Intelligent Fault Analysis in Electrical Power Grids

Biswarup Bhattacharya (University of Southern California) &
Abhishek Sinha (Adobe Systems Incorporated)

2017 – 11 – 08

Overview

- Introduction
- Dataset
- Forecasting maximum voltage deviation
- Classification of faults
- Faulted bus line determination
- Conclusion
- References

Introduction

Indian Power Grid

- Installed capacity = 229 GW (2013)
- Five regional grids - Northern, Eastern, North Eastern, Western, Southern
- Monitored via National Load Dispatch Centre (NLDC), 5 RLDCs, 33 SLDCs.
- SCADA/EMS system for visualization.

Synchrophasors

- Monitoring the magnitude and angle of each phase of the three phase voltage/current, frequency, rate of change of frequency.
- Data collected at every 40 ms interval.
- PMUs (phasor measurement units) provide us with real-time data.

Motivation

- Monitor the grid to check **vulnerability** by understanding the state of the grid.
- Take **preventive measures** based on the prognostics.
- Aimed at **diversification** and **distribution** of power irrespective of generator/load fluctuations.
- Should lead to less down-time, better scheduling, lesser losses for companies. Especially useful for renewable energy grids.

Problem Statement

- Current situation in Indian electrical power grids:
  Small disturbance noted → generate report → check with other dispatch centers.
- If the disturbance is found to be local → ignored.
- Else, if it is found to be correlated (similar disturbances observed at other dispatch centers) → further diagnostics are conducted.
- **Our goal**: Perform this automatically using ML.

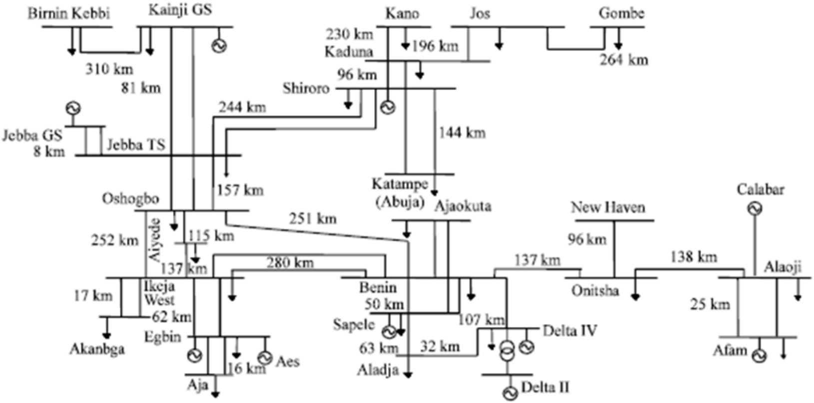

Figure: A typical power grid

Dataset

Dataset

Description

Power Grid network: 23 buses, 6 generators, 8 loads

- Each bus has a voltage and angle associated with it.
- Snapshots taken at **every** 40 **ms** from 0 s to 4 s.
- **Initial, transient and steady state** data was captured in this manner.
- **100 simulations** done per bus per fault (with different voltage fluctuations injected using an uniform distribution).
- Simulated for a total of **4 types of faults**: 3ϕ bus fault, branch trip, LL, LG.

Software

Siemens PSS/E software + psspy

- Simulation software used is **Siemens PSS/E**.
- This software enables simulation for networks with upto 0.2 million buses.
- Initially tried using *PowerWorld* but abandoned due to scripting issues.
- The handy psspy Python package available with PSS/E enables easy scripting of power system scripts according to our requirements.

Dataset

Faults: Any abnormal situation in the electric network.

Faults injected and cleared at certain timestamps

- 3ϕ **bus fault**: Symmetrical fault affecting all 3 phases of a bus equally.
- **Branch trip fault**: Trips the transmission line (all 3 phases) between two buses.
- **LL (line-to-line) fault**: This is an unsymmetrical fault and it short circuits two phases (in PSS/E, these are phases A and B).
- **LG (line-to-ground) fault**: This is an unsymmetrical fault and it short circuits one phase (in PSS/E, this is Phase A) with the ground.

Forecasting maximum voltage deviation

Forecasting maximum voltage deviation

Maximum Voltage Deviation

- The maximum deviation between bus voltages in the non-faulted scenario and the bus voltages in the faulted scenario.
- The deviation will be dependent on the load conditions, as well as transmission capacities of the lines.
- Predicting or having an estimate of possible extents of voltage deviation will enable us to consider the "vulnerability" of each bus in the grid.

