Machine Learning in Distribution Grids

Yang Weng

Arizona State University

(yang.weng@asu.edu)

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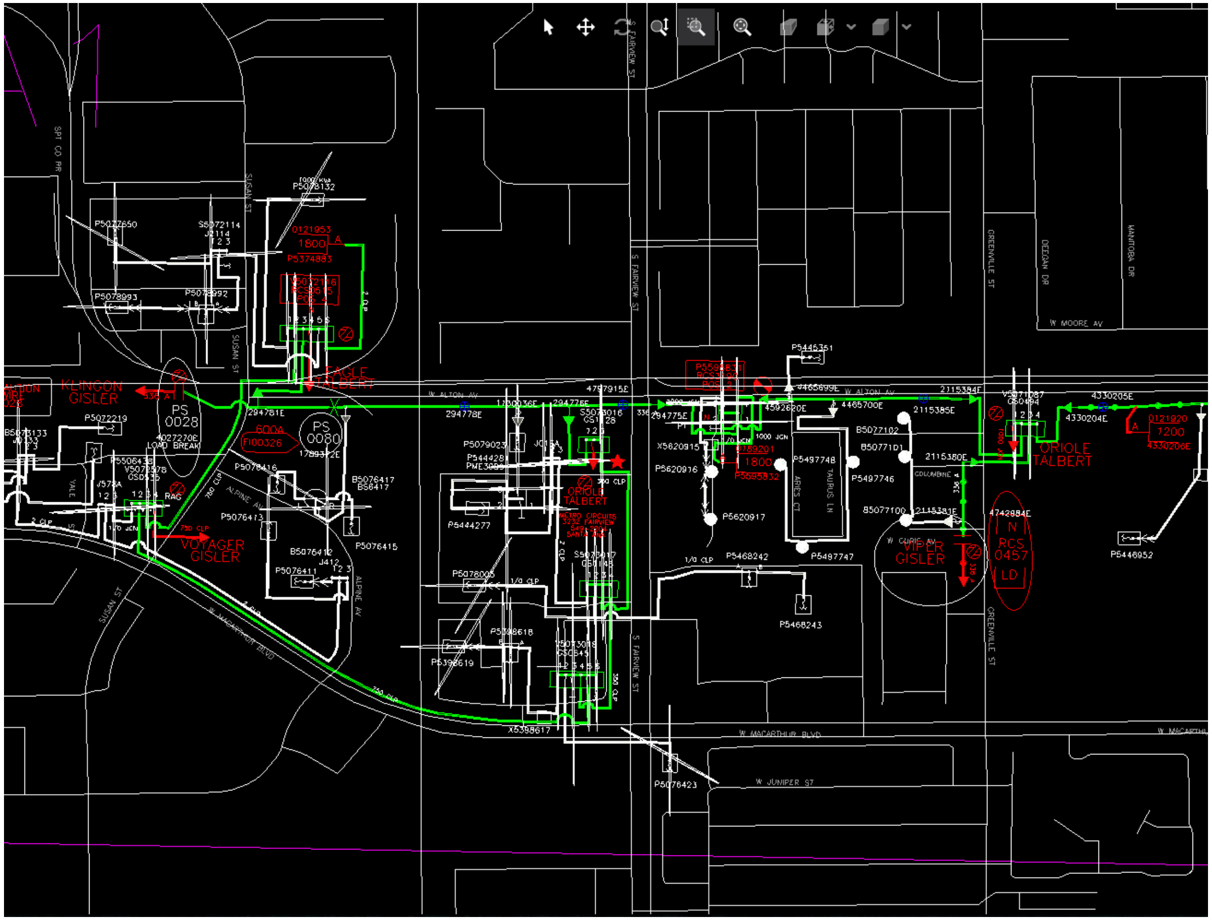
Presentation Outline

