Machine Learning in Distribution Grids

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Presentation Outline

• Challenges in Distribution Grids

• Integration between Machine Learning and Power Flow Models

• Tests in a California Grid and IEEE Benchmarks

• Conclusion and Future Work
Distribution Grid Management
Capability of Modeling Other Smart Devices in Distribution Grids

- Smart PV inverters [1]
- Smart EV chargers [2]
- Smart micro-grid centralized controllers [3]
- ...

Phasor Measurements in Distribution Grids

• Utility’s pilot program provides phasor measurements in some feeders.

• Emerging techniques can convert inexpensive smart meters to phasor measurement units in the near future [1, 2].

• We show the capability of machine learning-based representation as a technical validation.

Distribution Grid Management

- Given
  - Network topology
  - Network admittances
  - Load and DG injections
  - Active control laws

- Power Flow Equation Holds
  - Optimal power flow
  - Optimal voltage control
  - Situational awareness

- Models partially unknown in some utility (CA, AZ, PA) distribution grids...
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Existing Data-Driven Solutions

- Historical node measurements
  \[ p_i := \{p_1, \ldots, p_T\}, \quad q_i := \{q_1, \ldots, q_T\}, \quad v_i := \{v_1, \ldots, v_T\}, \quad \Theta_i := \{\theta_1, \ldots, \theta_T\} \]

- Topology reconstruction \((Deka et al, 2015), (Bolognani et al, 2013), (Liao et al, 2016), (Sevlian et al, 2016)\)

- Line parameter estimation \((Yu et al, 2017), (Yuan et al, 2016)\)

- Incapable when
  - Active controllers
  - Partial measurements
Machine Learning for System Modeling

- Historical node measurements
  \[ p_i := \{p_1, \cdots, p_T\}, \quad q_i := \{q_1, \cdots, q_T\}, \quad v_i := \{v_1, \cdots, v_T\}, \quad \Theta_i := \{\theta_1, \cdots, \theta_T\} \]

- Topology and Line Parameter Estimation
  \[ p_i = \sum_{k=1}^{m} |v_i| |v_k| (g_{ik} \cos \theta_{ik} + b_{ik} \sin \theta_{ik}) \]
  Physical model
  \[ + \sum_{k=m}^{n} |v_i| |v_k| (g_{ik} \cos \theta_{ik} + b_{ik} \sin \theta_{ik}) + h(v, \theta) \]
  Unknown unmeasured buses

- Machine Learning based Representation Estimation
  \[ p_i = f_{p_i} (v, \theta) \]
  \[ q_i = f_{q_i} (v, \theta) \]

Machine Learning Model?

Abstract Function Space
\[ \rightarrow \text{Generalization} \]
Generalization of Power Flow Equations

• Inner-product representation

\[ p_i = \left\langle [g; b], \phi_{p_i}([v; \theta]) \right\rangle \]
\[ q_i = \left\langle [g; b], \phi_{q_i}([v; \theta]) \right\rangle \]

• Abstraction

\[ y = \left\langle \beta, \phi_y(x) \right\rangle \]
Machine Learning Model Choice: SVR

- Linear regression
- Support vector regression
- Random forest
- ... (more models)
- Artificial neural network

Model Generalization

Interpretation

- Balance
- Equivalence to physical law model in some condition
SVR Model for Mapping Rule Estimation

Objective: minimizing the fitting error and coefficient regularization

\[
\text{minimize} \quad \frac{1}{2} \| \beta \|^2 + C \sum_{t=1}^{T} (\xi_t + \xi_t^*) \\
\text{subject to} \quad y_t - < \beta, \phi_y(x_t) > - b \leq \epsilon + \xi_t, \\
< \beta, \phi_y(x_t) > + b - y_t \leq \epsilon + \xi_t^*, \\
\xi_t, \xi_t^* \geq 0
\]

- dot-product coefficient
- weights: fitting - regularization
- fitting error penalty
- Function \( \rightarrow \) kernel space
- width: no-penalty zone
- constant coefficient term
Kernel-Based Mapping Rule Representation

• SVR-based Mapping Rule Representation

\[ y = f_y^*(x) = \sum_{t=1}^{T} \alpha_t^* K(x, x_t) \]

• Reproducing Hilbert Kernel Space (RHKS)

\[ K(x_1, x_2) := \langle \phi(x_1), \phi(x_2) \rangle = h(\langle x_1, x_2 \rangle) \]
Comparison between Representations

• Physical domain representation: line parameters and topology

\[ y = \langle \beta, \phi_y(x) \rangle \]

• SVR representation: (time domain) support vectors

\[ y = f_y^*(x) = \sum_{t=1}^{T} \alpha_t^* K(x, x_t) \]
Why This Works?

