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Predictive Model for Grid Stability Analysis Using Supervisory Control and Data Acquisition (SCADA) System

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Abstract: This paper presents a Predictive model for grid stability analysis using SCADA system. It has been a norm of instability recorded in Electrical power system in Nigeria. Fluctuations in grid parameters such as voltage and frequency have always been the issues. This has contributed to frequent power outage which has crippled businesses and make life miserable. This research is aimed at stabilizing the grid system using artificial intelligent technique in order to promote constant electricity supply. The grid system comprises of renewable energy source, substations at different voltage levels, and overhead electrical conductors, then consumers. In order to develop a sustainable model, data were gathered from an existing substation and used for the model training. The Supervisory Control and Data Acquisition (SCADA) system was designed and simulated using Intouch software and Allen Brandley micrologix 1000, the Programmable Logic Controller (PLC). The graphical user interface (GUI) was developed using web application tools for the model testing. Training and validation were conducted using extensive datasets from SCADA-monitored grids, with the model achieving an overall accuracy of 98.65% in predicting stability-related incidents. The results of the investigation showcase that the suggested predictive model significantly enhances the functionality of SCADA systems by providing them with foresight on grid instability and problems. This model provides proactive and useful grid management in advance times with precise forecasting for improving electrical power network effectiveness and reliability. This research contributes to the advancement of smart grid technology, offering a scalable solution for maintaining grid reliability in the face of evolving energy demands.
Keywords: Predictive Model, SCADA System, Grid Stability, Machine Learning, voltage, frequency

I. INTRODUCTION

Grid stability is fundamental to the reliability and resilience of modern power systems. With the growing complexity of power grids driven by increased demand, the integration of renewable energy sources and the move towards distributed generation, the ability to maintain stability has become more challenging. SCADA systems are instrumental in grid management, providing real-time monitoring of essential parameters such as voltage, frequency, and power flows across transmission and distribution networks. Grid instability can lead to blackouts, equipment damage, and increased operational costs, underscoring the need for advanced tools that predict and manage potential instability events before they disrupt service. Traditional approaches to grid stability often rely on manual intervention and post-event analysis, which can be insufficient in addressing the dynamic demands of today's grids. Predictive modeling has emerged as a valuable approach to proactively manage stability, providing actionable insights that enable grid operators to anticipate and respond to issues in real-time. SCADA's capacity to collect extensive, high-frequency data makes it well-suited for integration with predictive models. By analyzing historical SCADA data, machine learning algorithms can identify patterns and trends that precede stability events, thus offering a predictive capability that enhances traditional grid management techniques. This predictive model, developed from SCADA data, has the potential to transform grid operations, providing operators with advanced warnings and allowing preemptive actions that stabilize the system before issues escalate. Recent research has demonstrated the effectiveness of machine learning and artificial intelligence (AI) in predictive modeling for power systems. According to [1], machine learning models trained on historical grid data can predict instability with remarkable accuracy, significantly reducing the incidence of unplanned outages. These models use SCADA-derived datasets to predict fluctuations and vulnerabilities that contribute to instability, such as sudden changes in demand or generation.

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Moreover, AI techniques such as artificial neural networks (ANN) and support vector machines (SVM) have shown promising results in grid stability applications, proving capable of processing high volumes of SCADA data to provide actionable predictions. The integration of predictive models within SCADA systems present challenges, including model accuracy, data processing speed, and system adaptability to different grid environments. Addressing these issues requires not only the selection of appropriate machine learning algorithms but also the optimization of model parameters to align with specific grid characteristics and operational requirements. This study focuses on developing a predictive model for grid stability analysis using SCADA data and machine learning techniques, aiming to provide a proactive solution that enhances the stability and resilience of power systems. By leveraging on SCADA's real-time data capabilities and the predictive power of AI, this model aims to serve as an essential tool in the management of modern complex grids.

