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Investigation of Various NN Models for Power Flow Analysis with Line Outage

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Abstract: The on-line LFA with line outages requires the Neural Network model to be accurate, simple and structurally compact. This in turn to a large extent depends on the type of neural architectures and learning algorithms. In this paper, three types of neural architectures are considered for investigation. Each of the chosen neural architecture is trained off-line usingLM algorithms and tested on-line for load flow analysis. This paper carries out a novel investigation on various neural network models for on-line load flow analysis (LFA)with line outages. LFA is an important problem for real time power system planning and Operation. The conventional methods used for LFA are iterative techniques, takes longer time for computation and not suitable for on-line applications. Neural Network [NN] based approach is computationally less rigorous as compared to conventional methods and provides an alternate solution for on-line LFA in real time. Their performance is compared in terms of accuracy and structural compactness. The suitable neural architecture is identified for on-line LFA. The results are extensively validated for IEEE 30 bus system through MATLAB simulation. The promising results obtained are presented.

Keywords: On-line load flow analysis; NN architectures; LM algorithms; NN Models; cascade architectures; feed-forward architectures.

1. INTRODUCTION TO CONTIGENCY ANALYSIS

Most power systems are designed with enough redundancy so that they can withstand all major failure events. Contingency analysis is one of the major components in today's modern energy management systems[1-4]. For the purpose of fast estimating system stability right after outages, the study of contingency analysis involves performing efficient calculations of system performance from a set of simplified system conditions. Contingency analysis is one of the most important tasks encountered by the planning and operation engineers of bulk power system.

Contingency analysis is one of the "security analysis" applications in a power utility control center that differentiates an Energy Management System (EMS) from a less complex SCADA system. Its purpose is to analyze the power system in order to identify the overloads and problems that can occur due to a "contingency". Contingency analysis is abnormal condition in electrical network. It put whole system or a part of the system under stress. It occurs due to sudden opening of a transmission line, generator tripping, and sudden change in generation, sudden change in load value. Contingency analysis provides tools for managing, creating, analyzing, and reporting list of contingencies and associated violations. Contingency analysis is used as a study tool for the off-line analysis of contingency events, and as an on-line tool to show operators what would be the effects of future outages[5].

2. STEP-BY-STEP PROCEDURE OF CONTINGENCY ANALYSIS

Generally, once the current working state of a system is known, contingency analysis can be broken down into the following steps:

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(a) Contingency definition

(b) Contingency selection

(c) Contingency evaluation

Contingency definition involves preparing a list of probable contingencies. This typically includes line outages and generator outages. Contingency selection process consists of selecting the set of most probable contingencies; they need to be evaluated in terms of potential risk to the system. Usually, fast power flow solution techniques such as DC power flow are used to quickly evaluate the risks associated with each contingency. But in this work, the Newton-Raphson load flow method will be used to ensure higher accuracy.

Finally, the selected contingencies are ranked in order of their security, till no violation of operating limits is observed. The AC load flow method of contingency analysis is adopted. The Newton- Raphson load flow algorithm, an algorithm under the AC load flow method, was used to solve the power flow problems during the analysis using MATLAB. This is because the NRLF method has more accuracy than other AC Load flow methods and converges faster.

3. BASIS OF PERFORMANCE INDEX

There are many indices using which the performance of the power system during contingency can be analyzed. This can be done by considering various sensitive factors of the power system such as voltage, real power, reactive power etc.

In literature, many indices such as real power index, reactive power performance index, LMN index etc have been reported.

3.1. Real Power Index

$$\mathrm{PI}_p = w_i \sum_{i=1}^{\mathrm{L}} \left(\frac{\mathrm{P}_i}{\mathrm{P}_{i\max}} \right)^{2n} \tag{1.2}$$

Where,

P_i is the active power flow.

$\mathrm{P}_{i\max}$ is the maximum active power flow on line i.

W_i is the weight of active power flow on line i.

L is the total number of lines in the power system.

N is the specified exponent.

3.2. Reactive Power Index

$$\mathrm{PI}_v = \sum_{i=1}^{\mathrm{N}_{pq}} \left[\frac{2(v_i - v_{i\,\mathrm{nom}})}{v_{i\max} - v_{i\min}} \right]^2 w_i \tag{1.3}$$

Where,

V_i is the voltage of the bus i.

