Data-Driven Intermittent Earth Fault Detection in Compensated and Isolated MV Networks

Author(s): Razmi, Peyman; Pashaei, Meysam; Karimi, Mazaher; Kauhaniemi, Kimmo; Godoy Simoes, Marcelo

Title: Data-Driven Intermittent Earth Fault Detection in Compensated and Isolated MV Networks

Year: 2024

Version: Accepted manuscript

Please cite the original version:

Razmi, P., Pashaei, M., Karimi, M., Kauhaniemi, K. & Godoy Simoes, M. (2024). Data-Driven Intermittent Earth Fault Detection in Compensated and Isolated MV Networks. *2024 International Workshop on Artificial Intelligence and Machine Learning for Energy Transformation (AIE)*, 1-6. IEEE. https://doi.org/10.1109/AIE61866.2024.10561426

Data-Driven Intermittent Earth Fault Detection in Compensated and Isolated MV Networks

Peyman Razmi*[1], Meysam Pashaei*[1], Mazaher Karimi[1], Kimmo Kauhaniemi[1], Marcelo Godoy Simoes[1]
[1]School of Technology and Innovations University of Vaasa, Vaasa, Finland

***Abstract*—Finnish Distribution System Operators (DSOs) have extensive experience in operating compensated or isolated Medium Voltage (MV) networks. Intermittent earth faults, which can potentially lead to permanent ones, are a common phenomenon in MV underground cables, which can be attributed to a variety of factors including the natural aging process of the equipment, electrical overstress, mechanical deficiencies, unfavorable environmental conditions, chemical pollution, moisture ingress, poor insulation, and loose connections. Condition monitoring and early detection of such faults are crucial, especially with the increasing use of underground cabling to enhance the security of electricity supply. These measures can enable DSOs to carry out preventative maintenance, which in turn can reduce system interruptions and improve the delivery of MV electricity. This research aims to explore the effectiveness ML-based techniques and supervised learning namely multilayer perceptron (MLP), support vector machines (SVM), Long short term memory (LSTM) and Decision Tree algorithms in classification and detection of intermittent earth fault in an MV 20kV distribution system.**

***Index Terms*—Intermittent earth fault, earth fault, MV networks, compensated network, supervised learning**

I. Introduction

THE detection and location of Earth faults, which account for approximately 50-80% of faults in Nordic countries, have consistently posed a challenge for Distribution System Operators (DSOs) [1]. This is particularly the case in Finland, where close to 80% of the 20kV Medium Voltage (MV) networks are isolated and a 20 % of them are compensated. Both these types of networks are characterized by a low level of fault current [2]. These low-level earth fault currents often present difficulties for conventional functions such as the directional earth fault and residual overvoltage. However, the residual overvoltage function has a higher chance of detection due to the more stable behaviour [3]. What deteriorates the situation is intermittent earth faults, which often go unnoticed by traditional protection relays [4]. Traditional phasor-based relaying algorithms typically either dismiss high-frequency sampled signals of intermittent earth fault as noise or continually cycle between starting and resetting [5]. Instances of false starts for permanent earth fault function can also occur when intermittent earth faults are present in the network. This necessitates enhancing the security of the protection system by appropriately setting the pick-up and drop-off parameters [3].

*Peyman Razmi (e-mail: peyman.razmi@uwasa.fi).
*Meysam Pashaei (e-mail: meysam.pashaei@uwasa.fi).
Mazaher Karimi (e-mail: mazaher.karimi@uwasa.fi).
Kimmo Kauhaniemi (e-mail: kimmo.kauhaniemi@uwasa.fi).
Marcelo Godoy Simoes (e-mail: marcelo.godoy.simoes@uwasa.fi).