II. SUMMARY OF RELATED WORKS

In [2], a comprehensive review of stability monitoring in grids and highlighted the importance of integrating advanced data analytics with grid infrastructure to create systems capable of anticipating potential instabilities was conducted. These findings underscore the need for predictive tools that can adapt to diverse and dynamic power generation scenarios. In recent years, grid stability has emerged as a critical area of focus due to the increasing adoption of renewable energy and decentralized power generation. According to [3], the fluctuating natures of renewable sources like wind and solar poses unique challenges for grid stability, as these sources can introduce significant variability and unpredictability. Traditional stability analysis methods, which rely heavily on deterministic models, are limited in their ability to handle these complexities. New approaches, therefore, leverage real-time data and predictive analytics to enhance stability management. SCADA systems are central to real-time monitoring in modern power grids, providing critical data on voltage, frequency, and power flows that underpin stability analysis. In [4], the evolution of SCADA systems from simple monitoring tools to complex systems that support predictive modelling through data analysis was discussed. Their research emphasizes the significance of SCADA data in identifying patterns and trends that contribute to stability predictions, particularly as the demand for reliable power has increased alongside grid complexity. Furthermore, SCADA systems provide a scalable platform for implementing machine learning algorithms that can process high-frequency data and deliver near-real-time insights. [5] advocated for explainable AI (XAI) frameworks that provide insight into the decision-making process of these models, enhancing their acceptance among grid operators. As predictive models become more integrated within SCADA, additional research is necessary to refine these models for higher interpretability, faster processing, and scalability to various grid configurations. In [6], it was noted that SCADA's integration with AI not only enhances its functionality but also enables the proactive management of grid operations. Their study highlights successful cases where SCADA-enabled AI models reduced downtime and improved grid stability, reinforcing SCADA's role as a foundation for advanced predictive analytics in grid management. The application of machine learning to predict grid stability has been an area of significant research. Studies demonstrated the high accuracy of machine learning models, including artificial neural networks (ANN), support vector machines (SVM), and decision trees, in predicting grid stability issues. Their work shows that ANN, in particular, is well-suited for complex, non-linear data patterns commonly observed in power systems. Each model presents unique advantages; SVM is noted for its effectiveness in small datasets, while decision trees offer interpretability, which is critical for practical implementations where understanding the basis of predictions is essential. A study as in [7] expanded on these findings by highlighting the need for hybrid models that combine multiple machine learning techniques to enhance predictive accuracy. They developed a hybrid ANN-SVM model that demonstrated improved performance in scenarios with high data variability, typical of grids incorporating renewable energy sources. Practical implementations of predictive stability models provide insights into their real-world applicability and challenges. In [8], cloud-based SCADA implementation was suggested that could alleviate some of these issues by enabling faster processing and data storage capabilities. Another challenge involves the interpretability of machine learning models, especially complex ones like deep neural networks, which can be perceived as "black boxes." A case study was conducted in [9] on a North American power grid, implementing a predictive model using SCADA data to detect stability issues related to fluctuating renewable integration. Their findings show that the model accurately predicted instability events and allowed operators to take pre-emptive measures, such as load shedding and voltage regulation, to avoid disruptions. Similarly, [10] explored the use of machine learning-based predictive models in a grid network within a renewable-heavy European region. Their model achieved high prediction accuracy (93%) for instability events, indicating the potential of predictive models to support renewable integration and grid reliability. Lopez and Chen also noted that these models are cost-effective compared to traditional grid reinforcements, making them a viable solution for resource-constrained utilities.

These case studies demonstrate the practical benefits of predictive stability models in diverse geographic and operational contexts, supporting the scalability of this approach. Despite the advantages, integrating predictive models with SCADA systems poses several challenges. One primary concern is the processing speed and computational power required to analyse high-frequency data in real time.

III.SYSTEM METHODOLOGY

The research methodology adopted is two-prong approach that involve setting up a simulated Electrical Substation monitoring system to mimic process readings emanating from an electrical Substation. This involves writing of a PLC program and connecting this to a SCADA software for monitoring and visualization using the Wonderware Intouch platform and RSLinx classic software. The program, Wonderware intouch, also provides an interactive graphical interface through which operators can easily have real-time control and monitoring of the grid network. In principle, most SCADA systems have a historian server that is used for the storage and retrieval of historical data on plant parameters. From this data bank, these data were gotten and used in developing and testing machine learning model to analyze and predict the occurrence of faults within the entire electrical Power grid System. The typical Grid parameters stored are voltage, current, power factor, and frequency. The system can easily be extended to capture other data such as energy consumption, time of the day, seasons, generation plant operating conditions, and ambient temperature.

A. Grid Data Collection and Pre-Processing

Dataset used for the model development were sourced from Geometric Power plant Substation in Aba, Abia State Nigeria. This power plant substation contains all the primary data from the main and subsidiary Substations. During collation, it was realized that the data were not organized; different power stations stored different data at irregular periods. To avoid proposed model being bias, data cleaning was carried out. This exercise was done using python codes that helped to transform the raw data into a standardized format as shown in fig.1. Additionally, more cleaning was done as follows:

1) Remove Outliers: Identified and removed outliers that are unrealistic or fall outside expected ranges. Those voltage or current values that are significantly higher or lower than typical operational values were flagged for review or removed.
2) Check for Correlations: Examined correlations between variables. Any correlation that is too strong or unexpected, data generation process was revisited to ensure independence or realistic relationships between variables.
3) Normalization: Normalized the data where necessary, especially with different variables of widely varying scales. This helps in ensuring that each feature contributes proportionally to the analysis.

[181]:
```
#print first 5 rows
plant_data.head()
```

[181]:

	time_stamp	voltage_a	voltage_b	voltage_c	current_a	current_b	current_c	power_a	power_b	power_c	frequency	power_factor	fault
0	0	32123.620360	32120.922460	33189.99493	46.846538	51.118397	47.863060	1445.217557	1576.872133	1525.593694	49.890417	0.960354	0
1	8	27256.481700	21658.039580	26458.94304	60.701544	53.944118	43.022079	1556.740909	1099.284349	1071.052325	49.447143	0.940907	1
2	16	33195.981830	31528.461740	32039.91908	58.328395	49.780504	44.853878	503.236246	407.913841	373.506169	49.876196	0.259900	1
3	24	32795.975450	32821.800010	32989.84191	53.654677	43.947237	45.640642	1672.581866	1371.049749	1431.170013	49.947522	0.950516	0
4	32	4703.652067	5534.919722	20967.76981	48.284620	53.390578	44.979850	221.450972	288.143969	919.610298	50.908015	0.975065	1

[182]:
```
## number of rows and columns
plant_data.shape
```

[182]: (10000, 13)

Fig..1: Cleaned Dataset of the power plant for the model's training

B. SCADA system Simulation

The SCADA application consists of three components such as Programmable Logic Controller (PLC) program, Open Platform Communication (OPC) Server, and Human Machine Interface (HMI) Visualization using the wonder ware Intouch Software. The PLC used is the Allen Bradley Micrologix 1000 Analog controller. The MicroLogix 1000 programmable controller is a packaged controller containing a power supply, input circuits, output circuits, and a processor. The model used has 11 discrete inputs, 8 discrete outputs, 4 analog inputs and 1 analog output terminals. The SCADA system was designed with various content such as overview 1, overview 2, overview 3, power plant, 11KV Transformer, alarms, and trends. In power plant option shown in fig. 2, the SCADA screen is started with the run button which power up the turbine with 11KV generated. The transformer 60MVA, 11/33KV step this voltage to 33KV and the isolator breaker close the voltage flows into 33KV bus bar.

