THREE PHASE LINE FAULT DETECTION AND PROTECTION SYSTEM

Ayesha Azhar, Mohammad Saad Jawad, Muhammad Abu Bakar Dodhy, Muhammad Khuzaima

***Abstract*— This paper focuses on the development of a robust Three-Phase Line Fault Detection and Protection System, utilizing various machine learning algorithms. The system aimsto swiftly detect faults in three-phase electrical lines and triggerprotective measures to ensure uninterrupted power supply and safeguard electrical systems. Data for algorithm development was collected from Simulink simulations, and dedicated hardware was constructed to implement the protection system.**

Index Terms— Fault Detection, Protection Systems, Three-Phase Lines, Algorithms , Sensing Technologies

I. Introduction

Electrical power systems play a pivotal role in sustaining modern society, and ensuring their reliability and safety is of paramount importance. The timely detection and efficient mitigation of faults in power lines are critical to prevent damage to equipment, minimize downtime, and maintain continuous power supply. Traditional protection systems often face challenges in accurately identifying faults and responding promptly.

To address these challenges, this project presents a novel approach to fault detection and protection by integrating machine learning algorithms into the design. The utilization of different machine learning methodologies offers the potential for enhanced accuracy and efficiency in fault detection within three-phase electrical networks. This paper leverages Simulink, a widely-used simulation tool, to collect real-time data from simulated electrical circuits. This data serves as the foundation for developing, training, and validating the fault detection algorithms. Additionally, dedicated hardware has been designed and implemented to support the deployment of these algorithms in practical scenarios.

The primary objective of this endeavor is to improve the reliability and resilience of electrical networks by swiftly detecting and mitigating faults. The convergence of machine learning techniques, data collected from Simulink simulations, and purpose-built hardware forms the cornerstone of this innovative system.

Through this research, a comprehensive overview of the development process, methodologies employed, experimental results, and practical implications of the Three-Phase Line Fault Detection and Protection System will be presented, offering insights into its potential impact on advancing fault detection and protection in power systems.

II. Data Collection

For the formation of dataset, a Simulink model has been created based on real-life approximations, using the SimScape Electrical library. The nominal frequency of the model is set at 50Hz. The Simulink model is run by a Discrete powergui block of 0.0001s step time. This powergui block converts the model into a solution set of discrete-time step equations. Also, the powergui block provides advanced line and cable parameter calculations based on input values.

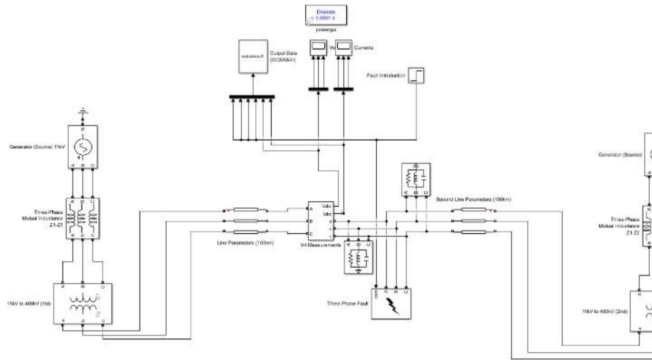


Figure 1: SimuLink model for data collection

As Fig 1. is indicating, two identical transmission grids have been installed either side of a 100km long cable line. The transmission grid involves an 11kV ideal programmable source as a generator module, whose output impedance is provided by a three-phase inductance module added in series with the generator. This topology then feeds into the primary side of a 11kV-to-400kV step-up transformer, which is a $\Delta - Y$ type transformer. This type is nominally used in such transmission grids, owing to the delta side preventing third and higher order harmonic currents from flowing in the transmission line. To model the cable line parameters, we have used ACSR Besfort three-bundle cable which prevents corona discharge and radio noise for very high voltages. The cable line parameters are calculated very efficiently using the Line Parameters Calculator section in the powergui block.

