Deep Fault Analysis and Subset Selection in Solar Power Grids

Biswarup Bhattacharya **& Abhishek Sinha**

University of Southern California & Adobe Systems Incorporated

bbhattac@usc.edu

Abstract

Non-availability of reliable and sustainable electric power is a major problem in the developing world. Renewable energy sources like solar are not very lucrative in the current stage due to various uncertainties like weather, storage, land use among others. There also exists various other issues like mis-commitment of power, absence of intelligent fault analysis, congestion, etc. In this paper, we propose a novel deep learning-based system for predicting faults and selecting power generators optimally so as to reduce costs and ensure higher reliability in solar power systems. The results are highly encouraging and they suggest that the approaches proposed in this paper have the potential to be applied successfully in the developing world.

Introduction

Electric power grids are an essential component of modern society. With the help of technology like **synchrophasors**, we can monitor the magnitude and angle of each phase of every bus in a network at every 40 ms interval. This data can be leveraged to incorporate intelligence into the system to make better predictions and design better schemes for generation and fault analysis.

In developing countries like India, renewable energy is often wasted due to mismanagement and irregularities in the generation process. For example, in case of solar energy, storage of generated power becomes an issue and non-optimal choices lead to wastage of generated power. Power outages are common in developing countries due to faults appearing in the system which could not be predicted earlier. Often the load forecast does not match the actual scenario and that leads to problems like **congestion** and **faults**.

Objectives & Contributions

- **Fault type classification and location identification** using LSTMs.
- **Determination of optimal number of solar energy generator subsets** to be selected for sustainable power generation.
- **Prediction of congestion** using neural networks.
- **Designed a grid to simulate various conditions** including stimuli like generator supply, weather and load demand using Siemens PSS/E software.

Fault Analysis

Currently, when a small disturbance is seen at a load dispatch center, then a report is generated and it is followed up with other dispatch centers. If the disturbance is found to be not local, then further diagnostics are conducted to find the source of the problem and repair it.

In our approach, we monitor the grid continuously and then in the case of a fault determine the type and location of the fault as and when it occurs. This automated process lessens human supervision and enables better management of the grid.

Data

We generated data for this problem using the **Siemens PSS/E** software, which can do fast and robust power flow solution for network models up to 200,000 buses. It also has a useful scripting system called `psspy` which we utilized for running the experiments. We designed a grid of 23 buses with 6 loads and 8 generators.

Determining the Fault Type

Four fault types: 3ϕ bus fault (Symmetrical fault), Branch trip fault (Symmetrical fault), LL fault (Line-to-line fault, Unsymmetrical fault), and LG fault (Line-to-ground fault, Unsymmetrical fault).

