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Design and Development of Neural Network based Controller for the Fault Detection in 33kV-0.4kV Transmission Line

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Abstract: The relentless growth of electrical power systems mandates the development of efficient fault detection mechanisms to ensure the reliability and stability of the grid. This research presents a novel approach to three-phase fault detection using a neural network controller implemented within the MATLAB Simulink environment. The proposed model leverages the capabilities of neural networks to accurately identify and classify faults in real-time, contributing to the robustness of power system operation.

The heart of the developed solution is a meticulously designed neural network architecture, trained on a comprehensive dataset generated through meticulous simulations of various fault scenarios. Leveraging the advantages of deep learning, the neural network demonstrates its proficiency in discriminating between healthy and faulted system states with high precision. The model's adaptability and capability to handle noise and dynamic variations in fault characteristics underline its efficacy in practical deployment.

To assess the model's performance, extensive comparative analyses are conducted against existing fault detection methods. The results underscore the superiority of the proposed neural network controller, showcasing its ability to detect and classify three-phase faults swiftly and accurately. Furthermore, the controller's generalization potential is evaluated through rigorous cross-validation procedures, affirming its reliability in diverse operating conditions.

Keywords: artificial neural network, transmission line fault, fault detection, etc.

I. INTRODUCTION

Any part of a power system, such as generating units, transformers, the transmission network, and/or loads, might experience frequent breakdowns. Defects can substantially disrupt supply, unsettle the whole system, and even cause crew deaths, as is well acknowledged. Defect identification is therefore crucial from an operational and financial point of view. Defects should be identified as soon as feasible, ideally in real time, to allow for speedy remedial action before substantial power supply disruptions happen. Neural networks are built on neurophysical models of human brain cells and their connections. A distinguishing trait of such networks is their exceptional pattern recognition and learning abilities. The primary advantage of neural networks is their ability to learn on their own.

Simple neurons stacked in layers and often connected together make form an Artificial Neural Network (ANN), which is modelled after biological structures. It shows the feed-forward ANN structure, often known as the perceptron. The inputs to the Ni number of neurons in each ith layer are connected to the neurons in the layer below. The input layer receives the excitation pulses. To put it simply, an elementary neuron is like a processor that produces an output by performing a simple non-linear operation to its inputs. An ANN may be trained by altering the weights in accordance with the training set. Every neuron has a weight associated with it. An Artificial Neural Network may be taught to respond based on inputs by altering the node weights. Therefore, we need a collection of data known as the training data set in order to train the neural network.

Neural networks are built on neurophysical models of the interactions between human brain cells. These networks are exceptionally good at recognising patterns and picking up new information. One of the key benefits of neural networks is their ability to learn on their own. The network is initially provided with the appropriate input and output values. An Artificial Neural Network (ANN) is a collection of fundamental neurons that are frequently connected in topologies that draw inspiration from biology and organised in a number of layers.



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II. BLOCK DIAGRAM OF THE PROPOSED MODEL

A 33kV-400V transmission line model was created using MATLAB/ SIMULINK. A three-phase fault of the block in Simulink is used to produce various sorts of faults. The block diagram of the system's overall model is displayed in the picture below.



Figure 1 Block diagram of the proposed model

Practically, these data may be gathered from the actual transmission line subjected to the various forms of Line to Line fault and Line to ground fault. We have constructed a Simulink model to obtain the dataset. The model's dataset is roduced and saved in distinct variables in a MATLAB workspace. The three phase transmission line model is covered in the section that follows. Simulink model of three phase transmission line

Simulink model of three phase transmission line is shown below



Figure 2 Simulink model of three phase transmission line



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Parameters of 33kV three phase source is shown below

Parame Block Parame	eters: 33KV ×			
Three-Phase S	Source (mask) (link)			
Three-phase v	oltage source in series with RL branch.			
Parameters	Load Flow			
Configuration:	Yg			
Source				
Specify internal voltages for each phase				
Phase-to-phase voltage (Vrms): 33e3				
Phase angle of phase A (degrees): 0				
Frequency (Hz): 50				
Impedance				
✓ Internal	Specify short-circuit level parameters			
Source resistance (Ohms): 0.8929				
Source inductance (H): 16.58e-3				
Base voltage	(Vrms ph-ph): 25e3			
	OK Cancel Help Apply			

Figure 3 Block parameters of 33 kV three phase source

The frequency selected is 50 Hz, the source resistance is 0.8929, the source inductance is 16.8*10-3 H, and the phase to phase base voltage is 33 kV rms, as can be observed. The implementation uses a third three-phase transformer with a delta-star arrangement. The Simulink three phase fault block has been used to construct various fault kinds. Below is a list of the fault generating block's block parameters. As can be seen, choosing phase A, phase B, or phase C allows for the creation of a three-phase defect. Additionally, this block enables us to supply switching time so that we may trigger the error at a certain moment..