$\mathrm{V}_{i\max}$ and $\mathrm{V}_{i\min}$ are the maximum and minimum voltage limits of the bus.

$\mathrm{V}_{i\,\mathrm{nom}}$ is the average of $\mathrm{V}_{i\max}$ and $\mathrm{V}_{i\min}$.

W_i is the weighting coefficient.

N_{pq} is the total number of load buses in the system.

3.3. Severity Index

To cumulate all the advantages of above mentioned indices, apparent power index, also known as severity index is considered in this research work. The apparent power index is considered for contingency due to line outages because severity of this particular contingency gets affected both by real and reactive power variations in the power system.

The severity of a contingency to line overload may be expressed terms of the following severity index, which express the stress on the power system in the post-contingency period:

$$I_{si} = \sum_{i \in L_0}^{n} \left(\frac{s_i}{s_L^{max}} \right)^{2m} \tag{1.3}$$

The line flows in Equation (1.3) are obtained from Newton–Raphson load flow calculations. While using the above security index for security assessment, only the overloaded lines are considered to avoid masking effects. In this research work, security index is chosen and the value of m is fixed as 1.

4. CONTINGENCY RANKING

The contingency ranking is investigated for IEEE30 bus test system[6]. The power flow analysis is carried by varying both the real and reactive load power demand (75%-125%) with the increment of 0.05%. Using this, real power flow and reactive power flow in line are obtained. Using the real and reactive power flow in the line, severity index is calculated. After this, contingency ranking is obtained for all the lines. The ranking obtained at 125% of loading is considered for further studies. The Table 1.1 shows contingency ranking using severity index method.

From the table 1.1, it is observed that line 2,1,8,5 have reached severe loading condition. The other lines are observed to have not reached the severe loading condition even at 125% of loading. Of the top four severe lines, only the most severe line (line 2) is considered for security assessment in this research work. This is because, if this relieves overload on the most severe contingency, then, this can relieve overload on lines for less severe contingencies.

Simulation of transmission line outage is carried out by the formulation of the corresponding admittance matrix. For instance, after outage of a line 2 connecting bus '1' and '2', the components of the Y bus that will be affected are Y_{11}, Y_{22}, Y_{12}, and Y_{21}. Line outages were simulated by simply removing the line information from the line data matrix[7-10]. This is similar to the line not existing initially as the information no longer exists.

After that power flow analysis was done on the power system at post contingency stage and 1000 data sheets were obtained by varying the load from 75% to 125%

5. TRAINING OF NN MODELS FOR POWER FLOW ANALYSIS

1000 data are collected by varying both real and reactive load power demand (75%-125%) with the increment of 0.05% with severe line outage. 750 data are used for training and 250 data are used for testing. The three architectures namely SLFF-NN, MLFF-NN, CC-NN are considered for investigation[11-13]. The LM algorithm is chosen for study as it is concluded to be best algorithm for off-line training in previous