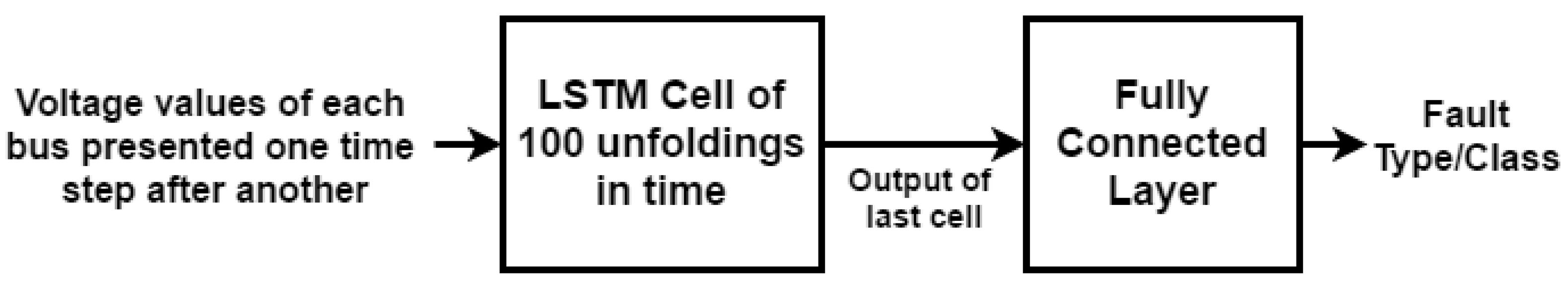


Figure 1: Determining the Fault Type

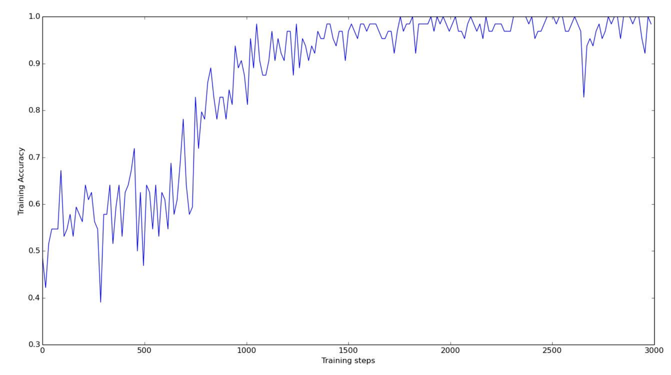
Every type of fault was simulated at every bus 100 times to generate different variations. The model consists of 100 unfoldings in time of LSTM cells corresponding to 100 time varying voltage values for each bus. The input to each LSTM cell is a vector of bus voltages at every time step. Both the hidden vector and output vectors are of size 128. The output vector of the last cell contains the temporal information present in the entire data. With this information, we can classify the type of fault. The classification model consists of 1 hidden layer (fully-connected layer) consisting of 64 neurons followed by an output layer of size 2, outputting the class/type of the fault.

With LSTM, the classification accuracy is around **95**%, an improvement of around 6% from the baseline SVM model. The plot of accuracy is shown in Figure 2(a).

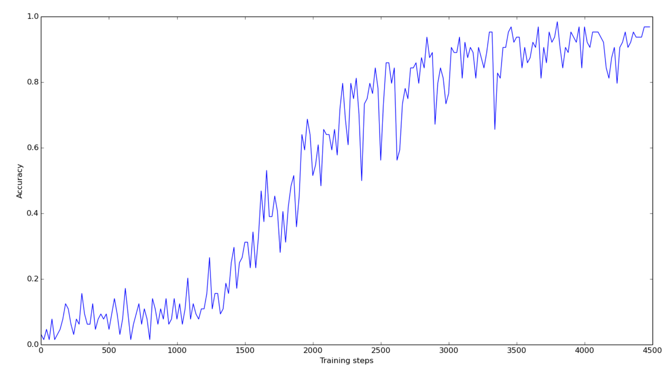
Determining the Fault Location

A similar LSTM network was used with the same input of the bus voltages to output: the bus number corresponding to where the fault has occurred, or "0" if the network data corresponded to a non-faulty one where no fault had been triggered on any bus line.

The classifier returned an accuracy of **97**% corresponding to predicting the bus number. The accuracy plot has been shown in Figure 2(b).



(a) LSTM Accuracy for Fault Classification



(b) Accuracy for Bus Line Classification

Figure 2: Accuracy Plots for Fault Analysis

Subset Selection

In order to participate in the electricity grids markets with a day-ahead commitment, solar power generators have to guarantee a power supply commitment in competition with the generally more reliable traditional (fossil-fuel based) generators. Our proposed technique enables selection of an optimal subset of these renewable energy generators to ensure **economic dispatch** keeping in mind the factors of congestion and load demand.

Data

We collected data for 16 days from March 1, 2017 to March 14, 2017 from the IIT Kharagpur Electrical Engineering department rooftop solar panels. To generate data for subset selection, we switched "on" and "off" all our renewable energy generator combinations to find the best subset to meet the demand at the least cost. We tried to observe the one step jumps and its effect on the grid, while simultaneously checking for congestion.

