2021 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE) | 978-1-6654-7849-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/WIECON-ECE54711.2021.9829558

A Robust Short-Circuit Fault Analysis Scheme for Overhead Transmission Line

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***Abstract*—This paper introduces a novel architecture for anomaly detection and classification of high-voltage transmission line using the self-attention convolutional neural network enhanced with wavelet-transform (WSAT-CNN). The transmission lines repeatedly face an aggregation of short circuit-faults and their impact in the real time system increases the vulnerability, damage in load, and line restoration cost. In this paper, we propose a WSAT-CNN model for enhanced noise immunity and to pay more attention to the fault features. The studied scheme consists of number of layer with self attention mechanism that allows the model to recognize the fault more accurately. The resilience of the presented framework is validated by reckoning the noises to the input data. The results indicate that the proposed approach is capable of accurately classifying and detecting faults in transmission line with high precision.**

***Index Terms*—Faults, Time-series image, neural network, time window and Discrete wavelet transform.**

I. Introduction

Because of the increased implications in today's expansive power distribution systems, convenient process of power system configuration has become a difficult challenge. Primarily, overhead transmission lines account for over 80% of power system faults due to their exposure to unpredictably varying atmospheric circumstances [1]–[4]. To guarantee the smooth execution of the power systems, it is necessary to identify, characterize, and locate such faults in the administering systems. The distribution system faults mainly includes line-to-line, single-line-to-ground, double-line-to-ground, and three-phase-to-ground fault. Among them, the major amount of faults, around 70%, are caused due to short circuit faults, which is a form of single-line-to-ground fault [5]–[8]. During this faulty state, definite amount of redundant data are carried out by the three-phase signal resulting in intense difficulties in fault classification from the raw three-phase signal. This barriers drives the researchers to a method namely feature extraction that enables the extraction of non-redundant data from the raw signal. With the help of this method, voltage and current waveforms are synthesized. The simplest form of feature extraction is transforming domain of the voltage and current waveform from time to frequency. To do so, Discrete Fourier Transform (DFT) is used commonly for interpreting the waveforms [9]. This technique is used in two different forms: 1) Full-Cycle DFT and 2) Half-Cycle DFT. Another commonly used method for feature extraction is Discrete Wavelet Transform (DWT) which is used in a specific range of frequency. This technique decomposes the signal into detailed coefficients which are used for feature generation [10]. The features are also created using a combination of principal component analysis, Shannon transform, and discrete wavelet [11]. The efficient use of signal processing based feature extraction methods depend on the specialist's knowledge however, they are found fruitful in fault analysis. Rather than using signals to analyze faults, images are used, which aids in the execution of contemporary object recognition methodologies in the application of power system fault identification [12]. This technique helps to overcome the problems experienced in signal processing based feature extraction.

Over the years, a significant changes have occurred in transmission line fault analysis technique based on feature extraction. As a result of higher accuracy and generalization capabilities, artificial intelligence algorithms are now widely practiced for fault detection and classification in electrical power system. Several kind of artificial neural networks (ANNs) [13]–[18] have been implemented for this purpose where it has been characterized as a single layer or multi layer perception. In order to detect and diagnosis faults in the transmission line, feed-forward neural network (FNN) have been introduced earlier [19]. The FNN is extended to the RBFN with the inclusion of Gaussian activation function and a hidden layer that increases its classification accuracy up to a precise level [20]–[28]. Another form of single-hidden layer FNN is known as Extreme Learning Machine (ELM) is schemed in [29]. The probabilistic neural network (PNN) is another fault diagnosis technique which has been practiced extensively due to its fast training capabilities [30]. The mentioned methods take much time to classify the faults from different models.

For the purpose of addressing the problems concomitant to the state-of-the-art, this paper develops a deep learning model assisted by self attention module for detecting and diagnosing the transmission line fault. The significant contributions of this particular research are as listed below:

- Implementation of the new methodology for the segmentation and monitoring of transmission line faults depend-

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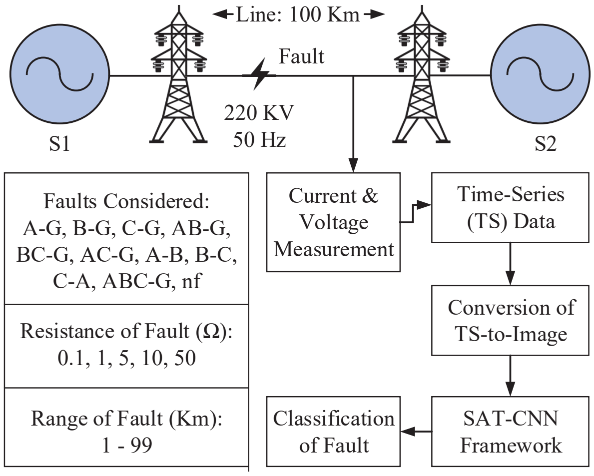

Fig. 1. An elemental functional delineation of the SAT-CNN based fault detection and classification

ing upon the convolutional neural network associated with wavelet transformation that enables the system to train and produce the key parameters effectively from the faulty three-phase information.

