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Line Current Estimation Using Deep Neural Network—A Generalized Approach †

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Abstract: Distribution system parameter estimation plays a vital role in the overall control and monitoring of the network. A conventional technique to obtain information about the system voltages and line currents involves iterative load flow procedures. Such methods sometimes do not converge due to the limited number of available measurements. This paper proposes a simulated data-driven approach for estimating feeder loadings under various operating scenarios of the IEEE 15 bus system. A deep neural network using the MATLAB nntool is implemented, and promising results are presented.

Keywords: neural network; line current estimation; load flow

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1. Introduction

Distribution systems are the largest sector of any power system. A planned and effective distribution network is the key to coping with the ever-increasing demand for domestic, industrial, and commercial load. The load flow information can be used for analyzing the normal operating mode, contingency analysis, and others [1].

To operate the distribution system in an efficient manner, information regarding the operational parameters, such as bus voltages, line currents, and system losses, is important. From the perspective of feeder designing, the line current is a key parameter to know. Conventionally, line currents are obtained by performing load flow analysis with different algorithms. Load flow analysis techniques use iterative methods, such as the forward–backward sweep method, and others. These techniques are time consuming, and sometimes solutions do not converge [2].

A neural network (NN) is a powerful artificial intelligence tool to overcome issues with conventional methods of load flow. They are well known for their properties of learning patterns and obtaining generalization from the provided data. A dataset serves as the backbone for an NN; therefore, we have used MATLAB coding for generating the required dataset with the load variation as the input and the line current of the network as the output. The deep learning model has been developed, and to check the robustness of the model, unseen data have been tested on the model. The key contributions of this research are:

- The development of a large dataset comprising possible loading scenarios in a distribution network.
- The development of a deep-neural-network-based model for line current estimation.

This work is organized as follows: Section 2 discusses the relevant work as the literature review. Section 3 describes the detailed methodology for preparing the dataset and for data pre-processing for neural network training. Section 4 explains the experimental procedure and the results, and, finally, Section 5 provides a conclusion to this work, with future aspects to explore.

2. Literature Review

Distribution system parameters estimation is an extensive area of research due to the realization of the smart grid, the integration of electric vehicles, and installing renewable-based distributed generation in the power grid.

Distribution systems, unlike the transmission system, have a smaller X/R ratio and are weakly meshed; therefore, they cannot rely upon the Gauss–Seidel or the Newton–Raphson methods of load flow because of ineffective and ill convergence [3]. Alternatively, the backward–forward sweep method is ideal for the distribution system.

In the field of power system state estimation, some authors have presented exceptional results using deep neural networks, like false data detection, in a power system, such as the voltage stability estimation stated in [4,5]. The distribution system voltage magnitude, phase angle, and line currents have been predicted by the author using a deep neural network [6].

Line currents are important to calculate because several control and monitoring actions are carried out using this information. Several articles have shown the importance of line current estimation using artificial neural networks. In [7], the author has used current signals for the purpose of fault localization. Researchers have calculated the short circuit current at various locations in the distribution network using neural networks [8].

A neural network has the capability to learn and generalize the dataset without being explicitly programmed. The benefits of using an ANN for feeder current prediction is that the well-trained model gives results quickly, robustly, and accurately. This significant reduction in real-time computational time makes DNN feasible for real-time operations in a distribution network.

3. Methodology

This section describes the procedure of dataset development and noise addition in detail. An IEEE 15 bus distribution network has been considered for our experiment. The system characteristics were obtained from [9]. It has 14 load buses and a slack bus. The input–output relationship is developed between the loads and line currents, respectively. The IEEE 15 bus distribution system is shown in Figure 1.

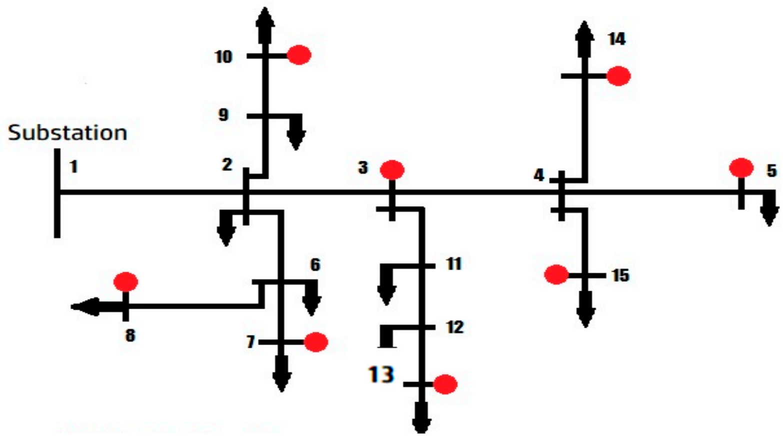

Figure 1. IEEE 15 bus distribution system with meter locations.

