Event Stream Processing for Improved Situational Awareness in the Smart Grid

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Preventive Model of Operation

- Based on forecasted load, generation and contingencies
- Safe operation point established to sustain contingencies
- Contingencies can never occur
- Not prepared for unforeseen contingencies
- Vertically integrated requirement driven industry
- Not optimal

Uncertainties in Power System

- Distributed generation
- renewable energy integration (solar/wind)
- De-regularization (generation/transmission/distribution)
- Market driven industry (bidding for rights)
- Electric vehicles

Corrective Model of Operation

- Industry should be able to handle unforeseen problems
- Real time surveillance of Power system needed
- Identification and action needed on real time
- Efficient, Environment Friendly
- Complements existing model of operation
- Handle uncertainties introduced in the system

Situational Awareness

- Prevent cascading failures
- Real time decision making using Synchrophasor data
- Mathematical methods/Machine learning methods
- Information extraction for effective decision making
- Coordinated actions to prevent cascading of failures

Problems with Analytical Solutions

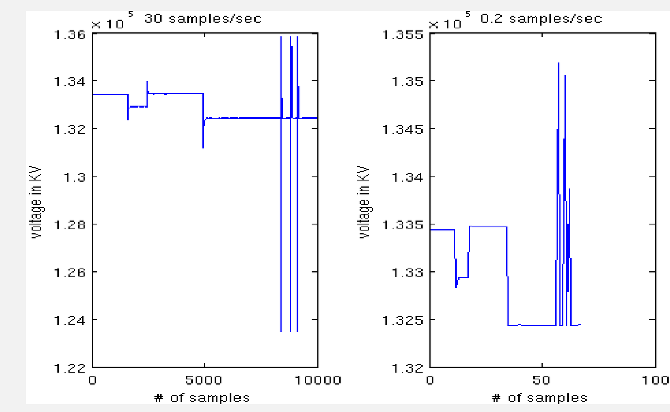
- Mathematical models cannot meet latency requirement of real time applications
- Utilize synchrophasor data for quick decisions
- Machine learning algorithms emulate power system behavior

Machine Learning

- SVM, ANN, Decision Trees etc. for static/dynamic security assessment and fault detection/classification
- Consume synchrophasor data
- Expected to meet the latency requirements

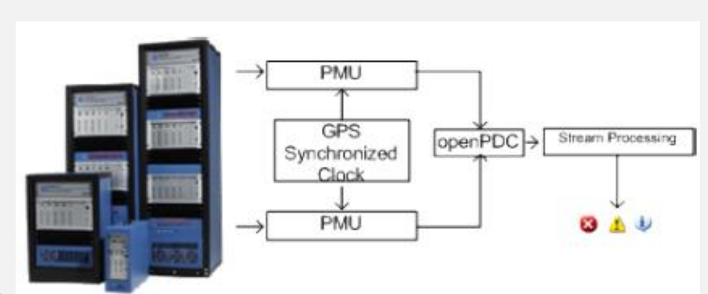
Challenges

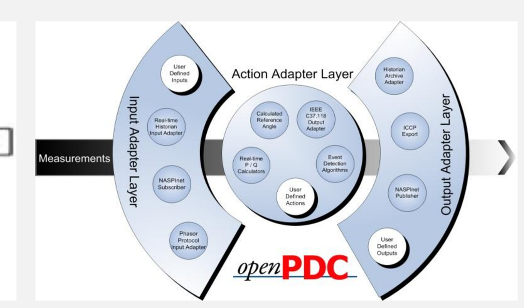
- Massive Data
  - 30 samples / second (>2 million samples/day)
  - Exponential increase with increase in deployed devices
  - Model may not fit in memory
  - Hampers latency
- Dynamic Behavior of Power system
  - Changes the operating condition
  - Should be able to update knowledge
  - Incremental learning is required
- Downsampling NOT an Option
  - Important information lost
  - Cannot portray dynamic behavior of Power systems
  - Undermines use of high speed synchrophasor

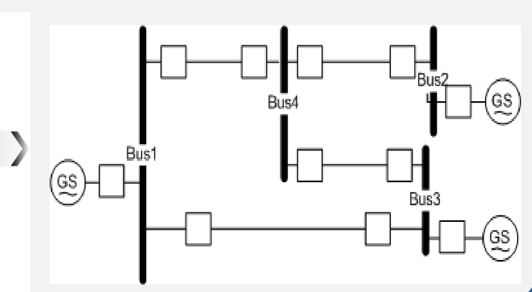


Experimental Setup

- hardware-in-the-loop Simulation
- SEL421 and GE N60
- 28 PMU measurements used as features
- Single Line to Ground, Transmission line loss, Generation Loss