Forecasting maximum voltage deviation

Model

- We created a grid as specified previously for simulation purposes using Siemens PSS/E.
- Data obtained from a 23 bus network corresponding to different types of faults.
- Neural network model constructed to predict maximum voltage deviation.
- **Input**: Vector of size 23 corresponding to pre-fault voltage data of each bus.
- **Output**: Forecasted voltage value for each bus.

Forecasting maximum voltage deviation

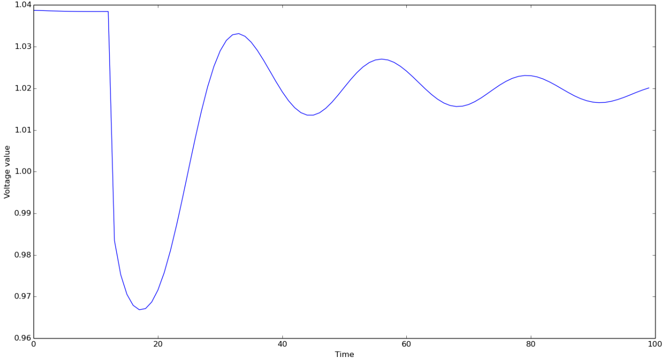

Figure: Typical voltage varying plot for a bus line when a fault is triggered at $t = 16$ ms. Without fault, the bus voltage should ideally remain at 1 pu level.

Forecasting maximum voltage deviation

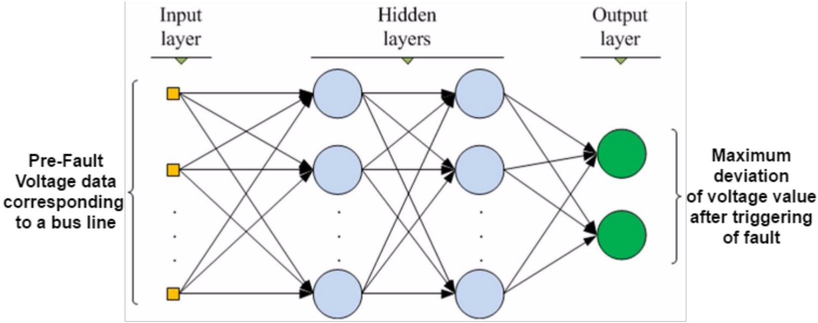

Figure: Prediction of max voltage deviation after fault triggering.

Forecasting done simultaneously

Input layer: All bus lines

Hidden layers: 60 and 40 neurons respectively

Output layer: All bus lines

Forecasting maximum voltage deviation

Results

After 5000 steps of training the following results were obtained:

- Mean L_2 error for each bus = $\mathbf{2.8 \times 10^{-3}}$ pu
- Mean L_1 error for each bus = $\mathbf{2.3 \times 10^{-2}}$ pu
- These are acceptable levels of accuracy.

Forecasting maximum voltage deviation

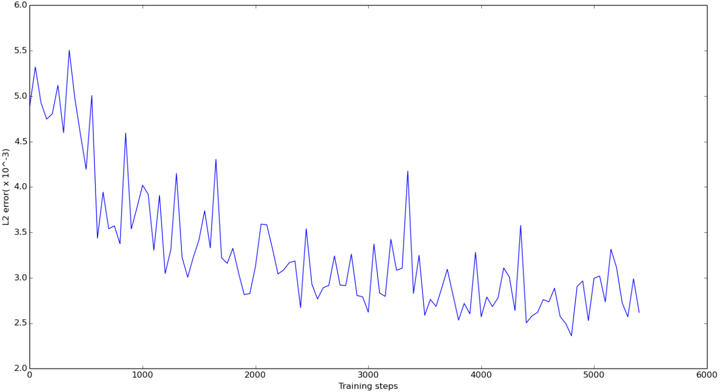

Figure: Variation of L_2 error with progress of training

Classification of faults

Classification of faults

Problem

- When a fault occurs in the network, it is difficult to identify immediately which type of fault has taken place.
- Engineers need to often go to the site to realize the nature of the fault.
- Using ML techniques, given enough previous data about faults, we hypothesized that the type of fault could be predicted.
- We show that ML techniques work by implementing the classification algorithm in case of LL and LG faults.
- This is important because all faults are not the same. For example, among the four types we have explored, LG faults are the most dangerous.

Classification of faults

Classification into LL and LG faults

- Voltage data corresponding to 100 time steps and for each bus is fed as input.
- Classifier gives an output corresponding to one of the two fault classes.