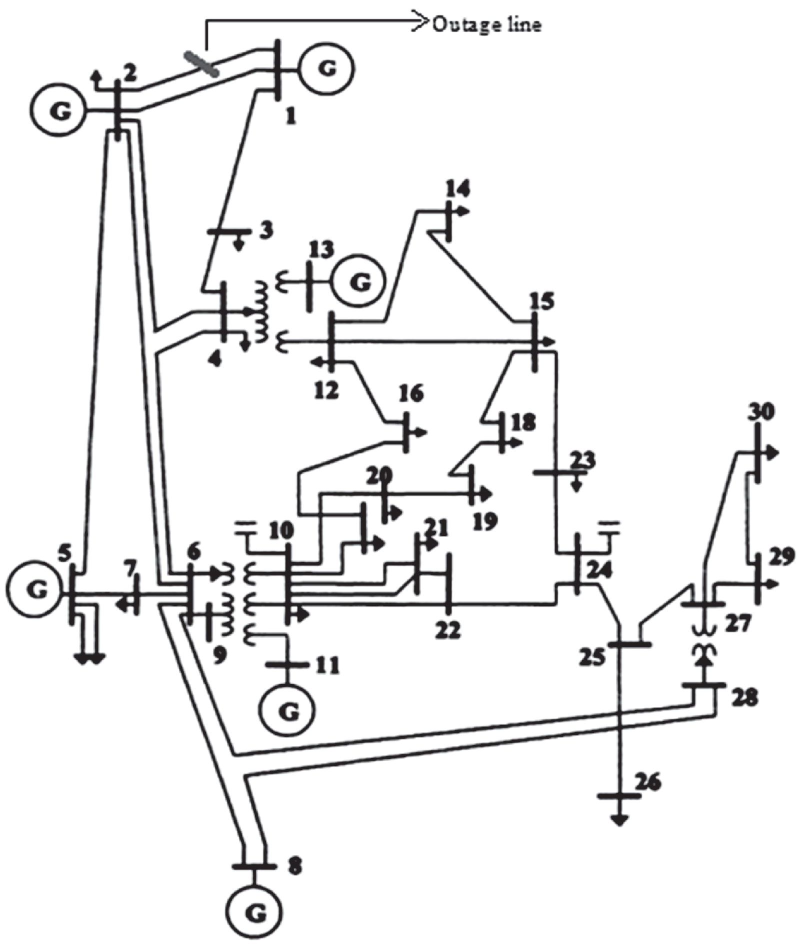


Figure 1.1: Single line diagram of IEEE 30 bus test system with outage line Marked

Table 1.1
Contingency ranking using severity index method

Contingency Ranking	*Severity Index*	*Line No.*
1	2.3041025	2
2	2.1297087	1
3	1.1586057	8
4	1.0204615	5

chapters. The three neural architectures are trained with LM learning algorithm using the training data. To design SLFF-NN, single neuron is added in the hidden layer at a time till the target MSE is reached. In MLFF-NN and cascade-NN, the choice of number of layers and number of neurons in each layer is decided by trial and error. The design of MLFF-NN and cascade-NN is more of an art than a science. Therefore, in this research work, MLFF-NN and cascade-NN with two hidden layers is designed by trial and error method. The results are extensively validated using IEEE30 bus test system.

In IEEE30 bus test system, totally there are 24 PQ buses, 5 PV buses and 1 slack bus. The total numbers of outputs are 53. The target MSE is chosen as 1×10^{-7}.

For training the neural network, the inputs to the NN model is chosen as real power load demand (P_D) and reactive power demand (Q_D). The real power load demand is presented in equation (1.4) and reactive power load demand is presented in equation (1.5).

$$P_D = \sum_{i=1}^{n} p_i \tag{1.4}$$

$$Q_D = \sum_{i=1}^{n} Q_i \tag{1.5}$$

where P_i is the real power and Q_i is the reactive power at i^{th} load bus, $i = 1, 2, \ldots n$.

The outputs from the NN model are voltage magnitude (|V|) of PQ buses and voltage angles (δ) of both PQ and PV buses. The block diagram of NN model for voltage magnitude and angle estimation with inputs and outputs is shown in Figure 1.2.

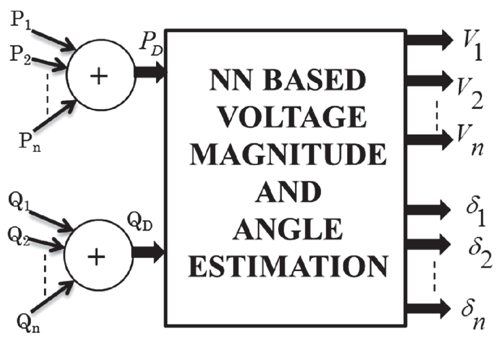


Figure 1.2: NN based voltage magnitude and angle estimator for severe line outage

The tan-sigmoid function is chosen for hidden layer neurons and pure-linear function is chosen for output layer neurons. The flow chart for training the NN architecture for power flow analysis with line outage is shown in Figure 1.3. The training MSE achieved for the NN model for IEEE 30 bus test case is tabulated in Table 1.2.