Strategy

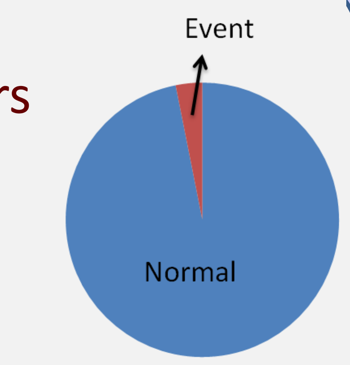
- Event stream mining algorithm
  - Event detection
  - Process synchrophasor data without exceeding memory and computational requirement
  - incremental learning
- Hoeffding Tree
  - creates a decision tree from data stream
  - analyzing each sample only once
  - stores sufficient statistics (required to grow itself) in its leaves
  - Finds the best attribute considering only a small subset of the training examples
  - Number of examples necessary at each node is solved using Hoeffding bound

$$\epsilon = \sqrt{\frac{R^2 \ln\left(\frac{1}{\partial}\right)}{2n}}$$

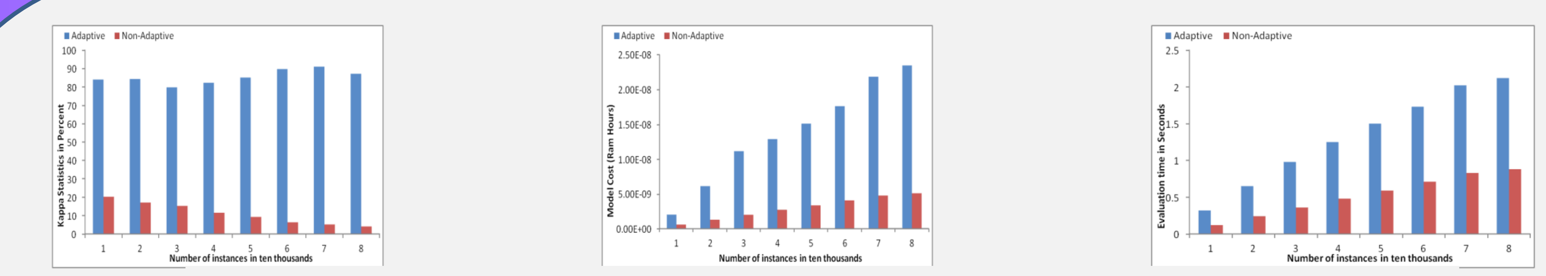
Evaluation Measures

- Kappa Statistics
  - normalizes the accuracy by that of the chance predictors
- Ram Hours
  - Every GB of RAM deployed for 1 hour
- Runtime
  - Time (seconds) required for algorithm to run.

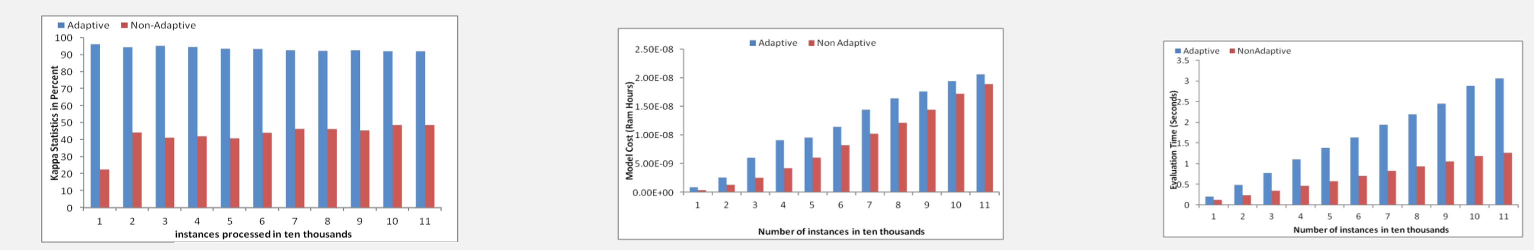
$$\kappa = \frac{\rho 0 - \rho C}{1 - \rho C}$$



Results

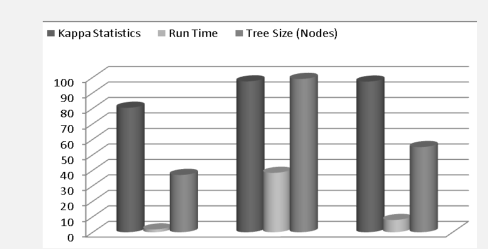


Performance measures of hoeffding tree in changing load



Performance measures of hoeffding tree in constant load

Kappa Statistics with fixed size of hoeffding tree



Performance Measure in comparison to multi scan algorithms

Other Applications

- Useful in any massive data analysis
  - Synchrophasor data
  - Advanced Metering Infrastructure (AMI) data processing
  - Online pricing signal processing
  - Process Demand Response data processing

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