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Machine Learning Based Power Distribution System Reliability Improvement

Muhammad Usama Farooqi[1], Insharah Salman[2], Muhammad Mudassir Hussain[3], and Sardar Muhammad Maaz[4,*]

NED University of Engineering & Technology, Karachi, Pakistan

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Abstract

The task of maintaining optimum values of reliability by assessing parameters is becoming an ever-increasing challenge for utilities. This study focuses on optimizing values of SAIDI and SAIFI indices by implementing a Machine Learning (ML) based method known as Artificial Neural Network (ANN) on the IEEE 9 bus system. The system is modeled in the Simulink environment of MATLAB. The load busses of the system are then subjected to different faults that occur on the distribution network, which affects the reliability of distribution systems. The data collected by this process is used to train the ANN so it can detect and classify these faults. Since the focus of this study is on the distribution section, this means that only the three load busses are being considered for analysis. After the faults had been correctly detected and classified by the ANN, these results were then used to optimize SAIDI and SAIFI. In the next phase, software named Windmill was used for reliability analysis. The fault detection time calculated previously was used here to observe the updated conditions of the system and in the calculation of the improved values of SAIFI and SAIDI.

Keywords: Machine Learning (ML); Artificial Neural Network (ANN); MATLAB.

1. Introduction

The reliability of the Electrical Distribution System is vital for a country in different aspects. A reliable power system ensures an uninterrupted power supply to the consumers. Different parameters, such as the frequency of power outages, duration, and fault clearance time, can assess reliability. These parameters are directly linked to customer-oriented indices (SAIFI, SAIDI) and utility-oriented indices (ENS, AENS). In this project, the sole focus will be on customer-oriented reliability indices, including SAIFI and SAIDI.

SAIDI stands for System Average Interruption Duration Index (Yeddanapudi, 2016). It is the ratio of interruption duration to the number of customers served. In contrast, SAIFI stands for System Average Interruption Frequency Index (Power, 2022). SAIFI is the ratio of the total number of interruptions to the number of customers served.

The value of both of these indices computed for Karachi as per the 2019-20 NEPRA Performance Evaluation Report of Distribution Companies (Authority, 2019-20), comes out to be 27.56 for SAIFI % 2,655 minutes for value of both of these indices computed for Karachi as per 2019-20 NEPRA Performance Evaluation Report of Distribution Companies (AUTHORTY, 2019-20), comes out to be 27.56 for SAIFI and 2,655 minutes for SAIDI. Both these values exceed the standard values set by NEPRA, which are 16.22 for SAIFI and 649.48 minutes for SAIDI. This observation led to pondering the question of what can be done to make the distribution systems more reliable, and this serves as the motivation for this research.

In order to ensure the smooth execution of the proposed study, this project was divided into two phases. The SAIDI index was improved in the first phase, while the SAIFI index was optimized in the second phase. For the execution of the proposed study, IEEE 9 Bus System was first modeled on Simulink. The system was then subjected to different faults that affected the reliability, and data was collected for the training of ANN. After that, ANN was used to classify and detect these faults. For the implementation of ANN, the Levenberg-Marquardt algorithm was used. The timely detection and classification of faults by ANN will reduce restoring time, thus improving the Reliability of the Distribution Network. The detection time of different faults were noted down. Then these detection times were used to run reliability analysis on a software named Windmil, where it was observed that these detection times, after the integration of ANN, had led to significant improvement in SAIDI and SAIFI.

This study is an attempt to reduce the gap between threshold values and the existing values of the customer-oriented reliability indices. The complexity of distribution systems due to loads of variable nature at different time durations complicates the reliability of distribution

[*] Corresponding author

network. This study aims to solve the challenging problem of low-reliability indices and ensure that the system operates at the maximum possible reliability, ensuring a continuous supply of power to the consumers.

2. Objectives

In order to achieve the ultimate goal of optimum reliability, the project has been divided into the following objectives:

- To model IEEE 9 bus system based on SIMULINK MATLAB.
- To create the dataset for the training of ANN.
- To evaluate reliability indices (SAIFI, SAIDI) under normal and faulty conditions.
- To improve the index by using fault detection diagnosis and fault localization.
- To benchmark reliability indices with the base case.

After creating the data set for the training of ANN, ANN was trained for the detection and classification of different fault conditions, which include three-phase faults (ABC), line-to-line faults (AB, BC, CA), single line to ground faults (AG, BG, CG) and double line to ground faults (ABG, BCG, ACG).