3.1. Dataset

Dataset generation is key to developing any deep learning model. For this purpose, we have developed a detailed dataset comprising 91,503 samples. These samples are obtained through MATLAB R2020a programming by considering a variety of operating scenarios in the network. The data generation procedure is visualized in Figure 2.

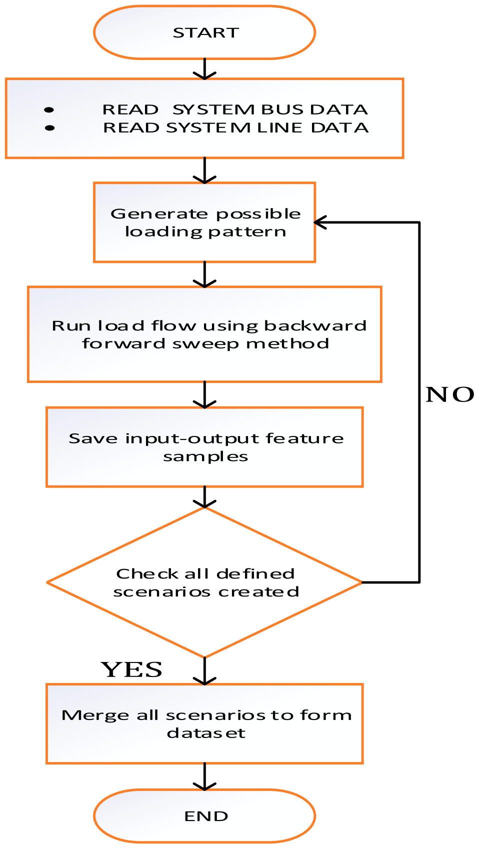

Figure 2. Data generation procedure.

The distribution system meters are not installed at each bus due to economic constraints. Therefore, considering this view, we have considered meter placement at buses 3, 5, 7, 8, 10, 13, 14, and 15 only. Therefore, we have 16 inputs (8 load active powers and 8 load reactive powers) and 14 outputs (magnitude of line currents). In all loading scenarios of the system, the load is varied from 0% to 160% of the rated loading conditions [10]. The details of the operating condition and its contribution to the main dataset are presented in Table 1.

Table 1. Summary of the dataset generation with various scenarios.

Cases of Loading Scenarios	No of Samples
1. Variation of P_L one by one (step size 0.0625 KW)	28,813
2. Variation of P_L simultaneously from light to heavy (step size 0.625%)	257
3. Variation of P_L Randomly (any sample from 0.625% variation)	10,000
4. Variation of Q_L one by one (step size 0.0625 KW)	31,919
5. Variation of Q_L simultaneously from light to heavy (step size 0.625%)	257
6. Variation of Q_L Randomly (any sample from 0.625% variation)	10,000
7. Variation of P_L and Q_L simultaneously, light to heavy (step size 0.625%)	257
8. Variation of P_L and Q_L Randomly (any sample from 0.625% variation)	10,000
Total Samples	91,503

3.2. Noise Addition

Metering data always have errors in them due to meter inaccuracies and the communication channel. In our experiment, the dataset is developed through coding; therefore, the results are obtained in ideal values. The dataset was subjected to Gaussian noise ($3 \times$ S.D = 2%) to obtain the finalized data for neural network training. The noise addition procedure in the input data is displayed in Figure 3.

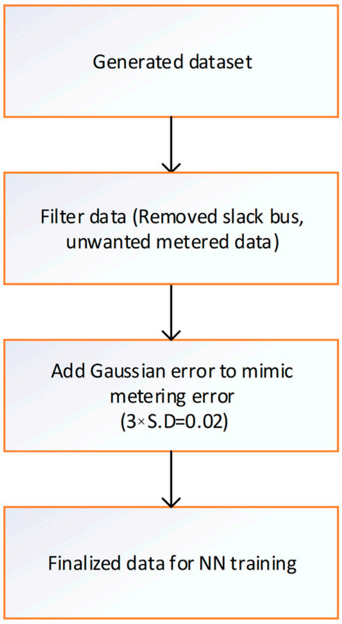

Figure 3. Noise addition.