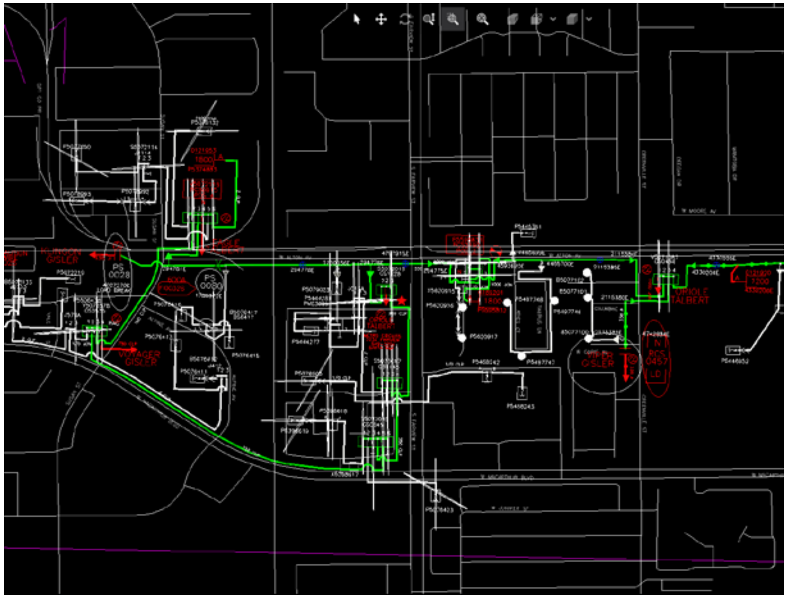
- Challenges in Distribution Grids
- Integration between Machine Learning and Power Flow Models
- Tests in a California Grid and IEEE Benchmarks
- Conclusion and Future Work

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]
- …



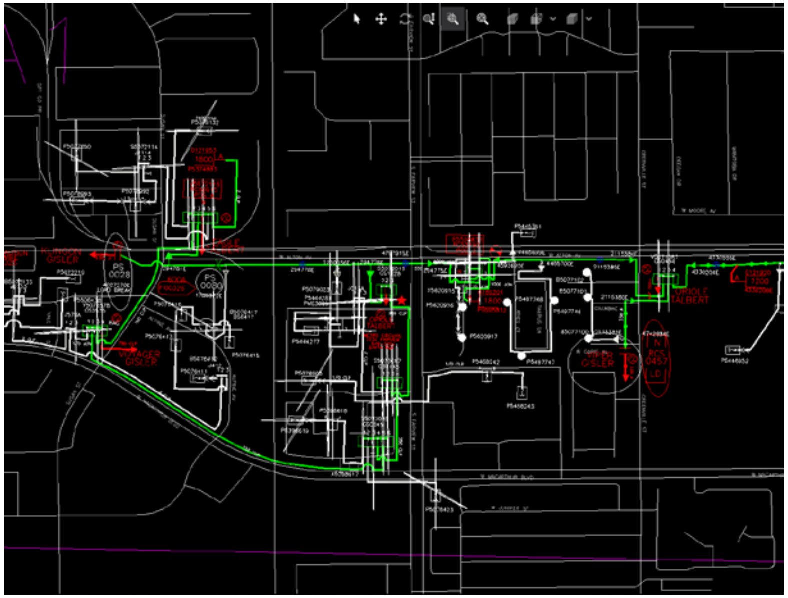
[1] Su, Xiangjing, Mohammad AS Masoum, and Peter J. Wolfs. "Optimal PV inverter reactive power control and real power curtailment to improve performance of unbalanced four-wire LV distribution networks." IEEE Transactions on Sustainable Energy 5.3 (2014): 967-977.

[2] Dias, F. G., et al. "Potential for Plug-In Electric Vehicles to provide grid support services." Transportation Electrification Conference and Expo (ITEC), 2017.

[3] Meng, Fanjun, et al. "Distributed generation and storage optimal control with state estimation." IEEE Transactions on Smart Grid 4.4 (2013): 2266-2273.

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.

