Design and Development of Artificial General Intelligence for Power System Operation

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***Abstract*— Power systems are vulnerable to faults that can lead to severe damage to critical components such as motors, generators, and transformers, as well as cause dangerous over-voltages, high currents, outages, and safety hazards. To address these challenges, an effective power protection system is essential for detecting, classifying, and locating faults to mitigate their impact. This project presents the development of an Artificial General Intelligence (AGI) system designed to control and optimize the algorithms of machine learning for fault classification and predicitons in power systems. Utilizing the IEEE 14 Bus Test Network, the AGI system integrates Random Forest Classifier and Support Vector Classifier (SVC) to enhance fault detection accuracy and system performance. AGI system processes real-time data to dynamically manage fault detection and classification tasks, ensuring timely identification and response. Through comprehensive testing and evaluation, the system demonstrates improved reliability and safety by providing precise fault predictions and minimizing operational disruptions. This approach offers a robust solution for managing power system faults, contributing to more reliable and efficient power infrastructure management [1].**

Keywords—Artificial General Intelligence, Machine Learning Algorithms, Power System Faults, Fault Localization, Fault Predictions.

I. Introduction

Development of an advanced AGI system designed to enhance management and control of power systems by leveraging machine learning algorithms and advanced neural network architectures. The dataset used for this project includes multiple sources to ensure robust coverage and complete coverage Primary data is collected from the Tamil Nadu Electricity Board (TNEB), providing detailed and relevant information about the power system operations in the local regions. To enrich the dataset and ensure its diversity additional data is obtained from publicly accessible sources such as Kaggle and Google datasets external datasets offer varied scenarios and conditions that contribute to the robustness of the model. MATLAB simulation datasets are included to simulate real-world conditions and test the performance of the model under controlled environments. It focuses on training and evaluating several machine learning algorithms including the random forest classifier and the support vector classifier (SVC). These algorithms are applied to the dataset to perform fault prediction and classification tasks the outputs generated by these machine learning models are then used to train an advanced deep reinforcement learning (DRL) model with long short-term memory (LSTM) networks. The integration of DRL with LSTM networks aims to create a sophisticated AGI system capable of dynamically controlling and optimizing power system operations from simple to complex, this includes the automation of circuit breakers, relays and other protective devices [4]. The DRL component of the AGI system is responsible for making optimal decisions based on real-time data while the LSTM networks handle the temporal dependencies and sequence information in the data set and the motive of this is to develop a complete AGI system that can effectively manage and control power system operations while improving system reliability and safety. This aims to deliver a robust solution for fault detection classification and system protection by integrating diverse data sources advanced machine learning techniques and neural network architectures [5].

II. Data Cleaning and Data Testing

A. *Deleting the duplicate values:*

Identified and removed 7,861 duplicate values from the dataset to ensure that the data is unique and accurate, eliminating redundancy.

```
[ ] df = pd. read_csv('final_dataset.csv')
    print('number of duplicate datas present in the datasets: ', df.duplicated().sum())
    cleaned_dataset = df.drop_duplicates()
    cleaned_dataset.to_csv('cleaned_dataset.csv', index=False)
    print('Cleaned dataset has been saved to the local access')

    number of duplicate datas present in the datasets:  7861
    Cleaned dataset has been saved to the local access

[ ] cleaned_dataset.shape

    (7861, 10)
```

Fig. 1 Elimination of duplicates

B. *Z – Score Calculations:*

Calculated the Z-Score for each data point to assess the distribution and detect potential outliers, aiding in the normalization and analysis of the data.

