Fault Detection And Identification Using Levenberg Machine Learning Algorithm

Dr. T. Anil Kumar, T. Dinesh

Abstract: In power system there is a vital importance for transmission lines for transport of bulk power. This paper presents an popularly Levenberg Machine Learning (LML) algorithm proposed to detect and identify faults. The performance of Levenberg Algorithm in detection and identification of various types of faults compared to principal component analysis. The effectiveness of proposed algorithm tested on simulated two area power system using Matlab Simulink.

Index Terms: PCA, Fault analysis, Fault Detection, Fault Identification, Error Statistic, Load Analysis, Levenberg Algorithm

1. INTRODUCTION

Fault Diagnosis is regarded in dispatch centre for system level fault diagnosis. The action data of different kinds and concentration of protective devices and circuit breakers, voltages and present measurement of electrical amounts shall be analyzed. Based on the security action experiences logic and operation, fault diagnosis infers possible sort of fault and place of fault, and gives the appropriate criteria for decision making of the dispatcher. When the grid fails, precise, fast, automatic fault diagnosis is of excellent importance for fast power grid recovery. A new fault detection and classification computational methodology using functional analysis presented [1]. A detailed review of fault detecting methods for HVDC transmission system presented [2]. A wavelet transform analysis and ANN methods implemented for fault detection, classification and analysis of power transmission system [3].An accurate fault location algorithmic rule for transmission lines remunerated by series FACTs device presented by identifying two fault stages either sides of series compensating devices and finally on fault point selected by the algorithm [4].A low cost fault detecting methodology based on measurement of magnetic field around the conductor using sensor technology presented [5]. A Wavelet Transform and Linear Discriminant Analysis (LDA) presented for fault detection and identification and proposed scheme is not affected by saturation of CT [6].A neural network based back propagation presented for detection and location of the fault, Discrete Wavelet Transform[DWT],Fast Fourier Transform[FFT] used for extraction of fault signal [7]. A new methodology for fault detection and analysis based on Power Spectral Density (PSD) in time, frequency domains presented [8]. A Fuzzy based algorithm for fault detection, classification in electrical distribution system and fault signal extracted using Discrete Fourier Transform[DFT] presented [9].An impedance dependency method presented for detection and classification of faults and effectiveness compared to knowledge based methods[10].A smart fault detection methodology and location identification achieved through PMU measurement presented [11].A state of art fault detection, classification with various methodologies proposed by the authors in recent past discussed [12].A hybrid algorithm presented for power system fault detection using SVM for analysis and classification of different faults ,this new algorithm detecting and classifying faults irrespective of number of buses if algorithm trained perfectly [14].The feed forward neural network along with back propagation technique presented [15].A Bad Data Detection and Identification(BDI) methodology for Wide Area Fault location presented [16].A Second Generation Wavelet(SGW) transform methodology demonstrated for extracting fault signal without any delay of data processing presented [17].Detection and classification of error based on ANFIS has been presented for identification of shunt and series faults in power system [18]. A Multi Resolution Analysis (MRA) presented for fault detection and location identification presented [19]. An One Terminal Post Fault voltage phasors for fault detection and identification presented [20].A new fault detection and identification methodology based on pre fault and post fault events presented [21].

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2 PRINCIPAL COMPONENT ANALYSIS (PCA) FOR FAULT ANALYSIS

The main idea of principal component analysis (PCA) is to reduce the dimensionality of a data set consisting of many variables correlated with each other, either heavily or lightly, while maintaining the variation present in the dataset, up to the maximum extent. The same is done by converting the variables to a new set of variables, known as principal components (or simply, the PCs)

