DBN BASED EKF ALGORITHM FOR DETECTION AND CLASSIFICATION OF HIF IN DISTRIBUTION SYSTEM

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Abstract

In the paper, identification and classification of high impedance faults (HIF) are analyzed with the Extended Kalman filter and Deep Belief Neural Network (DBN). Here, the proposed method is utilized for classifying the HIF in power system. To extract the features of the signals, EKF is introduced and the DBN is used for classify the signals. Initially, the distribution system, the No Fault (NF) signals are analyzed. After that, in the distribution system linear load and non-linear loads are applied to the system. In this proposed method, radial distribution system and meshed distribution systems are analyzed under the HIF conditions. Here, harmonic coefficients of 3rd, 5th, 7th, 9th and 13th are analyzed with the help of proposed method. The feature signals of current and voltage under the harmonic components are taken as the input of DBN. The feature signals are classified with the help of DBN classifier. The proposed method is implemented in MATLAB/Simulink working platform and the detection performance evaluated. The evaluated results are compared with Artificial Neural Network (ANN) and Neuro Fuzzy Controller (NFC) methods. In addition, the proposed method is tested with the statistical measures like, Accuracy, Sensitivity, and Specificity etc.

Keywords : DBN, EKF, linear load, non-linear load, ANN, NFS, harmonic coefficients, HIF

I. Introduction

Electric Power Systems (EPS) are liable to issues influencing the reliability, wellbeing and proficiency of intensity conveyed to customers. High Impedance Fault (HIF) furnishes the EPS security engineers with one kind of difficulties. This type of
flaw is the result of undesired contact between an invigorated conductor and a high resistivity surface, raising the issue current to levels that conventional overcurrent discovery gadgets can't detect [V]. Due to the random, asymmetric and nonlinear nature of high impedance fault (HIF) current, identification of high impedance shortcomings represents an exceptionally challenges issue. A great part of the time, customary over-current plans can't identify and recognize these flaws, since the size of issue current is extensively littler than the ostensible burden current [IX]. The low-impedance faults (LIF) are usually found within 0.5–2 cycles because of the high greatness of the issue present, yet on account of HIF because of its ambivalent nature, they go unnoticed for a considerable length of time together before they are outwardly examined [I]. Unidentified HIF can electrocute workers, which poses a significant threat to public safety. Frequently, during annoyance stumbling the crisis administrations, for example, traffic signals, medical clinics, and so on get influenced. Proficient, dependable and secure activity of intensity frameworks requires the opportune ID of high impedance flaws [X]. The likelihood of high impedance shortcoming happening in dissemination systems is more noteworthy than in transmission arrange, since appropriation feeders are bound to come into contact with high impedance ancient rarities, for example, trees and so on. The analyst is creating different strategies for recognizing the HIF deficiencies. The techniques are delegated as mathematical morphology (MM) technique, Artificial Neural Network (ANN), ANN-FIS (ANN-Fuzzy Interference System), Adaptive Neuro Fuzzy Interference System (ANFIS), Recurrent Neural Network (RNN), Support Vector Machine (SVM), and so on. While recurrence area procedures utilize diverse HIF highlights, time-changing signs, for example, HIF, are better characterized when data about recurrence segments and their worldly attributes are given at the same time [III]. The apps isolate the faults and which have been educated and checked with the various classifiers. Different imperfections are influenced from the above methodologies and neglect to accomplish the viable order of the deficiencies. Along these lines, to recognize the deficiencies in the distribution system, new strategy should be made.

II. Literature Review

In addition, numerous researchers have comprehensively explored different kinds of methods for fault detection and classification of HIF in distribution system. Some of them are studied here,

Junbo Zhao et al. [IV] proposed a vigorous, iterated, extended Kalman filter (EKF) in view of a generalized maximum likelihood approach (termed GM-IEKF) to assess the elements of the power framework state in case of unsettling influences. The last is weighted and dictated by methods for the projection insights by means of an element of strong separations of the double cross grouping of the normal state and development vectors. Meera R. Karamta et al. [VII] advocated the integration of the Extended Kalman Filter with the UPFC tool for the SMIB System Dynamic State Estimation. Kumari Sarwagya et al. [VI] proposed two rules-based security plans to assess the HIF inside the conveyance framework. Their plan depended on superimposed lingering voltage parts for HIF discovery and the most extreme estimation of a one-cycle complete of superimposed negative-grouping current

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segments for bombed feeder ID activity. Muhammad Sarwar et al. [VIII] utilized support vector machines (SVM) to assess the HIF in dissemination network. The information driven strategies were tried with the wrecked and whole conductor on IEEE 13-node distribution system to distinguish and characterize high impedance flaws.