Table 1.2
Performance comparison of NN models trained for same accuracy for IEEE 30 bus test system

Test case	*Architecture*	*NN Model*	*MSE achieved*
IEEE 30 bus system	Single Layer Feed Forward Architecture (SLFF)	2-15-53	1×10^{-7}
	Multi Layer Feed Forward Architecture (MLFF)	2-9-9-53	1×10^{-7}
	Cascade Architecture (CC)	2-3(h)-3(h)-53	1×10^{-7}

6. TESTING OF NN MODELS FOR POWER FLOW ANALYSIS IN TERMS OF ACCURACY

To determine the most suitable architecture, the performance of LM-trained NN models using three NN architectures is compared in terms of accuracy, structural compactness and computational complexity. Firstly, the performance of LM trained SLFF-NN, MLFF-NN and CC-NN models is compared in terms of accuracy. The off-line LM trained three NN models are tested for on-line estimation of voltage magnitudes and angles.

The sample results for voltage magnitude of PQ bus no. 17 and angle of PV bus no. 11 estimated using SLFF-NN, MLFF-NN and CC-NN for the IEEE30 bus test system is presented in Figure 1.4, Figure 1.5 and Figure 1.6 respectively. The Performance Comparison of LM Trained NN Models designed using SLFF-NN, MLFF-NN and CC-NN in terms of average test MSE is shown in Table 1.3.

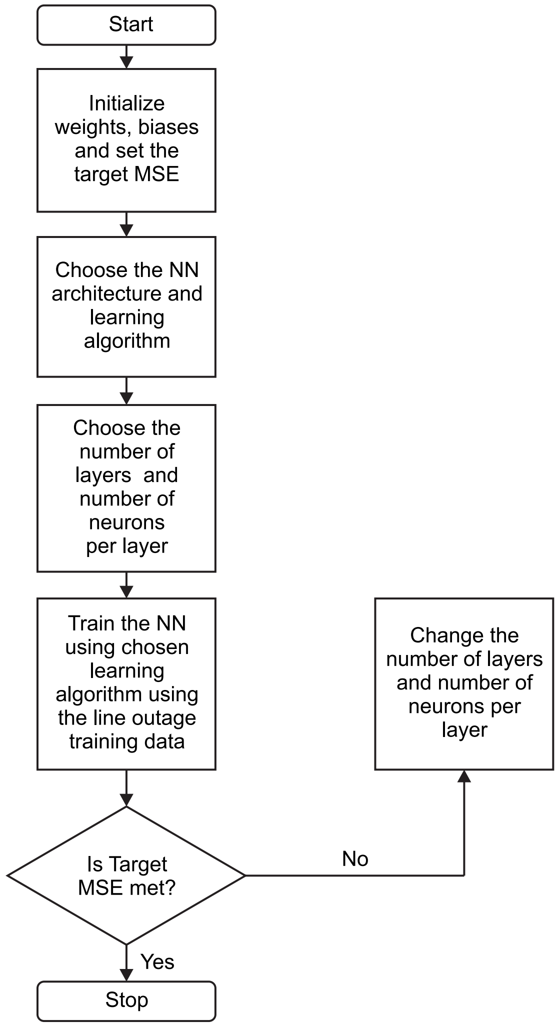
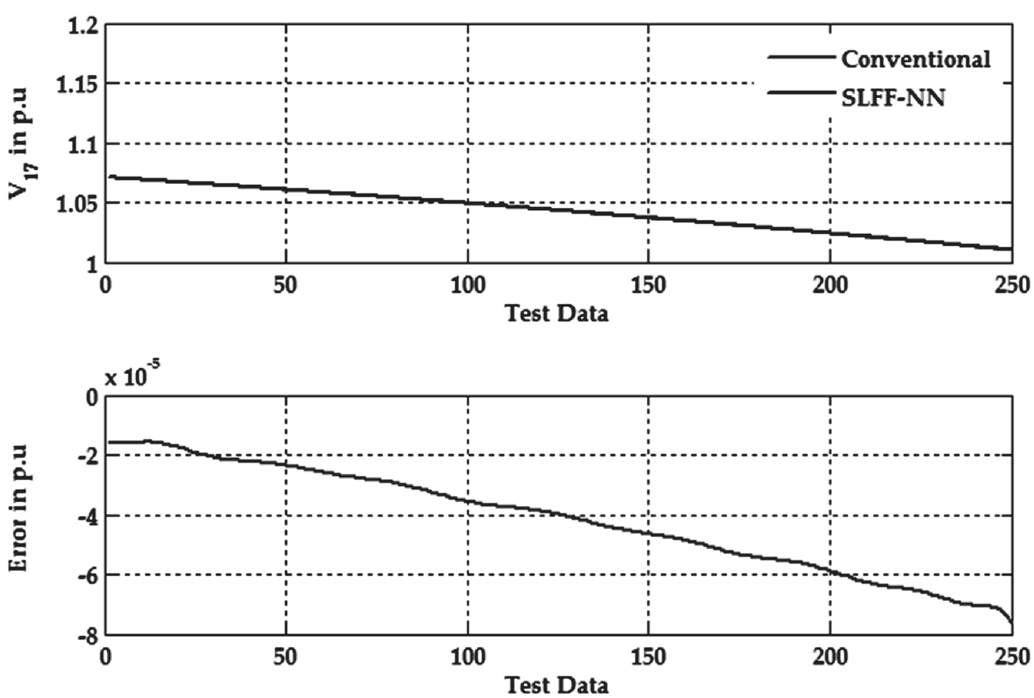


