

# Detection and Localization of Transmission Line Faults based on a Hybrid Two-Stage Technique considering Wind Power Generation

Shahabodin Afrasiabi, Mousa Afrasiabi,  
Behzad Behdani, Mohammad Mohammadi  
*Shiraz University*  
Shiraz, Iran

shpower77@yahoo.com, {musa.afra, b.behdani,  
m.mohammadi}@shirazu.ac.ir

Mohammad S. Javadi  
*INESC TEC*  
Porto, Portugal  
msjavadi@gmail.com

Gerardo J. Osório  
*REMIT/UPT and*  
*C-MAST/UBI*  
Covilhã, Portugal  
gjosilva@gmail.com

João P. S. Catalão  
*FEUP and INESC TEC*  
Porto, Portugal  
catalao@fe.up.pt

**Abstract**—The conflicting issues of growing demand for electrical energy versus the environmental concerns have left the energy industries practically with one choice: to turn into renewable energies. This duality has also highlighted the role of power transmission systems as energy delivery links in two ways, considering the increased demand of load centers, and the integration of large-scale renewable generation units connected to the transmission system such as wind power generation. Accordingly, it has become even more vital to provide reliable protection for the power transmission links. The present protection methods are associated with deficiencies e.g., acting based on a predefined threshold, low speed, and the requirement of costly devices. A two-stage data-driven-based methodology has been introduced in this paper to deal with such defects, considering wind power generation. The proposed approach utilizes a powerful feature extraction technique, namely the *t*-distributed stochastic neighbor embedding (*t*-SNE) in the first stage. In the second stage, the extracted features are fed to a robust soft learning vector quantization (RSLVQ) classifier to detect and locate transmission line faults. The WSCC 9-bus system is used to evaluate the performance of the proposed data-driven method during various system operating conditions. The obtained results verify the promising capability of the proposed approach in detecting and locating transmission line faults.

**Keywords**—*Fault Detection and Location, Robust Soft Learning Vector Quantization (RSLVQ), t-Distributed Stochastic Neighbor Embedding (t-SNE), Transmission System*

## I. INTRODUCTION

Transmission systems are prone to various disturbing factors, most importantly, the occurrence of short circuit faults. In order to preserve the safe and reliable operation of the power system, a fast and accurate fault detection scheme is necessary. As the population grows and the electrical energy demand increases accordingly, the protection of power transmission links becomes significantly important.

On the other hand, the present trend towards the integration of power networks with renewable energy sources has added a layer of complexity to the aforementioned issue. In addition, large-scale wind power generation units positioned in relatively remote areas, are necessarily connected to the network through a power transmission link, and thus are of high importance to protect. Failure in fast and accurate detection of faults in power systems greatly impacts the reliability of the power system's supply continuity [1]. Subsequent to fault detection, the protective devices try to isolate fault by disconnecting the faulty section.

In this regard, by determining the location of the faults, the reliability of the system can be enhanced by minimizing the disconnected sections and reducing service disconnection time [2]. Various methodologies have been so far proposed for the protection of transmission lines, which can be categorized into four main groups, given by traveling waves, time-domain analysis, phasor analysis, and data-driven methods. In the following, each group is explained.

At the instance of fault occurrence in the power network, current and voltage traveling waves are generated in the fault location. A group of methods have utilized such a concept to detect and locate power system faults. In [1], an algorithm is proposed for the classification of various fault types. The authors in [3] have proposed a traveling-wave-based fault location technique in distribution networks. The main disadvantage of these methods is the requirement to measure several frequency components. Moreover, advanced measurement devices with high sampling rates are needed.

The phasor-based fault detection schemes mainly benefit from the measurement of phasor components of the voltages and currents. In [4], an impedance-based method was introduced which is realized by frequency analysis of the system in harmonic orders other than the fundamental component. Authors in [5] have proposed an analytical method based on impedance calculation for determining fault locations. This method is realized by voltage and current measurements at the terminal of the transmission line. In this method, the symmetrical components of the three phases have been separated by modal analysis. The methodologies in this group defect depending on a predefined threshold. Moreover, the majority of these approaches are model-based.