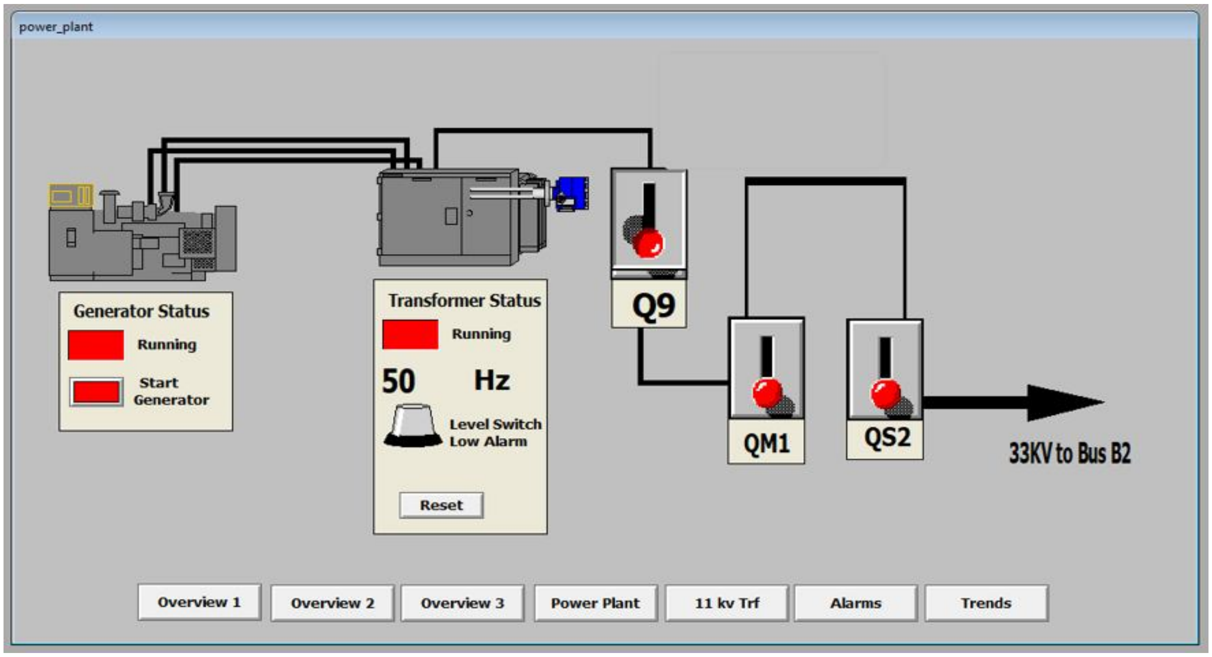

Fig. 2: Power Plant Substation

In overview 3 option shown in fig. 3, the entire electrical distribution network from generated.11KV is distributed through the 33KV and different Switchgear via outdoor feeder pole to different electrical feeders.

