Optimal Shunt Compensated Transmission Line Fault Detection And Classification In Power System Using KPCA-ELMNN Technique

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Abstract- *Traditionally, discrete Fourier transform and fast Fourier transform are utilized to analyze the power quality issues. A hybrid system is proposed to predict and classify the power system transmission line faults. The proposed approach has two modules: fault detection and fault classification.This is the consolidation of both the Kernel Principle Component Analysis (KPCA) and Elman Neural Network (ELMNN) and hence it is named as KPCA-ELMNN technique. Here, the KPCA approach was employed to dataset generation that involves the process of feature extraction and dimensionality lessening. T. The ELMNN is used for categorizing the sort of fault that happens in a shunt compensated transmission scheme such as No Fault, LG fault, LL fault, LLG Fault, LLL Fault and LLLG fault.The proposed system is activated in MATLAB platform, its performance is analyzed with existing systems.*

Keywords- Power system, Neural Network, Fault Detection, Kernel Principle Compound Analysis, Elman Neural Network.

I. INTRODUCTION

The energy relation conflicts, like power drop, brilliant, transitory interval, glimmer, nick, transients, harmonics is the major causes which normally degrading the quality of electric power.One of the important issues in protection scheme is for detecting and classifying the disturbances into different types to determine sources along causes of disturbances. Major requirement in protection scheme research is the capability for performing the automatic power quality monitoring as well as data analysis. The feature extraction together with classifying is the greatest portions of the power quality occurrence classification

II. IMPORTANCE OF FAULT DIAGNOSIS

In power systems, transmission lines are three-phase connections between various substations which transfer power from generating stations, to the distribution system at high voltage levels. In a transmission line system, a fault can be defined as contact between conductors or with the ground. In the three-phased transmission line, these faults are classified in Single Line to Ground (LG), Double Line to Ground (LLG) and Three Lines to Ground (LLLG) among others. In power system, a complex and critical infrastructure, the change in measurement data i.e. voltage and current signals, is frequently experienced. Along with several disturbances, the various

System faults in power systems are caused by number of reasons, out of which around 85% of them are contributed by faults in the transmission system. The faults in the power systems are unavoidable considering their physical nature e.g. in overhead transmission lines and in underground cables. These faults can cause substantial economic damage in addition to personal and equipment loss. These implications in the complex transmission line network have highlighted the need to diagnosis the fault in a fast and timely manner.

2.1 PROTECTION OF TRANSMISSION LINES

The fault detection is the procedure to detect the abnormal condition of the transmission line based on the data obtained by CT and VT protective relays and the status of circuit breakers of the protective zone. The goal of fault classification is to categorize the fault by its type i.e. which phase of the system is at fault and its nature.

In the protection system of transmission lines, the classical fault detection is done in several relays, in order to avoid common failure modes among different protection systems. However, all the relays can be classified as:

• **Pick-up Relays:** These relays respond to magnitude of input quantity. For example, an over-current relay which responses if the magnitude (generally rms value) of input current is above a set threshold, Ip.

• **Directional Relays:** These relays respond to phase angle between two AC inputs. For example, a common directional relay compares the phase angle of current and voltage signal. Another way is to compare the phase angle of one current to another current signal.

• **Ratio Relays:** These relays respond to the ratio of two input signals expressed as phasors. Since the ratio of two phasors is a complex number, the relay can be designed to respond to the magnitude of the complex number or the complex number itself. For example, the common ratio relays are impedance or distance relays.

• **Differential Relays:** These relays respond to the magnitude of the algebraic sum of two or more inputs. In the common form, the relays respond to the algebraic sum of currents entering a zone of protection.

• **Pilot Relays:** These relays are based on utilizing the communication infrastructure between two remote substations. For example, the decision of local relay is communicated to other terminals of the transmission line.

III.CLASSICAL FAULT ANALYSIS

Fault classification is important for fast and reliable operation of protective relaying in transmission lines. Classically the faults in transmission lines can be categorized in two types: series (Open circuit) fault or shunt (closed circuit) fault. Open circuit faults create abnormal change in phase voltage values whereas short circuit faults can be identified by abnormal phase current value. Short circuit faults are divided into two types, i.e. asymmetrical faults, and symmetrical faults. Asymmetrical faults are line to ground (LG), line to line (LL), and double line to ground (LLG), and symmetrical faults are triple line (LLL) and triple line to ground (LLLG) faults.