The rest of the portion of the paper is organized as follows, the HIF recognition and order related works are characterized in segment II. A detailed overview of the device model and architecture is given in section III and IV. The findings of the simulation and the study are presented in section V. The paper's ending portion is presented in section VI.

### III. Structure of HIF Model

In the section, the HIF models are designed with corresponding parameters based on the MATLAB/Simulink model. After that, the model was validated with the determination of simulated current signals with the coefficient $R^2$. The values of $R^2$ ranged from 0.8279 to 0.9884, ensuring the accuracy of the HIF model. It is composed by two time-varying resistances, connected in series, and two time-controlled switches. Resistance $R_1$ emulates the non-linearity and asymmetry during the entire fault time and $R_2$ is responsible for simulating build-up and shoulder, only on transient regime. Resistance $R_1$ is constant throughout the fault and $R_2$ is modeled by different polynomial curves, one for each contact surface. All coefficients for the polynomial curves as well as values for $R_1$ were provided by the authors based on field data. The switches connect resistances to the fault point and emulate intermittence and conductor breakdown. Thus, the method is able to properly emulate all the main features of a HIF. The structure of the radial distribution system and meshed network with the high impedance fault is illustrated in the Fig. 1.

![Fig. 1: Modelling structure of High Impedance Faults](image)

### IV. Proposed System for HIF

In this paper, HIF faults are analyzed in the distribution system. The faults are identified and classified with the help of the proposed method named as Deep Belief Neural Network (DBN) with Extended Kalman Filter (EKF). The generator is

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of 15 KV and 10 MVA capacities and connected through the transformer under the capacity of 13/25 KV and 10 MVA capacities. Totally, the distribution networks are working at 25 KV voltages. The distributed networks are implemented under the condition of linear and non-linear load. Mainly, the HIF system is introduced with DC source, non-linear resistance and anti-parallel diodes connected to each phase. The proposed system with HIF fault structure is illustrated in the Fig. 2. Initially, the features of the current and voltage signals of the distribution system are extracted with the help of the EKF filter. After that the extraction signals are sending to the DBN for classification purpose. The DBN classifier is working based on the training and testing phase. The overall process of the proposed method is explained in the below section.

**Fig. 2: Block Diagram of HIF with Proposed System**

**(A) Deep Belief Neural Network for HIF Classification**

DBNs were recently proposed by Hinton along with an unsupervised greedy learning algorithm for constructing the network one layer at a time. As described earlier, the subjacent idea consists of using a RBM for each layer, which is trained independently to encode the statistical dependencies of the units within the previous layer [XI]. Since a DBN aims to maximize the likelihood of the training data, the training process starts by the lower-level RBM that receives the DBN inputs, and progressively moves up in the hierarchy, until finally the RBM in top layer, containing the DBN outputs, is trained. This approach represents an efficient way of learning by combining multiple and simpler (RBM) models, learned sequentially. Here, the input of the HIF of three phases are given as the input and the normal voltage and current signals are given. The training process of the DBN is illustrated in the Fig.3.
The number of layers of a DBN can be increased in a greedy manner. Each new layer that is stacked on top of the DBN will model the output of the previous layer and aims at extracting higher-level dependencies between the original input’s variables, thereby improving the ability of the network to capture the underlying regularities in the data. The bottom layers are intended to extract low-level features from the input data, while the upper layers are expected to gradually refine previously learned concepts, therefore producing more abstract concepts that explain the original input observations. The training process, also called pre-training, is unsupervised by nature, allowing the system to learn non-linear complex mapping functions directly from data, without depending on human-crafted features. However, the output of the top layer can easily be fed to a conventional supervised classifier. Alternatively, it is also possible to create a classification model, by adding an additional layer to the unsupervised pre-trained DBN upon which the resulting network is fine-tuned using the BP algorithm. In this scenario the resulting network is also called a DBN. Moreover, it has been shown that the BP algorithm will barely change the weights learned in the greedy stage and therefore most of the performance gains are actually obtained during the unsupervised pre-training phase. Here, training of the DBN is attained with the help of the RBM algorithm. The background information of the RBM algorithm is presented below section.