The third group of methods utilize the direct voltage and current measurements in the time domain. A time-domain-based method was introduced in [6], which is independent of the line parameters for fault location, thus making it insensitive to transmission line parameters. This method utilizes voltage and current measurements and acts upon the distributed model of the transmission line. The method in [7] is a time-domain-based technique that can perform without needing to determine fault type in the presence of series compensation, which mainly results in the increase of the system's complexity level [8]. In [9], a metaheuristic teaching-learning-based optimization (TLBO) algorithm is proposed as a time-domain-based approach for fault detection in two-terminal transmission circuits. The fast solution of the fault location problem within several milliseconds is very complicated and computationally expensive. These methods are generally not suitable due to their high computational burden.

J.P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under POCI-01-0145-FEDER-029803 (02/SAICT/2017). G.J. Osório acknowledges the support by UIDB/00151/2020 research unit (C-MAST) funded by FCT.

Considering the complex nature of the power networks on the one hand, and the sudden variation of measured parameters at the instance of fault, on the other hand, a more complex structure is required to adequately analyze these data. The methods in the above three categories are unable to handle the complexities associated with the problem of detecting and locating faults in power networks. In this context, by the enhancement of the power systems' processing capabilities, the cost of data-driven methods has significantly reduced [10]. Accordingly, various methods have been proposed given by, fuzzy logic [11], incorporating artificial neural networks (ANNs) with the Fourier transform [12], [13], combining wavelet transform (WT) and ANN for detecting faults in multi-terminal transmission systems [14], adaptive neuro-fuzzy inference system (ANFIS) [15], decision tree (DT) [16], support vector machine (SVM) [17], and k-nearest neighbor (KNN) [18].

Table I gives a summary of the various fault diagnosis methodologies described above. The data-driven approaches generally require feature extraction to perform. The protection methods based on these approaches are not solely capable of learning and being properly trained the complex and varying behaviors reflected by the signal datasets. The majority of the present data-driven methodologies have employed methods for spectral feature extraction such as the Fourier transform and the wavelet transform. However, these techniques are highly noise-sensitive [19], making them improper for the power system applications, as for being subjected to noise. In this paper, this problem has been tackled by conducting the feature extraction based on t-SNE.

In addition, this study proposes a powerful fault detection and location technique based on an RSLVQ classifier [20], as an enhanced probabilistic version of the simple LVQ. The LVQ is a supervised artificial neural network that is realized by a codebook vector collection, being able to handle both binary and multiclass diagnosis problems. RSLVQ deals with the problem of LVQ to minimize the classification error through a solely heuristic process.

## II. PROPOSED METHOD

The proposed transmission line protection scheme is constituted of two stages. At the first stage, subsequent to anomaly detection, the powerful feature extraction method of t-SNE is used to extract the features of the measured signals. In the second stage, the features extracted within the first stage are fed to an RSLVQ classifier to specify the occurrence of the fault together with its type and location. In the following, the basics of the t-SNE feature extractor and the RSLVQ classifier are introduced.

### A. The t-SNE feature extractor

The t-SNE method is essentially an unsupervised nonlinear method applied for the extraction and visualization of features. This method generally determines the similarity between dataset samples with large dimensions. The main idea of the t-SNE is the utilization of the probability density between two points with high dimension and low dimension. The highest similarity is determined by an objective function based on the Kullback Leibler (KL) divergence. This method is implemented as follows.

Considering the measured points by the power system's phasor measurement unit (PMU) as  $\{x_1, x_2, \dots, x_N\}$ , the probability of similarity between two points is as:

TABLE I. BRIEF DESCRIPTION OF FAULT LOCATION METHODS IN TRANSMISSION NETWORKS

	Description	Advantage	Disadvantage
<b>Travelling-wave</b>	Generated current and voltage travelling wave	Stable and fast performance	Requirement to advanced measurement devices with high sampling frequencies
<b>Impedance-based</b>	Measured voltage and current signals to compute impedance or sequence component of impedance before/during/after fault occurrence An optimization distance function based on difference between distributed transmission line model and measured signals	Not sensitive to measurement devices	require predefined threshold and a precise transmission line parameters
<b>Time-domain based</b>		Do not require to a predefined threshold	High-computational burden
<b>Data-driven</b>	Training based on historical data	Fast and do not depend on predefined threshold and physical model of the transmission network	Require feature extraction/selection to perform

$$p_{ij} = \frac{\exp\left(\frac{-\|x_j - x_i\|^2}{2\sigma_j}\right)}{\sum_{k=1, k \neq j}^N \exp\left(\frac{-\|x_j - x_k\|^2}{2\sigma_j}\right)} \quad (1)$$