3. Scope and Limitations

This project aims to provide a simulation-based algorithm that can be used to improve the reliability of a power system. The data required for this project has been gathered by running simulations on Simulink. So, this study is based on steady-state data acquired through simulation, and real time data is not used in this study. The system used for this study is according to IEEE standards. For evaluation of SAIFI and SAIDI, it has been decided to set equal load at all three load busses operating under normal loading conditions, and the load value considered is that of the bus which is loaded the most among the three as per IEEE standards. The decision to set the load equal at all three load busses is taken to simplify the algorithm's implementation. Furthermore, the main focus of this study is the distribution side of the power system, so the sole focus has been on load buses. Generation and transmission sections haven't been taken into account during analysis. Also, since the project's main concern is the reliability of distribution systems, only technical attributes of load buses like voltage and currents are considered, while protection and control aspects are out of the scope of this study. In addition to this, economic and environmental factors are also out of the scope as only technical analysis of the distribution system is considered.

4. Significance

Power supply interruptions have long plagued the power sector and caused significant challenges. Consumers suffer due to the unreliability of the electric power supply. In remote areas, where power interruptions are more frequent, consumers struggle to carry out their daily activities without access to electricity. The interruption of power can also result in substantial financial losses for industries, reducing output and damaging products. These are only a few of the issues encountered by consumers. From the utility's viewpoint, if the utility fails to meet the reliability indices specified by regulatory authorities, it may face regulatory penalties. Moreover, if the utility's reliability standards are insufficient, customers may leave their services and opt for a utility with better standards. This study seeks to address this major issue of poor reliability by optimizing the system, thereby benefiting both the consumer and the utility.

5. Literature Review

Power System

It has been observed that as the electrical power demand increases day by day, so does the system's vulnerability to faults. The increasing complexity of the power system's structure further complicates this problem. Therefore, traditional fault detection and classification methods cannot be relied upon as they rely on a reactive mindset rather than a proactive one, which results in greater fault clearance times and an overall increased number of fault occurrences. Moreover, 85-87% of faults occur in distribution lines (Baskar & Selvam, 2019; Singh, Panigrahi, & Maheshwari, 2011), and the consumer end of the power system is greatly affected. A possible solution to these problems can be found in using artificial intelligence and machine learning techniques for detecting and classifying faults (Baskar & Selvam, 2019).

According to (Baskar & Selvam, 2019; Youssef, 2009), some of the most widely used algorithms in this area include support vector machine (SVM), Bayesian Learner, Sequential Minimal Optimization (SMO), Logistic Regression, Decision Tree, and KNearest Neighbor. Upon further analysis, (Baskar & Selvam, 2019) found out that among these algorithms, the ones that yielded the most accurate results in power systems' fault detection and classification were those that implemented the supervised learning approach.

Reliability

Reliability refers to a measure of continuous accessibility of power to consumers. This can be evaluated in terms of the measurement and frequency of system breakdowns and their reestablishment time (Hartati, Sukerayasa, Setiawan, & Ariastina, 2007; Sucita, Mulyadi, & Timotius, 2018). The optimum reliability of a system ensures a sustained electric power supply to consumers. The evaluation of annual shutdowns, failures, and maintenance timeouts is obtained from the installed systems to calculate reliability indices such as SAIFI and SAIDI. The outcomes of these calculations aid in assessing the existing state of the system's reliability as well as formulating necessary solutions to enhance reliability further (Sucita et al., 2018).

Reliability Enhancement

Due to unpredictability in loads and complexity in system structure, distribution systems suffer from approximately 90% reliability associated problems. This issue is to be mitigated to ensure uninterrupted supply. The approach used to rectify this issue involves implementing distributed generation (Ahmad, 2021; Short, 2018). Its impact was analyzed using modified particle swarm optimization for the placement of distributed generators (Ahmad, 2021; Gana, Aliyu, & Bakare, 2019). Analysis was performed for system reliability with and without distributed generation, and it was concluded that the SAIFI value decreased by 40% and SAIDI by 25% (Ahmad, 2021).

In (Hosseini, Shayanfar, & Fotuhi-Firuzabad, 2009), an algorithm for reliability testing is developed with the use of a Static Series Voltage Regulator (SSVR). SSVR can be employed efficiently to improve steady state voltage levels and reduce real and phantom power losses. According to (Hosseini, Shayanfar, & FotuhiFiruzabad, 2008; Hosseini et al., 2009), these can also be useful in reducing sags and under-voltage. The research involved testing a thirty-three and a sixty-six-bus standard distribution system. Both systems were evaluated for their reliability indices with and without the implementation of SSVR and then compared. To increase the efficiency of the performed test, it is evaluated with systems of two different proportions and placements. The results indicated an improvement in the system's reliability; however, the reliability was also affected by several other factors, including system capacity and placement as well as loading conditions.