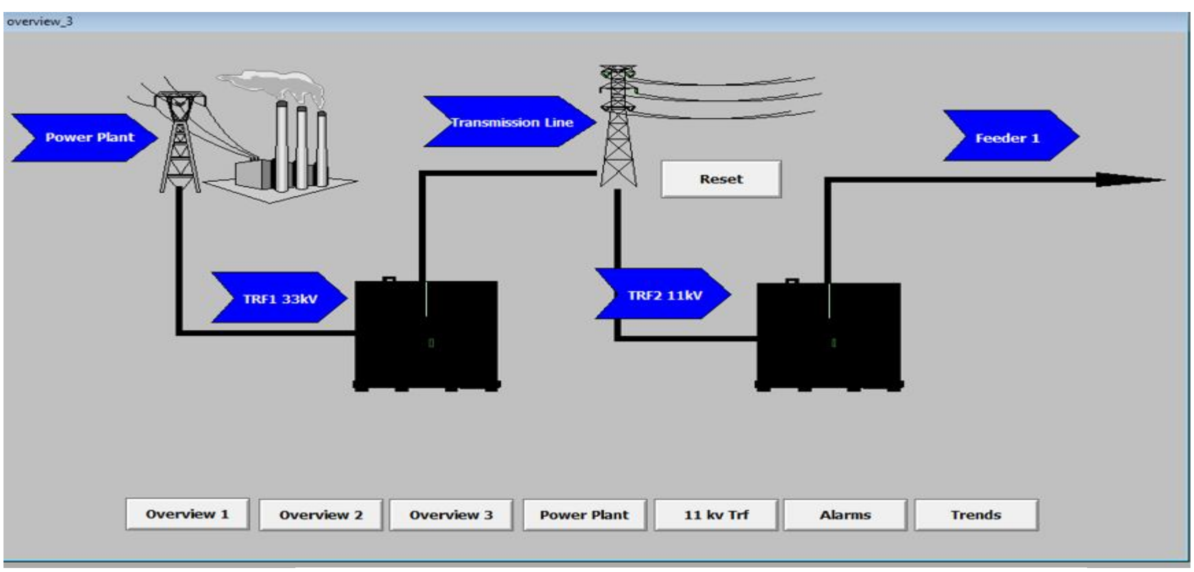

Fig..3: 11/33KV Electrical Distribution Network Distribution Network

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In 11kV transformer option shown in fig.4, 33KV flows into the transformer as soon as the breaker Q01 and Isolator Q0 are closed to allow voltage to flow into the 15MVA, 33/11K step down transformer. When Isolator Q02 is closed, 11KV goes into the distribution network which is further step down to 0.415KV for domestic use.

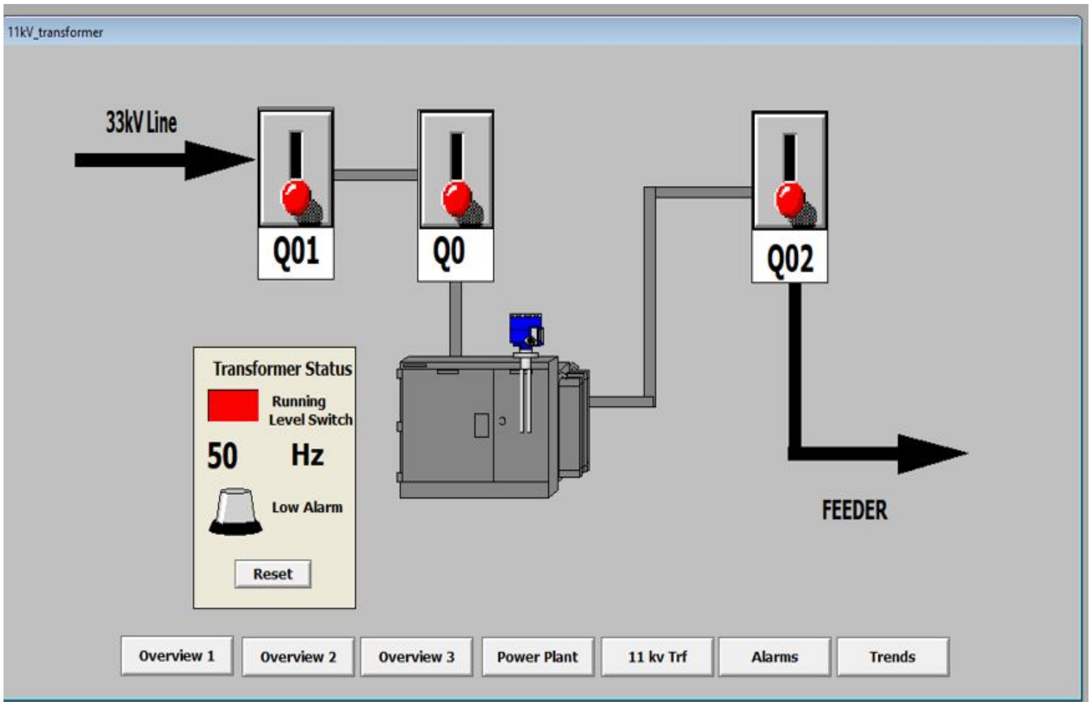

Fig.4: 33/11KV Electrical Power Distribution Network

The SCADA system provides real time monitoring and control in the entire substation. This makes the control of the Substation easier such that the operator can manipulate control from the control room. SCADA system works with Allen Bradley Micro Logix 1000 PLC ladder logic where RSLogix 500 software shown in fig. 5 is used for programming and configurations. The data received by the PLC is transferred to the SCADA monitoring system through RS 232 cable.