$$p_{ji} = \frac{\exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma_i}\right)}{\sum_{k=1, k \neq i}^N \exp\left(\frac{-\|x_i - x_k\|^2}{2\sigma_i}\right)} \quad (2)$$

where  $p_{ij}$  and  $p_{ji}$  show the likelihood of two different measurement points in the system, while  $\sigma_j$  represents the variance vector of Gaussian distribution considering  $j$  as the center point. Therefore, joint probability between two samples throughout a Gaussian space is defined as:

$$p_{ij} = \frac{p_{ij} + p_{ji}}{2N} \quad (3)$$

In lower dimensions, the t distribution with 1 degree of freedom is used. Thereafter, the joint PDFs,  $q_{ij}$  from the measurement signals in transmission networks, corresponding to the set  $\{y_1, y_2, \dots, y_N\}$  is:

$$q_{ij} = \frac{(1 + \|y_i - y_j\|^2)^{-1}}{\sum_{k=1, k \neq l}^N (1 + \|y_k - y_l\|^2)^{-1}} \quad (4)$$

The similarity between  $q_{ij}$  and  $p_{ij}$  is calculated based on the KL divergence criterion as:

$$C = \text{KL}(P||Q) = \sum_{i=1}^N \sum_{j=1}^N p_{ij} \log_2 \frac{p_{ij}}{q_{ij}} \quad (5)$$

In order to maximize the similarity, the KL divergence index should be minimized. Accordingly, the gradient descent optimization, the following has resulted:

$$\frac{\delta C}{\delta y_i} = 4 \sum_{j=1}^N (p_{ij} - q_{ij}) (y_j - y_i) (1 + \|y_i - y_j\|^2)^{-1} \quad (6)$$

Then, t-SNE gives a set of selected features from measured raw data by measurement devices in the networks, given as  $\{y'_1, y'_2, \dots, y'_N\}$ .

### B. The RSLVQ classifier

The RSLVQ, being essentially a probabilistic robust soft LVQ, is developed as a tool to enhance the basic LVQ considering heuristic reasons [21]. The classification capability of the basic LVQ with small-size datasets in the training stage, and its ability to be incorporated with other AI-based classifiers, show its superiority tool comparing to typical classification methods [20]-[22]. Therefore, RSLVQ is expected to introduce a much better performance.

Primarily, each of the classes labeled with ‘‘correct’’ and ‘‘incorrect’’ is assumed to have Gaussian mixture probability density functions (PDFs). Afterward, calculating the logarithmic ratio between the PDFs of the classes marked by correct and incorrect, a cost function is established, constituting two terms corresponding to the logarithmic probabilities of the correct and incorrect classes. The RSLVQ tool implemented here is defined by a modified cost function according to [20], as given by equation (7),

$$\begin{aligned} f_{\text{RSLVQ}} &= \prod_{k=1}^N \frac{P(X_k, Y_k \setminus \Gamma)}{P(X_k, Y_k \setminus \Gamma) + P(X_k, Y'_k \setminus \Gamma)} \\ &= \prod_{k=1}^N \frac{P(X_k, Y_k \setminus \Gamma)}{P(X_k \setminus \Gamma)} \end{aligned} \quad (7)$$

where the total number of samples is denoted by  $N$ . Here,  $X_k = \{i_k, \theta_k, v_k, \varphi_k\}$  and  $Y = \{c_j, c_{ln}\}$  are considered as the input set and label set, respectively. The quantities  $i_k, t_k, v_k$ , and  $\varphi_k$  correspond to the normalized measured gradient vectors of line current, line current angle, line voltage, and line voltage angle values in sample  $k$ . The dataset of the normal condition is marked by  $c_j$  for all the conditions, while  $c_{ln}$  corresponds to the dataset of fault types for the case of fault type determination, and to the dataset of the number of the faulty line for the case of fault location determination. The nearest prototype classifier  $\Gamma = \{(L_{f/ln}, c_{f/ln})\}$  is defined to consist of the data space vectors, i.e., non-fault plus fault type and faulty line number datasets, and their respective class labels. With the implemented cost function of RSLVQ, i.e.,  $f_{\text{RSLVQ}}$ , the correct classification rate is maximized, and the misclassification rate is minimized. Considering that the cost function is bound to an interval between 0 and 1, it should be optimized for the logarithm as:

$$\log(f_{\text{RSLVQ}}) = \sum_{k=1}^N \log \frac{P(X_k, Y_k \setminus \Gamma)}{P(X_k, Y'_k \setminus \Gamma)} \quad (8)$$