- Coordination of the self-attention technique with the suggested CNN to even more appropriately recognize the specific type of faults that allows the framework to conduct concise classification operation.
- For the validation of appropriateness of the proposed SAT-CNN approach, noise is taken into account in preparing the input data.

II. System description with Feature Generation

To design the $3-\varphi$ electrical networking system included in Fig. 1, a 220 kV, 50 Hz power transmission system containing a extent of 100 km was employed. In a MATLAB environment, the network connection is constructed, offering real - time equipment to prepare and analyze the desired information for conducting the FDC process. With a view to detect, the "non-faulty" wave is deliberated as a fault type i.e. associating all the faulty events and the "non-fault" conditions, there exists 11 fault types as presented in Fig. 1. The fault also seems to be known during the performance of the system shifts to a specific fault type. Training for the suggested SAT-CNN involves the use of actual voltage and current signals to perform feature extraction from the produced image. A number of 32,670 current and voltage signals are produced, which are further individually processed and transformed to the image of the time series to obtain the necessary function to identify the fault.

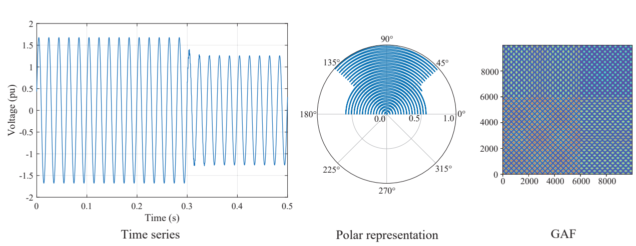

Fig. 2. Time series to GAF conversion stage.

A. Time series to image conversion

As an input, the suggested FDC approach requires the interpreted current and voltage data. The time series based current and voltage input are presented in this analysis as the Gramian-angular-field (GAF), signifying a depiction in the polar coordinate system of the time-series data instead of just the Cartesian system, as portrayed in Fig. 2. The algorithmic flow, to encode the signal into GAF image is manifested in Fig. 3 where the *step:7* and *9* articulates the procedure of polar map translation operation, which is accustomed to compute the commensurate image representation of the time-series. Every parameter across gram-matrix means cosine of the total of angles. Nevertheless, n is the size of actual time-series, where size of the GAF denotes $n \times n$.

III. Proposed Methodology

A. Constitution of the proposed architecture

An input of 64×64 pixel is taken for the proposed deep learning model and then the model performs 11 types of fault classification. A 2D convolutional operation is applied to the input GAF image for feature extraction. With any of the phases of feature extraction, the maximum value is determined by the max-pooling layers.

B. Self attention mechanism

On various computer vision applications, deep CNN methodologies have achieved impressive outcomes, but it is difficult to make a conclusion in the deduction phase of a CNN. When interacting with a large variety of input signals, the small range of the particular distribution for the efficient processing of features causes the convolutional operator troublesome. Therefore, in this study, a deep CNN structure with attentive mechanism (SATT) framework is developed to obtain the protracted dependencies. The SATT mapping are acquired from the extracted features at each convolutional layer where the weight vector of features is regarded as the attention point for all pixel. The self-attention point at a position can be formed as:

$$Y_p = \frac{1}{C\left(X_p\right)} \sum_q s\left(X_p, X_q\right) h\left(X_q\right) \tag{1}$$

where, p indicates the position where the responding is indexed, q enlists the entire position in the current image with different weights. The function s computes the transient severity at p & q. And h presents the input transients at q. The transient at a position p is instantly procured by the fault transients at an appropriate position. Furthermore, a residual-learning strategy is carried out in the attention layer whereas the results acquired from the layer (Z_p) contains 2 elements. One of the function maps the previous convolutional-layer, and the second is the maps of self-attention mechanism dedicated to providing non local data. The α metric handles the learnings that are obtained across all of training from each of these 2 elements in the responding. The α prior value is appointed to 0 and progressively increased during optimizing operation.

Algorithm 1 Enumerate Gramian Angular Field

```
function gramian
    for (each extracted time-series)
        T_min = Determine the min value in time-series order
        T_max = Determine the max value in time-series order
        scale up the time series within [-1,1]
        adjust the floating-point imprecision
        Φ = cos^-1 (resized time series)
        determine the range of the resized time-series
        R = t_s/n(t_s = time stamp and n =regularity constant)
        GAF= arrange (Φ, Φ, cos (Φ_i + Φ_i)
        save rescaled GAF as image
    end
end function
```

Fig. 3. Algorithm of the proposed architecture.