The severity and frequency of these faults are briefly explained to understand the need to identify and classify these faults accordingly. The most frequently occurring fault is LG fault though it's not the most severe fault. The next most frequent and severe faults are LL and LLG. The most severe faults for the stability of power system are LLL and LLLG faults, if occurred and not identified timely, these faults can collapse the system. So the protection system needs to detect the fault and classify the nature of the fault and location of the fault within less time to avoid the major adversarial impact on the system.

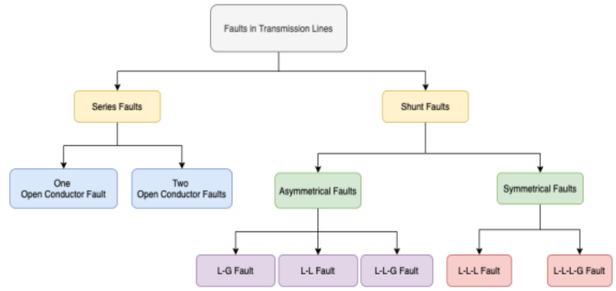

Fig 2.A: Classification of faults in transmission lines.

3.1 FAULT DETECTION

In the fault detection stage, the indication of output signal is issued from the beginning of the fault. In normal operation condition the voltage and current in power system is in sinusoidal signals. The indication of fault is introducing the sudden change of phase and amplitude in voltage signal and current signal. For detecting the inception of a fault the appearance of transient components and changes of phase and amplitude is followed. Phase flows IR, IY, and IB are reached after a trouble is perceived. Before the current is decomposed, it uses high-frequency distortion filter for extracting the high-frequency into current signals. Numerical analysis of detection fault is displayed in Fig. 2. An error is detected at the specified connection, whereas the limit value is greater than the coefficients of the corresponding connection currents. After finding an error in the link value of the output, logic 1 indicates that it is faulty or logic 0 indicates that it is not faulty. As the signal detection is high, if there is any disturbance in the detection signal and the 3-phase current is subjected to error classification, the types of error are determined.

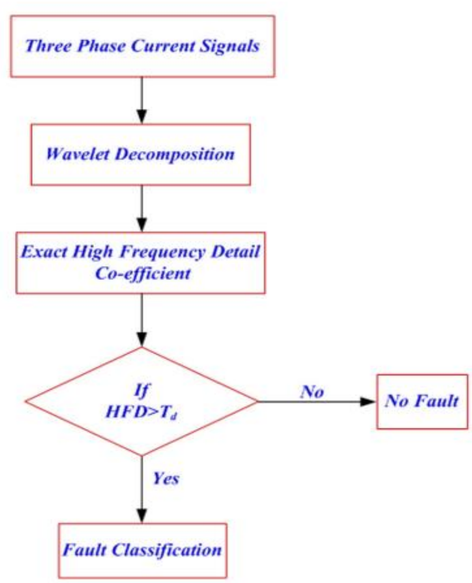

Figure 3.A: Flow chart of Fault detection

3.2FAULT CLASSIFICATION

The classification error uses a 2 Hz sample rate based on the main decay level db5 bandwidth. Samples are used in the algorithm, and they are collected and gradually spaced at 0.5 s. There are 2 types of classification error, depends on either they are on the ground or not. Features of ground-related faults are considered in many of them and they are not ground-breaking and are handled individually.

• Single phase and ground faults: L1–G, L2–G, and L3–G.
• Two phase and ground faults: L1–L2–G, L1–L3–G, L2–L3–G.
• Two phase faults: L1–L2, L1–L3, and L2–L3.
• 3 faults: L1–L2–L3. • 3 to ground faults: L1–L2–L3–G.