Stochastic gradient ascent is used for learning rule update:

$$L_{f/ln}(t+1) = L_{f/ln}(t) + \alpha(t) \frac{\partial}{\partial L_{f/ln}} \left\{ \log \frac{P(X, Y \setminus \Gamma)}{P(X \setminus \Gamma)} \right\} \quad (9)$$

where the learning rate is denoted by  $\alpha(t)$ . Thus, the learning rule is achieved by calculating the gradient as:

$$\begin{aligned} L_{f/ln}(t+1) &= L_{f/ln}(t) \\ &+ \alpha(t) \begin{cases} (P_Y(1 \setminus X) - P(1 \setminus X)) \left[ \frac{\partial f(X, L_{f/ln})}{\partial L_{f/ln}} \right], & c_1 = Y \\ -P(1 \setminus X) \left[ \frac{\partial f(X, L_{f/ln})}{\partial L_{f/ln}} \right], & c_1 \neq Y \end{cases} \end{aligned} \quad (10)$$

where the probability of  $X$  being assigned to the mixture’s component 1 corresponding to the correct class, and all classes is described by assignment probabilities  $P_Y(1 \setminus X)$  and  $P(1 \setminus X)$  as:

$$P_Y(1 \setminus X) = \frac{P(1) \exp f(X, L_{f/ln})}{\sum_{\{j:c_j=Y\}} P(j) \exp f(X, L_{f/ln,j})} \quad (11)$$

$$P(1 \setminus X) = \frac{P(1) \exp f(X, L_{f/ln})}{\sum_{j=1}^2 P(j) \exp f(X, L_{f/ln,j})} \quad (12)$$

Selecting a Gaussian mixture model by components of the same widths and strengths in conditional probabilities, we get:

$$f(X, L_{f/ln}) = \frac{-(x - L_{f/ln})^2}{2\sigma^2} \quad (13)$$

$$\frac{\partial}{\partial L_{f/ln}} f(X, L_{f/ln}) = \frac{(x - L_{f/ln})}{\sigma^2} \quad (14)$$

$$P_Y(1 \setminus X) = \frac{\exp \left( \frac{-(x - L_{f/ln})^2}{2\sigma^2} \right)}{\sum_{\{j:c_j=Y\}} \exp \left( \frac{-(x - L_{f/ln,j})^2}{2\sigma^2} \right)} \quad (15)$$

$$P(1 \setminus X) = \frac{\exp \left( \frac{-(x - L_{f/ln})^2}{2\sigma^2} \right)}{\sum_{j=1}^M \exp \left( \frac{-(x - L_{f/ln,j})^2}{2\sigma^2} \right)} \quad (16)$$

Consequently, we achieve the learning rule as:

$$\begin{aligned} L_{f/ln}(t+1) &= L_{f/ln}(t) \\ &+ \frac{\alpha(t)}{2\sigma^2} \begin{cases} (P_Y(1 \setminus X) - P(1 \setminus X))(X - L_{f/ln}), & c_1 = Y \\ -P(1 \setminus X)(X - L_{f/ln}), & c_1 \neq Y \end{cases} \end{aligned} \quad (17)$$

where the softness factor is denoted by a positive constant,  $\sigma$ .

### III. NUMERICAL RESULTS

The proposed method has been implemented and tested on the WSCC 9 bus system in the presence of the wind energy generation unit. The system under study, depicted in Fig. 1, is a modified version of the standard WSCC 9 bus system where a wind energy generation unit is added to the bus-7 of the network. The network information is adopted from [23].

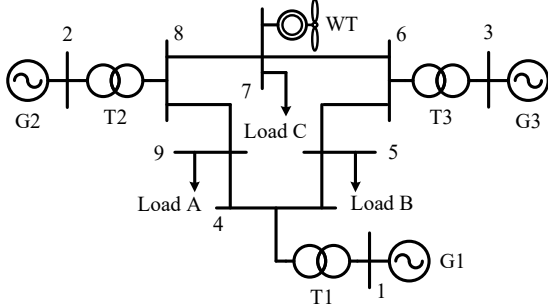


Fig. 1: Modified WSCC 9 bus system in presence of wind power generation.