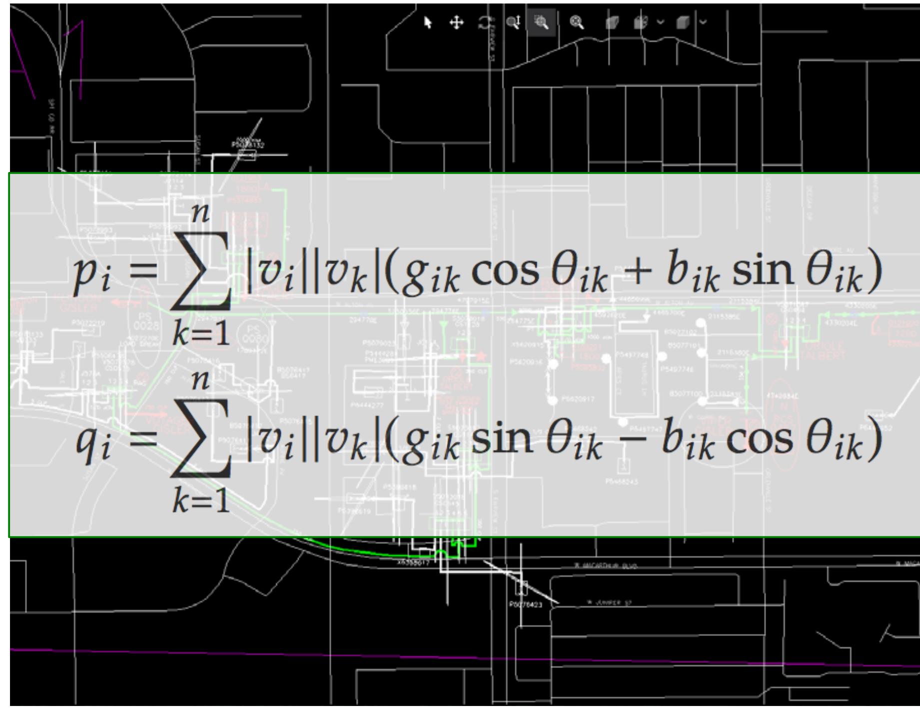


[4] Rhoads, Geoffrey B., and Conrad Eustis. "Synchronized metrology in power generation and distribution networks." U.S. Patent No. 9,330,563. 3 May 2016. [5] McKinley, Tyler J., and Geoffrey B. Rhoads. "A/B/C phase determination and synchrophasor measurement using common electric smart meters and wireless communications." U.S. Patent No. 9,230,429. 5 Jan. 2016.

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



$$p_i = \sum_{k=1}^{n} |v_i||v_k|(g_{ik}\cos\theta_{ik} + b_{ik}\sin\theta_{ik})$$

$$q_i = \sum_{k=1}^{n} |v_i||v_k|(g_{ik}\sin\theta_{ik} - b_{ik}\cos\theta_{ik})$$

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

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Existing Data-Driven Solutions

- Historical node measurements

  $\boldsymbol{p}_i := \{p_1, \cdots, p_T\}, \boldsymbol{q}_i := \{q_1, \cdots, q_T\}, \boldsymbol{v}_i := \{v_1, \cdots, v_T\}, \boldsymbol{\Theta}_i := \{\theta_1, \cdots, \theta_T\}$

- 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

$$\boldsymbol{p}_i := \{p_1, \cdots, p_T\}, \boldsymbol{q}_i := \{q_1, \cdots, q_T\}, \boldsymbol{v}_i := \{v_1, \cdots, v_T\}, \boldsymbol{\Theta}_i := \{\theta_1, \cdots, \theta_T\}$$

- 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

$$+ \sum_{k=m}^{n} |v_i| |v_k| (g_{ik} \cos\theta_{ik} + b_{ik} \sin\theta_{ik}) + h(\boldsymbol{v}, \boldsymbol{\theta})$$

Unknown unmeasured buses Unknown control

- Machine Learning based Representation Estimation

$$p_i = f_{p_i}(\boldsymbol{v}, \boldsymbol{\theta})$$

$$q_i = f_{q_i}(\boldsymbol{v}, \boldsymbol{\theta})$$

Machine Learning Model?