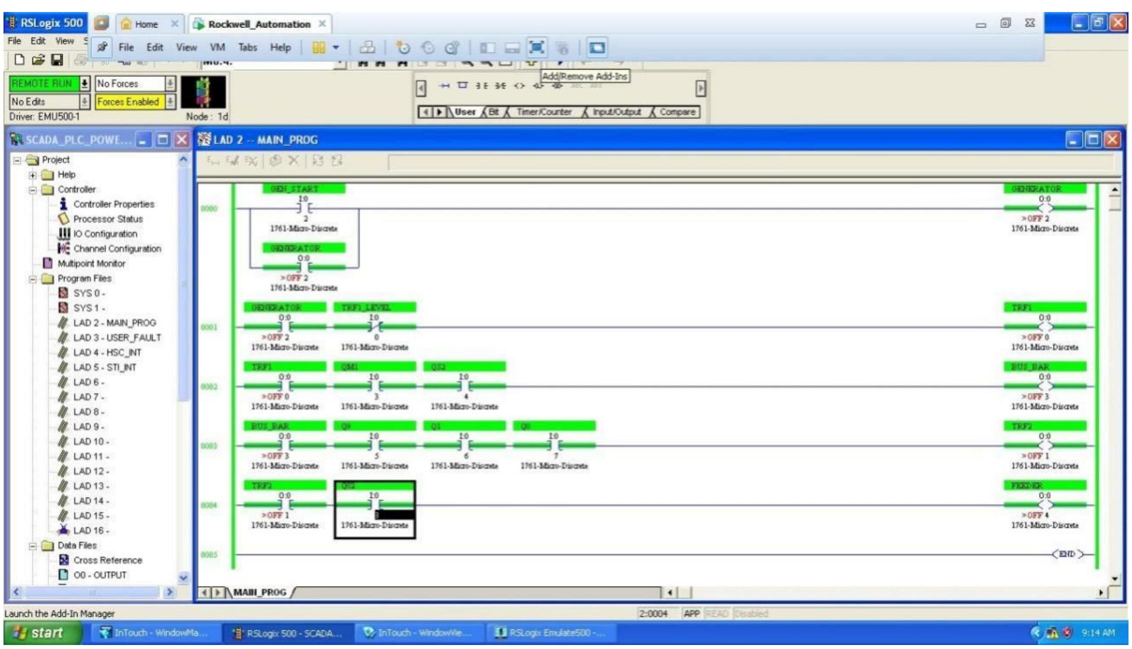

Fig. 5: PLC Ladder Logic Program with RSLogix 500

C. Model Development

1) Model Training: The predictive model uses machine learning algorithms selected for their suitability in handling SCADA data and grid stability prediction. The design process involves training, testing and selecting the optimal algorithm(s) based on accuracy, interpretability, and computational efficiency. The dataset was divided into two parts using the 7:3 ratio, 70% for training, and 30% for validation and testing. Various models were trained on a labeled dataset, with instability events marked according to SCADA data records. The training process includes hyper parameter optimization to achieve a balance between accuracy and computational efficiency, with cross-validation applied to evaluate model performance. Support Vector Machines (SVM) outperformed others on stability classification. SVM model can separate stable and unstable grid states with high accuracy, particularly when used with kernel functions that handle non-linear data.
2) Scatter Plot: Scatter plot shows the relationship between features in the data set. The relationship between voltage and current in the 3 phase line against the power to see how faults are caused is clearly shown in fig.6. The scattered plot is a plot from the data set showing the plot of every field in the dataset. In each graph plot, blue dot shows no faults condition (0), while the red shows fault condition (1). In graph plot of total power against the voltage, there is concentration of fault condition from 0 to 4000 on the vertical axis and from -5 to 1 on the horizontal axis. This gives an indication that fault is most likely to come from here and it should be taking seriously. The blue dots are an indication of no fault from the graph which is above 3000 total power and closer to 1 on the horizontal axis. Also, in the graph plot of total power against current, there is a concentration of fault condition below 4000 between -4 to +4 on the horizontal axis. Above 4000, has no fault condition.

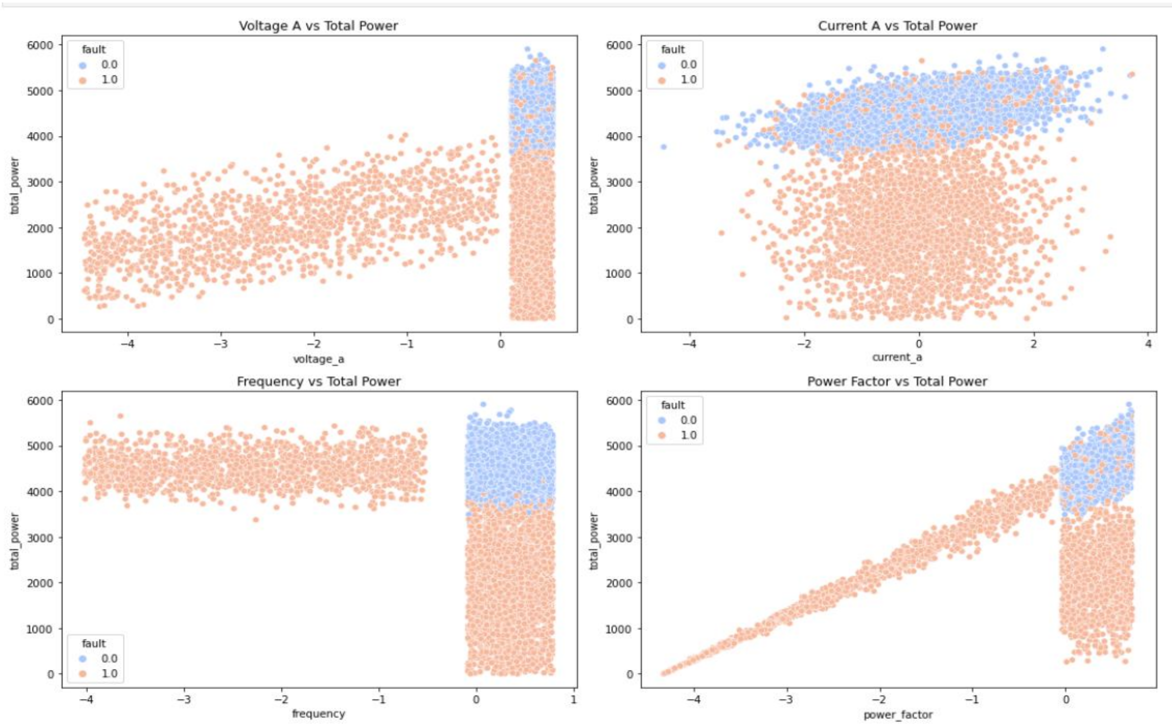

Fig. 6: Scattered Plot of total power against voltage, current, frequency and power factor

In the graph plots of total power against frequency and power factor, the fault condition is still high in both cases and these areas needs improvement in the future.