Prior to the condition that the information distinguishes the error type, the coupler effect of the evenly connected 3-phase transmit line was efficiently changed. Simple modification is used to achieve otherwise known as Karrenbauer transmit. The Karrenbauer transformation attained through summers/sub tractors in the absence of any requirement of multipliers. The transmitting matrix is expressed as,

$$T = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ 1 & 1 & -2 \end{bmatrix}$$

IV. EXISTING SYSTEM

The integration feature of an advanced machine learning algorithm (Summation-Wavelet Extreme Learning Machine (SW-ELM)) extracted in the learning process. The robust fault detection with discrimination (RFDD) for transmission lines uses a robust phasor rating to calculate accurate fault resistance using a feature value extract from samples of voltage and current signals. A smart backup tracking system was to detect and classify a power grid transmission line fault occurrence. Supernatural analysis utilizing discrete Fourier transform and fast Fourier transform are deemed for this persistence, nevertheless, the unsteady power nature excellence troubles that transmutes is in effective to detect the trouble waveforms. To avoid disadvantages together with DFT, FFT, the Wavelet transform (WT) is generally utilizes to analyze the power quality issues. However, depending on the sensitivity noise with the accuracy of the selected base band, it shows various drawbacks such as excessive computing. In maximum manuscript, ambiguous rules are used to form conclusions about occurrence and to classify the sort of disturbance. This method increases the exact detection rate of the disturbed count of inputs to the ambiguous method, which then maximize complexity of system and reduces its speed. Nevertheless, neglect to detect integrated power quality faults. Everywhere, additional methods are being offered to diagnose and classify power quality faults using various techniques. All violating approaches can detect energy value disturbances, and then the number of examples required is very large, so the complexity of the approach is quite sufficient, so it refuses to work immediately.

V. PROPOSED MODEL ARCHITECTURE

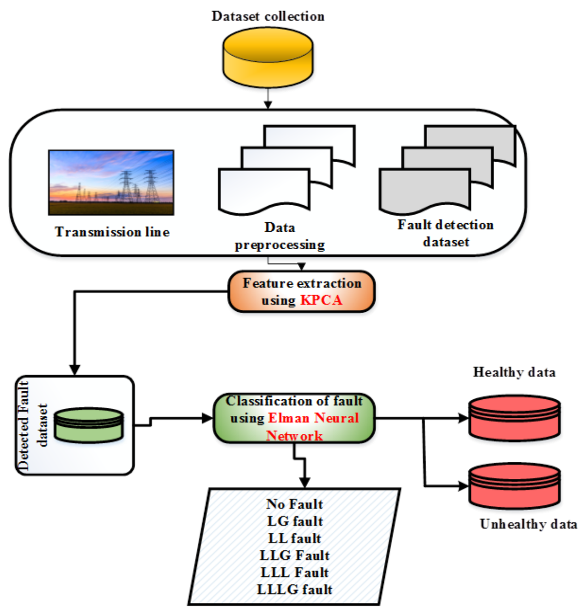

Fig 5.A: Block diagram of proposed method

Dataset creation is a variable attributes significantly to the detection with classification of fault analysis. A count of training data is produced through off-line simulation process.The fault signals are designed to KPCA feature extraction at the classification mode.When holding most of the significant data from the first signal, the input method dimension is reduced by feature extraction.KPCA eliminates the aspects of fault signals. Finally, ELMNN is used to classify the data as healthy or unhealthy.

5.1 FEATURE EXTRACTION

- KPCA generally tries to find the lower-dimensional surface to project the high-dimensional data.
- KPCA works by considering the variance of each attribute because the high attribute shows the good split between the classes.
- It reduces the dimensionality.
- Calculating the Covariance of matrix
- Calculating the Eigen Values and Eigen Vectors
- Sorting the Eigen Vectors

- Calculating the new features Or Principal Components
- Remove less or unimportant features from the new dataset

5.2. Kernel Principal Component Analysis

Principal Component Analysis is an unsupervised learning algorithm that is used for the dimensionality reduction in machine learning. It is a statistical process that converts the observations of correlated features into a set of linearly uncorrelated features with the help of orthogonal transformation. These new transformed features are called the **Principal Components**. It is one of the popular tools that is used for exploratory data analysis and predictive modeling. It is a technique to draw strong patterns from the given dataset by reducing the variances. KPCA generally tries to find the lower-dimensional surface to project the high-dimensional data.

Kernel Function: First, you choose a kernel function (e.g., radial basis function (RBF) or polynomial kernel) that measures the similarity between pairs of data points in the original input space.