Intermittent or restriking earth faults, with changing magnitude of spikes in unpredictable intervals, are predominantly found in compensated and isolated MV networks with underground cabling [3]. These faults can be attributed to various factors such as the aging process, electrical overstress, mechanical deficiencies, unfavorable environmental conditions, chemical pollution [6], moisture, poor insulation, loose connections, and destructive tests like insulation tests. Incipient faults, which is the early stage of earth fault development, characterized by low current, typically have a short duration that ranges from a quarter cycle (referred to as a sub-cycle incipient earth fault) to a multi-cycle one, generally 1 to 4 cycles [4,6]. This intermittent occurrence can affect the power quality of customers, leading to customer discontentment [7, 8]. Furthermore, due to the inability of traditional relays to detect intermittent earth faults, these faults will most likely be followed by a permanent earth fault or other types of faults if Distribution System Operators (DSOs) do not take preventative measures such as earth fault prediction, which can include the detection of intermittent earth faults [4,6,9]. Therefore, to improve the reliability of energy supply in medium-voltage (MV) distribution networks, it is essential to implement condition monitoring (CM) and predictive maintenance (PM) strategies. Condition monitoring (CM) provides distribution system operators (DSOs) with the opportunity to schedule maintenance and thereby minimize system outages [10]. The early detection of intermittent faults assists DSOs in planning maintenance to prevent these faults from becoming permanent. These include a comprehensive review of earth fault and intermittent fault detection and location methods in both isolated and compensated networks [11]. The methods examined include centralized approaches like impedance-based, artificial intelligence-based, and traveling wave-based methods, alongside decentralized approaches such as signaling, fault passage indication (FPI), and relay-based methods [11]. Fault location is also suggested based on sections, directional overcurrent and fault passage indicators (FPI). Altonen and Wahlroos have proposed a universal method for earth fault detection, referred to as multi-frequency admittance-based earth fault detection. This method is capable of detecting both restriking (intermittent) and permanent earth faults [12, 13]. Druml et al. have conducted field experiments to further investigate intermittent faults in MV systems. The findings from these studies can provide valuable insights to grid operators, particularly in rural areas where reliable information about the direction of earth faults is crucial [6,14]. Despite the proposal of various techniques in the time, frequency, and time-frequency domains, and the substantial advancements leading to commercial functions in relays, there remains a significant opportunity for enhancing the precision of detection and location of intermittent earth faults. This improvement can further bolster the security and selective operation of these functions. The advancement of artificial intelligence techniques over the past decade has led to their widespread use in condition monitoring and preventative maintenance. These techniques are capable of predicting emerging fault issues in medium-voltage distribution networks and developing automated tools for monitoring the condition of power system assets [15, 16]. Furthermore, due to the absence of distinctive fault features, artificial intelligence techniques, such as neural networks, have become a focal point of research [15, 16]. Therefore, due to the limitations identified in existing research, including the low performance of phasor-based methods in handling high-frequency sampled signals related to intermittent earth faults and the challenge of detecting short-duration and sometimes low-level incipient faults in isolated or effectively-grounded networks, this study aims to address these gaps. Leveraging machine learning (ML)-based techniques and a feature selection approach, we propose a new method for detecting intermittent earth faults. Additionally, we conduct a comparative analysis of various methods, including multilayer perceptron (MLP), support vector machines (SVM), Long short term memory (LSTM), Recurrent Neural network (RNN), and decision trees (DT). By bridging these research gaps, we contribute to advancing fault detection strategies in power systems, which can be particularly utilized at the edge or cloud in future centralized protection and control schemes.

II. METHODOLOGY

A. Data Generation process

The single line diagram of the test system is illustrated in Figure 1. The study focused on exploring the influence of intermittent earth faults by choosing different configurations within the simulated test system. A series of tests were conducted by altering several variables to simulate these ground faults: The study incorporated faults at varying resistance levels, specifically setting the resistance values at 0 ohms, 100 ohms, and 200 ohms. Fault occurrences were set at durations of 0.1 seconds, 0.2 seconds, and 0.3 seconds. Furthermore, the study differentiated the cable lengths into short, medium, and long categories. The timing for the onset of faults was adjustable, with increments of 2 milliseconds beginning at 0.1 seconds. The fault's location was another parameter that could be modified throughout the research. The sampling frequency for collecting data was set at 4 kHz. This study captured various electrical measurements, including voltages and currents for phase a, b, c and zero sequence voltage and current. The dataset for training and validation was composed of 4860 unique Runs, which is equally divided among the different fault types. The methodology for generating this data is outlined in Algorithm 1.