Congestion Prediction

Transmission congestion occurs when there is insufficient energy to meet the demands of all customers. Given that we know just the power committed by the solar power generators and not the actual power generated in the future, we predict this future supply using weather information (solar panel data). The congestion prediction was done by using a neural network with 1 hidden layer. The test accuracy was around $\mathbf{97-98}\%$ for the case where the future power was known, and around $\mathbf{91}\%$ for the unknown solar power case. In both cases, the neural network model achieved an accuracy improvement of around 5% over the baseline SVM model.

Choosing the optimal subset

To choose the optimal subset, we considered two penalties for training our model. **Power-miscommitment penalty** takes into account the difference between the promised power and the delivered power.

$$L_1 = (\text{predicted power} - \text{actual power generated}) \tag{1}$$

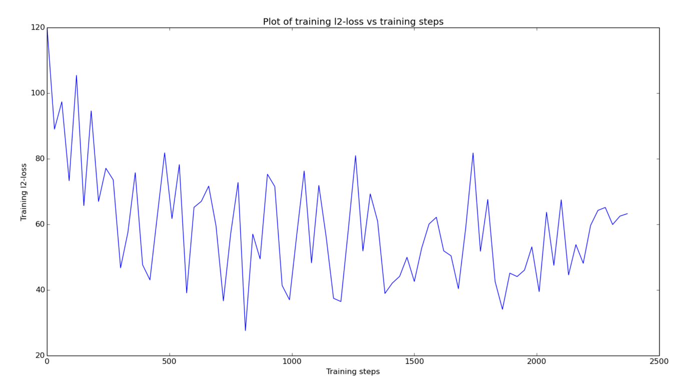
In certain cases, even if the mis-prediction penalty for choosing a subset is lower than choosing another subset, choosing the other subset might cause a congestion in the network which is extremely undesirable. Hence, we incorporated a second penalty: the **congestion loss** L_2 which is calculated as follows - if a subset causes a congestion in the network then $L_2 = 50$ otherwise $L_2 = 0$.

Model & Results

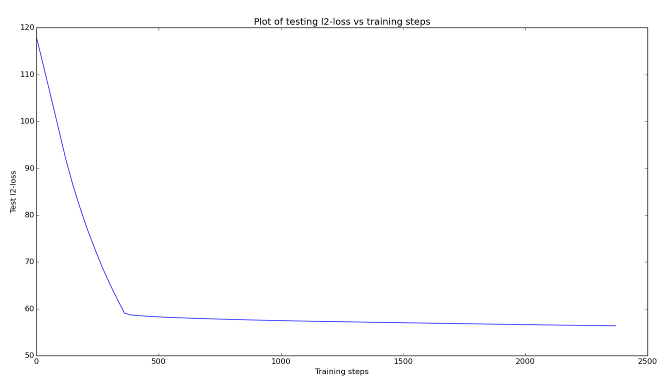
For all the possible subsets of generators, the L_1 and L_2 values were computed and scaled. The input to the model are the bus voltages before any subset is chosen, and a vector of size corresponding to the number of solar generators, with the elements of the vector being 1 or 0 depending on whether the generator forms a part of the subset. The model would be expected to output the total loss $(L_1 + L_2)$ incurred in selecting the input subset.

$$\mathcal{L} = (\text{model output} - (L_1 + L_2))^2 \tag{2}$$

The model consisted of 1 hidden layer with 200 hidden neurons. The Adam optimizer was used to train the model and minimize the loss $\mathcal{L}$. After training the model for around 2500 steps, the training minimum L_2 loss = **35**, the training minimum L_1 loss = **6**, the test L_2 loss = **59**, and the test L_1 loss = **8**. The plots for the training and test L_2 losses have been shown in Figure 3.



(a) Plot of training L_2 loss with progress in training



(b) Plot of test L_2 loss with progress in training

Figure 3: L_2 loss plots for Subset Selection

This working technique of intelligent fault analysis and subset selection is expected to be a step towards securing power security in developing countries where **clean and reliable power** is the requirement for rapid development.

References

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[2] Biswarup Bhattacharya and Abhishek Sinha. Intelligent subset selection of power generators for economic dispatch. *arXiv preprint arXiv:1709.02513*, 2017.

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