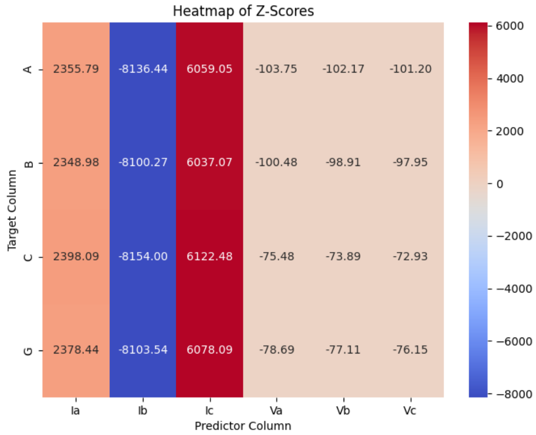

Fig. 2 Heat Map of Z – Scores

C. *T – Test:*

Values close to zero indicate weaker evidence against the null hypothesis whereas larger magnitudes both positive and negative indicate stronger evidence against the null hypothesis. This heatmap visualizes the t-state statistics showing the significance and direction of the relationship between each predictor and target. Red colours indicate higher positive T-Statistic values, and blue indicates lower or negative values. This heatmap shows the t-statistic values Higher values (positive or negative) indicate stronger evidence against the null hypothesis [13].

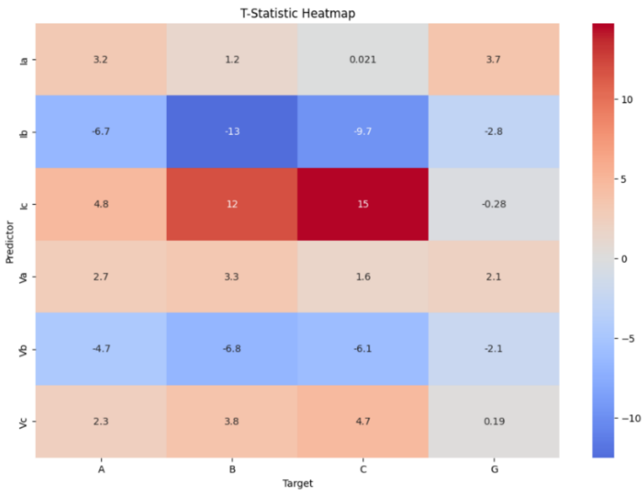

Fig. 3 T – Test Heat Map

D. *P – Test (Probability test):*

Lower P-Values (< 0.05) indicate notable results, meaning the null hypothesis can be rejected for that pair of features. This heatmap displays the P-Values, where smaller values (indicating statistical significance) are highlighted in blue. Visualizes the P-Values where values close to 0 indicate significant relationships. The heatmap is centered around a low value (e.g., 0.05) to emphasize significant results [13].

E. *Chi – Squared Test:*

The chi-squared test evaluates the independentness of categorical input features and multi-labeled output variables. The input features in the given dataset with outputs G, A, B, C, and inputs Ia, Ib, Ic, Va, Vb, Vc are first binned into categories. The chi-squared test is then applied to estimate the relationship between every output label and each input feature. Significant associations are identified by low p-

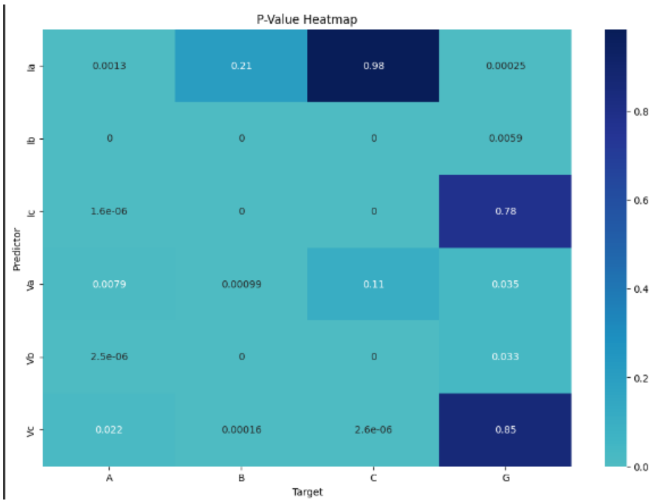

Fig. 4 P – test Heat Map

values (typically < 0.05) the results including chi - quaried values and p values are stored in an excel file for easy interpretation and analysis [12].