Classification of faults

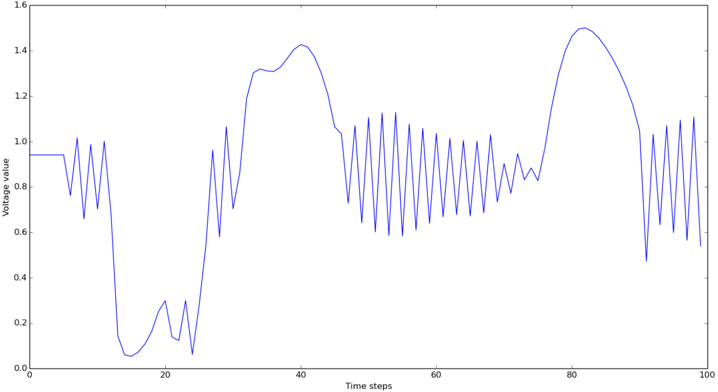

Figure: Variation of bus voltage value in presence of LL fault

Classification of faults

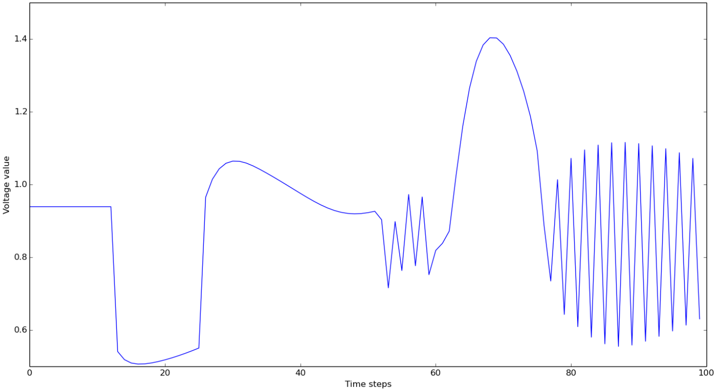

Figure: Variation of bus voltage value in presence of LG fault

Classification of faults

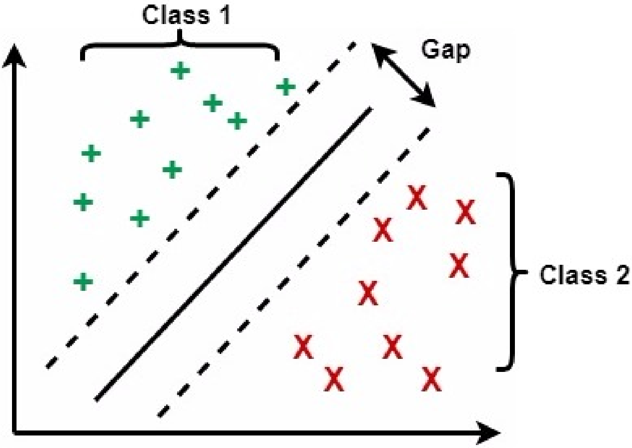

Figure: Standard SVM Example

Classification of faults using SVM

Using SVM

- Support vector machines (SVMs) are supervised learning models used for classification and regression analysis.
- The gap between the classes is kept as wide as possible.
- The classification accuracy on the test set was observed to be around **87 – 88**% for the SVM classifier.

Classification of faults using SVM

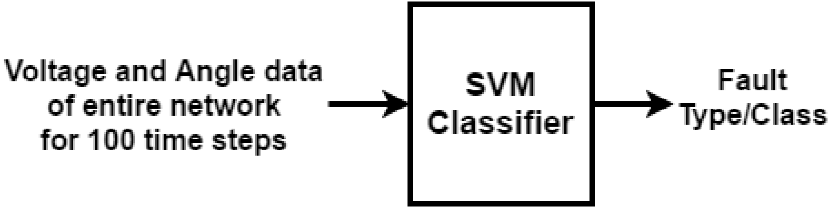

Figure: Block diagram showing SVM model used for classification

Classification of faults

Using LSTMs

- It is the variation of voltage with time that tells us as to what fault had occurred in the network.
- The SVM model had a major disadvantage in the sense that it did not utilize the temporal information present in the data.
- To utilize this time varying information we need other models which are suited to capture the temporal information.

What are LSTMs (recurrent neural networks)?

- The idea behind RNNs is to make use of sequential information.
- RNNs can be thought of as having some memory which captures information about what has been calculated so far.
- Theoretically they can model long sequences but in practise they are limited to small steps.