Figure 1.3: Training process of NN for power flow analysis with contingencies



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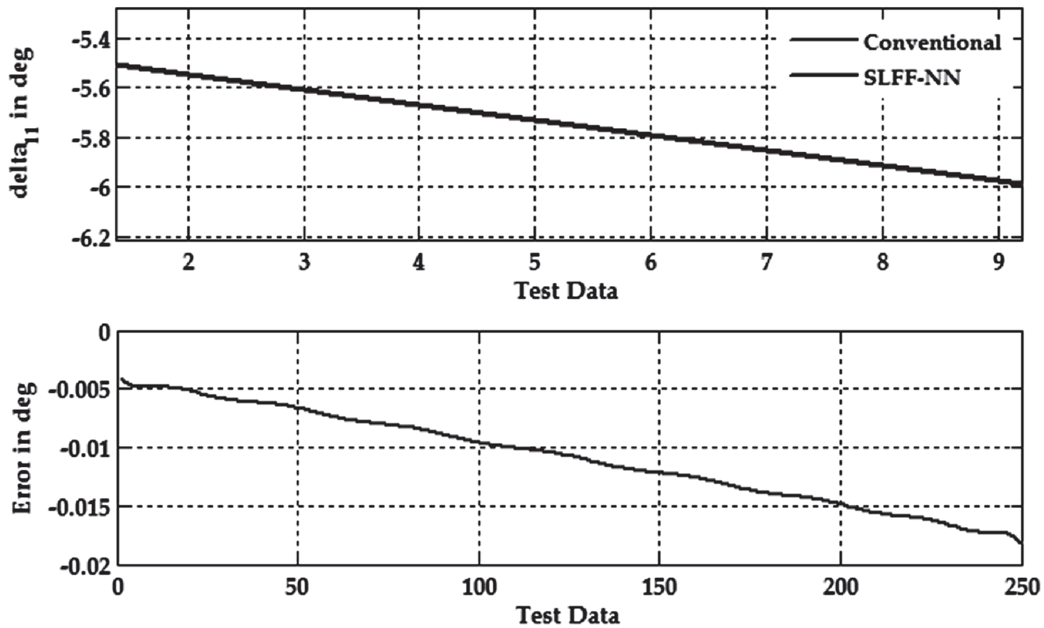