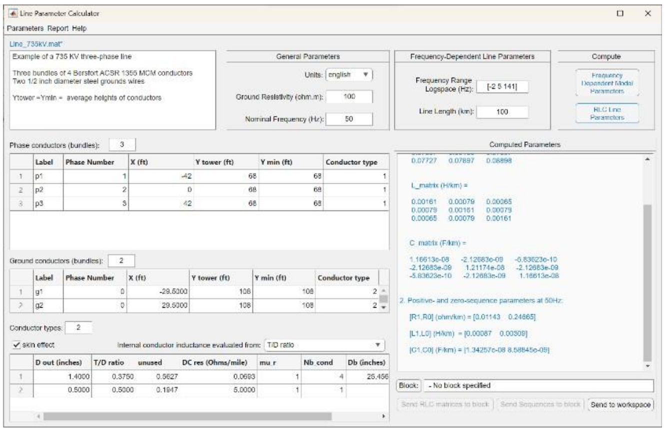


Figure 2: Line Parameters Calculator

The results of the calculator are the positive and zero sequence impedance values measured per kilometer. Positive sequence impedance is the AC impedance offered by the cable when it acts as a live wire and zero sequence impedance is the impedance when current is being through the wire into the ground or neutral.

$$Z_1 = Z_{aa} - Z_{ab}$$
$$Z_0 = Z_{aa} + Z_{ab}$$

Where Z_{aa} *and* Z_{ab} are self and mutual impedances between the cables. The total impedance parameters are shown in figure.

Line Parameters

Cable	Besfort ACSR (Three bundles)
Length of transmission line	$100km$
System Frequency	$50Hz$
Positive Sequence Resistance (R_1)	$0.01143 \frac{\Omega}{km}$
Positive Sequence Capacitance (C_1)	$1.3246 \times 10^{-8} \frac{F}{km}$
Positive Sequence Inductance (L_1)	$8.6839 \times 10^{-4} \frac{H}{km}$
Zero Sequence Resistance (R_1)	$0.24665 \frac{\Omega}{km}$
Zero Sequence Capacitance (C_1)	$8.5885 \times 10^{-9} \frac{F}{km}$
Zero Sequence Inductance (L_1)	$3.0886 \times 10^{-3} \frac{H}{km}$

Figure 3: Line Parameters used in model

A generic parallel RLC load has been attached at the end of both the transmission lines. The Three-Phase Fault block is used to introduce faults in the system. This block is in fact a three-phase circuit breaker which on the advent of a control signal or a timing mechanism, shorts out two pre-determined phases or ground with each other. As the figure is indicating, when any two switches are turned on, those two phases or ground are shorted. The value of R_{on} is minimal (around 0.01 ohms) while R_g has a value around a million ohms, as the ground should have minimal current through it.

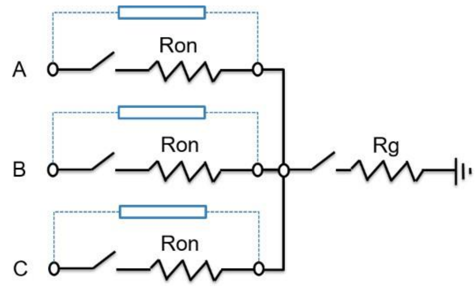


Figure 4: Three-Phase Fault block working

To control the introduction of faults in the system, a Step Input block has been used which sends a 1 or an ON signal to the Three-Phase Fault block at 0.1 seconds.

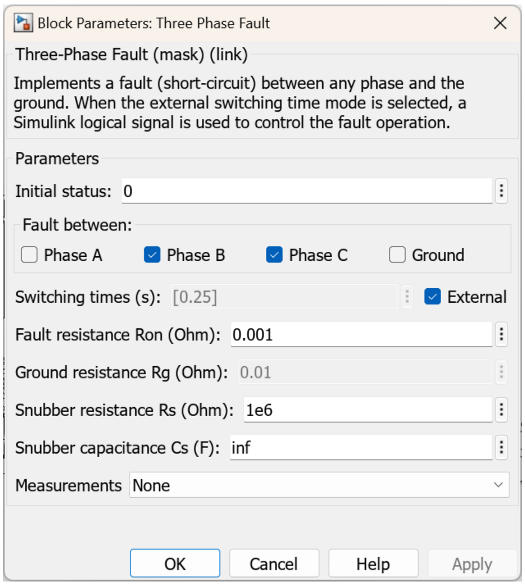


Figure 5: Three Phase Fault selection window

Also, measurements for the data collection are made using the Three Phase V-I Measurements Block which is connected to a Scope display and to the Workspace block, to record the data in tabular form. As stated earlier, we have a total of 12 conditions, which include 11 fault and 1 no-fault condition. Thus, the model has been simulated a total of 12 times, for a total running time of 0.2 seconds of each simulation. The values obtained are then sent to the MATLAB Workspace, from which we save a CSV file.