**Restricted Boltzmann Machines (RBMs)**

An RBM is an energy-based generative model that consists of a layer of $I$ binary visible units (observed variables), $v = [v_1, v_2, \ldots, v_I]$ where $i \in \{0,1\}$, and a layer of $J$ binary hidden units (explanatory factors), $h = [h_1, h_2, \ldots, h_J]$ where $j \in \{0,1\}$, with bidirectional weighted connections. RBMs follow the encoder-decoder paradigm. In this paradigm an encoder transforms the input into a feature vector representation from which a decoder can reconstruct the original input. In the case of RBMs both the encoded representation and the (decoded) reconstruction are stochastic by nature. The encoder-decoder architecture is appealing because: (i) after training, the feature vector can be computed in an expedited manner and (ii) by reconstructing the input we can assess how well the model captured the relevant
information from the data. Given an observed state, the energy of the joint configuration of the visible and hidden units \((v,h)\) is given by the below equation,

\[
E(v, h) = -CV^T - b h^T - h W v^T
\]

\[
= - \sum_{i=1}^{I} C_i v_i - \sum_{j=1}^{J} b_j h_j - \sum_{j=1}^{J} \sum_{i=1}^{I} W_{ji} v_i h_j
\]

Where \(W \in IR^{I \times J}\) is a matrix containing the RBM connection weights, \(c = [c_1, c_2, \ldots, c_I] \in IR^I\) is the bias of the visible units and \(b = [b_1, b_2, \ldots, b_J] \in IR^J\) the bias of the hidden units. In order to break symmetry, typically the weights are initialized with small random values (e.g. between \(-0.01\) and \(0.01\)). The hidden bias, \(b_j\), can be initialized with a large negative value (e.g. \(-4\)) in order to encourage sparsity and the visible units bias, \(c_i\), to \(\log\left(p_i / (1 - p_i)\right)\), where \(p_i\) is the proportion of training vectors in which \(v_i = 1\). Failure to do so will require the learning procedure to adjust (in the early training stages) the probability of a given visible unit \(i\) being turned on, so that it gradually converges to \(p_i\). The RBM assigns a probability for each configuration \((v, h)\) which described in the below equation,

\[
p(v, h) = \frac{e^{-E(v, h)}}{Z}
\]

Where \(Z\) is a normalization constant called partition function by analogy with physical systems, which is obtained by summing up the energy of all possible \((v, h)\) configurations.

\[
z = \sum_{v, h} e^{-E(v, h)}
\]

Since there are no connections between any two units within the same layer, given a particular random input configuration \(v\), all the hidden units are independent of each other and the probability of \(h\) given \(v\) becomes,

\[
p(h|v) = \prod_j p(h_j = 1 | v)
\]

Where,

\[
p(h_j = 1 | v) = \sigma(h_j + \sum_{i=1}^{I} v_i w_{ji})
\]

For implementation purposes, \(h_j\) is set to 1 when \(p(h_j = 1 | v)\) is greater than a given random number (uniformly distributed between 0 and 1) and 0 otherwise. Similarly given a specific hidden state, \(h\), the probability of \(v\) given \(h\) is obtained by,

\[
p(v|h) = \prod_i p(v_i = 1 | h)
\]

Where,

\[
p(v_i = 1 | h) = \sigma(c_i + \sum_{j=1}^{J} h_j w_{ji})
\]

When using (8) in order to reconstruct the input vector, it is vital to force the hidden states to be binary. Using the actual probabilities would seriously violate the information bottleneck, which acts as a strong regularizer and is imposed by forcing
the hidden units to convey at most one bit of information. The marginal probability assigned to a visible vector, \( v \), is given by,

\[
p(v) = \sum_h p(v, h) = \frac{1}{Z} \sum_h e^{-E(v, h)}
\]  

(9)

Hence, given a specific training vector \( v \) its probability can be raised by adjusting the weights and the biases of the network in order to lower the energy of that particular vector while raising the energy of all the others. To this end, we can perform a stochastic gradient ascent on the log-likelihood manifold obtained from the training data vectors. Based on the DBN network, the faults signals of distribution system are classified. The implementation results of the proposed method is explained in the below section. The DBN classifier is working based on the training and testing phase. The post-fault signals of HIF in distribution system are trained for classify the HIF faults in the linear and non-linear loading conditions of distribution system. The feature extraction of the signals is attained with the help of the EKF filter. The overall process of the proposed method is explained in the below section.