4. Experimental Procedure and Results

In our experiment, the filtered dataset comprised 91,503 samples, which were then segregated into two sets for training and for evaluating the robustness of the model, respectively. Set 1 consists of 91,000 samples, and the rest of the samples were treated as unseen data. Set 1 was pre-processed and then split as the train, test, and validation sets, with 80–10–10%, respectively. The furnished dataset was then used for DNN model training using 'nntool' GUI in MATLAB. The experiment was started using a single hidden layer with neuron ranges (half of the input features, number of inputs). A second hidden layer was added while keeping the number of neurons in the same range. The sigmoid activation function in hidden layers and the Lavenberg–Marquardt algorithm for error reduction were used. The best model was obtained with the configuration i/p-18-16-o/p, shown in Figure 4.

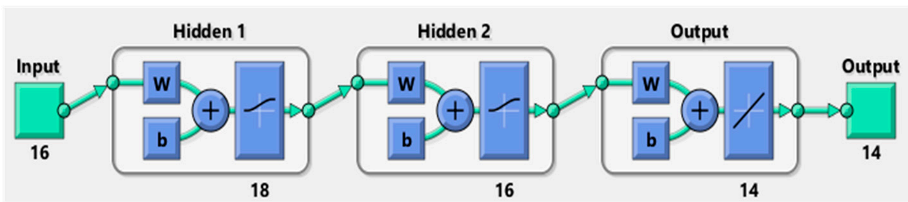

Figure 4. Best selected model.

To test the system in a robust way, two random samples, 'A' and 'B', were provided to the DNN model one by one. The training and estimation process using the best model is depicted in Figure 5. The model estimation was compared with the actual value, and the results are shown in Table 2 from two random samples.

Table 2. Comparison between actual and predicted values from the best trained model.

Sample 367			Sample 412		
Line Currents	Actual Values	Predicted Values	Line Currents	Actual Values	Predicted Values
I 1-2	153.9317	153.2078	I 1-2	160.3199	159.1047
I 2-3	85.5666	85.7791	I 2-3	91.5069	91.1343
I 3-4	41.4923	41.2510	I 3-4	47.5641	47.3722
I 4-5	5.9945	5.9920	I 4-5	6.0101	6.0080
I 2-9	28.2048	27.8327	I 2-9	28.2361	28.0619
I 9-10	9.4128	9.4029	I 9-10	9.4233	9.4198
I 2-6	34.2831	34.0720	I 2-6	34.3215	34.2601
I 6-7	5.9445	5.9477	I 6-7	5.9512	5.9517
I 6-8	18.9076	18.9098	I 6-8	18.9288	18.9273
I 3-11	34.6170	34.1341	I 3-11	34.6866	34.4924
I 11-12	15.5858	15.4256	I 11-12	15.6173	15.5891
I 12-13	6.0290	6.0403	I 12-13	6.0412	6.0422
I 4-14	9.5281	9.5250	I 4-14	9.5531	9.5513
I 4-15	14.6118	14.6195	I 4-15	19.128	19.1235

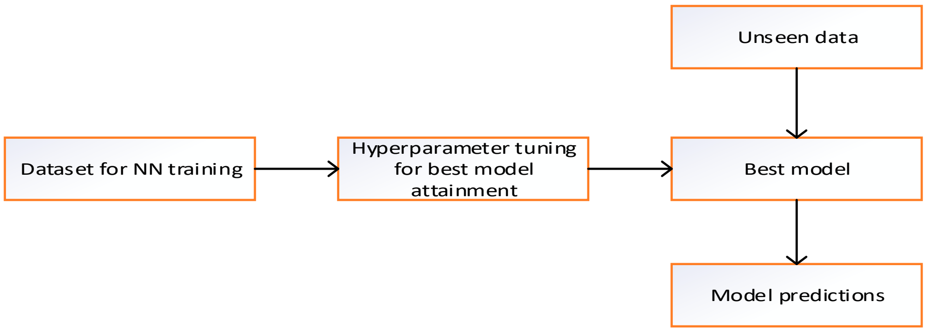

Figure 5. Model selection and estimation flow.

5. Conclusions and Future Work

In this paper, a framework has been proposed for distribution system feeder current prediction based on a large and generalized dataset. A deep-learning-based line current estimator has been developed, with satisfactory performance at various loading scenarios. In our experiment, a fixed topology was considered, and this limit will be considered in our future work. A small distribution system has been tested and it will incorporate a large network in our future studies.

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