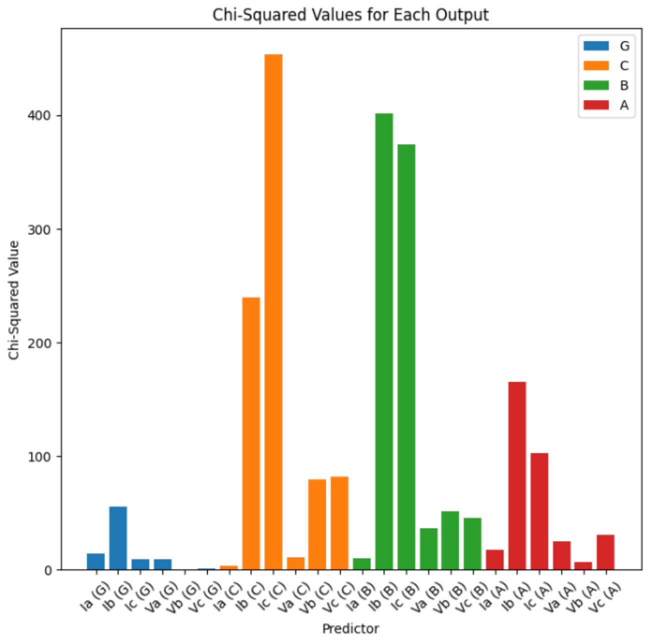

Fig. 5 Chi – Squared Values Histogram

III. Data Visualization

A. *Scatter Plots:*

The Scatter plots are used to examine the bond between every input and output variable for example you could create a scatter plot of the input feature Ia versus the output variable G each point on the plot represents a sample of data showing how changes in Ia correlate with changes in G. This visualization helps to identify the trends, patterns or outliers in data. For example, if points form a linear pattern it indicates a potential linear relationship, if the plot is scattered without a discernible pattern, it suggests a weaker or no relationship.

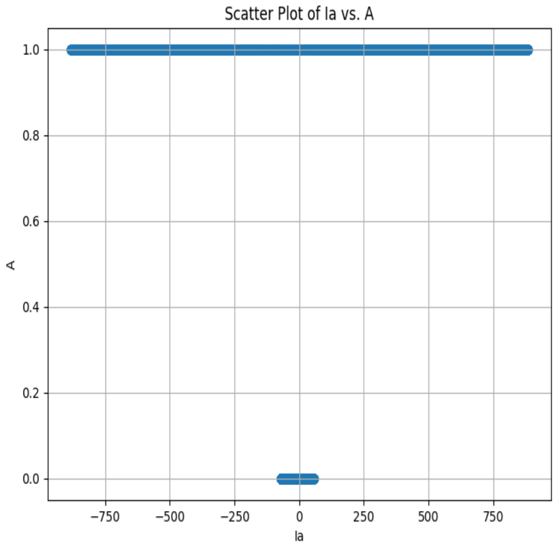

Fig. 6 Scatter Plot Ia vs A

B. Histogram Plots:

The Histograms are used to analyze the distribution of the input variables such as Ia, Ib and Ic by dividing the data into bins and enumerating the number of data that fall into each class histograms reveal the distribution of each feature in the dataset. This can show whether the feature is normally distributed skewed to the left or to the right or if it has multiple peaks. For instance, a histogram of Ia might show if most values cluster around a particular range or if there are several distinct value ranges.