Machine learning is developing rapidly over time and has been implemented in thousands of industrial and economic models. Likewise, it is expeditiously being utilized in power systems. In (Vaish, Dwivedi, Tewari, & Tripathi, 2021), the authors have established the importance of the use of ML-based techniques and methods in fault detection in power systems and how these methods provide an edge over conventional methods for fault detection and localization like impedance-based methods (Vaish et al., 2021; Verhelst, Van Ham, Saelens, & Helsen, 2017), traveling waves method (Vaish et al., 2021; Verhelst et al., 2017) and wide area fault localization (Mishra & Ray, 2018; Vaish et al., 2021) which are much more complex and time-consuming and due to the integration of DG's in existing grids, the complexity of these methods increases significantly.

Although ML-based methods are less complex and easy to implement, they also have downsides. For instance, the accuracy of detection and classification of faults depends upon the quality of the data set available. Since real data on power systems is not easily available, so simulation-based data is used for the implementation of ML-based methods. Neural Networks (Raza, Benrabah, Alquthami, & Akmal, 2020; Vaish et al., 2021) provide high accuracy when used for fault classification, but on the other hand, they require large amounts of data and memory for training. When using Support Vector Machines (Raza et al., 2020; Vaish et al., 2021), the chances of error in classification are quite low, but when used for multiclass classification, its complexity increases, and it requires a large amount of memory.

The K Nearest Method (MathWorks, 2016; Vaish et al., 2021) is easy to use and can be used as a base classifier; it takes a large amount of memory. All the discussion by (Vaish et al., 2021), leads to the conclusion that even though ML-based methods have certain lacking due to the unavailability of accurate power systems data available during their training, these methods can adapt more easily to the constant changes being made in modern grids due to integration of DG's as compared to conventional methods which would require extensive modifications with each change.

Deep learning is one example of a supervised learning approach in machine learning. Both (Mnyanghwalo, Kundaeli, Kalinga, & Hamisi, 2020) and (Jamil, Sharma, & Singh, 2015) have worked on this approach in the power sector. In (Mnyanghwalo et al., 2020), the authors have compared several deep learning approaches, including g Recurrent Neural Network (RNN), Long ShortTerm Memory LSTM), Gated Recurrent Unit (GRU), Feed Forward Neural Network (FFNN), and Artificial Neural Network (ANN). Among these, they found RNN to give the most accurate results. They also observed that the accuracy improved with the increase in network complexity, which is good for distribution systems since they are the most complex among all other electrical networks. In a study (Jamil, Sharma, Singh, 2015), the authors used Artificial Neural Networks to detect and classify faults

The neural net fitting tool of MATLAB has been used here to train the dataset using the Levenberg-Marquardt deep learning approach. The authors have trained a model for the detection and classification of single line-to-ground faults and have proposed that the same approach can also be used for all other types of faults.

After reviewing all of the discussions above, the authors concluded that machine learning has vast potential applications in improving the reliability of power systems. It was also observed that most of the contemporary research focuses either on fault detection and classification or on the improvement of reliability. The authors have therefore integrated the aforementioned two approaches so that the faults are detected and classified. At the same time, the impact of this is measured by measuring the reliability indices. The methods described in (Jamil et al., 2015b) have been used as the basis for this study, and the techniques described in it have been used to train fault detection and classification models for all kinds of faults. This study has also used the Levenberg-Marquardt approach for this purpose.

SAIDI Improvement

According to (Balijepalli, Venkata, & Christie, 2004), within the continuously evolving world and with more reliance on uninterrupted electrical supply, improving the reliability of existing systems has become even more essential. For the provision of quality supply while regulating operation and maintenance budgets, every country's regulating authority specifies reliability standards and ranges to be maintained. Thus, the systems need to be operational at maximum efficiency to keep them within range. Moreover, constant research and up-gradation methods are required to be implemented to improve customer satisfaction while enhancing business for the utility. An important aspect of improving a power system's reliability is reducing the system's average interruption duration commonly termed (SAIDI).

SAIDI can be simply defined as the duration for which a customer encounters an electricity outage in a predefined time. The value for this index can be calculated daily, weekly, monthly, or yearly; however, a yearly calculation is conventionally used. A series of events can predominantly affect SAIDI values, including adverse weather conditions, mechanical failures, and repair times amongst others (Ajenikoko & Oladepo, 2018).

SAIFI Improvement

With the increase of competition in the modern energy market, with various utilities vying for control of the market, utilities tend to be conscious about the allocated budget being spent on operation and maintenance to provide the cheapest possible electricity to the consumers. The power regulatory authorities who are well aware of this scenario have started to keep an eye on the reliability of power being supplied by utilities so that the strict cost control being applied to the Operation and Maintenance budget does not come at the expense of consumers being suffered from poor reliability. So, certain reliability standards are to be met by utilities which are assessed on the basis of different reliability indices like SAIFI, for example. Utilities are being monitored by power regulatory authorities to ensure that they meet the specific value of reliability indices. If the example of SAIFI is considered, then in this power regulatory authorities want to make sure that the Operation and Maintenance budget is being spent on timely and proper maintenance so that customers suffer from as few outages as possible (Balijepalli et al., 2004; Holland & Cawley, 2006), (Balijepalli et al., 2004; Pennsylvania Public Utilities Commission %J M-00991220, 1999).