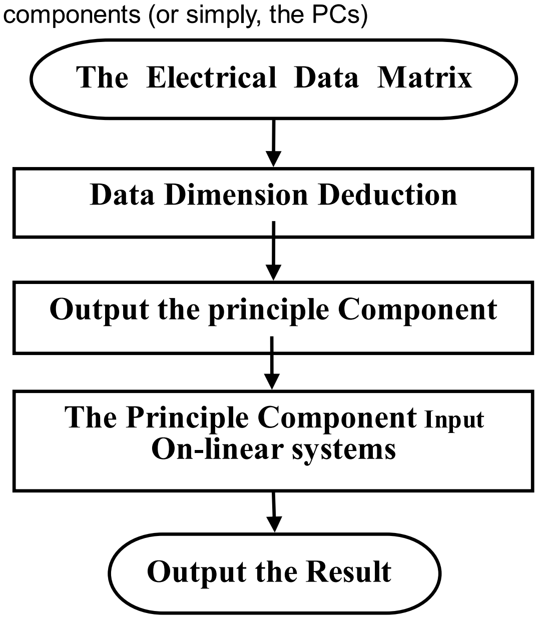

***Fig.1** Flow chart for Principal Component Analysis (PCA)*

Where in equation, μi represents a linear combination of d orthonormal vectors.

$$\bar{x} = \sum_{i-1}^{m} z_i \, \mu_i + \sum_{l-m+1}^{d} b_i \, \mu_i$$

The keynote of procedure mistake discovery as well as medical diagnosis based upon PCA is to accumulate the typical historic procedure variables information, taking advantage of PCA, essence the reduced dimensional principal elements, which can determine the origin of the variables in regular problem, and also develop the PCA version. When online procedure dimensions do not concur with the self-confidence restriction of the well-known PCA version, it can be evaluated that the mistakes have actually taken place while doing so. The mistakes can be discovered as well as identified by examining the damage payment price of the irregularity of the determining variables to PCA version.

2.1 Detection of Faults

In order to actualize the method fault diagnosing, the PCA model that responses the traditional production method, is established initially.In alternative words, the method historical variables information of fault is collected and analyzed, and also the PCA model is established. Thanks to the analysis result of the principal elements beneath the influence of the information scale, the variables information collected must be standardized, the mean of every variable is reduced, and so its variance is split. If m n X R × ∈ is collected for the method variables information in control condition, the standardization should be carried on per the formulae.

$$\bar{X} = [X - (1 \ 1 \ \cdots 1)^T M]\, diag\left(\frac{1}{s_1}, \frac{1}{s_2}, \dots\dots \frac{1}{s_n}\right)$$

Principle Component Analysis is carried out for the data matrix X , in practice, all the principal components need to be computed, so the main variation of the variables data is usually represented by the anterior $k \quad (k < n)$ principal components, the Principle Component Analysis model is obtained as follows. The formula consists of scores matrix and weight matrix T_k, the stochastic residual scores matrix P_k, and its weight matrix T_e. Its mathematics description is shown in formulae.

$$\bar{X} = T_k P_k^T + T_e P_e^T = \sum_{i=1}^{k} t_i P_i^T + \sum_{j=k+1}^{n} t_j P_j^T$$

When made even forecast mistake of the brand-new monitoring information surpasses the self-confidence limitation of the PCA version, the irregular circumstance can be evaluated at the same time, however cannot be ensured that what put the mistake shows up at the same time. The payment graph is an efficient device that is utilized to evaluation the mistake. The payment of each variable to the major elements is chosen with the variant level of the procedure variables as well as their appropriate packing vector.

3 LEVENBERG MARQUARDT ALGORITHM (LMA) FAULT DETECTION AND IDENTIFICATION METHOD

The Levenberg Marquardt algorithm (LMA or just LM), also known as the Damped Lower Squares (DLS) method, is used in mathematics and computing to solve minor square non-linear problems.Especially in the least square curve fitting, the issues occur. The LMA is used to solve generic curve-fitting issues in many software applications.However; the LMA discovers only a local minimum, as with many appropriate algo rithms, which is not necessarily the global minimum. The LMA interplays the Gauss Newton algorithm (GNA) with the gradien t descent technique.The LMA is more robust than the GNA, w hich means it finds a solution in many cases, even though it st arts very far from the final minimum.The LMA tends to be a littl e slower than the GNA for wellbehaved tasks and sensible be ginning parameters. You can also see LMA as Gauss – Newton using a area of confidence.