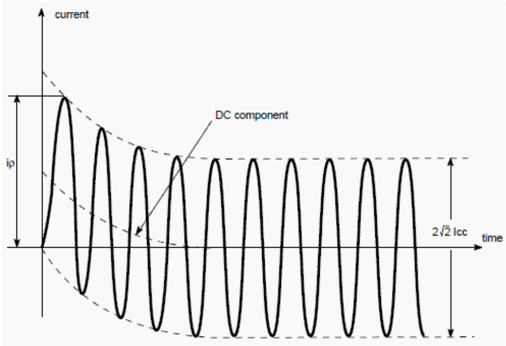


Figure 6:Stairing effect

When a fault is introduced in a phase, the current undergo a "stairing" sequence which is typical of fault currents. In such a current, a damped DC component is superimposed on the AC sinusoidal component while transient response to fault introduction raises the maximum peak of the current.

The output waveforms for the phase currents and phase voltages are indicative of the type of fault. The output waves attached here are a result of simulation time of 1 seconds. The fault is introduced at 0.1 seconds as evident from the figure. The output waveforms change as a result. Thus, we observe that when a fault is introduced between B and C (Phase BC Fault), both the phase currents undergo this stairing phenomenon. Because we have attached a balanced load, there is positive side stairing as well as negative side stairing.

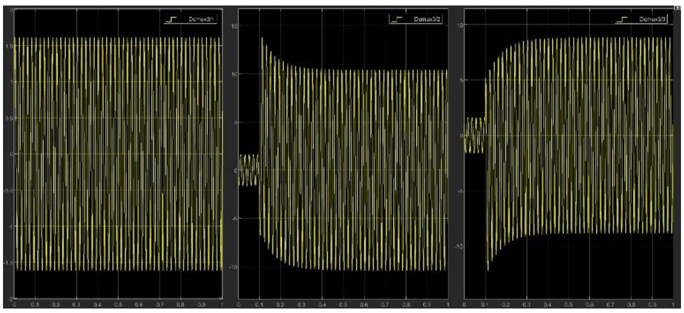


Figure 7:Phase BC fault - Phase Currents Plot

Meanwhile, on the voltage side, consider for example a symmetrical fault (Phase ABC) Fault. Since after 0.1 seconds the fault is introduced, all the three phases are shorted out, so almost no voltage appears across the phase, which is evident from the figure.

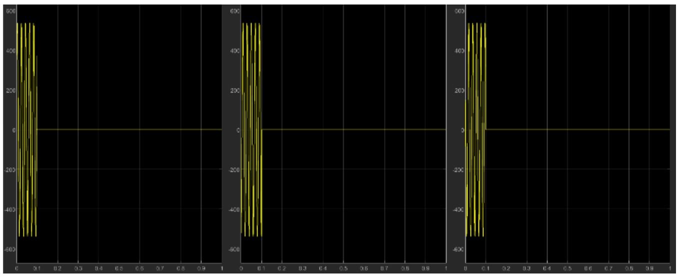


Figure 8: Phase ABC fault - Phase Voltages Plot

III. Fault Classification Techniques

In this section, we elaborate on the machine learning (ML) models employed for fault classification in 3-phase line fault detection and protection systems. The data collected is predominantly derived from the Simulink. Various algorithms were utilized to discern and classify these faults effectively.

1. Logistic Regression

Model Description: Logistic Regression is a linear model used for binary classification tasks. In this project, it serves as a baseline for fault classification.
Relevance: Despite its simplicity, Logistic Regression showcases respectable performance in fault classification tasks.