Various methods have been proposed to improve SAIFI. As Artificial Intelligence (AI) is being explored by researchers, many different AI-based methods are being put forward for the improvement of SAIFI. One such method is proposed in (Ahmad & Asar, 2021), in which Distributed Generations (DG) are being used, and by the application of AI, their optimum location of placement is determined as the farther the source is from the feeder less reliable the system is.

This study uses Artificial Neural Network (ANN), for this purpose and determines the optimal placement location of DG by considering different scenarios. The results show that by applying ANN, the authors were able to improve SAIFI by 40%.

6. Methods

To accomplish the study's objectives, the authors have used the MATLAB Simulink environment. The Simulink model of the IEEE-9 Bus System is taken from (Pettikkattil, 2022), and the methodology used for fault detection and classification has been adopted from (Jamil et al., 2015b), which has used binary logic to differentiate between different types of faults.

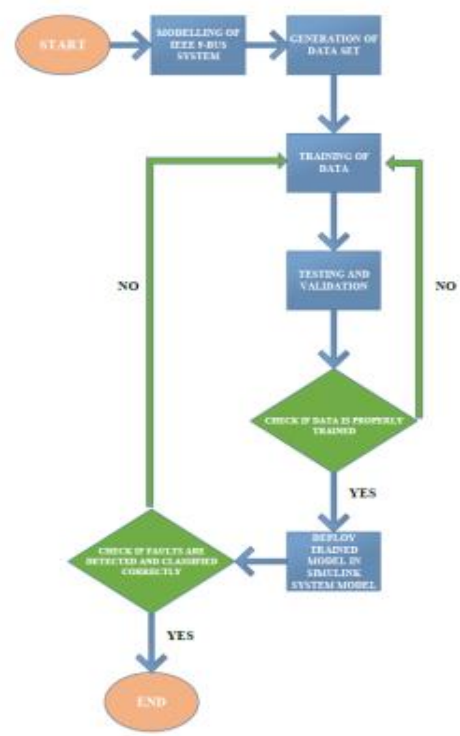


Fig. 1. Process Flow Chart

Modelling the Test System

An IEEE 9 bus system is modeled on SIMULINK to generate data for further analysis (Pettikkattil, 2022). It consists of three generation sources and three load buses. Focusing explicitly on the distribution buses, values of voltages, currents and sequence components are observed to identify fault cases.

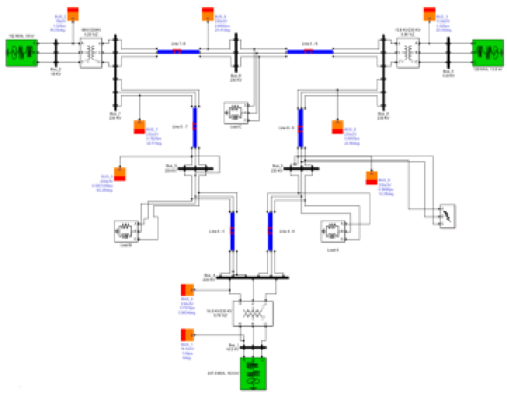


Fig. 2. Modelled Test System

Data Collection

The data is collected to perform two tasks as follows:

- Identify whether a fault has occurred or the system is un-faulted.
- Classify the type of fault that has occurred. To identify various fault cases, values of voltages, currents, and sequence components are recorded from simulations. Fault cases are identified based on the presence and absence of various sequence components. These values are stored in arrays and later used for training purposes.

Fault Type	Positive Sequence	Negative Sequence	Zero Sequence
Un-faulted	Present	Absent	Absent
Three phase faults	Present	Absent	Absent
Single line to ground fault	Present	Present	Present
Double line to ground fault	Present	Present	Present
Line to line fault	Present	Present	Absent

Fig. 3. Presence/Absence of sequence components of different faults

MATLAB codes are designed that use binary logic such as 0 for indication of un-faulted condition while 1 for faulted case, whereas, for fault classification, logic is designed such that the line on which fault occurs is 1, the remaining are labeled as 0 (Jamil et al., 2015b). The list of binary combinations generated is displayed below: A, B, and C represent lines, while G represents the ground—order of code bits: ABCG.