Abstract Function Space
→ Generalization

Generalization of Power Flow Equations

- Inner-product representation

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

- Abstraction

$$y = \left\langle \boldsymbol{\beta}, \boldsymbol{\phi}_y(\boldsymbol{x}) \right\rangle$$

Machine Learning Model Choice: SVR

Linear regression → Support vector regression → Random forest → ... → 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

dot-product coefficient

weights: fitting - regularization

$$\underset{\boldsymbol{\beta},\boldsymbol{\xi},\boldsymbol{\xi}^{\star},b}{\text{minimize}} \quad \frac{1}{2}\|\boldsymbol{\beta}\|^2 + C\sum_{\tau=1}^{T}\left(\xi_t + \xi_t^{\star}\right)$$

fitting error penalty

$$\text{subject to} \quad y_t - <\boldsymbol{\beta}, \boldsymbol{\phi}_y(\boldsymbol{x}_t)> - b \leq \epsilon + \xi_t,$$

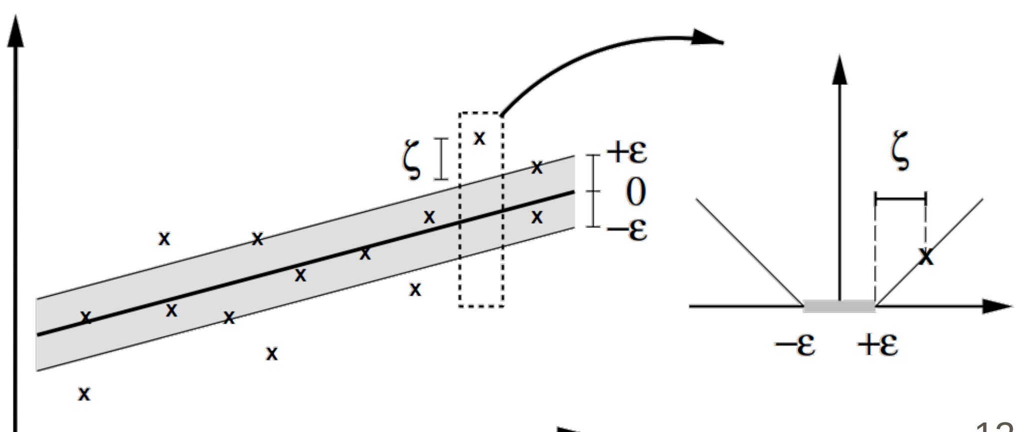
Function
→ kernel space

width: no-penalty zone

$$<\boldsymbol{\beta}, \boldsymbol{\phi}_y(\boldsymbol{x}_t)> + b - y_t \leq \epsilon + \xi_t^{\star},$$

$$\xi_t, \xi_t^{\star} \geq 0$$

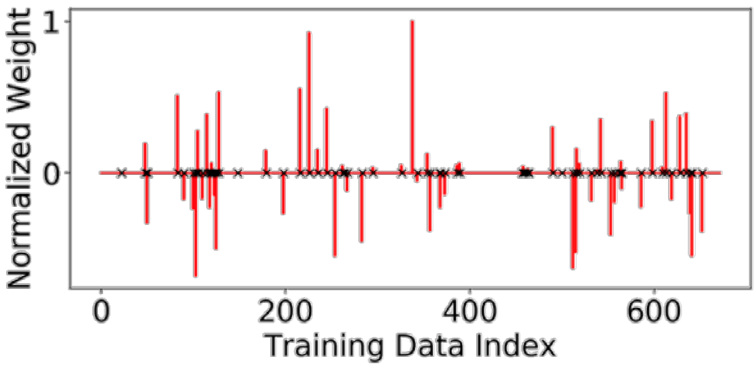
constant coefficient term



Kernel-Based Mapping Rule Representation

- SVR-based Mapping Rule Representation

$$y = f_y^\star(\boldsymbol{x}) = \sum_{t=1}^{T} \alpha_t^\star K(\boldsymbol{x}, \boldsymbol{x}_t)$$



- Reproducing Hilbert Kernel Space (RHKS)

$$K(\boldsymbol{x}_1, \boldsymbol{x}_2) := \langle \boldsymbol{\phi}(\boldsymbol{x}_1), \boldsymbol{\phi}(\boldsymbol{x}_2) \rangle = h\left(\langle \boldsymbol{x}_1, \boldsymbol{x}_2 \rangle\right)$$

