Fault Detection And Identification Using Levenberg Machine Learning Algorithm

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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].

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)

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

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Where in equation, \( \mu_i \) represents a linear combination of \( d \) orthonormal vectors.

\[
\bar{x} = \sum_{i=1}^{m} z_i \mu_i + \sum_{i=m+1}^{d} b_i \mu_i
\]

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 responds 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 \( m \) \( n \) \( X \) \( R \times \) is collected for the method variables information in control condition, the standardization should be carried on per the formulae.

\[
\bar{X} = [X - (1 \ 1 \ ... \ 1)^T M] \text{diag} \left[ \frac{1}{s_1} \frac{1}{s_2} \ ... \ \frac{1}{s_n} \right]
\]

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 \( k \) \( (k < n) \) 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 \( T_k \). Its mathematics description is shown in formulae.

\[
\bar{X} = T_k P_k^T + T_c P_c^T = \sum_{i=1}^{k} t_i p_i^T + \sum_{j=k+1}^{n} t_j p_j^T
\]

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 Quarters (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 algorithms, which is not necessarily the global minimum. The LMA interplays the Gauss Newton algorithm (GNA) with the gradiente descent technique. The LMA is more robust than the GNA, which means it finds a solution in many cases, even though its starts very far from the final minimum. The LMA tends to be a little slower than the GNA for wellbehaved tasks and sensible beginning parameters. You can also see LMA as Gauss–Newton using a area of confidence.

![Fig.2 Model of ANN circuit](image)

The Levenberg–Marquardt algorithm’s main implementation is in the least-square curve fitting issue given a set of autonomous and dependent variable empirical datum pairs \((x_i, y_i)\). The \( \beta \) parameters of the \( f(x, \beta) \) model curve to minimize the amount of the \( S(\beta) \) deviation squares.

\[
\beta \in \text{argmin}_\beta \sum_{i=1}^{m} \sqrt{(y_i - f(x_i, \beta))}
\]

As demonstrated in this document, the numbering for sections upper case Arabic numerals, then upper case Arabic numerals, separated by periods. Initial paragraphs after the section title are not indented. Only the initial, introductory paragraph has a drop cap.

### 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 it’s 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 \( S_a = \text{Summary of } 3\text{rd present level value in phase 'a'} \), \( S_b = \text{Summary of } 3\text{rd present level values for in phase 'b'} \) and \( S_c = \text{Summary of } 3\text{rd present level values in phase 'c'} \). If \( S_a + S_b + S_c = \text{zero} \), then the fault is classified as L-L-L fault. During this case the magnitude of all the summary values resembles to each other.
Step 1: Start
Step 2: Determine $S_a$, $S_b$, $S_c$
Step 3: If $(S_a + S_b + S_c = 0)$
Step 4: If Step 3 is valid then check for $(S_a + S_b = 0)$ or $(S_a + S_c = 0)$ or $(S_b + S_c = 0)$
Step 5: If Step 4 is valid then it is Line-Line fault
Step 6: If Step 4 is not valid then it is Line-Line-Line fault
Step 7: If Step 3 is not valid then calculate $|S_a| = |S_b|$ or $|S_a| = |S_c|$ or $|S_b| = |S_c|$
Step 8: If Step 7 is valid then it is Line-Ground fault zero
Step 9: If Step 7 is not valid then it is Line-Line-Ground fault
Step 10: 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%.

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.
REFERENCES


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.