B) Modelling EKF Analysis

The extended Kalman filter is non-linear time domain estimation. The EKF is mainly used to extract the features of the fault signals and which efficiently estimation of harmonic components of fault current signals during HIF. For example, let discrete signal that consists fundamental and harmonics with a DC component can be described as model under condition of HIF which are represented as below equation. The mathematical modelling and process of the EKF is explained in the below section.

\[
Z^K = H_1 \sin(KWT_S + \varphi) + H_2 \sin(3KWT_S + \varphi) + H_3 \sin(5KWT_S + \varphi) + H_4 \sin(7KWT_S + \varphi) + H_5 \sin(11KWT_S + \varphi) + H_6 \sin(13KWT_S + \varphi) + H_0 e^{-aKTS}
\]  

(10)

The transition matrix of the harmonic components are presented in the below equation,
\[ F^K = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} e^{-kT^2} \]

The gain of Kalman filter \( K^K \) can be presented as below equation,

\[ K^K = \frac{P^k}{H^K T (H^K P^k + R)^{-1}} \]

\[ \frac{P^k}{H^K T} = P^k - K^K H^K P^k \]

\[ P^k = P^k + Q \]

Where, \( Q \) is referred as the covariance matrix and \( R \) is mentioned as the noise covariance. The Kalman filter performance is improved with the help of updating of measurement error covariance which is explained in the below section [II]. The explanation for \( R \) is achieved based on the error among observed and estimated values of \( X^K \) as,

\[ R = (Z^k - H^K X^K) T (Z^k - H^K X^K) \]

The covariance error \( R \) is updated as,

\[ R^K = \lambda^K R^{k-1} + (1 - \lambda^k) e^{k^2} \]

Where, \( \lambda^K \) is defined as the forgetting factor which given by below equation,

\[ \lambda^K = \frac{1}{1 + |R(k)/R^0|} \]

Where \( R^0 \) is referred as the initial error covariance value of \( R \). After that, the model error covariance matrix \( Q \) can be attained with the help of covariance function \( CE \) as presented below,

\[ CE^K = \lambda^q * CE^{k-1} + (1 - \lambda^q) * e^k * e^{k-1} \]

If \( CE(K) > CE^{TH} \), \( Q = Q^1 \) and \( CE(K) < CE^{TH} \), \( Q = Q^0 \) where, \( Q^0 \) can be described as the model covariance and \( Q^1 \) is described as new value of \( Q \) and \( Q^1 > \alpha Q^0 , \alpha >

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1, and $CE^{TH}$ is described as the threshold value of covariance error. The adaption of $Q^K$ can be obtained and presented below,

$$Q^K = (1 - \alpha q) * Q^{k-1} + \alpha q * P^{k-1} * P^{k-1 \top} * CE^K$$

(19)

The extended Kalman filter is modelled to compute various harmonic components of HIF and NF current signals. The fault signals are nature so classify the fault is difficult. Generally, the harmonic components computations are fundamental such as 3rd, 5th, 7th, 11th and 13th harmonic components. The harmonic components are analyzed as the features and it is forwarded to the DBN for classification process. The harmonic components of the signals are analyzed under the HIF from NF and non-linear load. The harmonic components of 3rd, 5th, 7th, 11th and 13th are extracted as features which assigned to F1, F2, F3, F4, F5 and F6 respectively.

The implementation results of the proposed method is explained in the below section.

V. Results and Discussions

The proposed technique is implemented in MATLAB/Simulink platform and their performances are evaluated. Here, the proposed technique is based on the EKF and DBN for detecting and classifying the faults in the distribution system. Initially, the system behaviours are analyzed in normal and HIF conditions. Then the performances of voltages and currents are normalized to their rated peak values. Then the performances of fault behaviour of the line signals are extracted using EKF. By employing EKF, the feature extraction signals are gathered from the HIF cases. Subsequently, the extracted features are applied to the input of the DBN. The classified outputs are No fault, HIF in phase A, HIF in phase B and HIF in phase C fault. Here, the performance of the proposed method is analyzed and their performances are compared with the ANN and NFC. The simulation diagram of the HIF model in the power system is illustrated in the Fig. 4. The performance of the proposed method is analyzed with the non-linear load conditions.