For training, we generate a comprehensive dataset based on different fault types, different fault locations, fault inception times, and a dataset for the normal condition based on the stochastic characteristic of load consumption and the wind generation unit. The load consumption and wind power are constructed using forecasted probability density functions (PDFs) in our previous works in [24] and [25], respectively. Overall, 1440 different data has been generated, where about 70% and 30% of data is devoted to the training and testing processes, respectively. DIGSILENT was used to generate the datasets and their processing was conducted in MATLAB. To evaluate the performance of the method, confusion matrixes are used. There are four principal components integrated into the confusion matrix consists, given as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) 0.

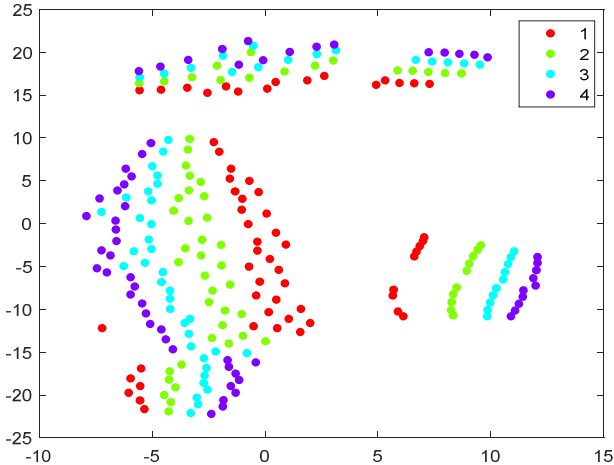


Fig. 2: t-SNE results on fault type identification in line #3.

TABLE II. CONFUSION MATRIX OBTAINED BY THE PROPOSED HYBRID METHOD FOR FAULT TYPE IDENTIFICATION IN LINE #3

	A'	B'	C'	D'	SUM
A	19	0	0	0	19
B	0	18	0	0	18
C	0	0	21	0	21
D	0	0	0	14	14
Total Sample	19	18	21	14	72

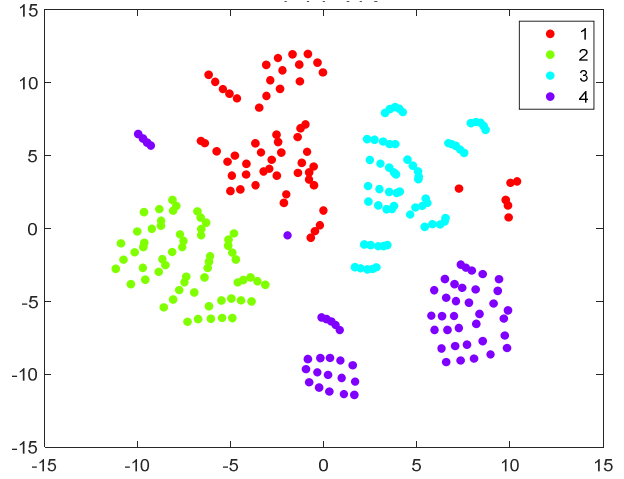


Fig. 3: The t-SNE results on fault location in line #3.

TABLE III. CONFUSION MATRIX OBTAINED BY THE PROPOSED HYBRID METHOD FOR FAULT LOCATION IDENTIFICATION

	A'	B'	C'	D'	SUM
A	15	1	0	0	15
B	1	11	2	0	11
C	0	1	15	0	15
D	0	0	2	15	15
Total Sample	15	11	15	15	56

#### A. Discussion on Result: Fault Type Identification

In this subsection, the results obtained for line number 3 (line connected from bus 8 to WT) are selected as a sample to evaluate the proposed structure. The results of t-SNE for fault type identification including non-faulty condition (Class A), 3-phase faults (Class B), two-phase faults (Class C), and single-line-to-ground faults (Class D), have been depicted in Fig 2. As can be seen from this illustration, fault type can be clearly distinguished based on the output of t-SNE. Therefore, Fig 2. shows that t-SNE is an appropriate feature selection method for fault type identification in the transmission networks.

The confusion matrix obtained by the proposed hybrid method is given in Table II. As can be seen, the accuracy of the proposed method in line #3 is 100% by distinguishing all fault types correctly.

#### B. Discussion on Result: Fault Location Identification

The fault location results are given in this subsection. Four different locations have been considered in this paper; thus, the fault location problem is solved as a four-class classification problem with classes marked as A, B, C, and D. Fig. 3 illustrates the output of t-SNE as a strong feature selection method. The t-SNE outputs are clearly discriminated by t-SNE and it can significantly enhance the classifier's accuracy.