S.NO	Fault Type	Code
1	Un-faulted	0000
2	ABC	1110
3	AB	1100
4	BC	0110
5	AC	1010
6	ABG	1101
7	ACG	1011
8	BCG	0111
9	AG	1001
10	BG	0101
11	CG	0011

Fig. 4. Binary logic Codes used to describe different faults.

Data Training

The information collected is then processed by the deep learning algorithms to generate detection and classification filters for the system. Deep neural networks are used to design filters that are able to function in contemporary circumstances. They use a multi-network system to develop significant features that are required for intelligent detections in outputs (Anastasia Kyrykovych, 2022). For training the system values, MATLAB's NFTOOL is used. This tool is used to generate high-level relations and mapping between statistical input values and target data sets. It takes input and target data sets, trains them through a neural network algorithm, and provides a filter of required characteristics through either a MATLAB script or Simulink model (Ciaburro, 2022). The algorithm used for detection and classification in this project is the LEVENBERG-MARQUARDT algorithm. This algorithm involves the computation of additions of squared value of errors, establishing implementation on loss functions, gradient, and Jacobian matrices. This is an effective method to train datasets quickly and efficiently; however, for relatively large datasets, the system of processes becomes significantly complex and hence requires more memory compared to other algorithms. However, for the size of the data set considered in this project, this algorithm provided satisfactory results (Alberto Quesada, 2022).

Validation And Testing of Data

Detection

A total of 12000 samples are used, divided into three sets with 70% samples (8400) in training, 15% samples (1800) in validation, and 15% samples (1800) in testing. The training phase refers to adjustments of input parameters while training and setting output parameters. Validation and testing are performed to ensure proper training and efficiency of training (MathWorks, 1994-2022).

Results

	Samples	MSE	R
Training:	8400	2.07672e-9	9.99999e-1
Validation:	1800	2.08952e-9	9.99999e-1
Testing:	1800	1.92744e-9	9.99999e-1

Fig. 5. Performance of the trained detection model

The aforementioned results indicate overall efficiency and error in the training of data. MSE refers to "mean squared error is the average difference between outputs and targets, it is required to keep this value as low as possible." Whereas Regression R refers to the "measure of the correlation between output and target, here the value of R closer to 1 is required for accurate training" (MathWorks, 1994-2022). The results indicate successful training for fault detection. Next, a Simulink model can be generated to integrate into the main system.

Classification

Likewise for classification, a total of 12000 samples are used, divided into three sets with 70% samples (8400) in training, 15% samples (1800) in validation and 15% samples (1800) in testing.

Results

	Samples	MSE	R
Training:	8400	1.03146e-2	9.78582e-1
Validation:	1800	1.08096e-2	9.77449e-1
Testing:	1800	1.05216e-2	9.78019e-1

Fig. 6. Performance of the trained classification model

Observations

Once Simulink models are generated for both detection and classification, they are integrated with the main model. This model is simulated and tested for the detection and classification of different types of faults. An identical approach is implemented for the training of bus 5 and bus 8. Each bus has the following setup and configuration:

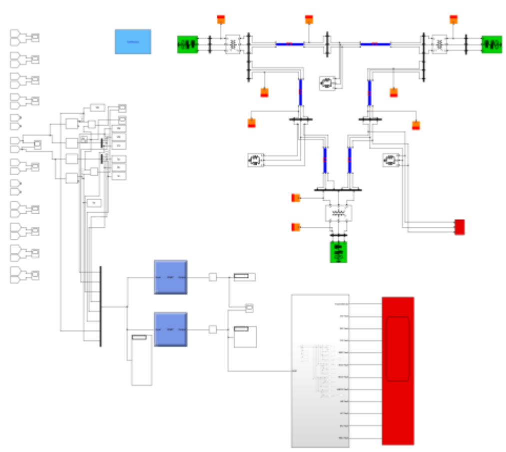


Fig. 7. Complete system setup for bus 6

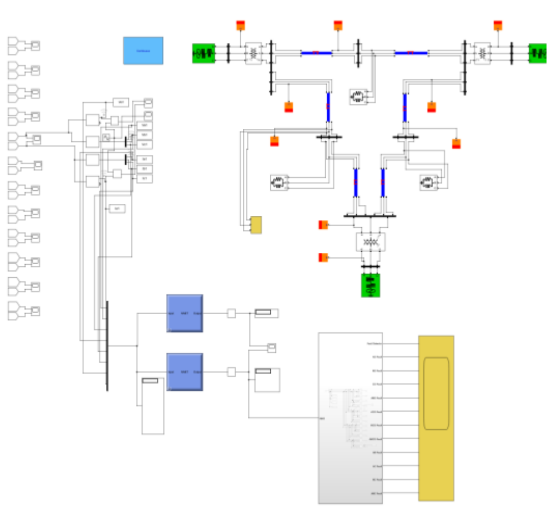


Fig. 8. Complete system setup for bus 5

The figures indicate data collection through workspace blocks, neural network blocks for detection and classification, bus voltages and currents through labels, and displays of various values through the scope. Through simulations, different faults can be induced in the system, which is successfully classified. For instance, when AG (line to ground fault is induced in the system's distribution buses), the detection block detects whether or not the system bus is faulted. Once this is determined, the type is configured. The following graphs indicate the presence and types of faults in the system. To summarize, to achieve the desired objectives of detection of classification of faults, the authors have first generated the required dataset by running simulations of the modeled IEEE 9-Bus System. Then MATLAB's Neural Fitting Tool was used for the training of this dataset, using the Levenberg-Marquardt algorithm of neural networks. Finally, a Simulink block has been generated after this training which is placed in the power system's model and is able to correctly identify and classify the different types of faults with speed and accuracy. Once fault detection and classification were implemented, the next task was to determine the fault detection duration. For this purpose, Simulink Profile Report was generated. This report displays the total simulation time, the time each block and process ran during each simulation cycle and other information.

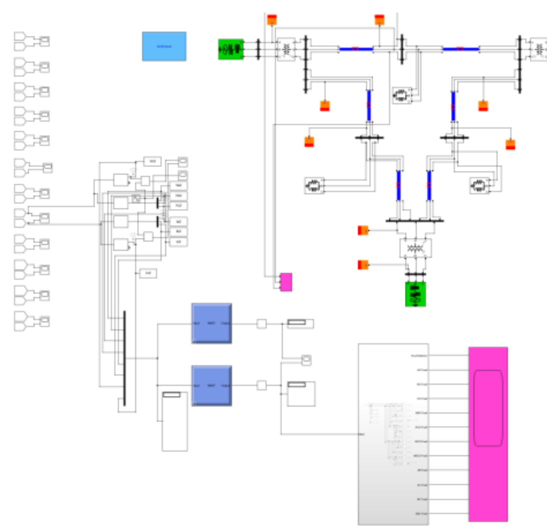


Fig. 9. Complete system setup for bus 8

Likewise, the detection time was calculated for all the fault cases and un-faulted conditions on each load bus. To analyze the system for the worst case, the highest detection time out of all three buses was selected for further calculations.

Reliability Analysis

To perform the reliability analysis, the authors used Windmil software, the idea for which came after reading (Bhusal, 2007). Windmil is software by Milsoft Utility Solutions that is used to run different simulated analyses on power systems. The IEEE 9-bus system was modeled on this software, as shown in figure 9.

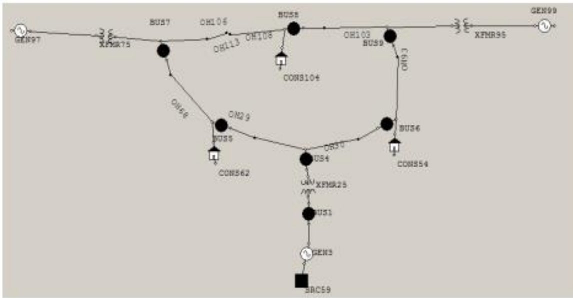


Fig. 10. Modelled System on Windmil Software

The time to detect and classify fault which came from MATLAB simulation was entered in the "Time to find problem" field of the Reliability Analysis Settings in Windmil, while all other settings were kept to their default values. Furthermore, the traveling time of the crew to the faulty location was selected as 30 minutes (DAZAHRA, 2021), as shown in figure 3.17, and it was considered that it would take equal time to reach any of the faulty busses for the sake of simplicity in analysis.

7. Results

This study was carried out using the MATLAB environment, while the reliability analysis was carried out on Milsoft Windmil software. The results from both of these softwares are discussed in this section.

Fault Detection and Classification

The phase and sequence values generated during a fault are captured and given as input to the trained Simulink model. Its results are sent to a binary logic classifier, which uses different logic gates to differentiate between different fault scenarios and displays the correct fault type that has occurred on the system. In the final output, the results are displayed on a scope, where a logic level of 0 determines which fault has not occurred on the system, and a logic level of 1 determines which fault has occurred on the system. One figure from each of the different fault scenarios (unfaulted, line-to-ground, double line-to-ground, triple line-to-ground, line-to-line) is shown below:

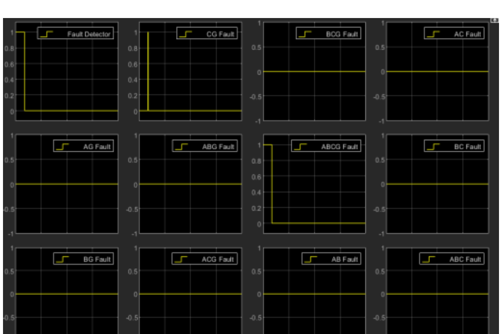


Fig. 11. Scope output showing no fault in the system.