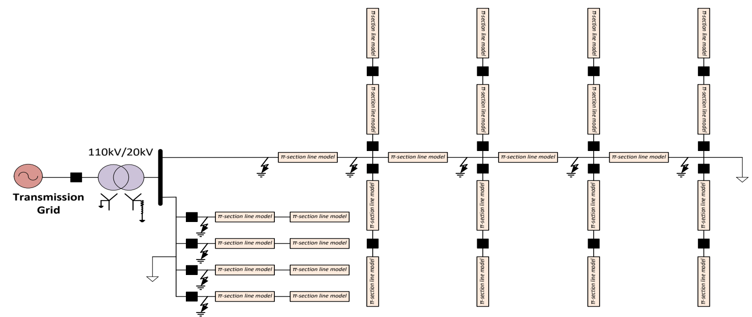

Fig. 1. Single line diagram of test system model[16]

Algorithm 1 Data Generation Process Algorithm

Input: Line Length, Resistance Value, Duration Time
Output: Voltage and Current Features

for *Run Iteration i=1:4860* **do**
  for *Line Length L=1:3 [Short, Medium, Long]* **do**
    for *Resistance R=1:3 [0, 10, 100]* **do**
      for *Fault Duration =1:3 [0.1, 0.2, 0.3]* **do**
        1) Run Short Circuit Analysis
        2) Extract current and voltage features:
        a) Three phase voltage
        b) Three phase current
        c) Positive sequence of current
        d) Residual current and voltage
        e) Fault current
        $Features \leftarrow save\ [a\ b\ c\ d\ e]$
      end
    end
  end
end
Return with all dataset

B. Supervised Learning

Machine learning (ML), an offshoot of artificial intelligence, empowers computers to assimilate new information and make decisions with minimal human intervention. Within this domain, supervised learning stands out by enabling algorithms to infer functions from labeled training data, which is instrumental in predictive modeling for classification and regression tasks. Techniques such as Support Vector Machines (SVM) [17], Decision Trees [18], Multilayer Perceptrons (MLP) [19], Recurrent Neural Networks (RNN) [20], and Long Short-Term Memory networks (LSTM) [20] are tailored for different aspects of supervised learning. SVMs, for example, excel in binary classification tasks like fault detection, whereas Decision Trees provide intuitive models that are easy to interpret. MLPs, RNNs, and LSTMs, which are types of neural networks, offer powerful frameworks for capturing complex patterns in data, particularly useful in time-series analysis and sequential data processing. Specifically, in the context of earth fault detection in electrical systems, these supervised learning models can be trained to identify and classify types of faults effectively. This showcases the versatility of ML in adapting to nuanced challenges and signifies its expansive potential for driving innovation across various industries.

III. Results and Discussion

In the context of our study, we employed a dataset comprising 4860 instances, evenly distributed across two distinct classes, namely earth fault and intermittent earth fault, with each class contributing 2430 instances. This dataset plays a pivotal role in training, validating, and testing our machine learning model, ensuring its ability to generalize well on unseen data.The dataset is characterized by voltage and current features, encompassing a broad spectrum of electrical signals and system indicators that are critical for accurately distinguishing between the two fault classes. This includes the magnitudes and phase angles of three-phase voltages, the magnitudes and phase angles of three-phase currents, residual values of voltages and currents, and the magnitude and RMS values of fault currents. We selected the Support Vector Machine (SVM) algorithm for its robustness in handling high-dimensional and extremely non-linear data, making it uniquely suited for our fault classification task. Unlike most algorithms that struggle with non-linear separability, SVM excels by employing the kernel trick to transform the input space into a higher dimension where a linear separation is possible. This capability allows SVM to effectively distinguish between different types of faults that are not linearly separable in the original input space, ensuring high accuracy in classification even under complex conditions. To ensure an unbiased assessment of our model's predictive capabilities, we divided our dataset into training and testing sets. This division allows the model to learn from one portion of the data and then be evaluated on a completely unseen portion, providing a clear measure of its generalization ability. To further validate our model's performance, we employed k-fold cross-validation, a technique that mitigates evaluation bias and variance by systematically using different data segments for training and validation. This approach guarantees that every data point is utilized in the validation process, enhancing the reliability of our performance estimate. Our algorithm initiates by setting up placeholders for the highest observed accuracy and the corresponding hyperparameters (C and Gamma). We navigate through a predefined grid of C and Gamma values to determine the optimal combination, employing k-fold cross-validation for each pair's performance assessment. This procedure involves partitioning the training data into smaller subsets, training the SVM model on each subset, and evaluating its accuracy. The average accuracy across all folds dictates the efficacy of each hyperparameter combination. We continuously update the best accuracy and its associated hyperparameters throughout the exploration. The process culminates in identifying and returning the C and Gamma values that maximize the cross-validation accuracy, ensuring our SVM model is both precise and generalizable. Figures 4 and 5 typically show the cross-validation accuracy and cross validation error of the SVM model across a grid of hyperparameter values. The axes represent different values for the BoxConstraint (C) and Gamma (γ), which are critical parameters in SVMs [17] with a radial basis function (RBF) kernel. Parameter C is a hyperparameter of the Support Vector Machine (SVM) that controls the trade-off between achieving a low error on the training data and maintaining a small margin. Algorithm 2 shows the hyperparameter tuning for SVM model with 5-Fold in cross validation.