Kernel Matrix: Using the chosen kernel function, you compute a kernel matrix that represents the pair wise similarity between all data points in the input space.

Centering the Kernel Matrix: The kernel matrix needs to be centered to perform PCA. Centering means subtracting the mean of each column and each row while adding the overall mean of the matrix.

Eigen Value Decomposition: Next, you perform Eigen value decomposition on the centered kernel matrix to find the eigenvectors and Eigen values. These eigenvectors are the principal components in the higher-dimensional feature space.

Dimensionality Reduction: Finally, you can project the original data into the lower-dimensional subspace spanned by the selected eigenvectors to obtain the transformed dataset.

5.2.1 Principal Components in PCA

As described above, the transformed new features or the output of PCA are the Principal Components. The number of these PCs is either equal to or less than the original features present in the dataset. Some properties of these principal components are given below:

- The principal component must be the linear combination of the original features.
- These components are orthogonal, i.e., the correlation between a pair of variables is zero.
- The importance of each component decreases when going to 1 to n, it means the 1 PC has the most importance, and n PC will have the least importance.

Based on the PCA algorithm optimal data features are extracted. Then ANN is to detect the fault and classify the corresponding faults.

5.3NEURAL NETWORK

The term "Artificial neural network" refers to a biologically inspired sub-field of artificial intelligence modeled after the brain. An Artificial neural network is usually a computational network based on biological neural networks that construct the structure of the human brain. Similar to a human brain has neurons interconnected to each other; artificial neural networks also have neurons that are linked to each other in various layers of the networks. These neurons are known as nodes. Basic neural network model is displayed in Figure 3.5.

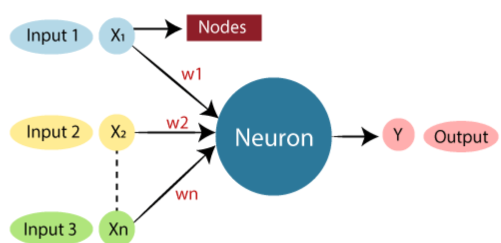

Figure 5.3.A: Basic structure of neural network

Input Layer: As the name suggests, it accepts inputs in several different formats provided by the programmer.

Hidden Layer: The hidden layer presents in-between input and output layers. It performs all the calculations to find hidden features and patterns.

Output Layer: The input goes through a series of transformations using the hidden layer, which finally results in output that is conveyed using this layer.

5.3.1ELMNN DESIGN

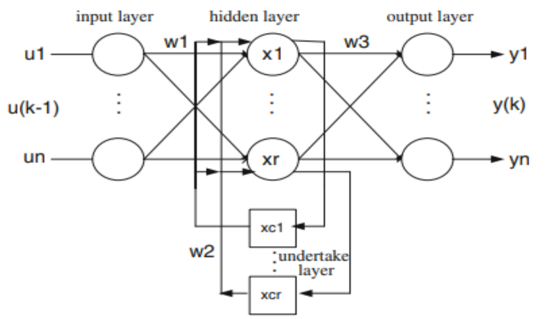

Figure 5.3.B: Structure of Elman NN

5.3.2ELMNN Design for Fault Classification

The network for fault classification has 6 inputs and 4 outputs where it was designed with 1000 training data set for each input and output. The training data consists of 100 samples for nine faults and no fault as input data. The four target output data presented fault state of the three phase lines A, B, C and ground line, G where 1 and 0 specified whether the fault occurred or not which it can be seen in Table II. The investigation has been done between the multilayer perceptron (MLP) feed-forward back propagation neural network with different configuration of hidden layers and transfer function. The preferred network is with 1 input layer of 6 neurons, 1 hidden layer of 3 neurons and 1 output layer with 4 neurons. The training algorithm of Scaled Conjugate Gradient (trainscg) was used where it provided less memory and suitable in low memory situation. The pattern recognition tool was used to classify the fault in neural network.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

RESULTS

The proposed method is implemented in MATLAB platform in the 2023 online version. Following are the output results of proposed method.