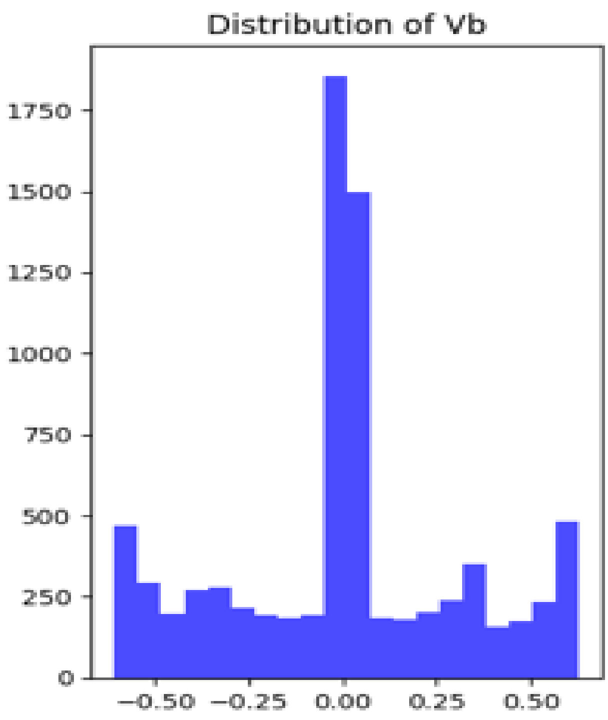

Fig. 7 Distribution of Vb

IV. Model Training

A. Deep Reinforcement Learning with Long Short Term Memory (RNN) Hybrid Network:

1) Deep Reinforcement Learning:

DRL is an advanced machine learning technique that allows agents to learn optimal actions through interaction with the environment. DRL agents can be trained to manage control systems like circuit breakers relays and other protective devices in order to maintain stability and minimize the impact of failures in power systems [10].

2) Long Short Term Memory (RNN) Network:

LSTM networks is a type of Recurring Neural Network (RNN) specifically designed to control sequences of data with long-term dependencies. In order to deal LSTMs are particularly useful in power systems for modeling the temporal behavior of the system capturing the relationships between current and past states which are crucial during transient periods when system conditions change rapidly [6].

3) Hybrid Architecture:

The LSTM network processes the time series data from the power system in this hybrid approach to capture the temporal dependencies and predict the state of the system. The DRL agent then uses this information to make informed decisions about how to control the various algorithms (e.g., Random Forest, SVC, XGBoost and KNN) used for fault prediction. The hybrid model allows for continuous adaptation and learning, making it suitable for managing complex, non-linear relationships and temporal dependencies in the power system.

4) Control of Fault Prediction Algorithms:

The DRL-LSTM network dynamically adjusts the parameters of algorithms of machine learning based on current situation of the power system. For example, In a transient period the DRL agent may prioritize the use of one algorithm over another based on their respective strengths in handling certain types of faults. If they are present the network can also reconfigure the predictive models in real-time to increase accuracy and reliability in fault prediction under varying load conditions and other operational constraints [5].

5) Handling Power System Transients:

Power System transients are short-duration events that can cause significant changes in system conditions such as a shutdown failure or an evacuation. These transients require rapid and accurate predictions to prevent cascading failures in the system. The ability to model time-dependent data of the LSTM network makes it particularly effective at predicting and responding to these transient events. The component DRL ensures that the system response to these transients is optimal minimizing damage and maintaining stability. The hybrid network can ensure that the most accurate fault prediction is made during these critical periods by controlling the predictive models in real-time.

V. Model Comparisions

1) Fault Classification Models Comparison:

Table I. Classification Model Comparison

Feature	Ant Colony Algorithm	Random Forest
Principle	Inspired by the behavior of ants searching for food, using pheromones to guide the search.	Construction of multiple decision trees and combine their output to make ensemble learning method.
Strengths	Effective optimization problems, can tackle huge datasets, and is immune to local optima.	Robust to overfitting, handles missing data well, and can handle both categorical and numerical features.
Suitability for Power System Fault Classification	Well-suited for optimization problems in fault location and classification, especially when the search space is large and complex.	Effective for handling noisy and incomplete data, and can accurately classify faults based on various features.
Key Considerations	Parameter tuning (pheromone evaporation rate, visibility factor), initialization of ants, and colony size [2-3].	Number of trees, tree depth, and feature selection [7].

2) General Intelligence vs Artificial Neural Network:

Table II. Intelligence Development Comparison

Feature	AGI (DRL+LSTM)	ANN
Decision Making	Complex, real-time decision-making	Simpler decision-making
Long-Term Dependencies	Captures temporal dependencies	May struggle with long-term dependencies
Adaptability	Highly adaptive	Less adaptive
Computational Complexity	High	Lower

VI. Model Results And Evaluation:

A. Classification Model Evaluation Techniques:

1) Accuracy:

The measure of proportion of exactly classified instances both True Positive (TP) and Ture Negative (TN) among the sum of all cases is known as Accuracy Eq. (1). It is a simple metric but can be inconsistent in the case of skewed datasets [12 - 13].