Algorithm 2 Hyperparameter Tuning for SVM with 5-Fold in cross validation

1: $bestAccuracy \leftarrow 0$
2: $bestC \leftarrow 0$
3: $bestGamma \leftarrow 0$
4: $CValues \leftarrow \{0.1, 1, 5, 10, 100, 200, 400, 450, 500, 700, 800\}$
5: $GammaValues \leftarrow \{0.01, 0.1, 1, 10, 100\}$
6: $k \leftarrow$ number of folds for cross-validation
for ***each*** c ***in*** $CValues$ **do**
  for ***each*** γ ***in*** $GammaValues$ **do**
    $cvAccuracy \leftarrow 0$
    for $fold = 1$ ***to*** k **do**
      1)Split data into training, Testing and Validation:
      a)Training samples ← 70% of all Data
      b)Testing samples ← 30% of all Data
      2)Select validation sets for fold
      3)$Model \leftarrow$ train SVM with $trainSet$, c, γ
      4)$cvAccuracy \leftarrow cvAccuracy +$ evaluate $model$ on $validationSet$
    end
    $cvAccuracy \leftarrow \frac{cvAccuracy}{k}$
    if $cvAccuracy > bestAccuracy$ **then**
      $bestAccuracy \leftarrow cvAccuracy$
      $bestC \leftarrow c$
      $bestGamma \leftarrow \gamma$
    end
  end
end
return $bestC$, $bestGamma$, $bestAccuracy$

A higher value of C tends to classify the training data as accurately as possible, even at the risk of overfitting, while a lower value encourages a larger margin and simpler decision boundary, potentially at the cost of some misclassifications. The Gamma (γ) parameter in an SVM with a Radial Basis Function (RBF) kernel determines the influence of individual training samples on the decision boundary. A low Gamma value means a point has a far reach, contributing to the decision boundary from a distance, while a high Gamma value indicates that the influence is more local, affecting only the decision boundary near the point, which can lead to a more complex, wiggly decision boundary that might capture more nuances or overfit. As figures the height of the surface at any point indicates the accuracy obtained with that specific combination of C and Gamma during cross-validation. A point labeled as "Best" highlights the combination of C and Gamma that yielded the highest accuracy, indicating the optimal hyperparameters for the SVM model based on the given dataset. In the validation phase, the highest accuracy achieved is 98.59%, with a corresponding error rate of 1.41%. These results were obtained using a BoxConstraint value (C) of 700 and a Gamma (γ) of 1. Dashed lines leading from this point down to the axes help visually trace which specific values of C and Gamma correspond to this best performance. Figures 2 and 3 show two confusion matrices in training and testing process for SVM algorithm. A confusion matrix is a table often used in classification models to visualize the performance of an algorithm. Each row of the matrix represents the instances in an actual class while each column represents the instances in a predicted class, or vice versa. Here's a breakdown of the components typically found in a confusion matrix:

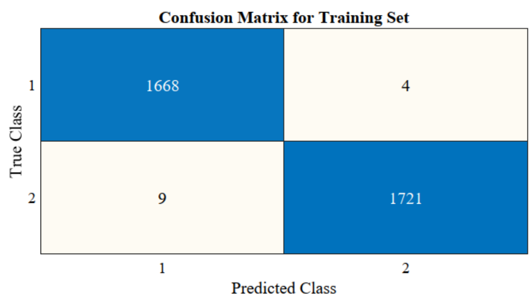

Fig. 2. Confusion Matrix in Training process

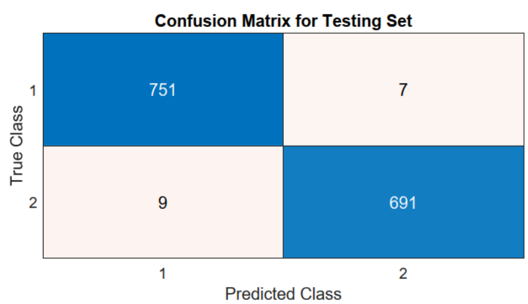

Fig. 3. Confusion Matrix in Testing process

- True Positive (TP): The cases in which the model correctly predicted the positive class.
- True Negative (TN): The cases in which the model correctly predicted the negative class.
- False Positive (FP): The cases in which the model incorrectly predicted the positive class.
- False Negative (FN): The cases in which the model incorrectly predicted the negative class.

