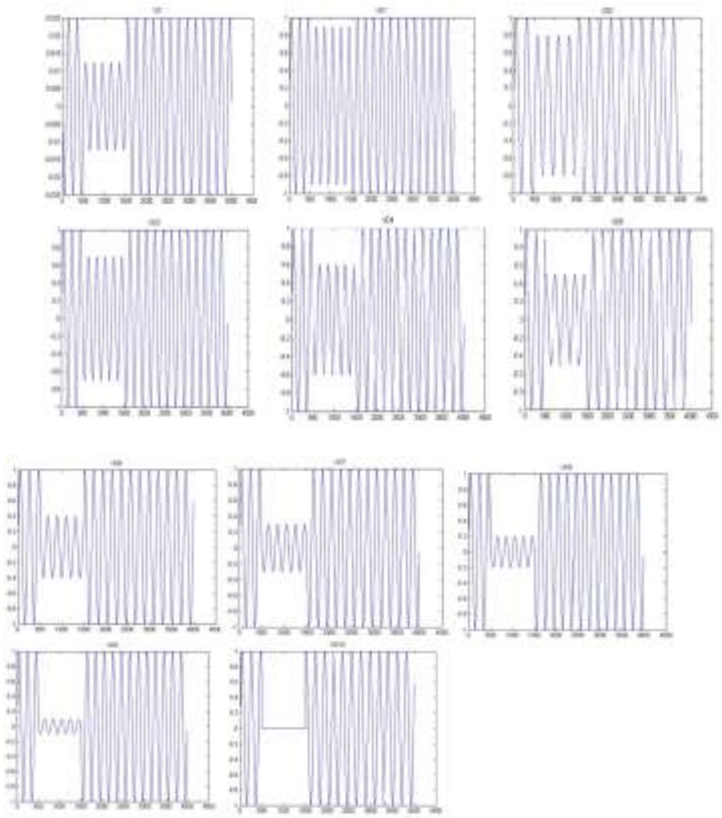

Fig -4 : Simulink model Waveforms of different variables obtained after FOM SVD

The parameters from substation 1 (15/132kV) taken are x_1- Voltage, x_2- current, x_3- Active power, x_4- Apparent power, x_5- Reactive power, and from substation 2 (15/6.6kV) x_6- Voltage, x_7- current, x_8- Active power, x_9- Apparent power, x_{10}- Reactive power. These parameters are explored by FOM, further dealt with SVD and are represented in fig (4), where x_1- x_{10} are represented by UD_1- UD_{10}. Hence by using this method, the same disturbance can be detected by analysis of various parameters.

4. 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 technique for disturbance detection has been discussed. The higher order analysis used for disturbance detection overcomes problems such as to explore non Gaussian information, further with the help of multivariate analysis, the presence of different disturbance can be detected by measurement of different variables. This is analyzed with the help of simulation model.

REFERENCES

[1] O. Samuelsson, et. al. “Monitoring of Power System Events at Transmission and Distribution Level”, IEEE transaction on power systems, Vol. 21, No.2, May 2006

[2] Inês M. Cecílio et al, “Nearest neighbors method for detecting transient disturbances inprocess and electromechanical systems”, in Elsevier Journal of process control, (2014).

[3] Inês M. Cecílio et al, “Multivariate Detection of Transient Disturbances for Uni- and Multirate Systems”, in IEEE Transactions on control systems technology vol. 23, NO. 4 (2015).

[4] M.H.J. Bollen, Understanding Power Quality Problems: Voltage Sags and Inter-ruptions, Wiley-IEEE Press, 2000.

[5] H. Bevrani, Robust Power System Frequency Control, Springer, New York, 2009.

[6] Qingqing Huang, et.al., “Dynamic Detection of Transmission Line Outages Using Hidden Markov Models”, IEEE transaction on power systems, 2015

[7] Ian Dobson, et. al. “Complex systems analysis of series of blackouts: Cascading failure, critical points, and self-organization", in American Institute of physics, 2007

[8] Flavio B. Costa “Fault-Induced Transient Detection Based on Real-Time Analysis of the Wavelet Coefficient Energy”, IEEE Transactions on power delivery, Vol. 29, No. 1 (2015)

[9] A. Farzanehrafat, et. al., “Power Quality State Estimator for Smart Distribution Grids” , IEEE transaction on power systems, 2013

[10] E. Barocio et al, “Detection and Visualization of Power System Disturbances using Principal Component Analysis”, IEEE TRANSACTIONS, 2015.

[11] Xiangshun Li, et al, “Statistical Process Monitoring with Biogeography-Based Optimization Independent Component Analysis”, in Hindawi, Mathematical Problems in Engineering, Volume 2018, (2018)

[12] Boaz Porat, et al, “Direction Finding Algorithms Based on High-Order Statistics”, IEEE Transactions on signal processing, Vol. 39, No. 9 (1991)

[13] Alkan ALKAYA, “Novel data driven-based fault detection for electromechanical and process control systems” (2012)

[14] Mano Ram Maurya, et. al., “A framework for on-line trend extraction and fault diagnosis”, in Elsevier, Engineering applications of artificial intelligence, January 2010