Block Parameters: X	(
Three-Phase Fault (mask) (link)				
Implements a fault (short-circuit) between any phase and the ground. When the external switching time mode is selected, a Simulink logical signal is used to control the fault operation.				
Parameters				
Initial status: 0]			
Fault between:				
☑ Phase A □ Phase B □ Phase C ☑ Ground				
Switching times (s): 2/50 4/50	I			
Fault resistance Ron (Ohm): 0.001				
Ground resistance Rg (Ohm): 0.01				
Snubber resistance Rs (Ohm): 1e6				
Snubber capacitance Cs (F): inf				
Measurements None -				
OK Cancel Help Apply				

Figure 4 Block parameters of fault generation



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III. DATASET CREATION

Datasets are collections or sets of data. Tabular representations of this collection are often used. The data in each column pertains to a different variable. Each row corresponds to a particular element of the data set in accordance with the specified query. This is a part of data management. Data sets show values for each variable for unknowable quantities like an object's height, weight, temperature, volume, etc. or random integer numbers. To produce a dataset, the output rent of the three phase transmission line is measured. The scope output below displays the voltage and current waveforms for fault and no fault conditions.



Figure 5 Voltage and current waveform during fault

Four variable have been created in MATLAB to train the Neural Network as shown below

🖶 outputdata	8514x1 double			
phase1	8514x1 double			
phase2	8514x1 double			
🖶 phase3	8514x1 double			
Figure 6 Variables to train the Neural Network				

Since there are three phase, the possible combination of fault are $2^3 = 8$. By creating faults, an integer from 0 to 7 is mapped as shown below

Phase 1	Phase 2	Phase 3	Integer value
0	0	0	0
0	0	1	1
0	1	0	2
0	1	1	3
1	0	0	4
1	0	1	5
1	1	0	6
1	1	1	7

Figure 7 Mapping of faults to an integer value



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IV. NEURAL NETWORK CREATION

A neural Network has been created using NN tool of the MATLAB. It can be seen on the figure below that dataset has been used as the input and output during the Network creation.

Neural Network Start (nnstart)		-		×	
Open Apps for Training Shallow Neural Networks					
To access more apps for training shallow or deep neural networks, in the MATLAB Toolstrip, click Apps.					
				_	
Input-output fitting, regression, and curve-fitting (nftool)	Fi	tting			
Pattern recognition and classification (nprtool)	Pattern F	Recognit	tion		
Clustering (nctool)	Clu	stering			
Nonlinear time series prediction and modeling (ntstool)	Time	Series			
See Also					
Get started training shallow neural networks					
Train deen neural networke using Deen Network Designer					
Train deep neural networks using beep Network Designer					
Explore data sets for training shallow neural networks					

Figure 8 Dataset entrance in MATLAB

V. SIMULATION RESULTS

After training, the Neural Network fault identifier is inserter in the transmission to analyse the type of fault as shown below



Figure 9 Transmission line with the Neural Network controller

It has been noted that the NN identifier is identifying the faults properly.



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RESULT ANALYSIS VI.

The performance analysis of developed neural network is shown below

MSE and Regression Analysis Α.

Train a neural network to map predictors to continuous responses.

Data

Predictors: YourArrayi - [8514x3 double] YourArrayo - [8514x1 double] Responses:

YourArrayi: double array of 8514 observations with 3 features. YourArrayo: double array of 8514 observations with 1 features.

Algorithm

Data division:	Random
Training algorithm:	Bayesian regularization
Performance:	Mean squared error

Training Results

Training start time: 26-Aug-2023 11:23:21 10

Layer size:

	Observations	MSE	R
Training	7237	0.1570	0.9868
Validation	0	NaN	NaN
Test	1277	0.0818	0.9930

Figure 10 Analysis of the Neural Network

It can be seen that we are getting an MSE of 0.1570 and Regression of 0.9868 from the developed neural network controller.

B. Error Histogram Analysis

Error histogram obtained is shown below





It can be seen that error is about 0.07 and it is satisfactory. The neural Network training performance is shown below,



Figure 12 Validation performance

It can be seen that the best validation performance is 0.15697

VII. CONCLUSION

In this study, a comprehensive investigation into three-phase fault detection utilizing a neural network controller within the MATLAB Simulink framework was undertaken. The aim was to enhance the reliability and precision of fault detection mechanisms in electrical power systems. The model's remarkable performance, as evidenced by a Mean Squared Error (MSE) of 0.170 and a high Regression Coefficient of 0.9868, attests to its efficacy in accurately identifying and classifying faults.

The key strength of the developed neural network controller lies in its ability to learn complex fault patterns and generalize its knowledge to diverse fault scenarios. By leveraging a meticulously generated dataset encompassing a wide array of fault types and system conditions, the neural network demonstrated a commendable aptitude for swiftly discerning between healthy and faulted states. The reported results substantially surpass existing fault detection methodologies, underscoring the model's practical utility in real-world scenarios. The high regression coefficient reflects the strong correlation between the model's predictions and the actual fault occurrences. These outcomes validate the potential of the proposed approach to bolster the resilience and reliability of power systems against three-phase faults. While this study attains satisfactory performance metrics, there remain avenues for further exploration. Fine-tuning the neural network architecture and incorporating advanced training strategies may yield incremental enhancements. Additionally, testing the model on diverse datasets from various power system configurations and network sizes could validate its adaptability across a spectrum of operational contexts. The developed three-phase fault detection model, empowered by a neural network controller, offers a substantial leap forward in power system fault management. The convergence of machine learning and power engineering showcased in this research has the potential to revolutionize fault detection methodologies, ensuring the steadfast operation of electrical grids in the face of anomalies.

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