As confusion matrix for testing set, it can be seen the model predicted 751 instances of Class 1 correctly as Class 1 (True Positives). Also the model predicted 9 instances of Class 1 incorrectly as Class 2 (False Negatives). The model predicted 7 instances of Class 2 incorrectly as Class 1 (False Positives). Also predicted 691 instances of Class 2 correctly as Class 2 (True Negatives). Therefore as equation (1) the accuracy is 98.9%.

$$Acuracy = \frac{TP + TN}{TN + TP + FP + FN} \tag{1}$$

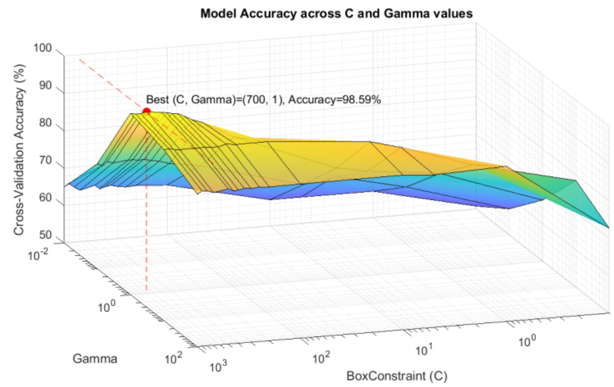

Fig. 4. Cross Validation Accuracy

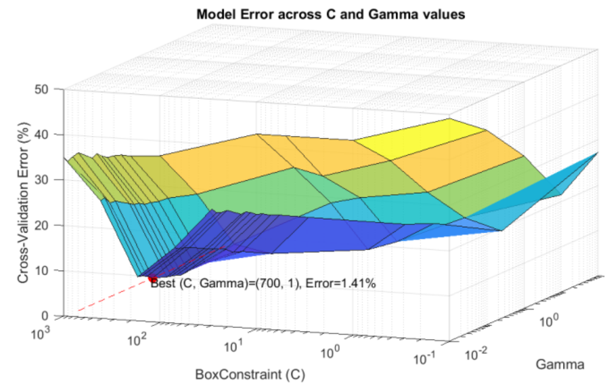

Fig. 5. Cross Validation Error

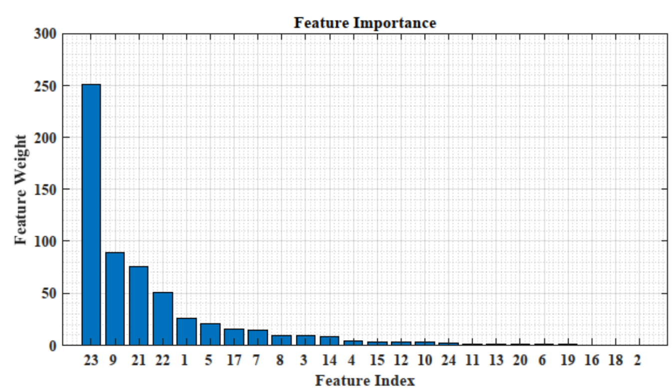

Fig. 6. Importance of features with SVM algorithm

The bar graph shown in Figure 6 represents the feature importance as determined by an SVM classifier. Feature importance in this context is likely derived from the magnitude of the coefficients associated with each feature in the linear version of the SVM model. The larger the coefficient (or weight), the more impact that particular feature has on the model's decisions. In this specific graph, feature 23 has the highest bar, indicating that it is the most important feature for the SVM model's classification decisions. Feature 23 corresponds to the "RMS value of residual current fault," significant predictor in distinguishing between the two classes within dataset. The other features are represented with bars of varying heights, indicating their relative importance. The lower the bar, the less impact that feature has on the model's classification output. It's worth noting that the exact order and the specific values of feature importance would depend on the data and the way the SVM model has been trained, including the choice of kernel, the penalty parameter C, and other hyperparameters.