2. Support Vector Machines (SVM)

Model Description: SVMs are adept at both linear and non-linear classification. They aim to find an optimal hyperplane that best separates data points of different classes.
Relevance: SVMs are employed here to potentially capture complex decision boundaries between different fault categories.

3. K-Nearest Neighbors (KNN)

Model Description: KNN is a non-parametric method used for classification by finding the most similar instances based on distance measures.
Relevance: KNN's utilization enables the system to classify faults based on the similarity to neighboring instances in the dataset.

4. Decision Trees

Model Description: Decision Trees use tree-like models to make decisions by splitting the data into branches based on feature values.
Relevance: Decision Trees are implemented for their interpretability and ability to discern different fault scenarios.

5. Random Forest

Model Description: A collection of Decision Trees is employed to improve predictive accuracy and control overfitting.
Relevance: Random Forests provide an ensemble approach, reducing variance and enhancing overall classification performance.

6. Gradient Boosting

Model Description: Gradient Boosting builds a strong learner by iteratively improving weak learners, forming a robust predictive model.
Relevance: Its iterative nature helps in refining the classification of faults by minimizing errors.

7. Multi layer Neural Networks

Model Description: Multi-layer Neural Network is a type of neural network that utilizes multiple layers to learn complex patterns.
Relevance: Neural Networks are employed to capture intricate relationships within the temporal data for fault detection.

8. Naive Bayes

Model Description: Naive Bayes classifiers are based on Bayes' theorem and assume independence among features.
Relevance: Its simplicity and efficiency make it a viable option for initial fault classification exploration.

9. AdaBoost

Model Description: AdaBoost combines weak classifiers to form a strong classifier, giving more weight to misclassified instances.
Relevance: AdaBoost aims to improve fault classification by focusing on instances that are harder to classify.
XGBoost:

Model Description: XGBoost is an optimized gradient boosting library known for its speed and performance.
Relevance: Its efficiency and robustness contribute to better fault classification performance.

Evaluation and Performance:

In our investigation of fault classification for 3-phase induction motors, a comprehensive range of machine learning (ML) models underwent rigorous evaluation to determine their efficacy in practical fault detection scenarios. Notably, the models exhibited diverse performances across cross-validation and test metrics.

1. Multi Neural Networks

Cross-validation Accuracy: 89.48%

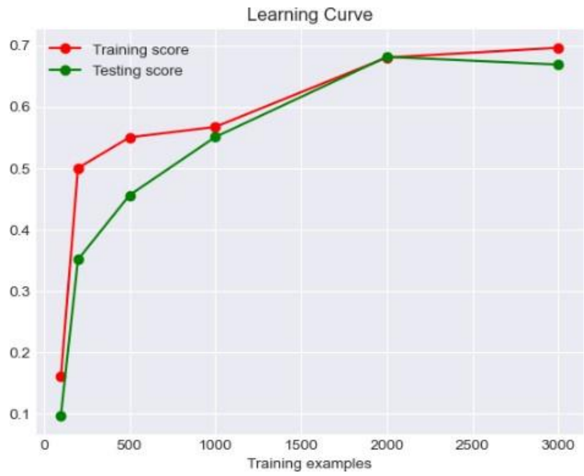
Test Set Accuracy: 88.00%

Insights: Multi Neural Networks emerged as the standout performer, showcasing remarkable consistency and high accuracy in both cross-validation and on the test set, making it a strong choice for practical deployment.

2. Logistic Regression

Cross-validation Accuracy: 23.90%

Test Set Accuracy: 23.45%



Insights: Logistic Regression displayed low accuracy in both cross-validation and on the test set, indicating limitations in capturing complex relationships inherent in the data.

3. Support Vector Machines (SVM)

Cross-validation Accuracy: 82.26%

Test Set Accuracy: 80.71%

Insights: SVM showcased reasonable accuracy during cross-validation but encountered a slight decrease in performance on the test set, suggesting challenges in generalization.

4. K-Nearest Neighbors (KNN)

Cross-validation Accuracy: 86.59%

Test Set Accuracy: 85.70%

Insights: KNN demonstrated good accuracy in both cross-validation and on the test set, showcasing consistency in performance and generalization capability.