Classification of faults using LSTMs

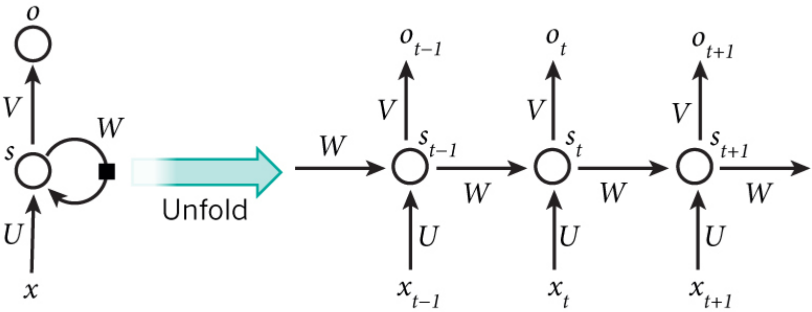

Figure: A recurrent neural network and the unfolding in time

Classification of faults using LSTMs

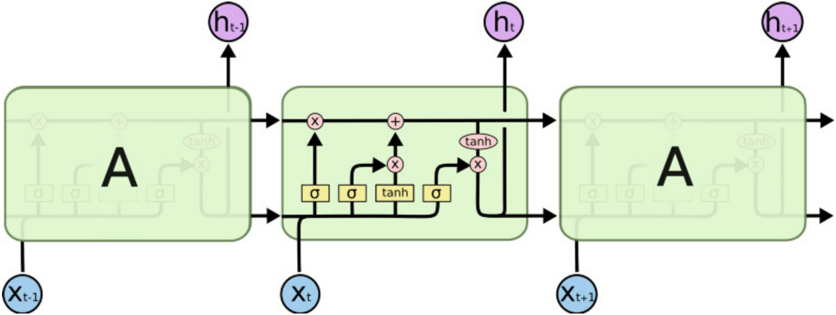

Figure: A basic structure of LSTM.

LSTM which is a variant of RNN is used to take care of long term dependencies.

Classification of faults using LSTMs

Stage 1

- Consists of **100 unfoldings** in time of LSTM cells.
- Each LSTM cell gets a vector of size 23 (all bus voltages) as input.
- The output coming out from the final LSTM cell contains the temporal information of data.

Stage 2

- The information extracted is passed to a classifier for classification.
- Fully connected hidden layer of 64 neurons.
- The output is of size 2 $\rightarrow$ probability of the two fault types.

Classification of faults using LSTMs

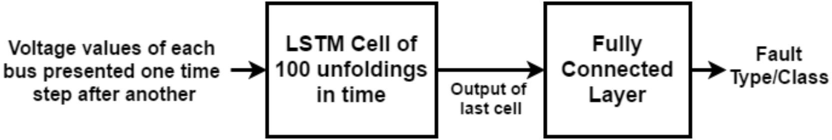

Figure: Model using LSTM for classification of faults

Results

With LSTM the classification accuracy jumped to **94 – 95**%, an improvement of around 6% over the SVM model.

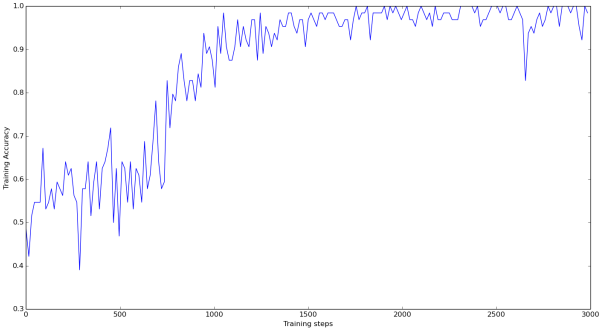

Figure: Variation of training accuracy with progress of training

Classification of faults using LSTMs

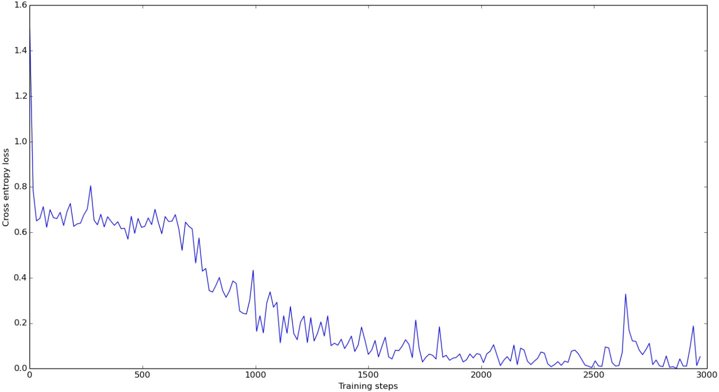

Figure: Variation of cross entropy loss with training

Faulted bus line determination

Faulted bus line determination

Problem

- Often it is unknown which bus is actually faulted, as a fault causes a deviation in voltage in many connected buses.
- Immediate identification takes time and often requires manual supervision.
- Using ML, we can identify the faulted bus line very quickly.