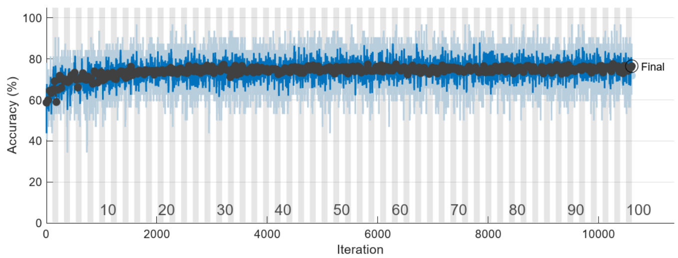

Fig. 7. Training accuracy in LSTM

The training progress for the deep learning model (LSTM) is depicted in the figure 7 showcasing the variation of accuracy across iterations and epochs during the training phase. The Figure 7 illustrates the fluctuation of training accuracy over iterations, with the smoothed line indicating the overall trend of increasing accuracy as the model learns from the training data. The model's accuracy appears to stabilize as the number of iterations grows, indicating that it is converging towards an optimal set of parameters. The final achieved validation accuracy is 76.47%, which is derived from the model's performance on a separate dataset not seen during training, used to gauge the model's generalization capabilities. The final validation accuracy achieved stands at 76.47%, which, while indicative of the model's capability to learn and generalize, also underscores a considerable margin for error. Figure 8 indicate confusion matrix for LSTM model in testing process. This matrix indicates that the model is better at identifying Class 1 correctly than Class 2, as seen by the higher number of true positives for Class 1. However, there is a significant number of samples that were incorrectly classified (390 samples), indicating potential areas for model improvement. Accuracy in the testing process is 73.2%. We trained our LSTM network by normalizing inputs for uniformity, splitting the dataset into 70% training and 30% test sets using MATLAB's stratified sampling. The network featured an LSTM layer with 100 units for sequence data, followed by fully connected and softmax layers for class predictions. Training utilized the Adam optimizer, a 0.001 learning rate, over 30 epochs with 32 samples per mini-batch. The process was efficient, completing in 39 seconds on a CPU, and achieved a 73.2% accuracy on the test set, underscoring our commitment to methodological rigor and result reproducibility. Figures 9 illustrates the classification performance of the MLP network. As depicted, the algorithm demonstrates limited capability in distinguishing between the two classes effectively. The accuracy during the testing phase is approximately 68%. Thable I sumarized the performance of supervised algorithm in classifiation of two type of fault, it shows that SVM and DT has a high process in classification. The similar effectiveness of Decision Trees (DT) and Support Vector Machines (SVM) in fault classification, as compared to LSTM and other algorithms, can be attributed to a number of factors. DT and SVM thrive with data that have distinct decision boundaries, which might suffice for clear-cut fault features, while LSTM's prowess in capturing temporal patterns may not be as crucial if the sequence of data points is less relevant.

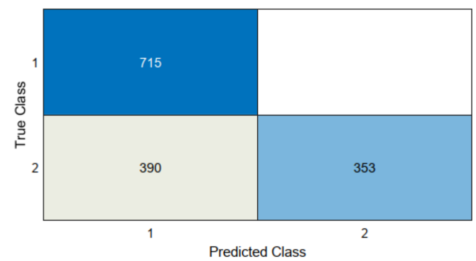

Fig. 8. Confusion Matrix in testing process in LSTM Model

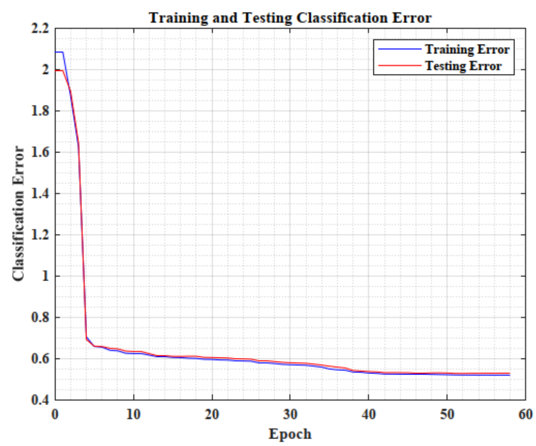

Fig. 9. Error in training and validation process of the MLP Network

TABLE I
SUPERVISED ALGORITHM PERFORMANCE

Algorithm	Validation		Testing	
	Accuracy	Recall	Accuracy	Recall
SVM	98.5 %	98.6 %	98.9 %	98.9 %
DT	99.1 %	98.4 %	98.8 %	98.7 %
LSTM	76.4 %	75.6 %	74.6 %	75.3 %
RNN	75.5 %	75.1 %	74.4 %	74.9 %
MLP	69.6 %	69.8 %	68.2 %	68.4 %

