VADER: Visualization and Analytics for Distributed Energy Resources

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Project Background and Goals

Current Goals:
[What Now] Situational Awareness – state estimation, device status …
[What If] Scenario Analysis - operations planning, impact of technology evaluation, resource placement …

Eventual Aim:
Closing the Loop - optimizing controls …

Research Output:
Develop algorithms, tools, methodologies for deployment
VADER Workflow
Data Sources

Utility
- SCADA – substation measurements
- non-SCADA – Smart Metering, Line Sensing
- GIS – nominal device specifications

Public
- Weather, Solar Irradiance
- Google Street View/Satellite

3rd Party
- EV : mobility+charging
- PV : voltage + injection
- Energy Storage
Virtual SCADA

SCADA ~ real time access to all instrumentation
Practical Limitations ~ Delays, Missing Data, non-aligned

Data Analysis Tasks
Imputation
Re-alignment/resampling
Other data cleaning tasks
Analytics Paradigms

Analytics Approaches

**Traditional Methods** - well defined input/output – Example: State Estimation, Load Flow
System Primitives - Network, Load, Supply, Device Parameters - System State

**Direct Methods** - Estimate desired quantities by empirical models
Estimate system primitives from sensor data
Use Cases

**DER Integration Use Cases**
- Locational Net Benefit Analysis
- Flexibility Estimation/Planning
- Performance Evaluation of Distribution Systems
- Overgeneration/Undergeneration/Reverse PF detection
Projects Summary and Progress Report

Estimating (DSN) System Primitives
   Supply and Demand Primitives
      1 - AMI Based Load Forecasting
      2 - Solar Disaggregation

Network Primitives
   3 - Estimation of Line Impedances via AMI (voltage)
   4 - Estimation of AMI connectivity

Estimating System State
   Topological State (discrete device status)
   4 - Detection of network configuration via AMI and Line Sensing
   5 - Distribution Outage Detection

Direct Learning of Power Flow Model
   6 - Machine Learning Based Based Power Flow

Choice of Projects:
   Where is there a lack of knowledge from utility perspective?
   Where can we leverage statistical models + physical intuition + sensor data?
Estimating Demand Primitives

**Aggregation Benchmarking**
[Sevlian2016]

**Methods** – SARIMA, NN, SVR

**Forecast Horizon** – $1/n$ hour ahead

**Aggregations** – 1 – 100K user

Bias-Variance Decomposition

Quadratic growth of MSE

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**Method Benchmarking**
[Yu2017]

**Methods** – (many)

**Forecast Horizon** – $1/n$ hour

**Aggregations** – 1

Show SVR is reliable the best performing: 56% the best procedure

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<tr>
<td>SVR</td>
<td>56.09%</td>
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</tbody>
</table>
Solar Disaggregation [Kara2016]

**Net metering:** No knowledge of individual generation.

**Side information:** solar irradiance, net load, line measurements,

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**Contextually Supervised Source Separation**

Source Separation Method
Convex Optimization
5-15% error using AMI and Line Sensing alone
Estimating Network Primitives

Reconstruction of Device Connectivity [Weng2016]
Where are my AMI's connected?
Detect GIS Errors from sensor data
Voltage Mag (phase) known at each bus

Conditional Independence of AMI-voltage
Graphical Model formulation

\[ p(v) = \prod_{i=2}^{n} p(v_i | v_{pa(i)}) \]

GM network reconstruction: Chow-Lui Algorithm

Can be extended to Mesh Networks [Liao2016]
Assume joint-Gaussian model
Conditional independence model of v-observations
Group-Lasso Formulation
Estimating Network Primitives

Estimation of Line Impedances [Yu2017]
Assume only additive error \( \Rightarrow \) Least squares approach

\[
y = \begin{bmatrix} p \\ q \end{bmatrix} \quad X \text{ depends on voltage magnitude + phase}
\]

\[
(g_{LS}^*, b_{LS}^*) := (X^T X)^{-1} X^T y
\]

Error in power injection + voltage mag? Error in Variable (EIV) model.

Formulate Maximum Likelihood Estimation
Generalized Low Rank Approximation (solved via SVD)
Estimating the System State

Network State:
- Radial Topology
- Outage Condition

Power System State:
- Voltage Mag/Phase
- Power Injections
Estimating Network State [Sevlian2016]

AMI + Line Measurements Model
Detect Switch Status s.t. fully connected

Traditional Approach:
General State Estimation; Voltage, Current

Flow Based Detection
Simple assumptions, detection guarantees
Robust to noise, unknown impedance

Spanning Tree Detection
Nodal Injection
Edge Flows
Estimating Network State (Outage Topology)

AMI (kwh) + Line flows [Sevlian2017]

Optimal Hypothesis Testing
Real Time Current Measurements
AMI Forecast of aggregates
Compare RT-line flows to AMI forecast

Optimal Sensor Placement
Greedy Algorithm
Minimize Maximum Missed Detection

AMI (V) [Liao2016]

Optimal Change Point Detection
Real time stream of voltage data
Data driven estimation of pre/post stats

Evaluated Scenarios
Islanded DERs
mesh network
Standard Radial

\[ v^{1:N} = \{ v[1], v[2], \ldots, v[N] \} \]
Traditional Approach:
Use methods so far to extract primitives
(p, q, v) – observed \( \rightarrow \) min MSE leads to estimate

Direct Approach: *(machine learning for power flow)*
Assume only noisy \( p,q \) are observations
Want to determine voltages
No reliance on topology/impedance/devices/active devices + dynamics

Use Kernel Mapping
Support Vector Regression w/ poly kernel
Physical Domain
Line Params + topology

Observation Domain
Support Vectors + weights

\[ y = f^*_y(x) = \sum_{t=1}^{T} \alpha^*_t K(x, x_t) \]
References

[Sevlian2016]: R. Sevlian and R. Rajagopal. A Scaling Law for Short Term Load Forecasting on Varying Levels of Aggregation. (under review)