D. System Algorithm and Flow chart

The following algorithms were used to simulate the power system**:**

1) Step 1: Click on Overview 1 option, press Stop / Reset button to start the turbine.
2) Step 2: Go to power plant option, click start generator button to energize the turbine.
3) Step 3: is turbine energized? If yes, transformer 1 60MVA, 11/33KV is energized with both 11KV and 33KV bus bars. If no, go to step 1

4) Step 4: close Breaker Q9 for power flow to isolator QM1.
5) Step 5: close Isolator QM1 for power flow to QS2.
6) Step 6: is power flow to QM1 & QS2? If yes, 33KV supplied to Bus 2. If no, go to step 4
7) Step 7: Go to 11KV Overview and close Breaker Q01 and Isolate Q0 to energize Transformer
8) Step 8: Is transformer 2 energized, yes, Close Breaker Q 02 and Isolator Q0 for power to flow into feeder network. If no, go back to step 7
9) Step 9: Click Overview 2, to see the entire electrical network.
10) Step 10: Click Overview 3 to see the entire distribution.
11) Step 11: Go to alarm Status to see the various alarms status
12) Step 12: Go to trends and observed it
13) Step 13: Stop.

The system simulation flow chart is shown in fig. 7.

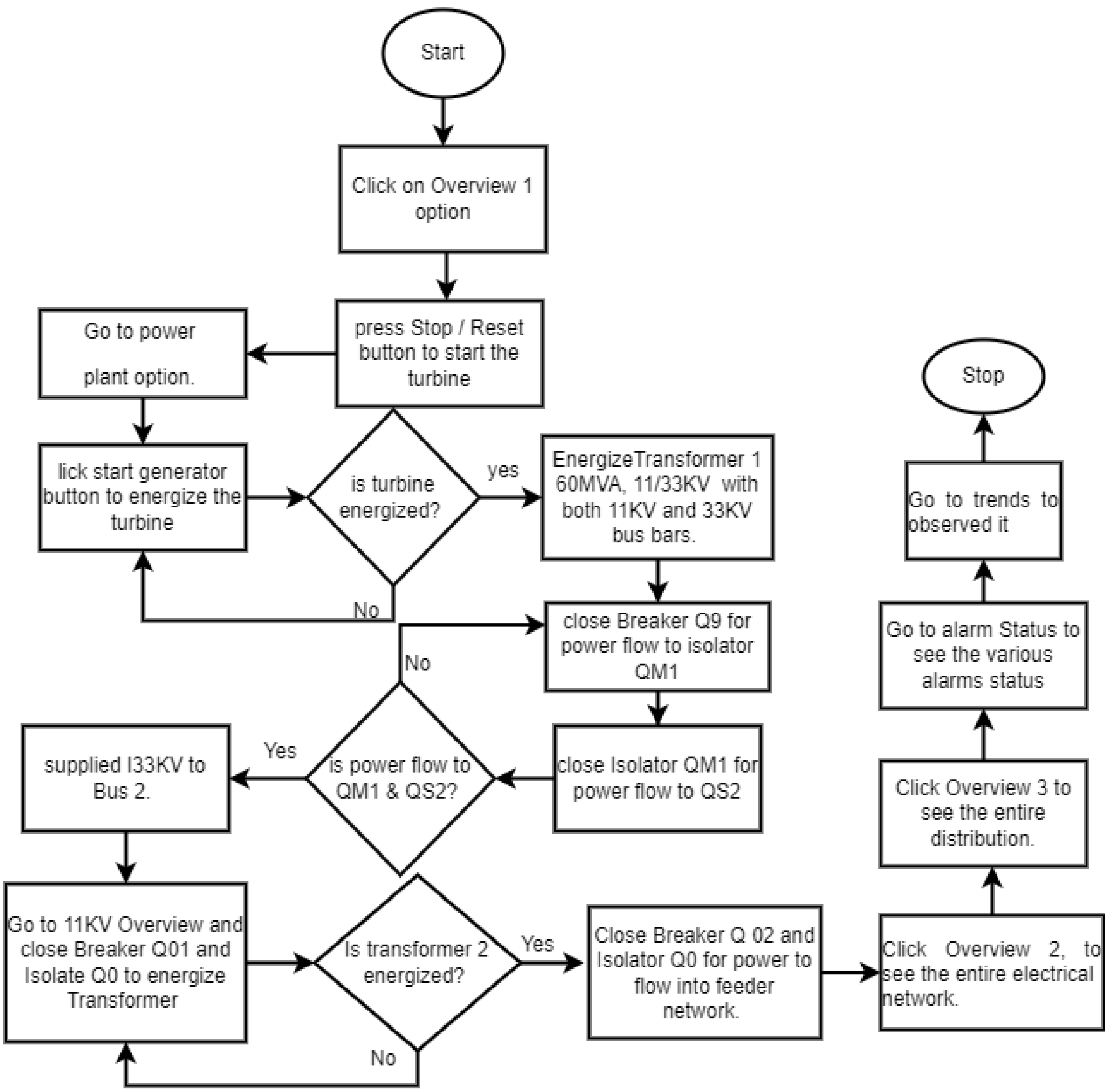

Fig. 7: The System simulation operation flow chart

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IV. RESULT OBTAINED

A. SCADA System Test

Testing the SCADA system is to ensure that the different components in the simulation environment work together. First, the RSlinx and the RSlogix were connected for communication via PLC Ladder Logic program. It was observed that the Allen bradley Micro logic 1000 PLC connected successfully to the SCADA system for monitoring, controlling and grid system supervision as shown in fig. 8.