The less complex nature of DT and SVM could lead to better performance on smaller datasets due to fewer parameters and a reduced risk of overfitting, along with greater immunity to the curse of dimensionality. Additionally, the performance of DT and SVM might be enhanced with well-tuned hyperparameters. SVM, in particular, can become even more effective when the parameters like the regularization constant C and the kernel function parameter γ are optimized, as these adjustments help in maximizing the margin between classes and dealing with non-linear decision boundaries. When it comes to non-linear separability, SVMs equipped with non-linear kernels are particularly adept, potentially outperforming simpler models and LSTMs when the temporal dimension is not of essence.

IV. Conclusion

Detecting intermittent earth faults in MV distribution networks has always been a challenge for Distribution System Operators (DSOs). The sporadic nature and short duration of these faults make them difficult to detect using traditional methods like phasor-based algorithms. To address this issue, this study explored the application of machine learning techniques, specifically MLP, SVM, and Dtree, for classifying intermittent earth faults and normal ones. The outcomes of the study validated the effectiveness of the employed methods, especially emphasizing that the Support Vector Machine (SVM) and Decision Tree algorithms demonstrated a classification accuracy surpassing 98%. This level of accuracy significantly outperformed the Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Multilayer Perceptron (MLP) models, which were prone to higher rates of classification errors. These findings emphasize the significance of employing machine learning approaches for accurate intermittent earth fault detection. Furthermore, the proposed method can be implemented in cloud environments, where we have valuable data to enhance the learning and performance of the detection methods. For future studies, it would be beneficial to consider the inclusion of different types of faults and events, expanding beyond the binary classification approach to better align with real-world power system scenarios.

Acknowledgment

This research has been supported by the University of Vaasa under the CIRP-5G project with financial support provided by Business Finland with Grant No. 6937/31/2021. The financial support provided through the research project is highly acknowledged.

References

[1] T. Treider and H. K. Høidalen, “Estimating distance to transient and restriking earth faults in high-impedance grounded, ring-operated distribution networks using current ratios,” Electr. Power Syst. Res., vol. 224, p. 109765, 2023, doi: https://doi.org/10.1016/j.epsr.2023.109765.

[2] A. Nikander and P. Jarventausta, “Methods for earth fault identification and distance estimation in a compensated medium voltage distribution network,” in Proceedings of EMPD ’98. 1998 International Conference on Energy Management and Power Delivery (Cat. No.98EX137), 1998, vol. 2, pp. 595–600 vol.2., doi:10.1109/EMPD.1998.702754.

[3] Altonen, Janne, Olavi Mäkinen, Kimmo Kauhaniemi, and Kent Persson. ”Intermittent earth faults-need to improve the existing feeder earth fault protection schemes.” In Proc. CIRED, p. 6. 2003, available online at :”https://www.semanticscholar.org/paper/INTERMITTENT-EARTH-FAULTS-NEED-TO-IMPROVE-THE-EARTH-Altonen-M%C3%A4kinen/a60a76ef018b556382a620253f78fab62c5e4306”.

[4] Druml, O. Skrbinjek, U. Schmidt, K. Frowein, and P. Schegner, ”New method for identification and localisation of an earthfault in compensated networks,” 2019, http://dx.doi.org/10.34890/291, available online at ”https://www.cired-repository.org/server/api/core/bitstreams/8a856a99-12d4-493c-a689-a48e02f1ef0f/content”.

[5] K. Qu, W. Zhang, S. Zhang, X. Xiao, Y. Xi, and H. Zhang, “Model-free underground cable incipient fault location using two-terminal zero-sequence measurements,” Int. J. Electr. Power Energy Syst., vol. 140, p. 108057, 2022, https://doi.org/10.1016/j.ijepes.2022.108057.