5. Decision Trees

   Cross-validation Accuracy: 88.19%

   Test Set Accuracy: 84.45%

   Insights: Decision Trees exhibited high accuracy during cross-validation but faced challenges in generalization to the test set, displaying a slight decrease in performance.

6. Random Forest

   Cross-validation Accuracy: 85.86%

   Test Set Accuracy: 84.86%

Insights: Random Forest showed relatively high accuracy in cross-validation but encountered minor difficulties in generalization, resulting in slightly lower performance on the test set.

7. Gradient Boosting

   Cross-validation Accuracy: 86.38%

   Test Set Accuracy: 86.24%

Insights: Gradient Boosting displayed promising accuracy during cross-validation, maintaining competitive performance on the test set.

8. Naive Bayes

   Cross-validation Accuracy: 61.83%

   Test Set Accuracy: 60.04%

   Insights: Naive Bayes exhibited moderate accuracy during cross-validation and on the test set, facing challenges in achieving higher performance.

9. AdaBoost

   Cross-validation Accuracy: 27.41%

   Test Set Accuracy: 48.27%

   Insights: AdaBoost displayed low accuracy during cross-validation, showing a significant increase in performance on the test set but still falling short of achieving high accuracy.

10. XGBoost

   Cross-validation Accuracy: 86.01%

   Test Set Accuracy: 85.24%

Insights: XGBoost demonstrated competitive accuracy during cross-validation but encountered minor challenges in generalization, maintaining relatively high performance on the test set..

MODEL	*Cross Validation n score*	*Test Accuracy*
Multi Layer Neural Networks	89.48	88
Support Vector Machines	82.3	80.7
K-Nearest Neighbors	86.6	85.69
Decision Trees	88.2	84.24
Random Forest	85.8	84.86
Gradient Boosting	86.3	86.23
Naive Bayes	61.8	60.04
AdaBoost	27.4	48.27
XGBoost	85.9	85.19
Logistic Regression	23.9	23.45

Table 1:Model Training and Cross-Validation result

IV. Hardware

Electrical Power System is a highly invested area. The more reliable electricity we want, the more is need to protect it. First, we need to look at **why protecting the power system is crucial?** Protection is essential to keep equipment and personnel safe from any kind of damage caused by an electrical load unbalance or fault conditions. Power system protection's main objective is to maintain the reliability of the running power system and to save the equipment from getting damaged by keeping faulty part completely isolated from the circuit so that the remaining system operates normally. To isolate faulty circuit, protection devices such as fuses, Relays, Circuit Breakers etc can be used. These devices interrupt the circuit whenever a fault occurs. Therefore, only a faulty element is disconnected without affecting the rest of the system.

Three phase power systems (less then 100kVA) are usually protected using fuses only. Fuses are connected in series in circuit and provide automatic disconnection upon a fault or overcurrent. Fuse rating must be selected carefully. It must be high enough to prevent the fuse from blowing on a momentary current overload. On the other hand it must not be too high in order to provide effective overcurrent protection. The main disadvantage of using fuses to protect three phase system is their long operating time under low overcurrent conditions. This is especially true for fuses having high current ratings. This delays transformer disconnection and in certain cases provides little protection to the transformer and rather protects the system.

The protection schemes of large 3 phase power transformers is achieved by CB and relays. This additional protection serves as a backup in case of failure of main protection system . Over current protection is applied to the primary winding and controls disconnection of power transformers.

In overcurrent protection system the power transformer primary currents are measured using three Current Transformers and the output of CTS are connected to overcurrent relays. When any of overcurrent relay trips transformer disconnection is initiated. This eliminates excessive delays in disconnection that may happen when a transformer is protected using fuses in low over current conditions.