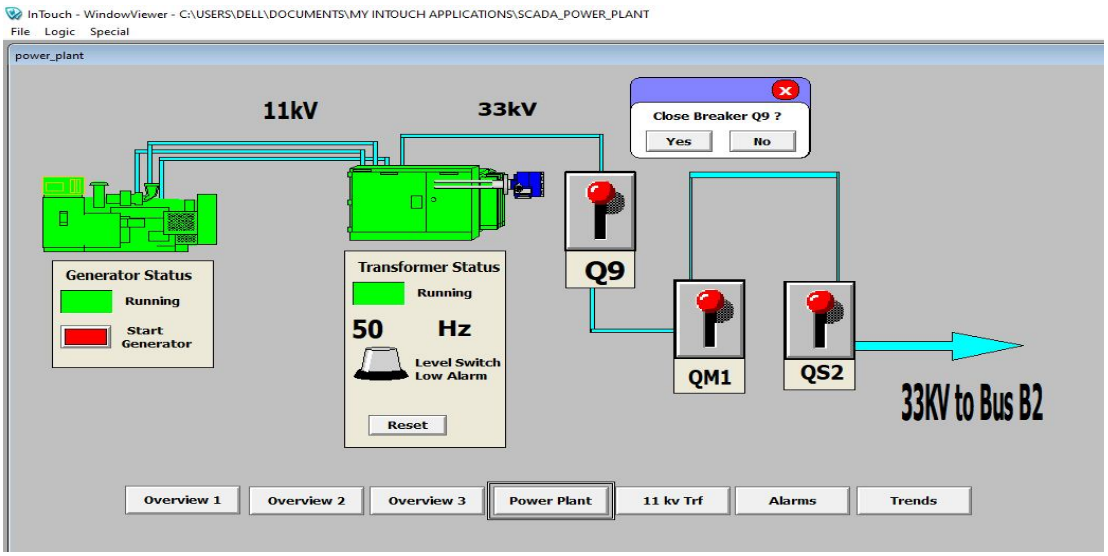

Fig.8: Energized Power Plant Substation

B. Model Testing

The graphical user interface (GUI) shown in fig. 9 was developed using web application to test the model. The interface is a simple hyper test markup language (HTML) form that receives inputs of current, voltages, frequency and power factor from the user. Upon clicking on the submit button, the data is submitted to the model for prediction. It is expected that the model predicts fault condition or normal condition.

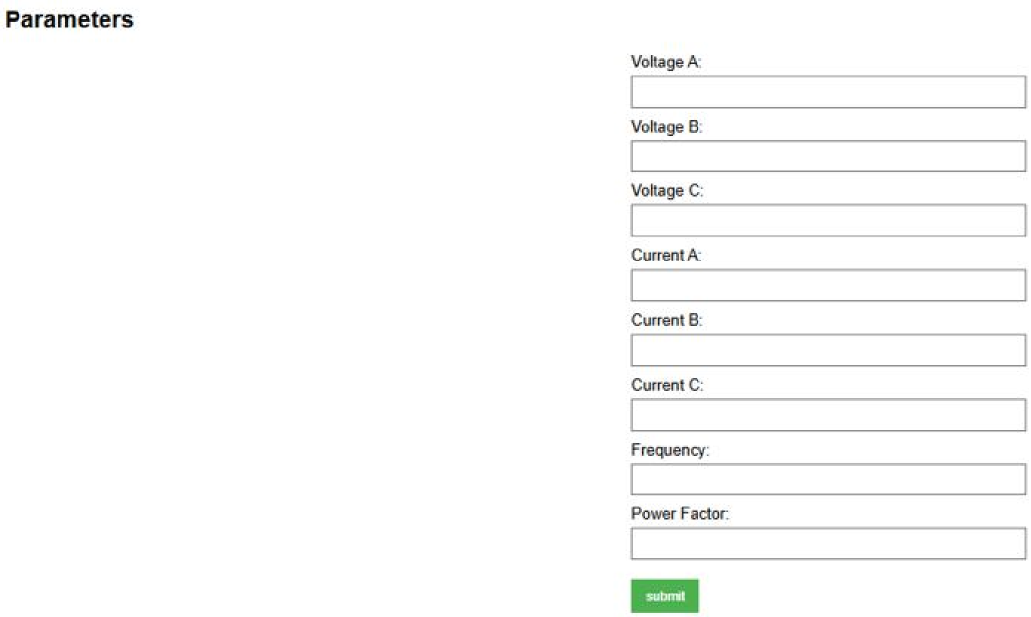

Fig.9: Graphical User Interface for the Model's testing

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C. Testing Grid Parameters

The following parameters were inputted and submitted such as voltage A = 32123.62, Voltage B = 32120.922, Voltage C = 33189.995, Current A = 46.846538, Current B = 57.118397, Current C = 47.86306, Power A = 1445.2176, Power B = 1576.8721, Power C = 1525.5937, Frequency = 49.890417, Power Factor 0.9603538 as shown in figure 10. After clicking on the submit button, the model made prediction 'the circuit condition is (0,'normal condition')'.

