Towards Detecting Stealthy Attacks in Power Grid using Deep Learning

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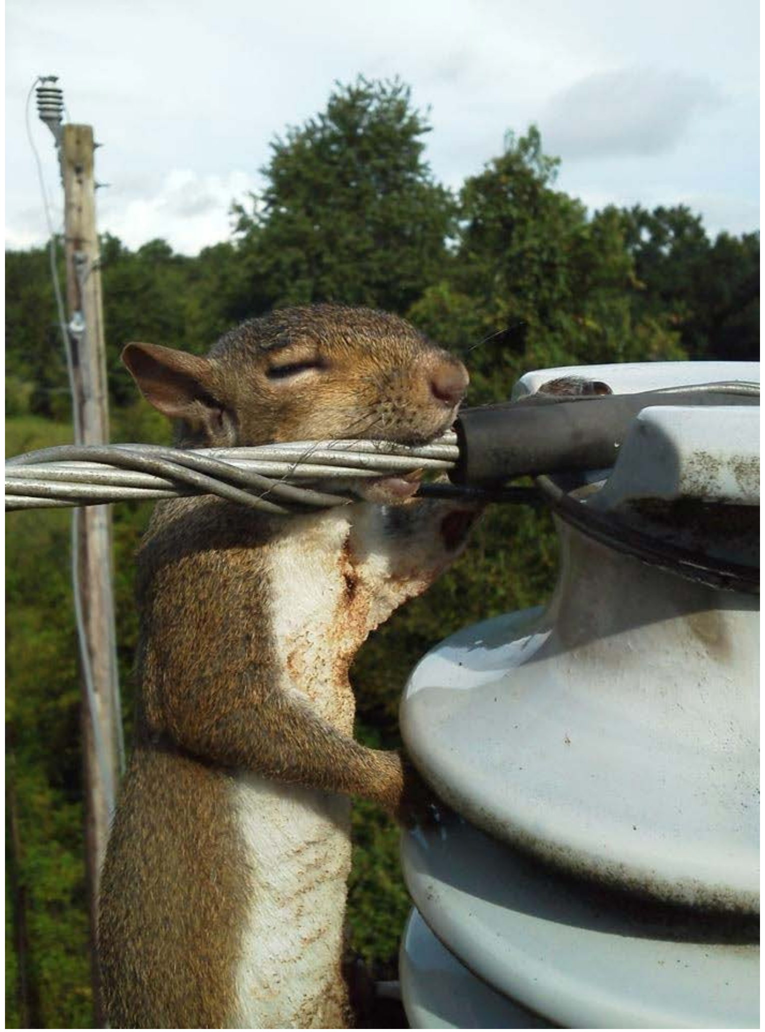
Stealthy Data Integrity Attacks

- Surreptitiously changing data
- Intelligently and incognito
- Fooling the SCADA operators
- Cumulative ripple effect can be disastrous

Insider Threat

Outside Attacker



Stealthy Attacks in Power Grid

- Get access to one or more SCADA control Centers (in a Substation)
- Modify actual measurement data to deceive operators

Detection Mechanism:

- Find anomalous data pattern

Statistical and Machine Learning Approaches

- Statistical Methods
  - Weighted Least Squares
  - Least Trimmed Squares
  - Chi Squares
  - And more
- Machine Learning Methods
  - Distance Ratio Estimator
  - K-Nearest Neighbor
  - Support vector Machines
  - And more

Deep Learning Based Approach

- Deep Learning is being used for predictive analytics and anomaly detection in many different and diverse areas.
- Why not then to detect bad data in power grid!

So Many Deep Learning Methods

- Stacked Auto-Encoder
- Deep Belief Network
- Deep/Restricted Boltzmann Machine
- Convolutional Neural Network
- Recurrent Neural Network
- And many more!!

Each of these have variations on the theme.