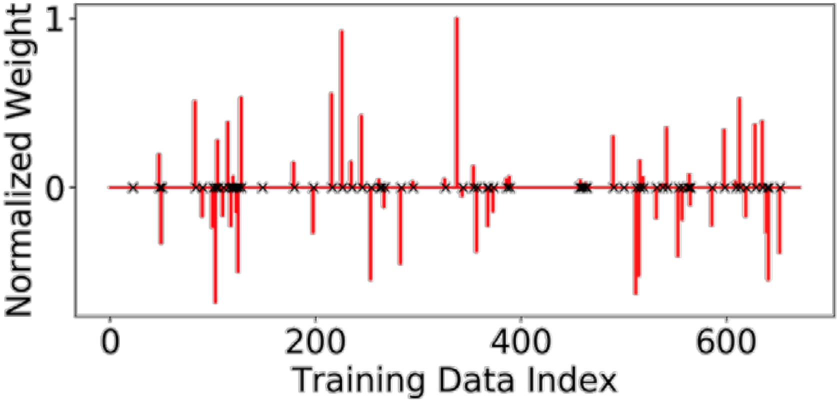
Comparison between Representations

- Physical domain representation: line parameters and topology

$$y = \left\langle \beta, \phi_y(x) \right\rangle$$

- SVR representation: (time domain) support vectors

$$y = f_y^\star(x) = \sum_{t=1}^{T} \alpha_t^\star K(x, x_t)$$



Why This Works?

- Feature map 2nd polynomial kernel

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

- Notice

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

where

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

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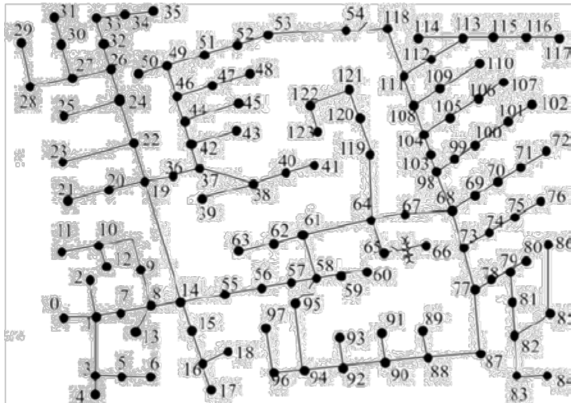
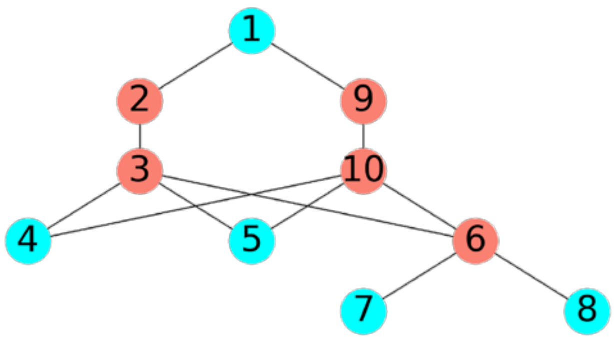
Test Cases

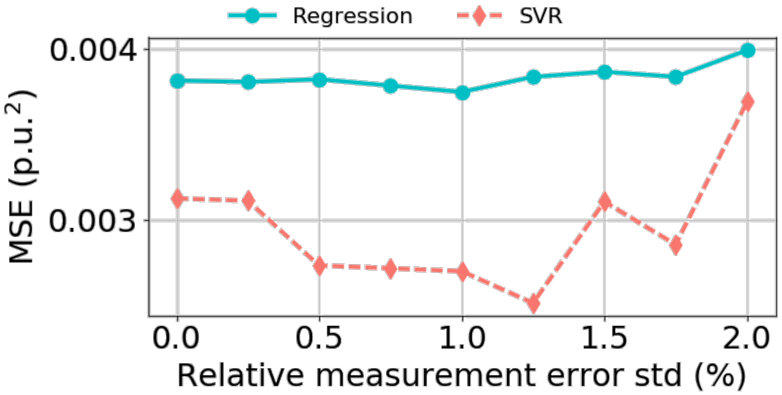
- A utility's power and voltage measurement data
- IEEE's standard test feeder model from 8-bus to 123-bus to generalize our results
- Only use topology and line parameter information when generating training data



Test on Model Generality: Mesh Structure?