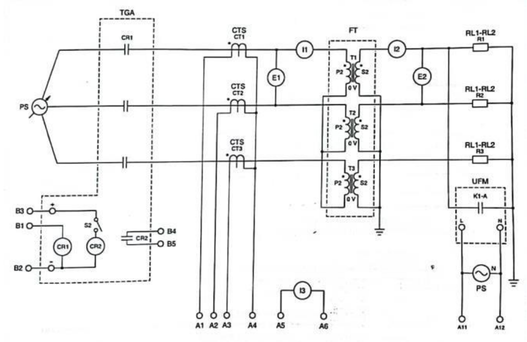


Figure 9: Circuit Diagram

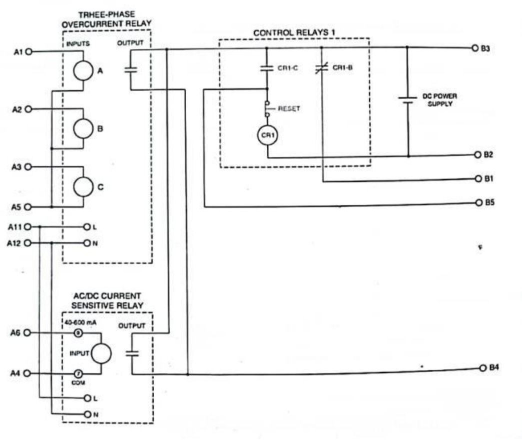


Figure 10: Protection System

Working: Power is generated from a source and then transmitted through Transmission Grid A via transmission lines. Subsequently, it passes through transformers for voltage reduction before being supplied to homes and other loads. To simulate a fault condition, Faultable Transformers and a Fault Initialization Unit; Universal Fault Module (UFM) is connected across the load, inducing a surge of high current.

Current Transformers (CTs) are strategically placed on the transmission lines to detect any abnormal current due to a fault. Whena fault is detected, the CTs generate an output signal that activates relays. These relays, in turn, are connected to control devices, effectively interrupting the circuit within no time. This interruption serves as a protective measure to safeguard equipment from potential damage caused by the fault. Following the removal of the fault from the circuit, the control relays are reset via a reset button to re-establish the circuit.

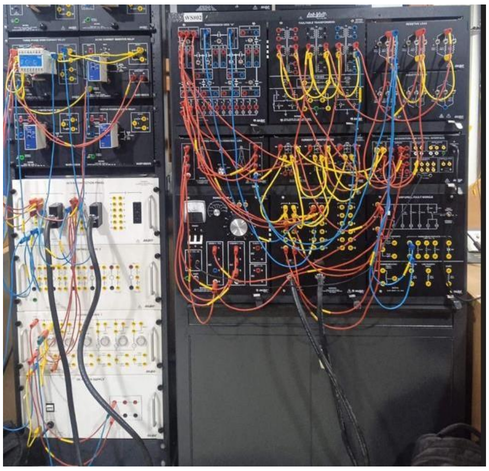


Figure 11: Hardware

Implementation: The modules that we have used to implement protection system are given below:

- Power Source (PS): It provides fixed and variable AC and DC voltage sources. Independent circuit breakers, reset atthe front panel, protect the Power Supply input and outputs. A voltmeter, connected through a selector switch, to monitor the output voltages.
- Transmission Line Module: It consists of three iron-core inductors. The inductors are specifically designed to simulate a high-voltage AC transmission line.
- Transmission Grid A (TGA): It consists of a transmissiongrid. This module is used to open and close an AC Power circuit under normal conditions or to interrupt this circuit contactors, a solid-state relay (SSR), current-limiting resistors, and an inductor. These components allow faultsto be inserted into the electrical power system for training in protective relaying applications. Typical faults include line-to-line and line-to-earth resistive faults as well as resistive and inductive faults.
- Current Transformers (CTS): These were used to detect fault current in three-phase transmission lines. Upon detection of fault current it will send output signal to relays that will trip and break the circuit.
- Faultable Transformers (FT): It consists of three single-phase power transformers.
- Resistive Load: The Resistive Load consists of nine wire wound power resistors arranged in three identical banks. Each bank consists of three resistors connected in parallel that can be switched on or off with toggle switches to obtain various resistance values. The Resistive Load is commonly used in conjunction with other basic load modules, like the Inductive Load and the Capacitive Load.
- Universal Fault Module: The Universal Fault Module consists of control relays, adjustable time delay relays, contactors, a solid-state relay (SSR), current-limiting resistors, and an inductor. These components allow faults to be inserted into the electrical power system for training in protective relaying applications. Typical faults include line-to-line and line-to-earth resistive faults as well as resistive and inductive faults.
- AC/DC Current Sensitive Relay: The AC/DC Current Sensitive Relay is a protective relay that is sensitive to either alternating current (ac) or direct current (ac). It can be set to respond to either undercurrent or overcurrent conditions. Current setpoint and hysteresis adjustments, ac/dc and undercurrent/overcurrent selection switches are provided along with a single set of contacts.
- Three Phase Over Current Relay: It is a protective relay that is sensitive to overcurrent conditions in three-phase power systems. It trips when the current in any one of thethree phases exceeds the current setpoint.
- Control Relays: These will indicate that the relays tripped, and circuit is open. After removing the fault connection can be reestablished via pressing reset button.
- Banana cables: These were the cables that were used to patch circuit.