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

2) Precision:

Precision measures the proportion of TP instances among all instances classified as positive Eq. (2). It is crucial when the cost of False Positive (FP) is high [12 - 13].

$$P = \frac{TP}{TP+FP} \tag{2}$$

3) Recall (Sensitivity):

The percentage of positive instances amidst the real positive cases is important when the cost of false negatives is high Eq. (3) [12 - 13].

$$R = \frac{TP}{TP+FN} \tag{3}$$

4) F1 Score:

The F1 Score is the periodic repeating mean of precision and recall Eq. (4). It's used when you need a non - skew between recall and precision [12 - 13].

$$F1 = 2 \times \frac{P \times R}{P+R} \tag{4}$$

5) ROC – AUC Score:

a) Formula:

The ROC curve plots TP Rate (Recall) against FP Rate, and AUC (Area Under the Curve) represents the model's ability to discriminate between binary classes.

b) Explanation:

The ROC-AUC Score evaluate the total result of a classification model across all threshold values. A higher AUC indicates better performance [12 - 13].

6) Confusion Matrix:

a) Formula:

Not a formula but a table showing the TP, TN, FP, and FN.

b) Explanation:

Provides detailed insight into the performance of the classification model, showing the number of win and lose situation for each class [12 - 13].

B. Regression Algorithm Model Evaluation Techniques:

1) Mean Absoulte Error:

MAE measures the average magnitude of errors in a set of predictions without taking into account their direction in any way Eq. (5). It is a basic metric and is less sensitive to extreme values than other metrics [16].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

2) Mean Squared Error:

MSE measures the average of powered difference between actual and predicted values Eq. (6). It punishes larger errors more than MAE and is sensitive to extreme values [16].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (6)$$

3) Root Mean Squared Error:

The RMSE gives standard deviation of the residuals allowing a better understanding of the average magnitude of errors Eq. (7). It is more interpretable than MSE because its units are the same as the target variable [16].

$$RMSE = \sqrt{MSE} \quad (7)$$

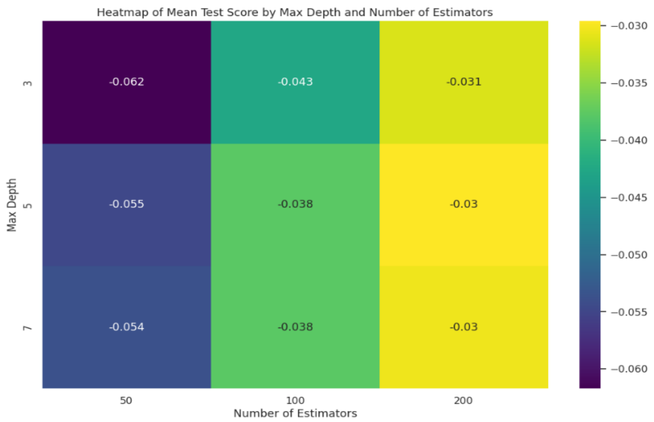

Fig. 8 Heat Map Max_Depth, N – Estimators

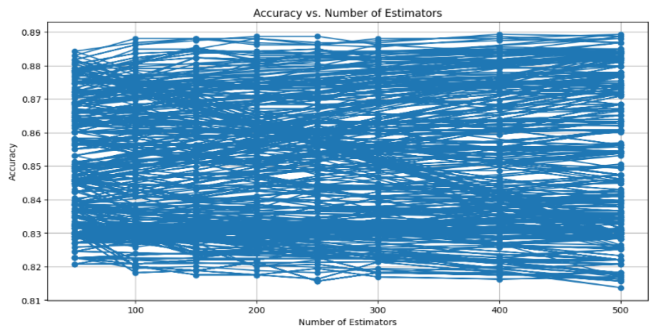

Fig. 9 Accuracy vs N – Estimators

4) R – Squared Error:

R-squared is the percentage of variance in the dependent variable predicted by the independent variables. A higher R-squared indicates better fit for the model [16].