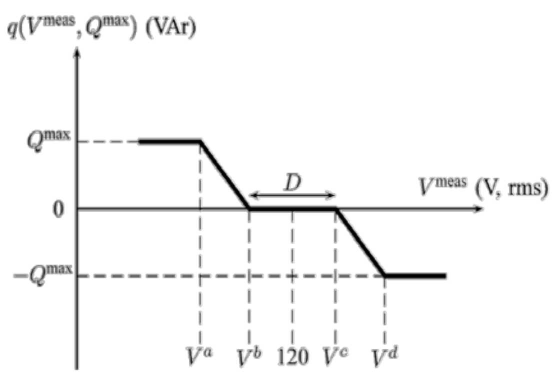


Grid with partial measurement on root and leave nodes

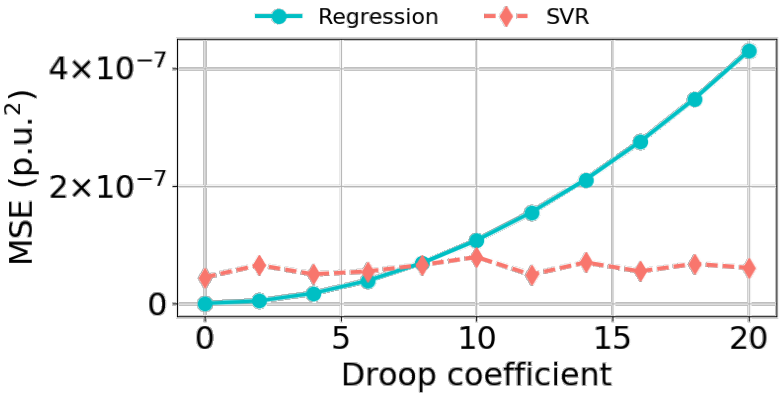


SVR: constantly better than learning (nominal) physical parameters

Test on Model Generality: Unknown Controller



Droop controller of reactive power injections for voltage regulation



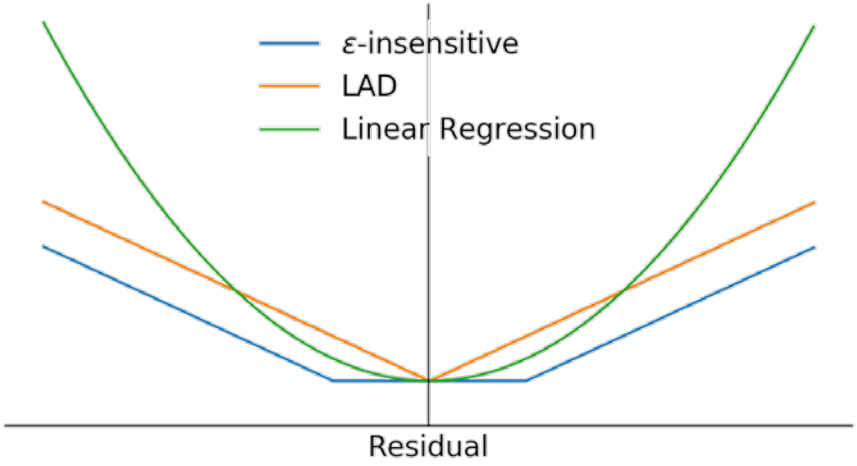
SVR: robust up to 20 droop coefficient while physical model fails to reveal the truth