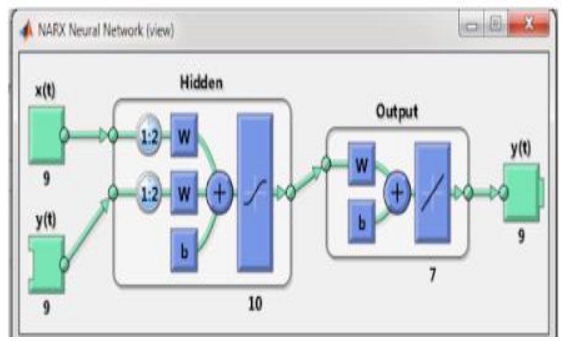

Fig.2 *Model of ANN circuit*

The Leven berg–Marquardt algorithm's main implementation is in the least-square curve fitting issue given a set of autonomous and dependent variable empirical datum pairs (xi, yi). The β parameters of the f(x, β) model curve to minimize the amount of the S(β) deviation squares.

$$\bar{\beta} \in argmin_{\beta}$$

$$S(\beta) = argmin_{\beta} \sum_{i=1}^{m} sqrt\left[\left(y_i - f(x_i, \beta)\right)\right]$$

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4 IMPLEMENTATION OF LMA ALGORITHM FOR FAULT ANALYSIS

The types of faults thought about within the analysis are Line-Ground, Line-Line-Ground, Line-Line, Line-Line-Line Faults. The simulation shows that fault origin angle has a substantial impact on the section current samples and so additionally on moving ridge remodel output of post fault signals, because the waves are periodic ,its adequate to check the impact angle within the vary of 0' to 180". Though associate thorough going experimentation, the parameter known for the classification is that the summation of the third level output for the 3 section currents.

If Sa=Summary of,3rd present level value in phase 'a',

S_b=Summary of 3rd present level values for in phase 'b' and

S_c=Summary of 3rd present level values in phase 'c'.

If S_a+S_b+S_c = zero, then the fault is classified as L-L-L fault. During this case the magnitude of all the summary values resembles to each other.

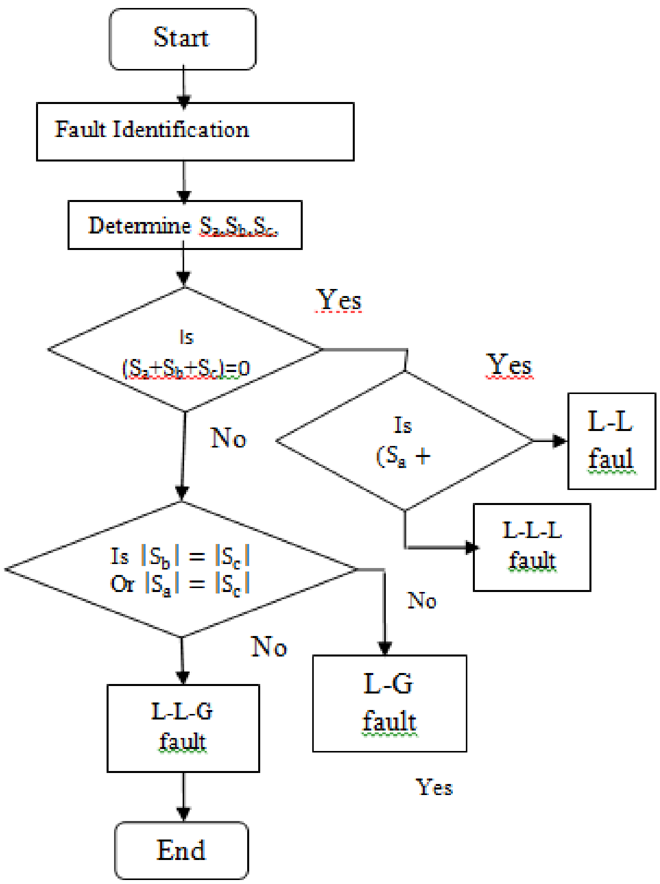
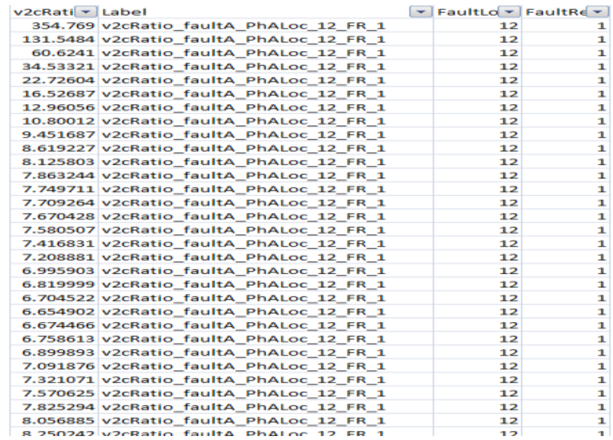