Figure 11 indicates all faults are shown to be at a logic level of 0 that means no fault is induced on the system.

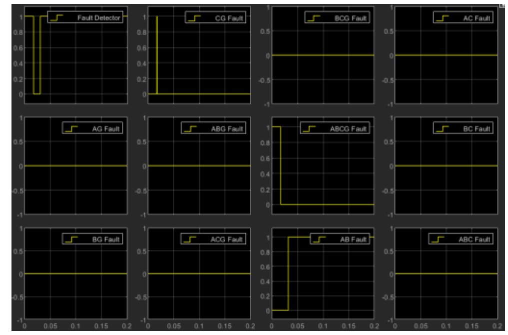


Fig. 12. Scope output showing Line-to-Line Fault between Phase A and B

Figure 12 shows that when a fault between Phase A and B is induced in the system the only the fault AB is shown to be at a logic level of 1, while the others are at a logic level of 0.

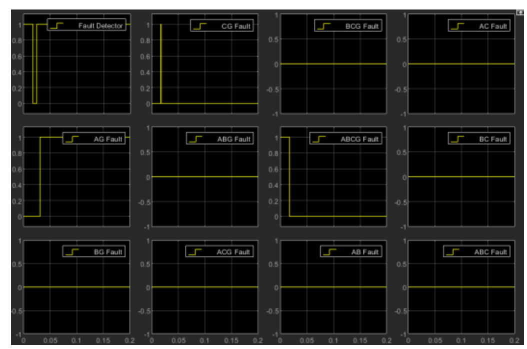


Fig. 13. Scope output showing Line-to-Ground Fault between Phase A and Ground

Figure 13 shows that when a fault between Phase A and ground is induced in the system only the fault AG is seen to be at a logic level of 1, while the others are at a logic level of 0.

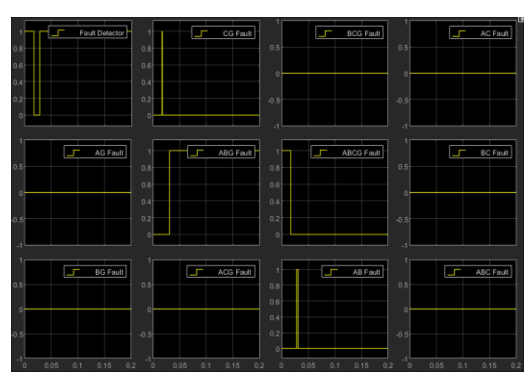


Fig. 14. Scope output showing Double Line-to-Ground Fault between Phase A, Phase B, and Ground

Figure 14 shows that when a fault between Phase A, B and ground is induced in the system only the fault ABG is seen to be at a logic level of 1, while the others are at a logic level of 0.

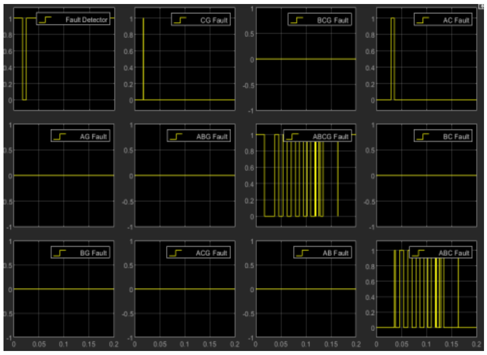


Fig. 15. Scope output showing Triple Line-to-Ground Fault between Phase A, Phase B. Phase C, and Ground

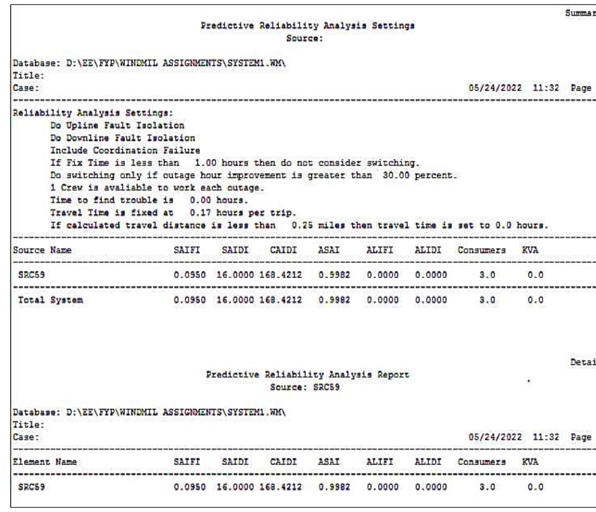
Figure 15 indicates that when a fault between Phase A, B, C, and ground is induced in the system, only the fault ABCG remains at a logic level of 1, while the others eventually reach the logic level of 0.