The confusion matrix for fault location is depicted in Table III. As can be seen, the hybrid method detects all 168 different conditions accurately. Thus, the proposed method performs perfectly, accuracy = 100%. The highly accurate results validate the great potential of the proposed hybrid method in the fault localization in the distribution networks. It should be noted that the chosen line is connected to the wind generators.

#### IV. CONCLUSION

A hybrid two-stage technique based on t-SNE and RSLVQ has been proposed to detect faults in transmission lines. In this method, first, the faulty type is identified from the dispatching center of the network. Afterward, using the data measured from one terminal of the line, the location of the fault is specified. The proposed approach is implemented and tested on the WSCC 9 bus transmission system in the presence of the wind energy generation unit. The results from the confusion matrix for the fault location along line #3 of the test system demonstrate the promising capability of the protection scheme proposed for fault type and location identification. Therefore, the capability of the proposed method is verified for transmission networks even in the presence of wind power generation units.

#### REFERENCES

- [1] S. Afrasiabi, M. Afrasiabi, M. Mohammadi, B. Parang, "Fault localisation and diagnosis in transmission networks based on robust deep Gabor convolutional neural network and PMU measurements" *IET Generation, Transmission & Distribution*, vol. 14, no. 26, pp. 6484-6492, Dec. 2020, doi: 10.1049/iet-gtd.2020.0856.
- [2] S. Afrasiabi, M. Afrasiabi, B. Parang, M. Mohammadi, "Designing a composite deep learning based differential protection scheme of power transformers" *Applied Soft Computing*, vol. 87, Feb. 2020, doi: j.asoc.2019.105975.
- [3] L. Xie, L. Luo, Y. Li, Y. Zhang and Y. Cao, "A Traveling Wave-Based Fault Location Method Employing VMD-TEO for Distribution Network," in *IEEE Transactions on Power Delivery*, vol. 35, no. 4, pp. 1987-1998, Aug. 2020, doi: 10.1109/TPWRD.2019.2959188.
- [4] F. M. Aboshady, D. W. P. Thomas, and M. Sumner, "A new single end wideband impedance based fault location scheme for distribution systems," *Elec. Pow. Syst. Research*, vol. 173, pp. 263-270, Aug. 2019, doi: 10.1016/j.epsr.2019.04.034.
- [5] M. A. Gabr, D. K. Ibrahim, E. S. Ahmed, and M. I. Gilany, "A new impedance-based fault location scheme for overhead unbalanced radial distribution networks," *Electric Power Systems Research*, vol. 142, pp. 153-162, Jan. 2017, doi: 10.1016/j.epsr.2016.09.015.
- [6] M. Davoudi, J. Sadeh, and E. Kamyab, "Parameter-free fault location for transmission lines based on optimisation," *IET Generation, Transmission & Distribution*, vol. 9, no. 11, pp. 1061-1068, Aug. 2015, doi: 10.1049/iet-gtd.2014.0425.
- [7] M. Ghazizadeh-Ahsae, "Time-domain based fault location for series compensated transmission lines without requiring fault type," *Electric Power Systems Research*, vol. 181, p. 106171, Apr. 2020, doi: 10.1016/j.epsr.2019.106171.
- [8] B. Behdani, M. Allahbakhshi, M. Tajdinian, "On the impact of geomagnetically induced currents in driving series capacitor compensated power systems to ferroresonance," in *International Journal of Electrical Power & Energy Systems*, vol. 125, Feb. 2021, doi: 10.1016/j.ijepes.2020.106424.
- [9] F. Poudineh-Ebrahimi and M. Ghazizadeh-Ahsae, "Accurate and comprehensive fault location algorithm for two-terminal transmission lines," *IET Generation, Transmission & Distribution*, vol. 12, no. 19, pp. 4334-4340, Sep. 2018, doi: 10.1049/iet-gtd.2018.6084.
- [10] V. H. Ferreira et al., "A survey on intelligent system application to fault diagnosis in electric power system transmission lines," *Electric Power Systems Research*, vol. 136, pp. 135-153, Jul. 2016, doi: 10.1016/j.epsr.2016.02.002.