Fig.3 *Flow Chart*

Step1: Start
Step2: Determine S_a, S_b, S_c
Step3: if (S_a+ S_b+S_c=Zero)
Step4: if Step3 is valid then check for (S_a+ S_b=0) or (S_a+S_c=0) or (S_b+S_c=0)
Step5:if step 4 is valid then it is Line-Line fault
Step6:if step 4 is not valid then it is Line-Line-Line fault
Step7:if step 3 is not valid then calculate $|S_a|$ = $|S_b|$ or $|S_a|$ = $|S_c|$ or | S_c | = | S_b|
Step8:if step 7 is valid then it is Line-Groung fault zero
Step9:if step 7 is not valid then it is Line-Line-Ground fault
Step10:Stop

5 Simulation Results

The simulation variables information originates from a continual commercial surveillance procedure. Initially, a collection of depictive regular as well as mistake efficiency procedures information is obtained with the sensible dimension, consisting of 290 regular team examples as well as 10 mistake team examples, and also each team example consists of 11 dimension variables. Via PCA, the former 4 primary elements' build-up amount payment price is 89.1866%.



v2cRati	Label	FaultLo	FaultRe
354.769	v2cRatio_faultA_PhALoc_12_FR_1	12	1
131.5484	v2cRatio_faultA_PhALoc_12_FR_1	12	1
60.6241	v2cRatio_faultA_PhALoc_12_FR_1	12	1
34.53321	v2cRatio_faultA_PhALoc_12_FR_1	12	1
22.72604	v2cRatio_faultA_PhALoc_12_FR_1	12	1
16.52687	v2cRatio_faultA_PhALoc_12_FR_1	12	1
12.96056	v2cRatio_faultA_PhALoc_12_FR_1	12	1
10.80012	v2cRatio_faultA_PhALoc_12_FR_1	12	1
9.451687	v2cRatio_faultA_PhALoc_12_FR_1	12	1
8.619227	v2cRatio_faultA_PhALoc_12_FR_1	12	1
8.125803	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.863244	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.749711	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.709264	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.670428	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.580507	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.416831	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.208881	v2cRatio_faultA_PhALoc_12_FR_1	12	1
6.995903	v2cRatio_faultA_PhALoc_12_FR_1	12	1
6.819999	v2cRatio_faultA_PhALoc_12_FR_1	12	1
6.704522	v2cRatio_faultA_PhALoc_12_FR_1	12	1
6.654902	v2cRatio_faultA_PhALoc_12_FR_1	12	1
6.674466	v2cRatio_faultA_PhALoc_12_FR_1	12	1
6.758613	v2cRatio_faultA_PhALoc_12_FR_1	12	1
6.899893	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.091876	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.321071	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.570625	v2cRatio_faultA_PhALoc_12_FR_1	12	1
7.825294	v2cRatio_faultA_PhALoc_12_FR_1	12	1
8.056885	v2cRatio_faultA_PhALoc_12_FR_1	12	1
8.250242	v2cRatio_faultA_PhALoc_12_FR_1	12	1