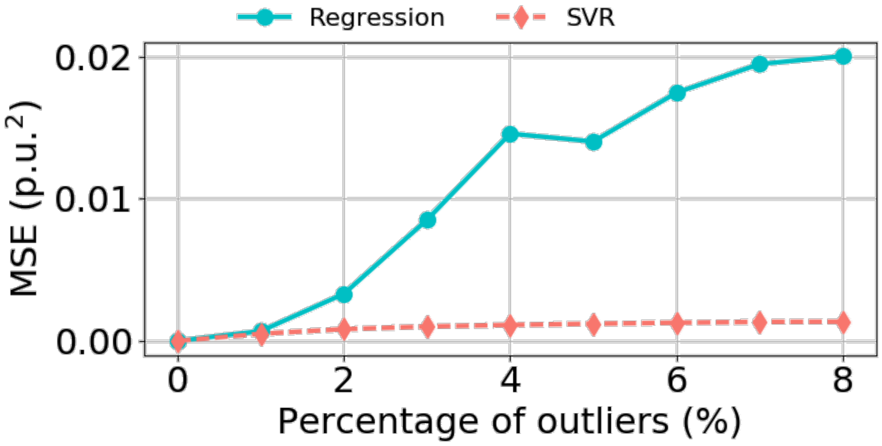
Test on Robustness Against Outliers

$$\underset{\beta,\xi,\xi^{\star},b}{\text{minimize}} \quad \frac{1}{2}\|\beta\|^2 + \boxed{C\sum_{\tau=1}^{T}\left(\xi_t + \xi_t^{\star}\right)}$$

Cost function of fitting error:

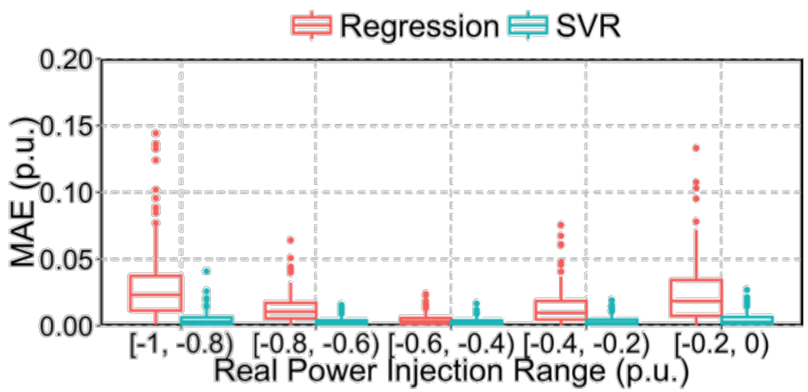
- Asymptotic linear
- Insensitive to outliers



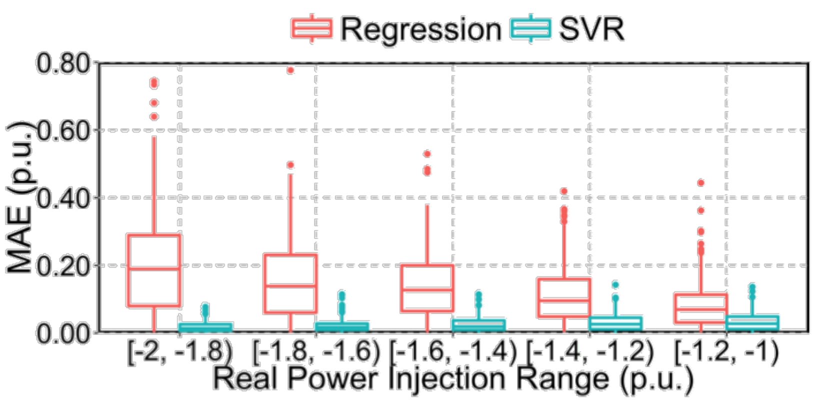


Test on Model Extrapolation

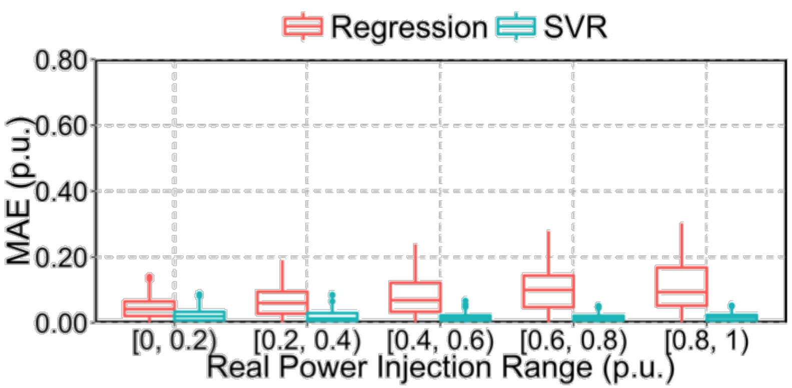
No DER, training and testing data in same range



Testing data with high demands.