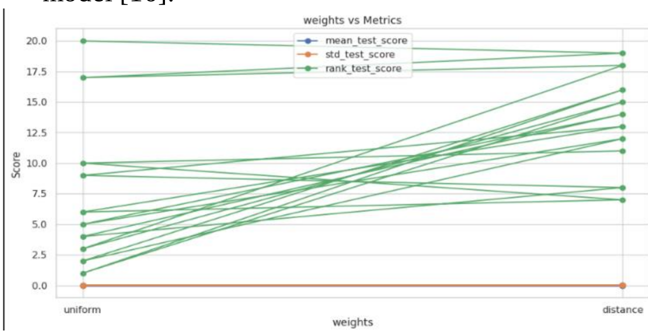

Fig. 10 Weights vs Metrics

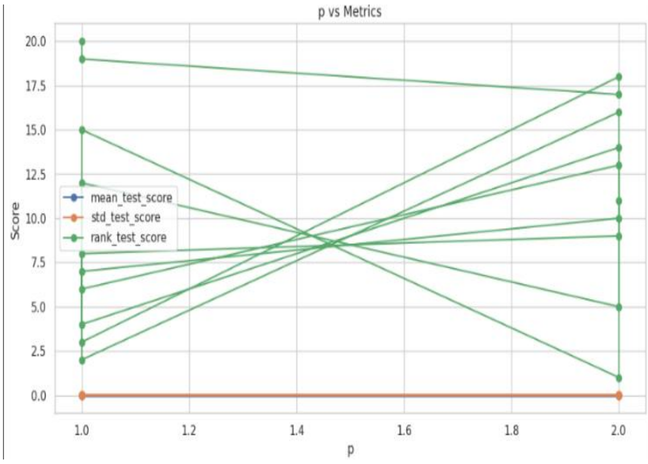

Fig. 11 Learning Rate vs Mean Test Score

VII. Conclusion and Results

The model undergone the simulation testing in the IEEE 14 bus a generalized and approximated model of the American Electric Power System. The output of the models are added below,