Faulted bus line determination

Which bus line is faulted?

- Different models were constructed for each of the different fault types to determine the bus line in which the fault had been triggered.
- To extract the temporal information from the network data LSTM was used.
- The extracted information was then fed to a classifier which gave as a *non-zero output* corresponding to the faulted bus number and 0 for buses with no triggered faults.

Faulted bus line determination

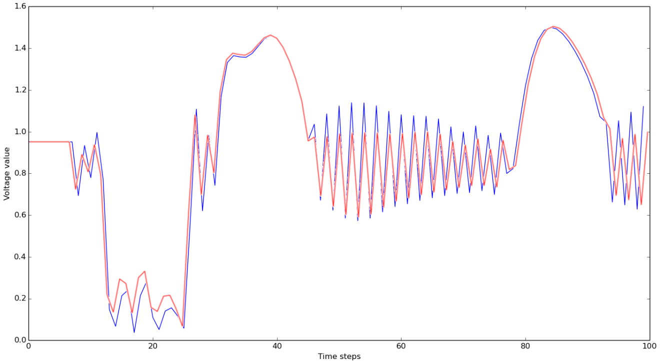

Figure: Blue - Voltage variation with time for the bus line in which fault was triggered. Red - Voltage variation with time for the bus line in which no fault was triggered.

Results

- For the LL fault the accuracy was **97**%.
- For the 3ϕ bus fault the accuracy was **97**%.

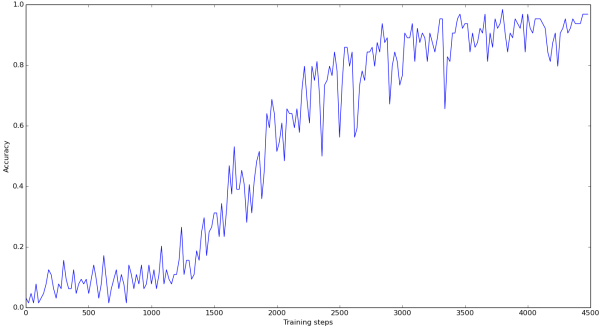

Figure: Variation of training accuracy with progress of training

Faulted bus line determination

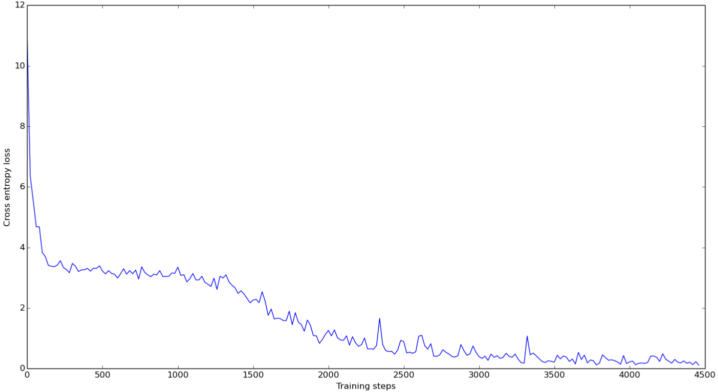

Figure: Variation of training loss with progress of training

Conclusion

Further Work

- Predicting congestion in the grid was attempted in [2].
- In the renewable energy context, selecting generation schedules optimally for economic dispatch was also attempted in [2] with reasonably good results.
- Combining these predictive models, a complete power grid security tool can be formally built and verified.

Conclusion

Future Work

- Determination of health metrics which can appropriately measure the grid vulnerability.
- Yet to be applied on real-world data.

Final Words

Ultimate aim: To make power grids scalably artificially intelligent

- Especially useful for renewable energy grids. The Indian government wants to raise USD 1 trillion to quadruple current global solar power to 1 terawatt by 2030.
- Issues like load shedding and power cuts can be optimally handled.
- Building the intelligence for a grid of national scale is possible with enough data and sophistication to handle several micro-situations apart from the broad issues.

References

1. B. Bhattacharya and A. Sinha. Intelligent fault analysis in electrical power grids. In Proceedings of the 29th IEEE International Conference on Tools with Artificial Intelligence, ICTAI 2017. IEEE, 2017.
2. B. Bhattacharya and A. Sinha. Intelligent subset selection of power generators for economic dispatch. arXiv preprint arXiv:1709.02513, 2017.
3. B. Bhattacharya and A. Sinha. Deep fault analysis and subset selection in solar power grids. In Proceedings of the Machine Learning for the Developing World Workshop (ML4D), 31st Neural Information Processing Systems, NIPS 2017. 2017.

Thank You!

Email: bbhattac@usc.edu