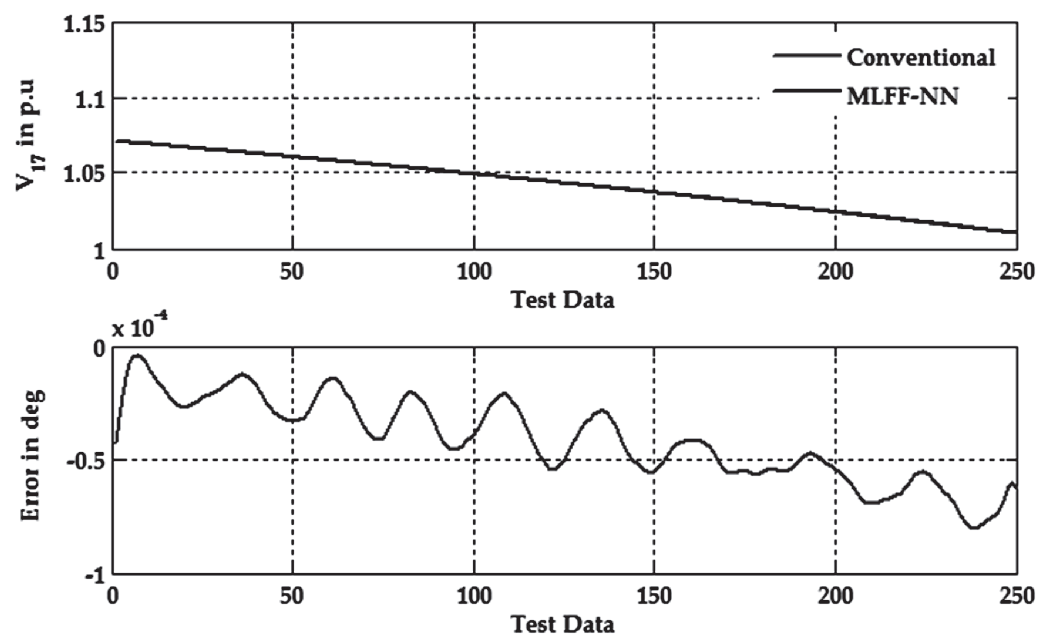
(b)

Figure 1.4: Voltage magnitude and angle estimated using SLFF-NN for IEEE30 bus test system with contingency (a) Voltage magnitude for bus No. 17 (b) Voltage angle for bus No. 11

Table 1.3
Performance comparison of LM trained NN Models designed using SLFF-NN, MLFF-NN and CC-NN in terms of average test MSE for IEEE30 bus test system

Test Case	*Average Test MSE for SLFF-NN*	*Average Test MSE for MLFF-NN*	*Average Test MSE for CC-NN*
IEEE 30 bus test system	7.3895×10^{-4}	7.1286×10^{-4}	7.4451×10^{-4}

From the above investigation, it is understood that the voltage magnitude and angle with line outage obtained from the LM trained NN models using all the three NN architectures is found to closely match with the voltage magnitude and angle estimated using conventional method. Thus all the LM trained NN models performed equally well.