C. Softmax classifier

In FC condition of the system, multi-class classification is supervised by the application of softmax classifier. If there are $\hat{K}$ classes and n defined sample of training, the softmax classifier will create a $\hat{K}$-dimensional vector for every test input, where the elements add to 1. The estimated probability of each class is described by those output vectors from each element and necessary mathematical representation is as follows,

$$\bar{P}(y_i = m|x_i; \bar{W}) = \hat{a}_i = \frac{e^{w_i^T x_i}}{\sum_{j=1}^{\hat{K}} e^{w_j^T x_j}} \tag{2}$$

here, paremeter $\bar{W} = w_1, w_2, w_3, ..., w_k$ is learned from back propagation algorithm. For the softmax classifier, the cost function is formed by the fucntion of cross entropy loss and the depiction is,

$$\bar{J}(\bar{W}) = -\sum_{i=1}^{\hat{N}} \sum_{j=1}^{\hat{K}} y_{ij} \log \left(\frac{e^{w_j^T x_i}}{\sum_{m=1}^{\hat{K}} e^{w_m^T x_i}} \right) \tag{3}$$

here, $\hat{N}$ is the data points' number in the training set. To reduce the cost function to zero, the gradient descent techniue is utilized,

$$\bigtriangledown_{\bar{W}} \bar{J}(\bar{W}) = \sum_{i=1}^{\hat{N}} x_i (\hat{a}_i - y_1)^T \tag{4}$$

IV. Robustness enhancement with noise tolerant feature extraction

A. Signal denoising using wavelet

In discourse, environmental disturbance or statistical irregularities influence the three-phase signals, leading to deteriorated classification efficiency. The wavelet transform is then used to denoise the signals to allow the suggested classifier resist the noise. It is the breakdown of the transients to the element sequence where the analogous signal to a time-domain is presented by each transient. In this study, this turning in wavelet transformation is used to demonstrate the properties of a signal throughout the state of the fault. Here, the l and m indicate the integer variable and a_0^m, $la_0^m b_0$ is the scale and time shift parameter. The a_0 and b_0 parameters are considered as 2 and 1 in respective.

In this research, the measured fault signals are incorporated to the additive white Gaussian noise (AWGN) and are provided as an input to the multi-resolution wavelet transform analysis to acquire the elements of the estimation and information relating to the faulty signal information. The Daubechies (dB4) mother wavelet is implemented as it is proven to be carried out adequately from the comprehensive coefficient of level three.

B. Investigation of performance for the proposed classifier

For achieving the evaluation of efficacy of the suggested FDC strategy while confronting contemporary noises in the measurement of signal, which are contaminated with additional noise with a certain signal-to-noise ratio (SNR). The precomputed dataset is now attributed to as dataset-I and is used to train the SAT-CNN. On the other hand, dataset-II is attributed to as the newly created dataset, and is utilized for assessment of the model accompanied by wavelet denoiser. This scheme rebuilds the initial signal, executes the imaging operation of the time series, and then, estimates the fault type in accordance with the input image. A comparative analysis of the SAT-CNN and denoising SAT-CNN classification accuracies is demonstrated in Fig.5 at a sampling frequency of 20 Hz. From the figure, it can be observed that the accuracy of the denoising model for a particular SNR values is not below than 97%, that is in relation to the line of anticipation. Contrarily, for the SAT-CNN architecture, a drop in classification results has been observed at a small SNR value. The SAT-CNN architecture executes the classification of faults with more than 91.26% accuracy, at 10 dB SNR.

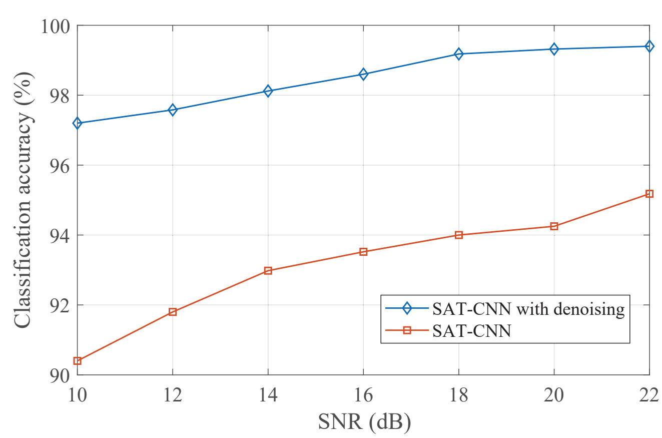

Fig. 4. Variation of classifiction accuracy for SAT-CNN and SAT CNN with the wavelet denoising.

V. Conclusion

This paper develops a novel technique for the identification and categorization of transmission line faults. For detection and classification tasks, the envisaged DBN process employs both the three-phase current and voltage waveforms. The substantial benefit of the implemented approach is that it can obtain information dynamically from the fault information that eventually improves the system's generalization ability. The findings performed in this study prove that for all forms of fault, the suggested technique categorizes faults with precision near 100%. The output of various sampling frequencies and signal types included shows that it is possible to obtain desirable results by using both current and voltage signals inside the frequency range considered. The effectiveness of the presented method is subsequently evaluated by using the error variance disturbance to clarify the classifier's capacity to resist. Authentic information obtained by the equipment installed in the functional power network may be considered in the future development of the classifier.

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