Preprocessing

- Need to pre-process data before applying deep learning method
- For example: For selecting appropriate predictors or features

So Many Methods Again

- Random Forest Classifier or Regressor
- Principal Component Analysis (PCA)
- Quadratic Discriminant Analysis (QDA)
- Regularized Discriminant Analysis (RDA)
- Linear Discriminant Analysis (LDA)
- Even, unsupervised deep learning

More Variations

- Each of these methods can further be fine-tuned and optimized by varying the hyper-parameter values

How to Measure

- Use Confusion Matrix

Total=n	Predicted Normal	Predicted Attack
Actual Normal	TN	FP
Actual Attack	FN	TP

How to Measure

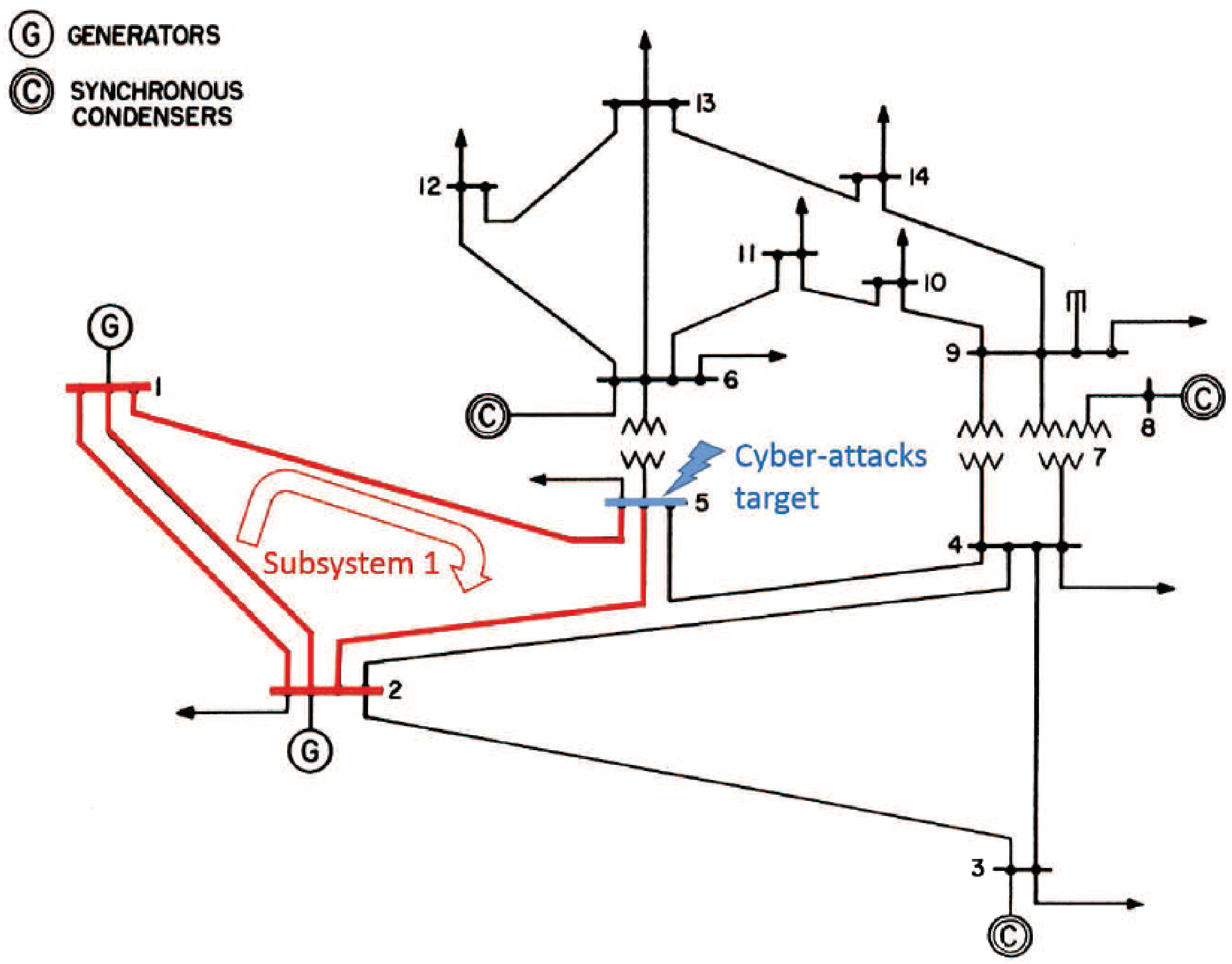
- Metrics to Evaluate
  - Accuracy [(TP+TN)/Total]
  - Precision [TP/(FP+TP)/Total]
  - Recall [TP/(FN+TP)/Total], aka, Detection rate
  - False Positive Rate [FP/(FP+TN)/Total]
  - Misclassification Rate [(FP+FN)/Total]
  - Specificity [TN/(TN+FP)]
  - Prevalence [(FP+TN)/Total]
- Execution Time
  - Time for Training
  - Time for real-time detection