E1	E2	E3	I1	I2	I3
378.8	352.2	131.5	0.346	0.322	0.018
378.9	352.1	131.6	0.346	0.322	0.018
378.9	352.3	131.5	0.346	0.323	0.018
377.4	343.1	131.6	0.926	0.899	0.02
0.283	0.217	131.2	0.008	0.011	0.013
0.269	0.23	131.1	0.008	0.011	0.014
0.267	0.232	131.1	0.008	0.011	0.014
0.271	0.239	131.2	0.008	0.011	0.013
0.269	0.232	131.2	0.008	0.011	0.014
86.4	86.1	131.3	0.349	0.319	0.017
378.9	352.2	131.6	0.346	0.323	0.017
379.1	352.3	131.7	0.346	0.322	0.017

Table 2: Hardware readings

V. Results

The readings obtained after implementing the circuit indicate a normal current flow through the circuit, typically around 0.33 A, as indicated by **I1** and **I2**. However, when a faultis introduced into the circuit by the Universal Fault Module, the current increases to approximately 0.91 A (highlighted in red in the above table). Upon detection of the fault current by the Current Transformer Switch (CTS), an output signal is promptly sent to the relay, causing it to trip and immediately reducing the current to 0 A. Even after the fault is removed from the system, the current remains at 0 A (displayed in blue in the table) because the connection is not reestablished until the reset button on the control relays is pressed. Upon pressing thereset button, the current flow returns to normal, around 0.33 A.

VI. Conclusion

Our study aimed at advancing fault detection in three-phase electrical systems by integrating machine learning algorithms with Simulink-simulated data and dedicated hardware construction. This fusion established a robust framework for precise fault detection. Moving from theory to real-world deployment necessitates adaptable fault detection algorithms capable of swift identification in dynamic electrical networks. Our focus now lies in refining these algorithms for real-time operation, emphasizing resilience and continuous enhancement. Our commitment remains steadfast in revolutionizing fault detection methodologies for three-phase systems. Lessons learned guide our ongoing efforts to develop adaptable and robust algorithms, setting new standards for faultdetection and ensuring the reliability of critical electrical systems.

VII. References

[1] S. Zhao, F. Blaabjerg and H. Wang, "An overview of artificial intelligence ipplications for power electronics," IEEE Transactions onPowerElectronics, accepted

[2] E. I. Amoiralis, P. S. Georgilakis, T. D. Kefalas, M. A. Tsili and A. G.Kladas, "Artificial intelligence combined with hybrid FEM-BE techniquesfor global transformer optimization," IEEE Transactions on Magnetics,vol. 43, no. 4, pp. 1633-1636, April 2007

[3] Y. LeCun, Y. Bengio and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436–444, May 2015.

[4] R.P. Hasabe and A.P. Vaidya. Detection Classification and Location of Faults on 220 Kv Transmission Line Using Wavelet Transform and Neural Network. International Journal of Electrical Engineering & Technology. 2014: 5(7):32–44.

[5] Kincic S, Papic, M. Impact of Series Compensation on the voltage profile of transmission lines. Powerand Energy Society General Meeting PES. 2013; 1-5.