**A PROJECT REPORT**

on

**IDENTIFICATION OF SUITABLE NEURAL LEARNING ALGORITHM AND ARCHITECTURE FOR ON-LINE LOAD FLOW ANALYSIS**

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**BONAFIDE CERTIFICATE**

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**ABSTRACT**

This project identifies suitable learning algorithm and architecture for neural network based On-line Load Flow Analysis. Load flow analysis is a basic problem in real time power system planning, operation and is required to carry out further studies on the power system like economic scheduling. The conventional methods used for load flow studies are iterative in nature and needs longer time for data computation. Neural Network (NN) based models provide an alternative solution for on-line load flows.

The on-line load flow analysis requires the NN model to be accurate, simple and structurally compact to ensure faster execution time so that the results of the analysis can be applied instantly to the real time control operations of the complex power systems. This desired performance to a large extent depends on the type of neural architecture and neural learning algorithm used in the NN model.

This project investigates various types of neural learning algorithms and neural architectures for on-line load flow analysis. Their performance is compared in terms of accuracy, computational complexity and structural compactness. The results are validated extensively for IEEE 30, IEEE 57, IEEE 118, and Indian Practical 76 Bus systems. The promising simulation results obtained are presented.

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**LIST OF SYMBOLS AND ABBREVIATIONS**

|  |  |
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| **NOTATION** | **MEANING** |
| ANN | Artificial Neural Network |
| LFA | Load Flow Analysis |
| BPM | Back Propagation with Momentum |
| VLR | Variable Learning Rate |
| LM | Levenberg Marquardt |
| SLFF | Single Layer Feed Forward |
| MLFF | Multi Layer Feed Forward |
| CC | Cascade |
| NN | Neural Network |
| FF | Feed Forward |
| MSE | Mean Square Error |
| γ | Momentum Factor |
| α | Learning rate |
| Sm | Sensitivity Factor of mth layer of neural network |
| J | Jacobian Matrix |
| µ | Scalar Constant |
| PD | Power demand |
| V | Voltage Magnitude |
| δ | Voltage Angle |