The Matrix

- Perform an experiment with
  - a feature selection method
  - a deep learning method
  - A set of hyper-parameter values
- Tabulate the performance metrics
- Repeat with changing one of the three above

Will yield a comparison matrix

IEEE 14-Bus System

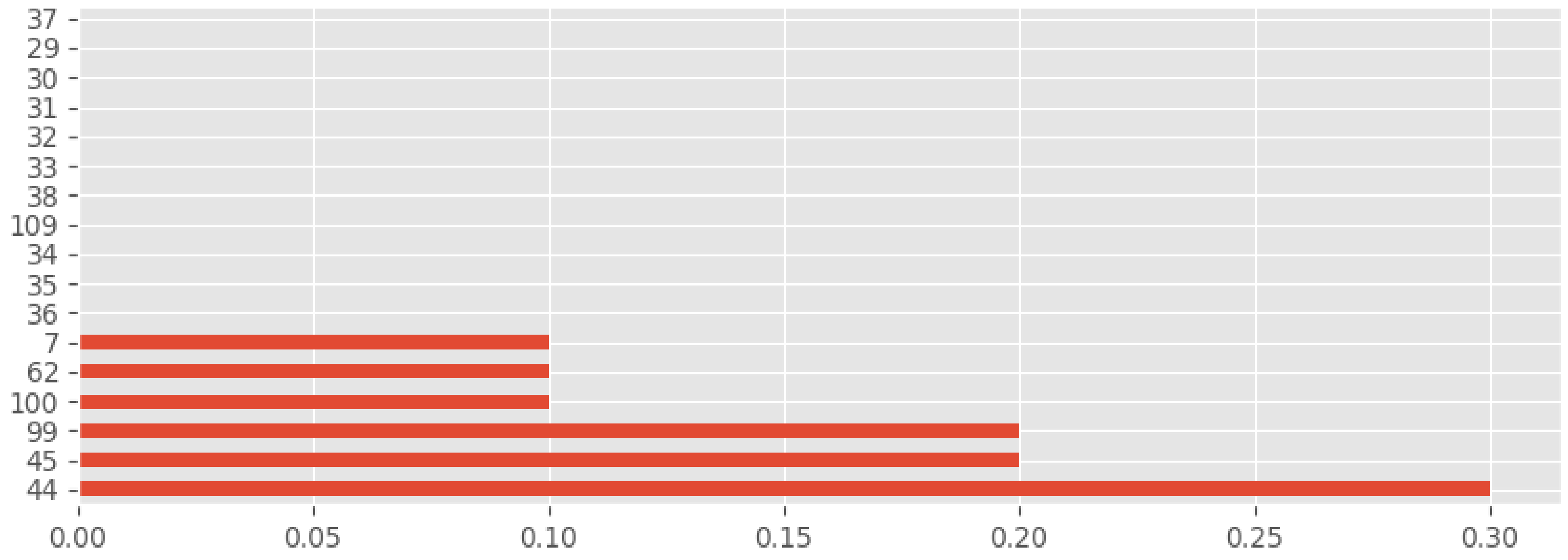


Data Set

- Power Grid SCADA dataset:
  - 40 active power-flows
  - 14 active power-injections and
  - 68 reactive power and voltage measurements.
- 10,000 sets of measurement data
- 1 bus is compromised
- Attack simulated by randomly modifying data at slack Bus

Feature Selection

- Random Forest Classifier



Anomaly Detection

- Stacked Autoencoder
  - Feedforward
  - 4 hidden layers
  - 50 hidden cells in each hidden layer
  - Tanh activation function
  - 50 epochs
  - 0.005 learning rate
  - 70%-30% train-test split

Performance Matrix

Accuracy [(TP+TN)/Total]	93%
Recall [TP/(FN+TP)/Total]	84%
Precision [TP/(FP+TP)/Total]	47%
False Positive Rate [FP/(FP+TN)/Total]	5.8%
Misclassification Rate [(FP+FN)/Total]	6.9%
Specificity [TN/(TN+FP)]	94%
Prevalence [(FP+TN)/Total]	90%

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