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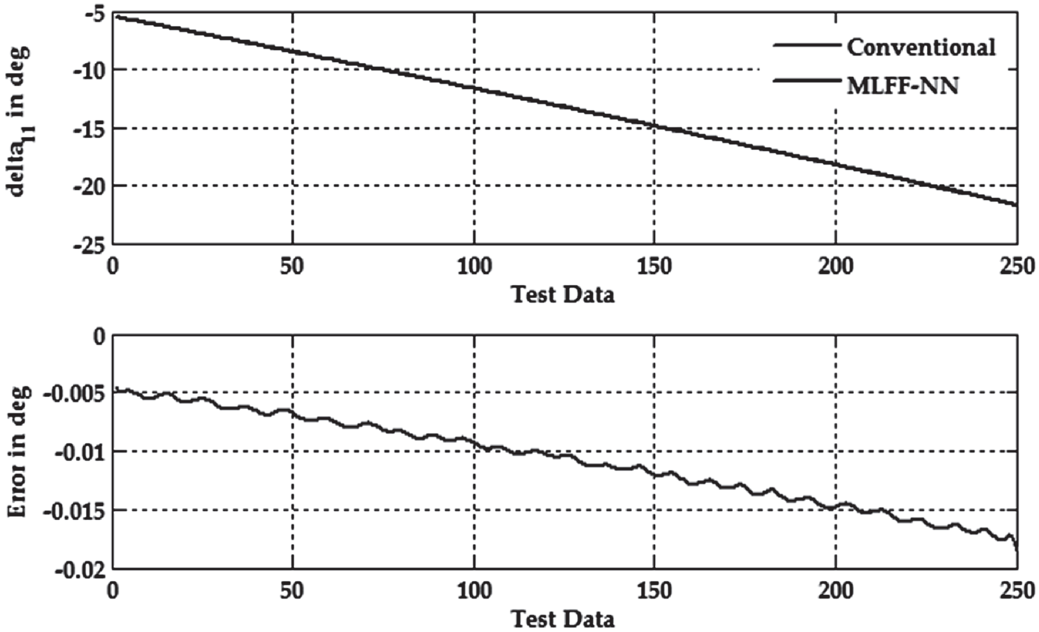
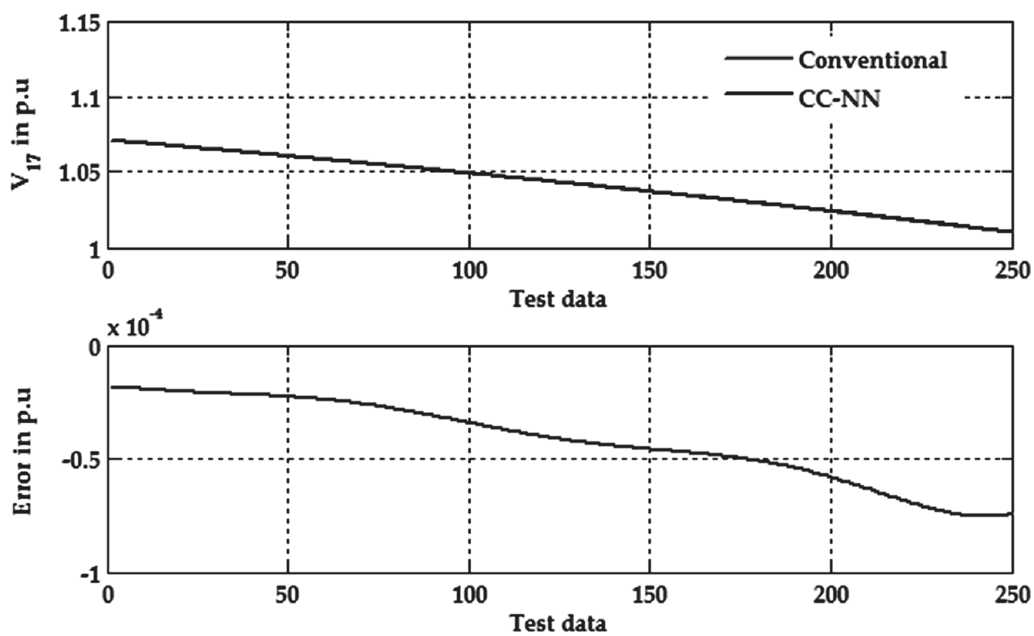


(b)

Figure 1.5: Voltage magnitude and angle estimated using MLFF-NN for IEEE30 bus test system with contingency (a) Voltage magnitude for bus No. 17 (b) Voltage angle for bus No. 11

7. TESTING OF NN ARCHITECTURES FOR POWER FLOW ANALYSIS IN TERMS OF STRUCTURAL COMPACTNESS AND COMPUTATIONAL COMPLEXITY

The structural compactness and computational complexity assumes importance in real time implementation. This is the motivation to compare all the NN models in terms of structural compactness and computational complexity. For the desired accuracy, the number of hidden neurons is used as an index to measure the structural compactness of model. The neural network architecture with lesser number of hidden neurons is found to be compact and gives ease in real time implementation of the on-line power flow analysis with line outage. The number of parameters and nonlinear function extraction in the network indicates its computational complexity. Each parameter warrants some mathematical operations.