Fig.4 *Error analysis across NNM*

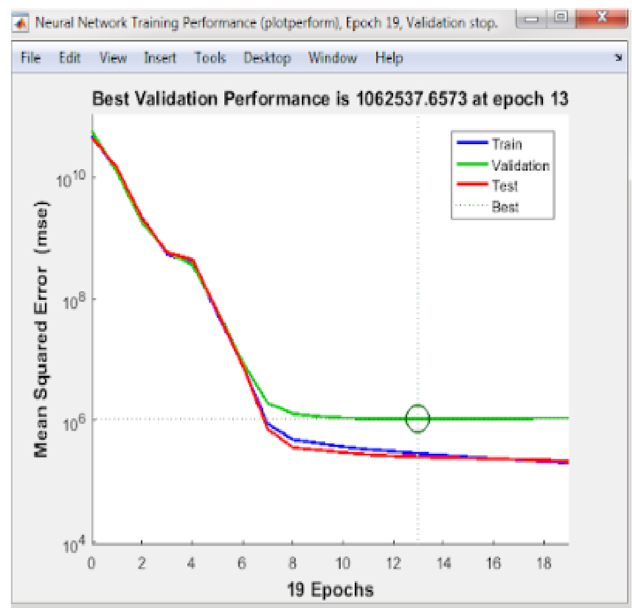


Fig.5 *Output results of error representation*

By utilizing Levenberg Algorithm On contrasting the efficiency of the ANN version with PCA and also ANN design without PCA under loud problems, the mean square mistake for training & screening was reduced. The gotten outcomes given up Fig. programs that the ANN design with PCA offers boosted efficiency under loud problems.

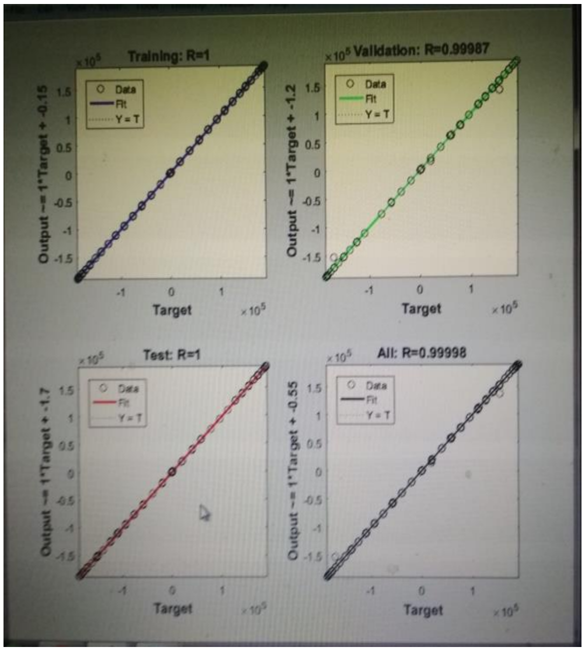


Fig.6 *Results of Levenberg Algorithm*

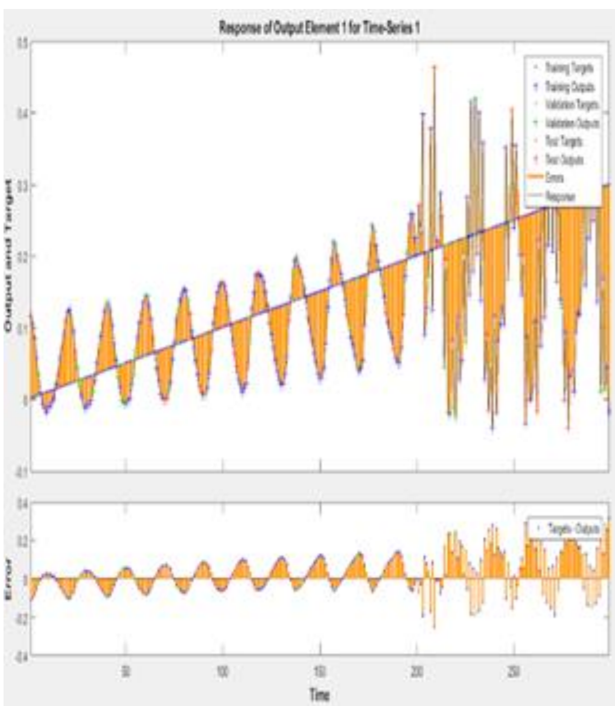


Fig.7 *Output results with respective of time*

6 HELPFUL HINTS

In this paper a Levenberg Machine Learning (LML) algorithm presented to detect and identify faults. The performance of Levenberg Algorithm in detection and identification of various types of faults compared to principal component analysis. The effectiveness of proposed algorithm tested on simulated two area power system using Matlab/Simulink. The proposed LMA is quite capable in detecting and localizing fault compared to PCA.

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