- Feature map $2^{n}$/nd polynomial kernel

$$\phi(x) = [x_1^2, \cdots, x_m^2, \sqrt{2}x_1x_2, \cdots, \sqrt{2}x_1x_m, \sqrt{2}x_2x_3, \cdots, \sqrt{2}x_{m-1}x_m, \sqrt{2}cx_1, \cdots, cx_m, c]$$

- Notice

$$p_i = \sum_{k=1}^{n} |v_i||v_k|(g_{ik}\cos \theta_{ik} + b_{ik}\sin \theta_{ik}) = \langle \beta^*, \phi(x) \rangle$$

where

$$\beta^*_j = \begin{cases} 
  g_{ii}, & \text{if } \phi(x)_j = (v_i \cos \theta_i)^2 \text{ or } \phi(x)_j = (v_i \sin \theta_i)^2, \\
  \frac{1}{\sqrt{2}} g_{ik}, & \text{if } \phi(x)_j = \sqrt{2}(v_i \cos \theta_i)(v_k \cos \theta_k), i \neq k, \\
  \frac{1}{\sqrt{2}} g_{ik}, & \text{if } \phi(x)_j = \sqrt{2}(v_i \sin \theta_i)(v_k \sin \theta_k), i \neq k, \\
  \frac{1}{\sqrt{2}} b_{ik}, & \text{if } \phi(x)_j = \sqrt{2}(v_i \sin \theta_i)(v_k \cos \theta_k), \\
  -\frac{1}{\sqrt{2}} b_{ik}, & \text{if } \phi(x)_j = \sqrt{2}(v_i \cos \theta_i)(v_k \sin \theta_k), \\
  0, & \text{otherwise.}
\end{cases}$$
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Test Cases

- A utility’s power and voltage measurement data
- IEEE’s standard test feeder model from 8-bus to 123-bus to generalize our results
- Only use topology and line parameter information when generating training data
Test on Model Generality: Mesh Structure?

Grid with partial measurement on root and leave nodes

SVR: constantly better than learning (nominal) physical parameters
Test on Model Generality: Unknown Controller

Droop controller of reactive power injections for voltage regulation

SVR: robust up to 20 droop coefficient while physical model fails to reveal the truth
Test on Robustness Against Outliers

\[
\text{minimize } \beta, \xi, \xi^*, b \quad \frac{1}{2} \| \beta \|^2 + C \sum_{\tau=1}^{T} (\xi_\tau + \xi^*_\tau)
\]

Cost function of fitting error:
- Asymptotic linear
- Insensitive to outliers

![Graph showing the comparison of cost functions](image)
Test on Model Extrapolation

No DER, training and testing data in same range

Testing data with high demands.

Testing data with deep DER penetration.
Test on Model Extrapolation

**TABLE I: Benchmark of forward mapping**

<table>
<thead>
<tr>
<th>Test Case</th>
<th>RMSE (p.u.)</th>
<th>Time Cost (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SVR</td>
<td>Reg</td>
</tr>
<tr>
<td>8-Bus</td>
<td>0.023</td>
<td>0.060</td>
</tr>
<tr>
<td>16-Bus</td>
<td>0.030</td>
<td>0.060</td>
</tr>
<tr>
<td>32-Bus</td>
<td>0.031</td>
<td>0.060</td>
</tr>
<tr>
<td>64-Bus</td>
<td>0.035</td>
<td>0.59</td>
</tr>
<tr>
<td>96-Bus</td>
<td>0.040</td>
<td>0.060</td>
</tr>
<tr>
<td>123-Bus</td>
<td>0.055</td>
<td>0.061</td>
</tr>
<tr>
<td>123-Bus w/ loop</td>
<td>0.050</td>
<td>0.062</td>
</tr>
</tbody>
</table>
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3-Phase Power Flow in Distribution Grids

• Balanced system
  • 1-phase model $\rightarrow$ A good approximate for 3-phase system [1, 2, 3]

• Unbalanced system
  • Current Work $\rightarrow$ OpenDSS and Opal-RT
  • Real time 3-phase system $\rightarrow$ Both simulation and hardware-in-the-loop
  • Develop machine learning-based models $\rightarrow$ 3-phase system

Conclusions and Future Work

Physical Law Model
Incapable of partial measurements
Unable to model active controllers

Machine Learning Model
• SVR: A balance between generality and interpretability
• Partial measurements
• Active controllers
• Outliers

Future work:
• ML power flow-based OPF
• Use ML power flow for system control
• Metrics for confidence
Questions?

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