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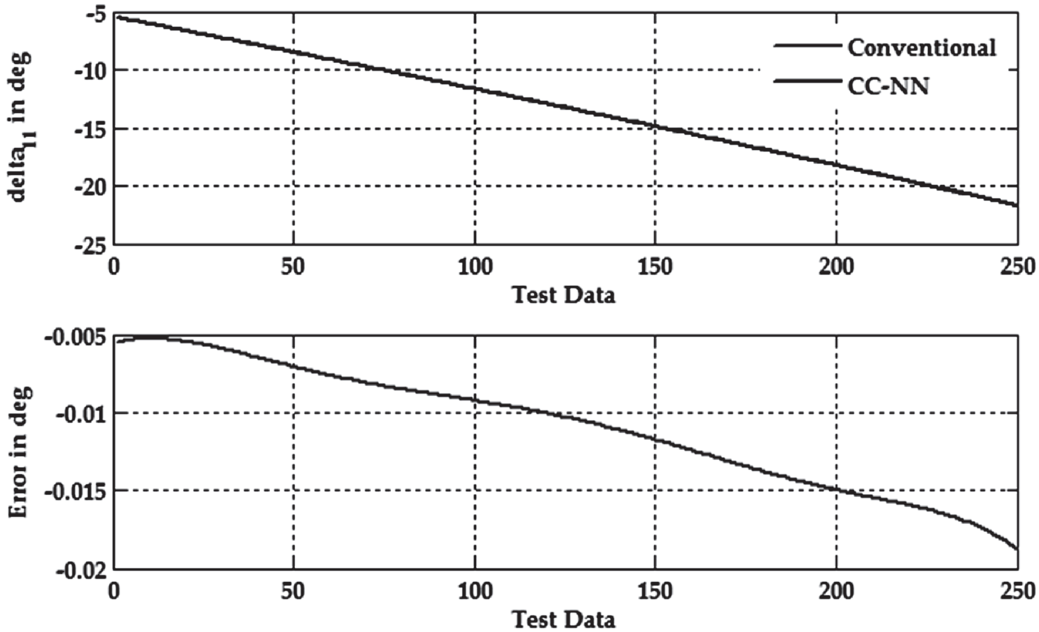

(a)

Figure 1.6: Voltage magnitude and angle estimated using CC-NN for IEEE30 bus test system with contingency (a) Voltage magnitude for bus No. 17 (b) Voltage angle for bus No. 11

For 30 BUS Systems, the parameters, neurons and computations required by the SLFF-NN, MLFF-NN and CC-NN models are tabulated in Table 1.4. From the Table 1.4, it is seen that for IEEE30 bus test system, SLFF-NN and MLFF-NN requires 15 and 18 hidden neurons respectively, where as CC-NN model requires much lesser number of hidden neurons 6 as compared to SLFF-NN and MLFF-NN models.

Table 1.4
Performance comparison of LM trained NN models for power flow analysis in terms of structural compactness and Computational complexity

Test Case	*NN Architectures*	*NN Models*	*No. of Hidden Neurons*	*No. of Parameters*	*No. of Additions*	*No. of Multiplications*	*No. of Tan-sigmoids*	*Execution Time in milliseconds*
IEEE 30 bus test System	SLFF	2-15-53	15	893	825	825	15	5782
	MLFF	2-9-9-53	18	647	576	576	18	7842
	CC	2-3(h)-3(h)-53	6	504	445	445	6	33032

On Intel(R) Core(TM) i5 32-bits processor with the clock frequency of 2.53GHz, 4 GB RAM, the execution time required to compute voltage magnitude and angle using SLFF-NN, MLFF-NN and CC-NN are computed and presented in Table 1.4. From the Table 1.4, it is seen that for IEEE30 bus test system, SLFF-NN and MLFF-NN requires 5782ms and 7842ms respectively, where as CC-NN model requires much lesser execution time of 3032 ms as compared to SLFF-NN and MLFF-NN models.Hence CC-NN model results in structurally compact model as compared to SLFF-NN and MLFF-NN model. The total number of parameters and computations time required for CC-NN is found to be lesser as compared to SLFF-NN and MLFF-NN. Hence, CC-NN model is of lesser complexity as compared to SLFF-NN and MLFF-NN model for power flow analysis with line outage.

8. CONCLUSION

Thus, from the above simulation result, it can be summarized that CC-NN architecture provides the required accuracy, structurally compact, computationally less complex model for real time power flow analysis with contingency. Hence, cascade architecture trained with Levenberg Marquardt algorithm is identified to be most suitable NN model for on-line Power flow analysis with contingency.

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