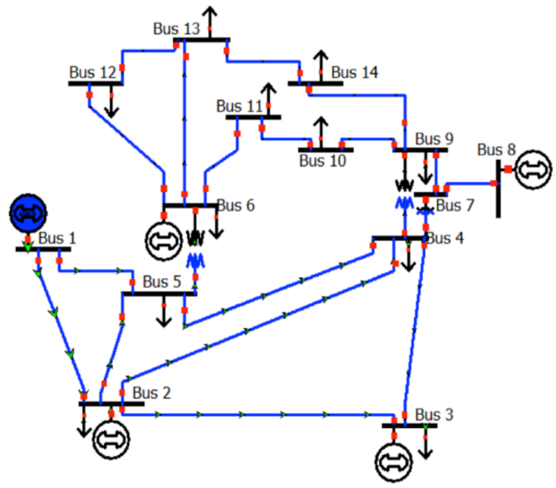

Fig. 12 IEEE 14 Bus System

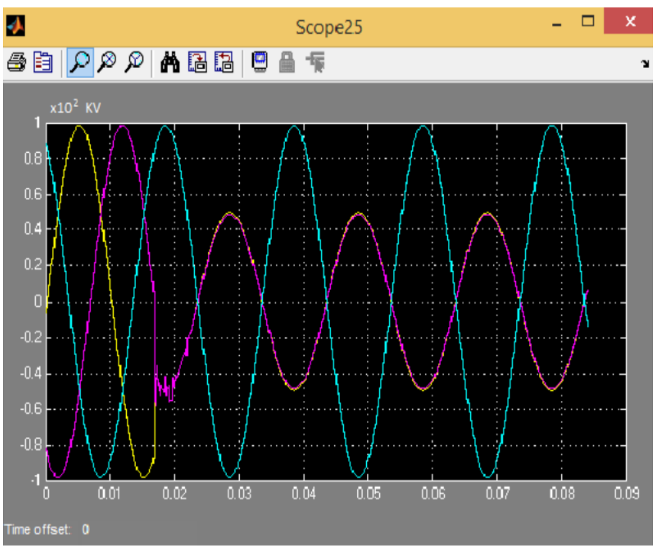

Fig. 13 Line to Line Fault Identification

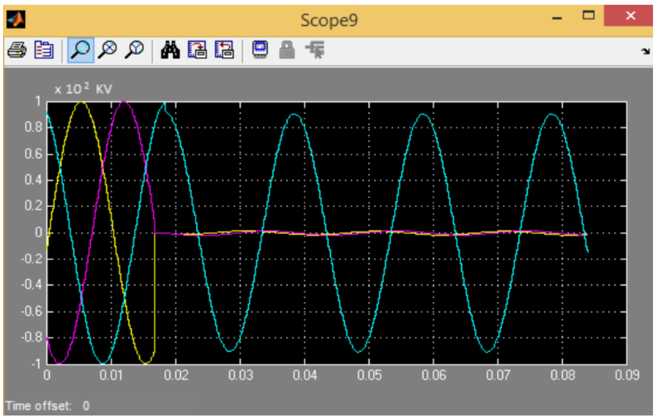

Fig. 15 Double line to Ground Fault Identification

The accuracy of the Fault classification models are almost 88%. Error values produced by the Fault predictors are less than 2%. Error value produced by Fault localizer are also less than 2%. The network developed using these output values will not have any errors as the previous models have very less values of errors. The hybrid network of the Deep Reinforcement Learning and Long Short Term Memory automatically learns from its incorrect outputs and learns all type of the non – linear and transient conditions in the Power.

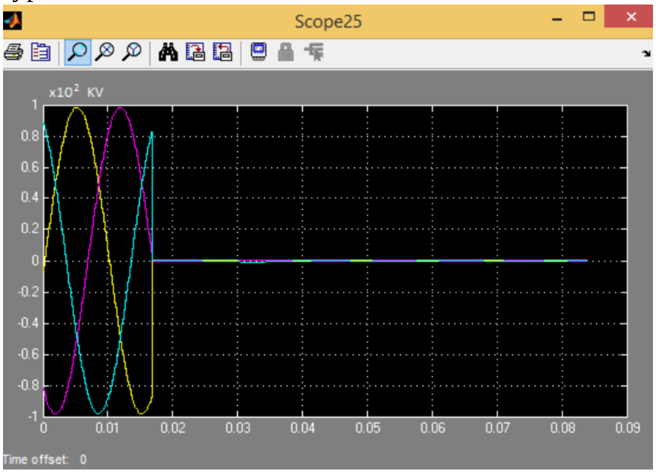

Fig. 16 Three phase balanced Identification

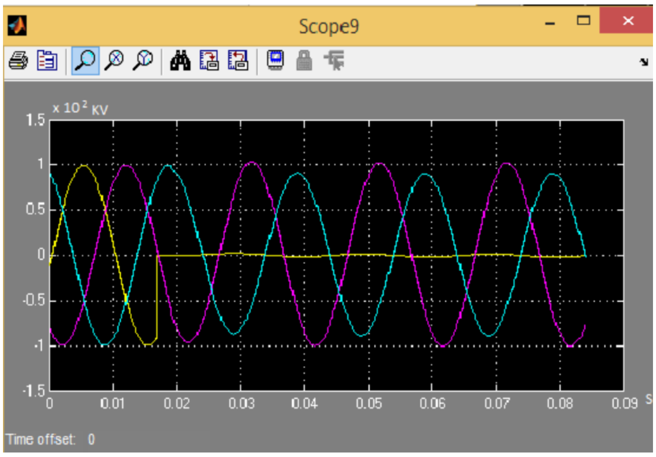

Fig. 17 Single Line to Ground Fault Identification

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