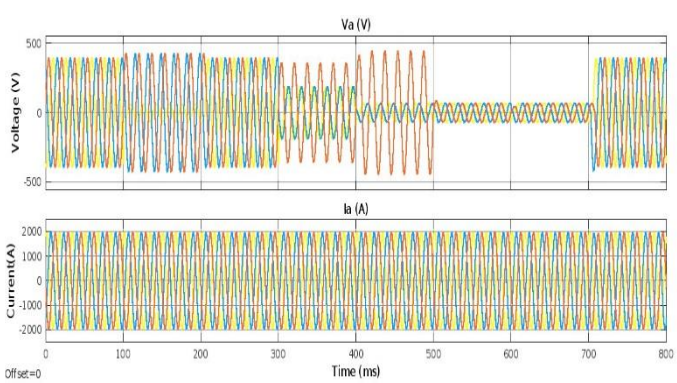

Fig 6.1: Fault Voltage waveform

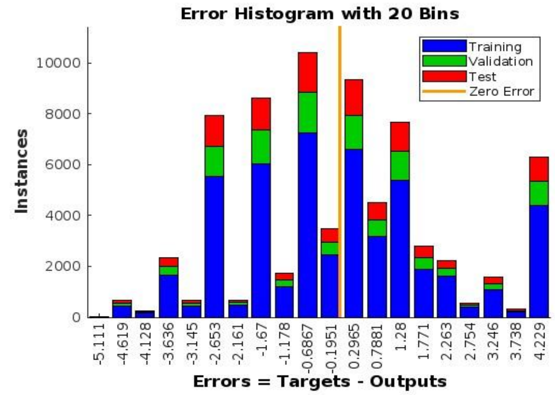

Fig 6.2: Validation Curve

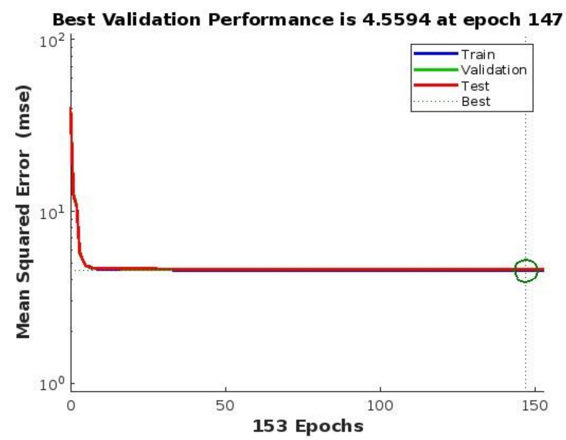

Fig 6.3: Mean Square Waveform

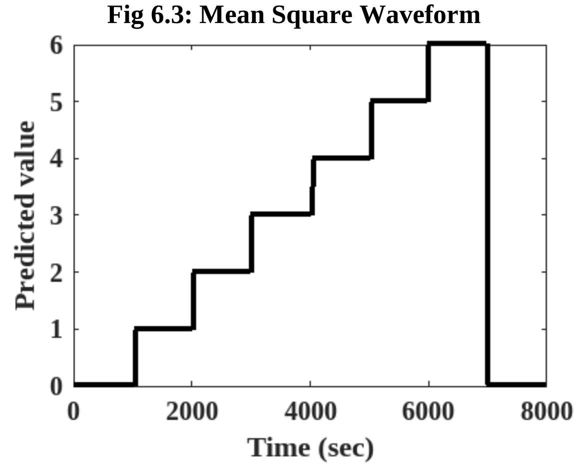

Figure 6.4: ELMNN fault classification performance

VII. CONCLUSION

This work proposes a KPCA-ELMNN approach for fault identification of line signal in transmission power system. Here, the KPCA method is employed to dataset creation that involves the process of feature extraction along dimensionality lessening. The signal behavior is extracted through the KPCA that is sent to the ELMNN learning procedure to classify faults on power system. To examine the performance of the KPCA-ELMNN technique, the results prove that the power variation at power system is precisely identified utilizing KPCA-ELMNN approach. Moreover, the KPCA-ELMNN is effectively categorized the fault using lesser computation and lessens the difficulty of algorithm. Future work will involve improving the algorithm for incorporating multiple types of faults, real deployment in sensor node, and improving its performance accuracy for accurate and rapid detection with classification.

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