Also another set of parameters were entered and submitted such as voltage A = 27256.482, Voltage B=21658.04, Voltage C = 26458.943, Current A = 60.701544, Current B = 53.944118, Current C = 43.022079, Power A = 1556.7409, Power B = 1099.2843, Power C = 1071.0523, Frequency = 49.447143, Power Factor = 0.9409072 as shown in figure11. After clicking on the submit button, the model made prediction 'the circuit condition is (1,'fault condition').

Fig.10: Sample test of the model on normal condition

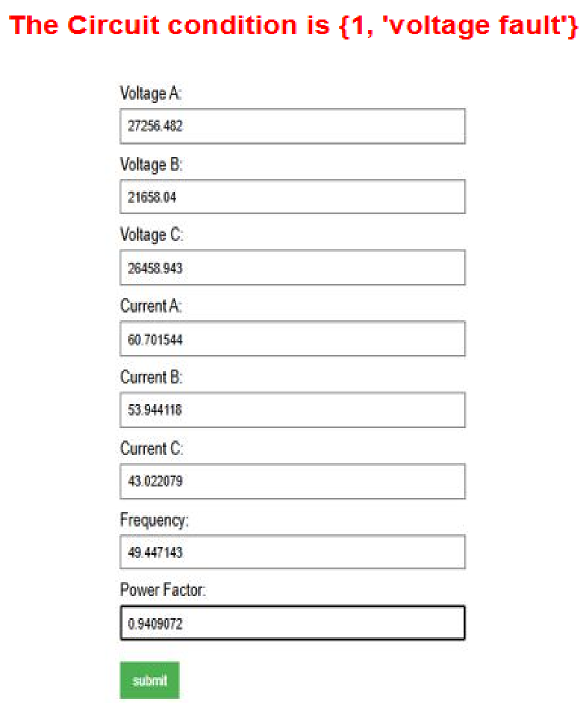

Fig. 11: Sample test of the model on normal condition

E. Performance Evaluation

After training all the selected models, the result summary of each model based on the accuracy, precision, recall and F1 score recorded is shown in table 1. The comparison graph plot of the various models is shown in fig. 12.

Table 1: Results Summary (Based on different model outcomes for Data)

	Accuracy	Precision	Recall	F1 Score
SVM	0.9865	0.88	0.90	0.89
Decision Tree	0.85	0.78	0.82	0.80
Neural Network	0.87	0.81	0.84	0.82
Logistic Regression	0.82	0.77	0.79	0.78

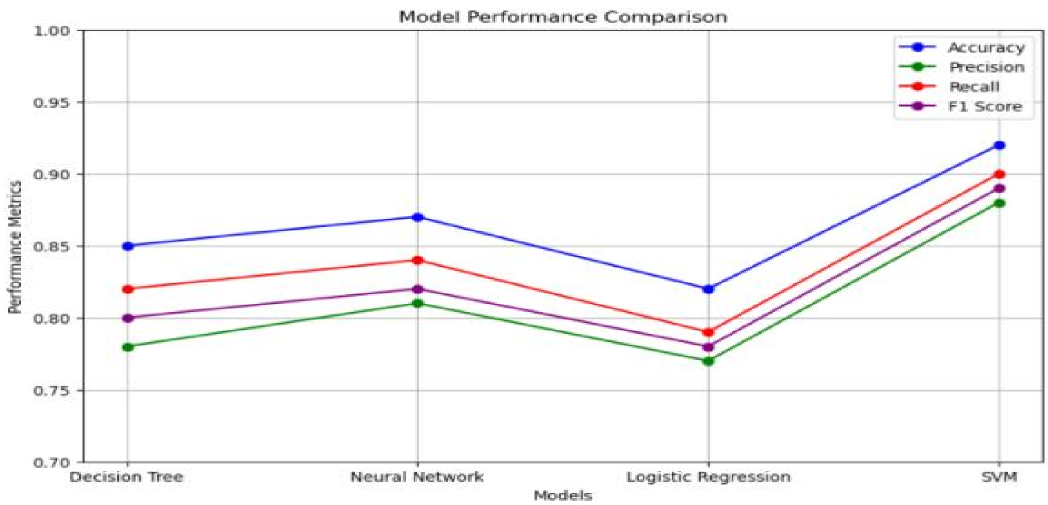

Fig. 12: result summary of each model based on the accuracy, precision, recall and F1 score

The development and implementation of a predictive model for grid stability analysis using SCADA systems represent a significant advancement in the management of power systems. By harnessing real-time data and sophisticated machine learning techniques, the model has demonstrated the potential to accurately forecast grid stability conditions, enabling proactive interventions that enhance operational efficiency and reliability. The results from simulations and preliminary validations show that the model achieved high accuracy rates of 98.6%) in predicting stability and instability events, significantly reducing the likelihood of power outages and improving overall system resilience. Furthermore, the predictive capabilities allow operators to respond to potential issues with a lead time of several minutes, which is crucial in maintaining grid stability amidst fluctuating demand and the increasing integration of renewable energy sources. Moreover, the operational efficiencies gained through the predictive model contribute to reduced downtime, optimized resource allocation, and improved decision-making processes within grid management. The proactive risk management strategies facilitated by this model not only enhance the safety of grid operations but also lay the groundwork for a more resilient power infrastructure capable of adapting to future challenges. Future research should consider exploring hybrid modeling approaches that combine various machine learning techniques (e.g., ensemble learning) to improve prediction accuracy and robustness against diverse operational conditions.

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