Testing data with deep DER penetration.



Test on Model Extrapolation

TABLE I: Benchmark of forward mapping

Test Case	RMSE (p.u.)			Time Cost (s)		
	SVR	Reg	Ave	SVR	Reg	Ave
8-Bus	0.023	0.060	0.058	14.5	0.0010	0.0003
16-Bus	0.030	0.060	0.058	13.1	0.0011.8	0.0003
32-Bus	0.031	0.060	0.057	13.3	0.0054	0.0007
64-Bus	0.035	0.59	0.058	14.1	0.010	0.0004
96-Bus	0.040	0.060	0.057	14.0	0.092	0.0005
123-Bus	0.055	0.061	0.060	15.0	0.15	0.0005
123-Bus w/ loop	0.050	0.062	0.058	15.0	0.09	0.0006

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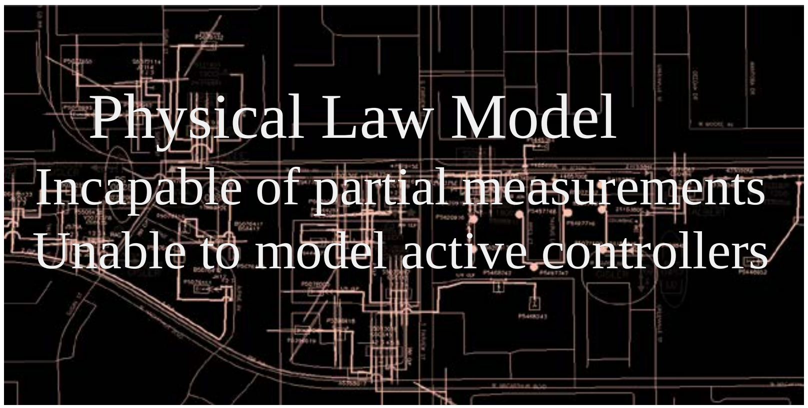
3-Phase Power Flow in Distribution Grids

- Balanced system
  - 1-phase model → A good approximate for 3-phase system [1, 2, 3]

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

[6] Abur, Ali, and Antonio Gomez Exposito. Power system state estimation: theory and implementation. CRC press, 2004.
[7] Crow, Mariesa L. *Computational methods for electric power systems*. Crc Press, 2015.
[8] Glover, J. Duncan, Mulukutla S. Sarma, and Thomas Overbye. Power System Analysis & Design, SI Version. Cengage Learning, 2012.

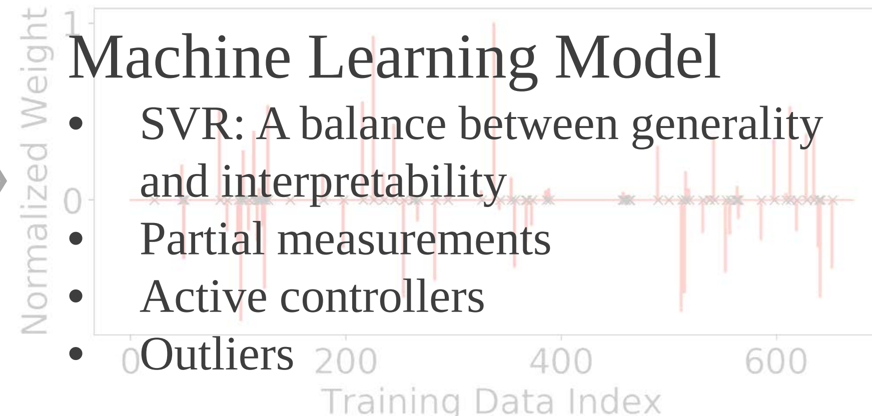
Conclusions and Future Work



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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