![Fig. 4: Simulation analysis of HIF fault model](image-url)
a) Performance Analysis of Non-Linear Load Conditions

In this case analysis, the non-linear load can be applied to the distribution systems and fault signals are analyzed in this section. The fault signals are extracted with the help of EKF filter. It filters the harmonic components of the signals which are analyzed in this section. At non-linear load condition, the faults are analyzed in the faults of phase A and Phase B and Phase C respectively. The performance of the fault signals is illustrated in the Fig.5. Under the non-linear load conditions, the EKF filter is extract the features in terms of harmonic components. The harmonic components of the fault’s signals are illustrated in the Fig.6. The 3\textsuperscript{rd}, 5\textsuperscript{th}, 7\textsuperscript{th}, 11\textsuperscript{th} and 13\textsuperscript{th} harmonic components are analyzed for fault signals. The feature extracted signals are sending to the DBN for classification process. The DBN is working based on the training and testing phase. The extracted features are used to training and testing phase. Finally, the feature extraction signals are classified with the DBN and EKF.
Fig. 5: Performance analysis of non-linear load HIF faults (a) phase A, (b) phase B and (c) phase C.

(a)

(b)

(c)

(d)
Fig. 6: Harmonic components of HIF under non linear load conditions

b) Statistical Analysis of the Proposed Method

The performance analysis of the proposed method is calculated based on the statistical measurements. The statistical measurements are used to analyze the performance of the DBN and EKF based classification. They are considered in linear load and non-linear conditions. Furthermore, they are dogged from the True positive (TP), False positive (FP), True negative (TN) and False negative (FN) values that are engaged to evaluate the accuracy, sensitivity and specificity of the normal and fault signals in A, B and C of the distribution system signals. The proposed technique output is dogged and exhibited in a tabular form. Furthermore, the accuracy, sensitivity and specificity vales in respect of the current methods and existing methods are estimated and tabularized in Table I under the fault signals of the phase A. Similarly, the phase B and phase C are analyzed.

Table 1: Analysis of fault signal in phase A

| Fault signal in phase A | Accuracy | Sensitivity | Specificity |
|------------------------|----------|-------------|-------------|
|                        | Proposed | ANN NFC     | Proposed ANN NFC | Proposed ANN NFC |
| S.No                   |          |             |              |                |
| 1                      | 90.22    | 88.34 82.32 | 81.25 78.32 76.25 | 100 95 83.333  |
| 2                      | 90.36    | 86.47 87.365 | 81.39 78.32 76.48 | 83.33 95 92     |
| 3                      | 90.36    | 86.32 80.96 | 99.25 95 92 | 100 82.45 92    |
| 4                      | 90.36    | 88.39 82.47 | 83.33 76.31 76.28 | 100 95 82.45    |
| 5                      | 89.24    | 88.45 83.333 | 99.25 92.14 91.09 | 83.45 82.48 68.81 |

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The proposed technique turns out accuracy, sensitivity and specificity values of 90.108%, 88.894% and 93.356% congruently. In the similar manner, all the other traditional methods are evaluated separately for non-linear conditions in numerous defective situations. Afterwards, the efficiency in implementation of the well-conceived method is compared with those of ANN and NFC methods and their performances are compared, contrasted and demonstrated. The outcomes evidently point out the fact that the proposed technique has been able to produce best outcomes in relation to peer methods. Thus, we can accurately conclude that the newly-launched proposed method is the most operative tool for the classification of the faulty state of the distribution generators.

VI. Conclusions

In the paper, the HIF in distribution system was analyzed with the utilization of DBN and EKF. The normal and HIF signals were applied to the input of EKF and the output was extracted features of the signal. The extracted features were in the form of vector and that was applied to the DBN. The output of the DBN was identified the condition of the signal whether HIF or normal. The proposed method was compared with the ANN and NFC techniques. From the comparative analysis, the classification rates are analyzed at different loading conditions such as linear load and non-linear load. The analysis results are showed the proposed technique (EKF-DBN) is better than that compared to ANN, and NFC. The performances were analyzed with the help of the statistical measurements such as accuracy, sensitivity and specificity. From the analysis, the proposed method was attaining the best classification results compared with the existing methods.

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