- [11] M. Afrasiabi, S. Afrasiabi, B. Parang, and M. Mohammadi, "Power transformers internal fault diagnosis based on deep convolutional neural networks," *Journal of Intelligent & Fuzzy Systems*, vol. 37, no. 1, pp. 1165-1179, Jul. 2019, doi: 10.3233/JIFS-182615.
- [12] B. Behdani, M. Allahbakhshi and M. Tajdinian, "A Method for Measurement, and Monitoring of Earth Return Current Flow in Medium Voltage Transformers," *2020 28th Iranian Conference on Electrical Engineering (ICEE)*, 2020, pp. 1-5, doi: 10.1109/ICEE50131.2020.9260629.
- [13] Y. Aslan and Y. E. Yağın, "Artificial neural-network-based fault location for power distribution lines using the frequency spectra of fault data," *Electrical Engineering*, journal article vol. 99, no. 1, pp. 301-311, Mar. 2017, doi: 10.1007/s00202-016-0428-8.
- [14] B. Rathore and A. G. Shaik, "Wavelet-alienation based protection scheme for multi-terminal transmission line," in *Electric Power Systems Research*, vol. 161, pp. 8-16, Aug. 2018, doi: 10.1016/j.epsr.2018.03.025.
- [15] A. Yadav and A. Swetapadma, "A single ended directional fault section identifier and fault locator for double circuit transmission lines using combined wavelet and ANN approach," *International Journal of Elec. Pow. & Ener. Syst.*, vol. 69, pp. 27-33, Jul. 2015, doi: 10.1016/j.ijepes.2014.12.079.
- [16] A. Swetapadma and A. Yadav, "A Novel Decision Tree Regression-Based Fault Distance Estimation Scheme for Transmission Lines," in *IEEE Transactions on Power Delivery*, vol. 32, no. 1, pp. 234-245, Feb. 2017, doi: 10.1109/TPWRD.2016.2598553.
- [17] P. Ray and D. P. Mishra, "Support vector machine based fault classification and location of a long transmission line," *Engineering Science and Technology, an International Journal*, vol. 19, no. 3, pp. 1368-1380, Sep. 2016, doi: 10.1016/j.jestch.2016.04.001.
- [18] A. Asadi Majd, H. Samet, and T. Ghanbari, "k-NN based fault detection and classification methods for power transmission systems," *Protec. and Control of Modern Pow. Syst.*, vol. 2, no. 1, p. 32, Jan. 2017, doi: 10.1186/s41601-017-0063-z.
- [19] S. Afrasiabi, M. Afrasiabi, B. Parang and M. Mohammadi, "Integration of Accelerated Deep Neural Network Into Power Transformer Differential Protection," in *IEEE Transactions on Industrial Informatics*, vol. 16, no. 2, pp. 865-876, Feb. 2020, doi: 10.1109/TII.2019.2929744.
- [20] T. Villmann, M. Biehl, A. Villmann and S. Saralajew, "Fusion of deep learning architectures, multilayer feedforward networks and learning vector quantizers for deep classification learning," *2017 12th International Workshop on Self-Organizing Maps and Learning Vector Quantization, Clustering and Data Visualization (WSOM)*, 2017, pp. 1-8, doi: 10.1109/WSOM.2017.8020009.
- [21] S. Seo and K. Obermayer, "Soft Learning Vector Quantization," *Neural Comput.*, vol. 15, no. 7, pp. 1589-1604, Jul. 2003, doi: 10.1162/089976603321891819.
- [22] D. Hofmann, A. Gisbrecht, and B. Hammer, "Efficient approximations of robust soft learning vector quantization for non-vectorial data," *Neurocomputing*, vol. 147, pp. 96-106, Jan. 2015, doi: 10.1016/j.neucom.2013.11.044.
- [23] A. Mitra and D. Chatterjee, "Active Power Control of DFIG-Based Wind Farm for Improvement of Transient Stability of Power Systems," in *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 82-93, Jan. 2016, doi: 10.1109/TPWRS.2015.2397974.
- [24] M. Afrasiabi, M. Mohammadi, M. Rastegar, L. Stankovic, S. Afrasiabi and M. Khazaei, "Deep-Based Conditional Probability Density Function Forecasting of Residential Loads," in *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3646-3657, July 2020, doi: 10.1109/TSG.2020.2972513.
- [25] M. Afrasiabi, M. Mohammadi, M. Rastegar and S. Afrasiabi, "Advanced Deep Learning Approach for Probabilistic Wind Speed Forecasting," in *IEEE Transactions on Industrial Informatics*, vol. 17, no. 1, pp. 720-727, Jan. 2021, doi: 10.1109/TII.2020.3004436.