Similarly, for faults between Phase B and ground, the logic level of BG on the scope will be 1. For faults between Phase C and ground, the logic level of CG on the scope will be 1. For faults between Phase A, C and ground, the logic level of ACG on the scope will be 1. For faults between Phase B, C and ground, the logic level of BCG on the scope will be 1. For faults between Phase B and C, the logic level of BC on the scope will be 1. For faults between Phase A and C, the logic level of AC on the scope will be 1. For faults between Phase A, B and C, the logic level of ABC on the scope will be 1. In this way, all the types of faults are correctly classified by the trained model.

Reliability Analysis

According to (Abubakar & Aiyub, 2020), for an IEEE 9-bus test system, having the distribution section operating at 20kV, the values of SAIDI and SAIFI are calculated as 17.306 hour/customer.year and 1.130 faults/customer respectively. To enhance the reliability of the distribution system under observation, a machine learning algorithm termed Levenberg Marquardt algorithm was implemented. The values of SAIDI showed a decrease by 7.546% whereas SAIFI calculated after its implementation showed an improvement by 91.5%. The changes in the values of these parameters indicate a significant improvement in the overall reliability of the power system under inspection.

The main point to be noted here is that our modeled system was a small test system that was run mainly on theoretical conditions. That is why we see a significant improvement in the values of the desired indices. The improvement might not have been significant if it was a larger system with practical data. The main point to take away from this is that it is entirely possible to improve the reliability of a power distribution system by using Machine Learning algorithms, such as ANN, that have been used here, which was the whole purpose of this study.



Summary

Predictive Reliability Analysis Settings
Source:

Database: D:\EE\FYP\WINDMIL ASSIGNMENTS\SYSTEM1.WM\
Title:
Case: 05/24/2022 11:32 Page 1

Reliability Analysis Settings:
Do Upline Fault Isolation
Do Downline Fault Isolation
Include Coordination Failure
If Fix Time is less than 1.00 hours then do not consider switching.
Do switching only if outage hour improvement is greater than 30.00 percent.
1 Crew is avaliable to work each outage.
Time to find trouble is 0.00 hours.
Travel Time is fixed at 0.17 hours per trip.
If calculated travel distance is less than 0.25 miles then travel time is set to 0.0 hours.

Source Name	SAIFI	SAIDI	CAIDI	ASAI	ALIFI	ALIDI	Consumers	KVA
SRC59	0.0950	16.0000	168.4212	0.9982	0.0000	0.0000	3.0	0.0
Total System	0.0950	16.0000	168.4212	0.9982	0.0000	0.0000	3.0	0.0

Detail

Predictive Reliability Analysis Report
Source: SRC59

Database: D:\EE\FYP\WINDMIL ASSIGNMENTS\SYSTEM1.WM\
Title:
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Element Name	SAIFI	SAIDI	CAIDI	ASAI	ALIFI	ALIDI	Consumers	KVA
SRC59	0.0950	16.0000	168.4212	0.9982	0.0000	0.0000	3.0	0.0

Fig. 16. Reliability Analysis Results

8. Conclusion

This study is a comprehensive take on the major issue of low reliability in current distribution systems. Ensuring optimum reliability in power supply systems is essential for both the utility and consumers. To track reliability, several indices have been formulated; however, in this study, the authors predominantly focused on SAFI and SAIDI, referring to the number of interruptions in the system and average interruption duration over a specified time duration. The main objective of this study was to model, simulate and analyze an IEEE 9 bus test system. Establish a dataset consisting of various parameters such as voltage, current, and sequence components. The generated dataset was then used to develop a fault detection and identification model. Levenberg-Marquardt algorithm was implemented for this purpose. Once a successful model was developed, it was used to determine fault detection time. This fault detection was used to calculate the values of SAIDI and SAIFI for the system under observation. The values were then compared to a benchmark system of similar specifications. A significant improvement in reliability indices was observed that was calculated after the implementation machine learning algorithm on the test system. A decrease of 7.546% in SAIDI and an improvement of 91.5% were observed in SAIFI. Hence by the implementation of Machine Learning, appreciable improvement in reliability was observed, thus, Machine Learning can provide exceptional assistance in improving the reliability of existing power systems.

9. Future Recommendation

The sole focus of this study has been on the distribution side of the system. In the future, this study can also be extended to transmission systems. In addition, real-time data of power systems can also be fed to the algorithm to give results in real-time, with the algorithm responding to real-time load fluctuations.

Besides this, by acquiring the maintenance and repair history data of key components of distribution systems like Transformers, Circuit Breakers, and Cables from any utility company, a comprehensive study can be conducted about the predictive maintenance of these components by the integration of any ML-based method.

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