[6] T. Cui, X. Dong, Z. Bo, and A. Juszczyk, “Hilbert-Transform-Based Transient/Intermittent Earth Fault Detection in Noneffectively Grounded Distribution Systems,” IEEE Trans. Power Deliv., vol. 26, no. 1, pp. 143–151, 2011, 10.1109/TPWRD.2010.2068578.

[7] T. S. Sidhu and Z. Xu, “Detection of Incipient Faults in Distribution Underground Cables,” IEEE Trans. Power Deliv., vol. 25, no. 3, pp. 1363–1371, 2010, 10.1109/TPWRD.2010.2041373.

[8] G. Druml, O. Skrbinjek, U. Schmidt, K. Frowein, and P. Schegner, ”New method for identification and localisation of an earthfault in compensated networks,” 2019, http://dx.doi.org/10.34890/291.

[9] G. Druml, C. Raunig, P. Schegner, and L. Fickert, ”Fast selective earth fault localization using the new fast pulse detection method,” 2013, doi: 10.1049/cp.2013.1068.

[10] G. Druml, O. Skrbinjek, W. Hipp, L. Fickert, U. Schmidt, and P. Schegner, ”First results concerning localisation of earthfaults in compensated 20-kV-networks based on travelling waves,” 2019,http://dx.doi.org/10.34890/320.

[11] A.Farughian, L. Kumpulainen, K.Kauhaniemi, ”Overview of methodologies for earth fault indication and location in compensated and unearthed MV distribution networks,” Electric Power Systems Research, vol. 154, 10.1016/j.epsr.2017.09.006.

[12] J. Altonen and A. Wahlroos, ”Performance of modern fault passage indicator concept in compensated MV-networks,” CIRED Workshop 2016, Helsinki, 2016, pp. 1-4, doi: 10.1049/cp.2016.0733.

[13] A. Wahlroos and J. Altonen, ”Application of novel multi-frequency neutral admittance method into earth-fault protection in compensated MV-networks,” 12th IET International Conference on Developments in Power System Protection (DPSP 2014), Copenhagen, Denmark, 2014, pp. 1-6, doi: 10.1049/cp.2014.0032.

[14] Druml, G., Schegner, P., Fickert, L., Schlömmer, M. (2015). Advantages of the new combination: Petersen-coil and faulty-phase-earthing, available online at: https://cired.at/fileadmin//user_upload/CIRED2015_1450_final.pdf.

[15] E. Balouji et al., ”Distribution network fault prediction utilising protection relay disturbance recordings and machine learning,” 27th International Conference on Electricity Distribution (CIRED 2023), Rome, Italy, 2023, pp. 2273-2277, doi: 10.1049/icp.2023.1220.

[16] M. Pashaei, M. Karimi, K. Kauhaniemi, A. Asadi, S. Pil Ramli and A. Pourdaryaei, ”Intermittent earth fault detection in distribution network based on the voting classification technique,” 27th International Conference on Electricity Distribution (CIRED 2023), Rome, Italy, 2023, pp. 3759-3763, doi: 10.1049/icp.2023.0726.

[17] Li Meng, Jin-Wei Shi, Hao Wang and Xiao-Qiang Wen, ”SVM with improved grid search and its application to wind power prediction,” 2013 International Conference on Machine Learning and Cybernetics, Tianjin, 2013, pp. 603-609.

[18] O. Ozgonenel, D. W. P. Thomas and T. Yalcin, ”Superiority of decision tree classifier on complicated cases for power system protection,” 11th IET International Conference on Developments in Power Systems Protection (DPSP 2012), Birmingham, UK, 2012, pp. 1-6, doi: 10.1049/cp.2012.0054

[19] M. N. Mahmud, M. N. Ibrahim, M. K. Osman and Z. Hussain, ”Comparison of MLP network training algorithms for fault classification in transmission lines,” 2014 IEEE International Conference on Control System, Computing and Engineering (ICCSCE 2014), Penang, Malaysia, 2014, pp. 208-213, doi: 10.1109/ICCSCE.2014.7072716.

[20] D. Oslebo, K. Corzine, T. Weatherford, A. Maqsood and M. Norton, ”DC Pulsed Load Transient Classification Using Long Short-Term Memory Recurrent Neural Networks,” 2019 13th International Conference on Signal Processing and Communication Systems (ICSPCS), Gold Coast, QLD, Australia, 2019, pp. 1-6.